



*journalism
and media*

Special Issue Reprint

Journalism, Media, and Artificial Intelligence

Let Us Define the Journey

Edited by
Rashid Mehmood and João Canavilhas

mdpi.com/journal/journalmedia



Journalism, Media, and Artificial Intelligence: Let Us Define the Journey

Journalism, Media, and Artificial Intelligence: Let Us Define the Journey

Guest Editors

Rashid Mehmood

João Canavilhas



Basel • Beijing • Wuhan • Barcelona • Belgrade • Novi Sad • Cluj • Manchester

Guest Editors

Rashid Mehmood

Faculty of Computer and

Information Systems

Islamic University of Madinah

Madinah

Saudi Arabia

João Canavilhas

Department of Communication,

Philosophy and Politics

University of Beira Interior

Covilhã

Portugal

Editorial Office

MDPI AG

Grosspeteranlage 5

4052 Basel, Switzerland

This is a reprint of the Special Issue, published open access by the journal *Journalism and Media* (ISSN 2673-5172), freely accessible at: https://www.mdpi.com/journal/journalmedia/special_issues/BO96C746U3.

For citation purposes, cite each article independently as indicated on the article page online and as indicated below:

Lastname, Firstname, Firstname Lastname, and Firstname Lastname. Article Title. *Journal Name* **Year**, Volume Number, Page Range.

ISBN 978-3-7258-4843-0 (Hbk)

ISBN 978-3-7258-4844-7 (PDF)

<https://doi.org/10.3390/books978-3-7258-4844-7>

© 2025 by the authors. Articles in this book are Open Access and distributed under the Creative Commons Attribution (CC BY) license. The book as a whole is distributed by MDPI under the terms and conditions of the Creative Commons Attribution-NonCommercial-NoDerivs (CC BY-NC-ND) license (<https://creativecommons.org/licenses/by-nc-nd/4.0/>).

Contents

About the Editors	vii
Preface	ix
Rashid Mehmood	
Journalism, Media, and Artificial Intelligence: Let Us Define the Journey Reprinted from: <i>Journal. Media</i> 2025, 6, 122, https://doi.org/10.3390/journalmedia6030122	1
Iban Albizu-Rivas, Sonia Parratt-Fernández and Montse Mera-Fernández	
Artificial Intelligence in Slow Journalism: Journalists' Uses, Perceptions, and Attitudes Reprinted from: <i>Journal. Media</i> 2024, 5, 1836–1850, https://doi.org/10.3390/journalmedia5040111	12
Vasile Gherheș, Marcela Alina Fărcașiu and Mariana Cernicova-Buca	
Are ChatGPT-Generated Headlines Better Attention Grabbers than Human-Authored Ones? An Assessment of Salient Features Driving Engagement with Online Media Reprinted from: <i>Journal. Media</i> 2024, 5, 1817–1835, https://doi.org/10.3390/journalmedia5040110	27
Mahmoud Sayed Mohamed Ali, Khaled Zaki AbuElkhair Wasel and Amr Mohamed Mahmoud Abdelhamid	
Generative AI and Media Content Creation: Investigating the Factors Shaping User Acceptance in the Arab Gulf States Reprinted from: <i>Journal. Media</i> 2024, 5, 1624–1645, https://doi.org/10.3390/journalmedia5040101	46
Saud Binlibdah	
Investigating the Role of Artificial Intelligence to Measure Consumer Efficiency: The Use of Strategic Communication and Personalized Media Content Reprinted from: <i>Journal. Media</i> 2024, 5, 1142–1161, https://doi.org/10.3390/journalmedia5030073	68
Moisés Costa Pinto and Suzana Oliveira Barbosa	
Artificial Intelligence (AI) in Brazilian Digital Journalism: Historical Context and Innovative Processes Reprinted from: <i>Journal. Media</i> 2024, 5, 325–341, https://doi.org/10.3390/journalmedia5010022	88
Fátima C. Carrilho Santos	
Artificial Intelligence in Automated Detection of Disinformation: A Thematic Analysis Reprinted from: <i>Journal. Media</i> 2023, 4, 679–687, https://doi.org/10.3390/journalmedia4020043	105
Abeer Abdullah Alaqf, Fahad AlQurashi and Rashid Mehmood	
Data-Driven Deep Journalism to Discover Age Dynamics in Multi-Generational Labour Markets from LinkedIn Media Reprinted from: <i>Journal. Media</i> 2023, 4, 120–145, https://doi.org/10.3390/journalmedia4010010	114

Pilar Sánchez-García, Alba Díez-Gracia, Ignacio Repilado Mayorga and Pedro Jerónimo Media Self-Regulation in the Use of AI: Limitation of Multimodal Generative Content and Ethical Commitments to Transparency and Verification Reprinted from: <i>Journal. Media</i> 2025, 6, 29, https://doi.org/10.3390/journalmedia6010029	140
Yi Shi and Lin Sun How Generative AI Is Transforming Journalism: Development, Application and Ethic Reprinted from: <i>Journal. Media</i> 2024, 5, 582–594, https://doi.org/10.3390/journalmedia5020039	159
Angelica Lermann Henestrosa and Joachim Kimmerle The Effects of Assumed AI vs. Human Authorship on the Perception of a GPT-Generated Text Reprinted from: <i>Journal. Media</i> 2024, 5, 1085–1097, https://doi.org/10.3390/journalmedia5030069	172
Steffen Heim and Sylvia Chan-Olmsted Consumer Trust in AI–Human News Collaborative Continuum: Preferences and Influencing Factors by News Production Phases Reprinted from: <i>Journal. Media</i> 2023, 4, 946–965, https://doi.org/10.3390/journalmedia4030061	185
Cristian González-Arias and Xosé López-García Rethinking the Relation between Media and Their Audience: The Discursive Construction of the Risk of Artificial Intelligence in the Press of Belgium, France, Portugal, and Spain Reprinted from: <i>Journal. Media</i> 2024, 5, 1023–1037, https://doi.org/10.3390/journalmedia5030065	205
Fabia Ioscote, Adriana Gonçalves and Claudia Quadros Artificial Intelligence in Journalism: A Ten-Year Retrospective of Scientific Articles (2014–2023) Reprinted from: <i>Journal. Media</i> 2024, 5, 873–891, https://doi.org/10.3390/journalmedia5030056	220
Alem Febri Sonni, Vinanda Cinta Cendekia Putri and Irwanto Irwanto Bibliometric and Content Analysis of the Scientific Work on Artificial Intelligence in Journalism Reprinted from: <i>Journal. Media</i> 2024, 5, 787–798, https://doi.org/10.3390/journalmedia5020051	239
Paulo Nuno Vicente and Catarina Duff Burnay Recommender Systems and Over-the-Top Services: A Systematic Review Study (2010–2022) Reprinted from: <i>Journal. Media</i> 2024, 5, 1259–1278, https://doi.org/10.3390/journalmedia5030080	251

About the Editors

Rashid Mehmood

Rashid Mehmood is a Professor of High-Performance Data Analytics (HPDA) at the Islamic University of Madinah, Saudi Arabia, and directs the Centre for Technology Governance. He holds academic qualifications and professional experience from prestigious institutions, including the University of Cambridge and the University of Oxford. With nearly three decades of expertise in computational modeling, simulations, and design, Rashid specializes in leveraging artificial intelligence, big data, high-performance computing (HPC), and distributed systems, with applications in smart cities and its various sectors. His interdisciplinary research aims to advance science and technology to improve quality of life and drive a smart economy, focusing on real-time intelligence and autonomous system management. Rashid has an extensive publication record, with over 250 research papers and 11 edited books, and he has organized and chaired numerous international conferences and workshops across diverse fields such as vehicular communication, healthcare, transportation, smart cities and societies, and HPC. He has led and contributed to academia–industry collaborative projects with a combined funding value exceeding GBP 50 million, supported by organizations including EPSRC, the European Union, UK regional funds, the Technology Strategy Board UK, and institutions in Saudi Arabia.

João Canavilhas

João Canavilhas is a full professor at the Universidade da Beira Interior (Covilhã, Portugal) and a member of the board and researcher at LABCOM, a Communication Sciences Lab. He is the author or co-author of more than 100 scientific works, including books, book chapters, and papers in national and international publications. His research work focuses on various aspects of communication sciences and new technologies, particularly the links between journalism and the Internet, portable devices, and artificial intelligence. He is an invited researcher in international research groups and a project consultant/evaluator in Portugal, Spain, Brazil, and in the programme Creative Europe (Media). From 2013 and 2021, he was vice-rector for Teaching and Internationalization at the University of Beira Interior.

Preface

This volume brings together the fifteen contributions published in the Special Issue “Journalism, Media, and Artificial Intelligence: Let Us Define the Journey”, along with the editorial. The collection explores the evolving relationship between journalism and artificial intelligence, addressing topics such as AI-assisted content production, data-driven investigative reporting, governance and ethics, audience trust, and the wider scholarly discourse surrounding AI’s role in the media.

The contributions included in this volume represent the work of 36 authors from 12 countries, highlighting the international and interdisciplinary scope of current research in this area. Together, they provide a broad and timely view of how AI is reshaping journalism in both theory and practice, from editorial decision-making to technological implementation.

We would like to thank all the authors whose work is featured in this volume, as well as the reviewers who offered thoughtful and constructive feedback during the peer review process. We are grateful to the MDPI Journalism and Media journal staff, particularly Ivana Vuleta, Managing Editor, for her professionalism, responsiveness, and continuous support throughout the editorial process.

We hope that this collection will serve as a valuable resource and reference point for scholars, practitioners, and students exploring the intersection of journalism, media, and artificial intelligence. Looking ahead, we view this volume not as a conclusion, but as a step in an ongoing journey. The title of the Special Issue was both an invitation and a shared commitment to shaping the future of journalism in the age of AI. We hope the ideas and insights gathered here will continue to spark dialogue, guide innovation, and inspire future research and collaboration.

Rashid Mehmood and João Canavilhas

Guest Editors

Journalism, Media, and Artificial Intelligence: Let Us Define the Journey

Rashid Mehmood

Faculty of Computer and Information Systems, Islamic University of Madinah, Madinah 42351, Saudi Arabia;
r.mehmood@gmail.com or r.mehmood@iu.edu.sa

This editorial introduces the Special Issue “Journalism, Media, and Artificial Intelligence: Let Us Define the Journey,” which explores the evolving relationship between journalism and artificial intelligence (AI). This issue collates fifteen peer-reviewed contributions from 36 authors spanning 12 countries, collectively examining AI’s role in content production, investigative reporting, ethical governance, audience perception, and scholarly reflection. A parameter-based framework is used to classify each contribution under one of five core themes so as to organize this diverse collection of work, while also recognizing their cross-cutting relevance. This editorial synthesizes key insights, identifies emerging trends, and proposes a conceptual framework to guide future research. It highlights the challenges and opportunities posed by AI, particularly in relation to trust, transparency, accountability, and professional responsibility. This collection of research aims to support a more informed, inclusive, and critically grounded understanding of AI’s role in shaping the future of journalism.

1. Introduction

We live in an information age, yet, ironically, achieving the core function of journalism—i.e., to provide people with access to unbiased, accurate, and trustworthy information—has never been more difficult. The late 20th-century critique by Herman and Chomsky, articulated in their propaganda model (Herman & Chomsky, 1988), remains alarmingly relevant: the structural inequalities of wealth and power continue to shape what news is produced, how it is framed, and what ultimately reaches the public. These dynamics are exacerbated by contemporary phenomena such as partisanship, misinformation, platform-driven content cycles, and algorithmic opacity.

As UN Secretary-General António Guterres noted, “at a time when disinformation and mistrust of the news media are growing, a free press is essential for peace, justice, sustainable development, and human rights” (UN News, 2019). Yet, despite its foundational role in democratic societies, journalism today struggles to meet these expectations, challenged by financial pressures, weakened editorial independence, and increasing technological disruptions.

This Special Issue, titled “Journalism, Media, and Artificial Intelligence: Let Us Define the Journey”, was created in response to these deep-rooted concerns. Through it, we asked the following questions: What role can artificial intelligence (AI) play in building the next generation of journalism? How can AI be used, responsibly and effectively, across the journalism lifecycle, from news gathering and production to editorial curation and audience engagement?

In the call for papers for this Special Issue, we emphasized the transformative potential of AI-powered and data-driven methods (Beckett, 2019; Canavilhas, 2022), such as those

under the umbrella of deep journalism (Ahmad et al., 2022; Mehmood, 2022). These approaches promise not only scalable information discovery but also multi-perspective, cross-sectional, and impartial reporting that challenges bias and makes rigorous insights accessible to all.

We received 29 submissions to this Special Issue, of which 15 were accepted for publication following peer review. These contributions represent 36 authors from 12 countries, reflecting the global and interdisciplinary nature of this Special Issue. The papers cover a rich diversity of geographies, disciplines, and research methods, encompassing both empirical studies and critical reviews. To meaningfully analyze these contributions and reflect on the collective journey they chart, we have organized them into the following five core thematic parameters:

1. AI in Journalistic Content Production;
2. AI for Investigative and Data-Driven Journalism;
3. Ethical and Governance Frameworks;
4. Audience Trust, Perception, and Human–AI Collaboration;
5. Scholarly Reviews, Meta-Analysis, and Risk Discourse.

We use the term parameter to refer to a thematically cohesive construct that synthesizes fragmented research around a shared conceptual or functional concern. These parameters serve not only to organize the discussion but also to act as design elements for identifying, aligning, and evolving the key dimensions of AI integration into journalism. Each parameter reflects a dynamic area of transformation, enabling us to trace the applications, challenges, and directions across both research and practice.

Each paper is assigned to one primary parameter, where it is discussed in detail. Some papers also engage with other parameters. These are identified as secondary papers and will be briefly noted within the relevant sections to highlight their cross-cutting relevance; however, they are only fully discussed in the section focused on the parameter to which they hold primary membership. This two-tiered classification allows us to balance thematic clarity with intellectual depth and avoid duplication, while also recognizing the interdisciplinary nature of this field. Together, the fifteen papers in this Special Issue form a timely and insightful body of work that helps us to define and interrogate the evolving relationship between journalism, media, and artificial intelligence.

To provide a structured view of this Special Issue's contributions, we have developed a taxonomy that maps all fifteen papers to the five core parameters (see Figure 1). Each paper is placed under its primary thematic focus using short, general titles that aid comprehension and highlight the article's central contribution. These titles are deliberately broad to point to the wider domains where future research and development can evolve, while still remaining specific enough to reflect the content of each paper. This visual structure offers readers a clear overview of the Special Issue's scope and thematic distribution, and the diversity of the methodological and conceptual insights presented.

In the sections that follow, we examine each of these thematic parameters, highlighting how they individually and collectively shape the evolving relationship between journalism and artificial intelligence. This is followed by a synthesis of their cross-cutting insights, the introduction of a conceptual framework for future research, and concluding reflections on the journey defined by this Special Issue.

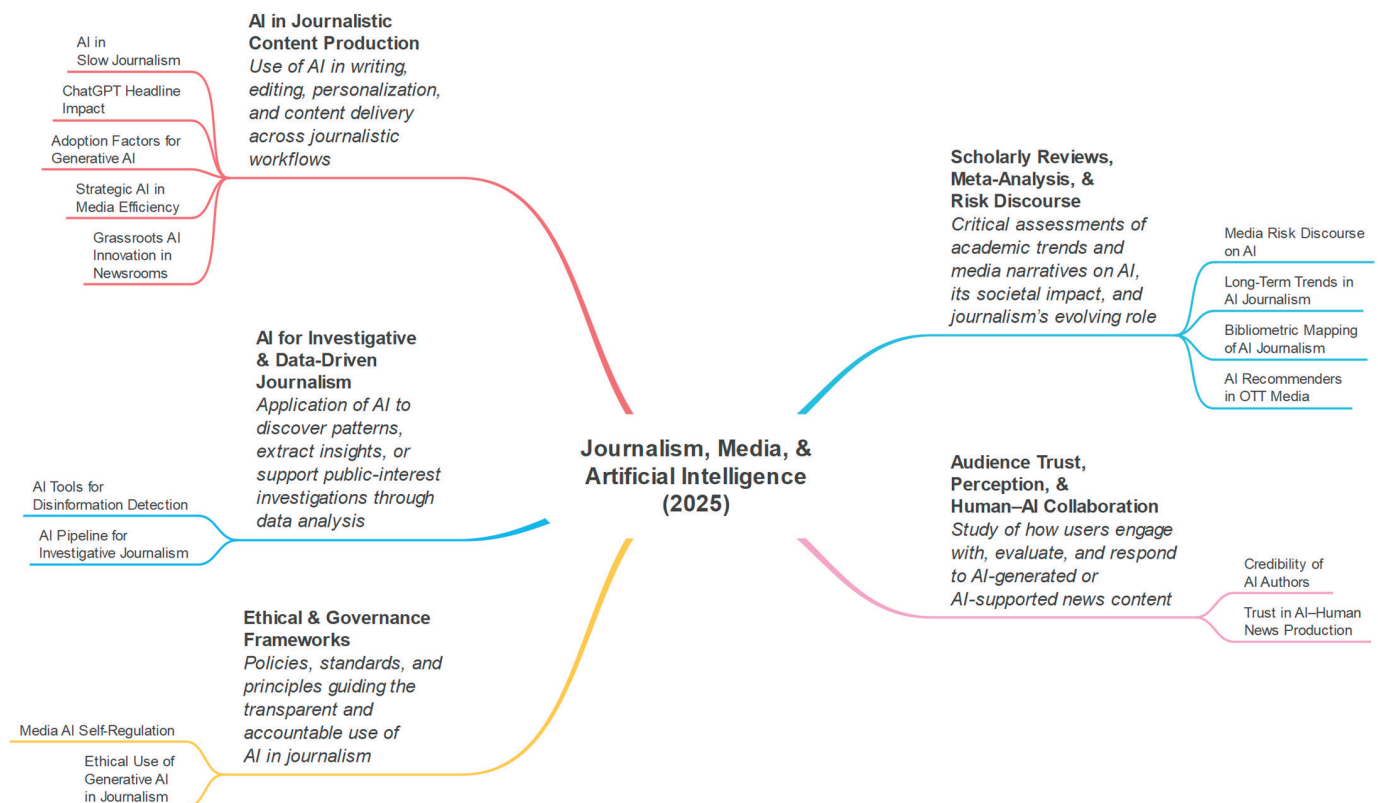


Figure 1. Taxonomy of journalism, media, and AI, as seen through the lens of this Special Issue's contributions organized by five core parameters.

2. AI in Journalistic Content Production

One of the areas where AI's introduction into journalism is most visible is in content production. This includes writing, editing, headline generation, content personalization, and the optimization of media workflows. The five primary contributions under this parameter illustrate how AI is being introduced into the foundational tasks of media creation, both in large organizations and in resource-constrained environments.

Albizu-Rivas et al. (2024) investigate the application of AI among Spanish slow journalism practitioners. Based on interview data, their study finds that current usage of AI tools is minimal, though participants express cautious interest in learning more about them. Concerns are raised around ethical boundaries and job security, and the authors emphasize that quality, creativity, and emotional value are still firmly rooted in human authorship.

Gherheş et al. (2024) compare ChatGPT-generated and human-authored headlines in the context of Romanian media. Survey results show that the majority of respondents were more attracted to the AI-generated headlines, despite expressing distrust of clickbait styles in principle. This study highlights the effectiveness of AI in creating content that attracts engagement, while also raising its ethical implications.

Ali et al. (2024) examine the behavioural factors influencing the adoption of generative AI tools for media content creation in the Arab Gulf region. Using a model based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and data from nearly 500 users, they find that hedonic motivation, trust, and habit are among the strongest predictors of an individual's intention to use such tools. Their study points to growing familiarity with and interest in AI-supported content workflows.

Binlibdah (2024) presents a study on AI use in strategic communication among Saudi social marketing firms. The findings show that AI acts as a mediator between strategic inputs and personalized media content, improving service efficiency. Although the context

is commercial rather than journalistic, the application of AI to enhance content delivery and audience engagement aligns with the broader transformations in media production which are occurring.

Pinto and Barbosa (2024) document the integration of AI into Brazilian digital journalism. Their analysis shows that small- and medium-sized newsrooms are increasingly using bots and open-source tools to support content creation. These efforts are often developed independently of large institutional infrastructures and offer an alternative model of AI-driven media innovation.

Three other papers make secondary contributions to this parameter. Sánchez-García et al. (2025) discuss editorial self-regulation and the importance of setting boundaries for generative AI in content production. Alaql et al. (2023), while primarily focused on data-driven journalism, develop a machine learning pipeline that can assist in the discovery of newsworthy themes, which has implications for content creation. Vicente and Burnay (2024) analyze recommender systems in the OTT context and touch on the automation of content distribution, a topic which connects to AI-assisted content delivery workflows.

Together, these studies reflect the growing use of AI to support or augment media production. While the motivations, tools, and levels of adoption differ across settings, the central observation remains: AI is becoming a component of journalistic practice in ways that challenge traditional workflows, professional identities, and notions of authorship.

3. AI for Investigative and Data-Driven Journalism

Investigative journalism often seeks to uncover patterns, behaviours, or irregularities that are not immediately visible to the public. The papers in this parameter demonstrate how artificial intelligence can be used to support such efforts by processing large-scale data, extracting insights, and enhancing journalists' capacity to inform the public on complex societal issues.

Santos (2023) conducts a thematic analysis of how AI technologies are being applied in the detection of disinformation, identifying core strategies such as fact-checking, sentiment analysis, and hybrid systems involving human oversight. While being focused on disinformation detection tools, the paper also directly addresses the infrastructure required for investigative work in the digital age and contributes to discussions on transparency, credibility, and scalable content verification.

Alaql et al. (2023) present a machine learning pipeline developed to extract and analyze labour market trends from LinkedIn posts. Their approach classifies data into generational, industrial, and employment-related categories using parameter modelling. By designing a software tool to generate these insights from user-generated media, the paper demonstrates how AI can be embedded into the process of investigative journalism, enabling more structured, holistic, and multi-perspective reporting.

In addition to these primary papers, Pinto and Barbosa (2024) provide relevant secondary insights. Although their study is focused on Brazilian digital journalism broadly, they note how open-source AI tools are being used for data mining and pattern recognition, particularly in contexts where investigative capacity is limited by financial or institutional constraints. Their work highlights how lightweight AI systems are increasing the accessibility of investigative functions.

These papers collectively show that AI is not only an asset for routine reporting, but also a means to pursue deeper, evidence-based stories. By automating elements of data collection, classification, and verification, AI is positioned to expand the investigative capabilities of journalists, especially in circumstances where human resources are limited or time constraints are severe.

4. Ethical and Governance Frameworks

As artificial intelligence becomes more integrated into journalism, questions around ethics, regulation, and accountability become increasingly urgent. This parameter examines how media institutions, scholars, and practitioners are responding to these challenges through the frameworks of transparency, self-regulation, and professional responsibility.

Sánchez-García et al. (2025) analyze a collection of editorial stylebooks and internal AI guidelines from 45 journalistic organizations. Their findings show that media institutions are actively crafting rules to limit the use of generative AI in content creation, emphasizing human oversight, verification, respect for copyright, and a commitment to transparency. This paper is a valuable contribution to understanding how internal governance is emerging from within the industry.

Shi and Sun (2024) review the development and application of generative AI in journalism and explore its ethical implications. They argue that while generative AI tools offer substantial opportunities, they also raise concerns related to professional integrity and epistemic responsibility. The authors propose that journalists, media organizations, and audiences must share the responsibility of ensuring that these technologies are deployed in a manner consistent with journalistic values.

Several other papers make secondary contributions to this parameter. Lermann Henestrosa and Kimmerle (2024) study how readers perceive the credibility of articles labelled as AI- or human-authored. Their findings reveal a drop in perceived trust and intelligence when content is presented as AI-generated, suggesting that transparency in authorship has ethical implications for reader engagement. González-Arias and López-García (2024), while primarily focused on discourse, examine how national press systems construct the risks associated with AI, often basing this on professional norms and institutional expectations.

Ioscote et al. (2024) and Sonni et al. (2024) both conduct meta-level studies of AI in journalism and identify ethical concerns as a recurring research theme. Their work shows that questions of professional responsibility, algorithmic fairness, and regulatory standards are gaining visibility in the scholarly discourse on this topic. These contributions strengthen the argument that ethical governance must be integral to both journalism in practice and relevant research.

Together, the papers in this parameter highlight that governance in AI journalism is no longer a future concern; it is already being shaped by internal media practices, public perception, and academic critique. Addressing this dimension is essential if AI is to enhance rather than undermine journalism's role in democratic societies.

5. Audience Trust, Perceptions, and Human–AI Collaborations

The public's perception of AI-generated content and their willingness to trust or engage with it play a central role in shaping the future of journalism. This parameter focuses on how audiences respond to AI involvement in news production and what levels of automation they find acceptable across the different phases of journalism.

Lermann Henestrosa and Kimmerle (2024) conduct an experiment to test how readers evaluate a science article when it is labelled as being AI-authored versus human-authored. Although the content is identical in both cases, the AI-labelled version is consistently perceived as less credible, less intelligent, and less human. This study reveals the cognitive and emotional barriers that audiences may experience when interacting with AI-mediated journalism.

Heim and Chan-Olmsted (2023) analyze consumer preferences across various stages of news production, from information gathering to editing. Their structural equation modelling suggests that audiences generally prefer lower levels of AI integration. However, if human editorial control is maintained, trust and usage intentions can remain stable or

even improve. These findings suggest that transparency, clear role division, and human oversight remain critical for audience acceptance of AI.

Other contributions offer secondary insights into this parameter. Gherheş et al. (2024) demonstrate that although users claim to reject clickbait, they are more likely to select AI-generated headlines that mimic such features as being preferable. This dissonance between stated preferences and actual behaviour points to a more complex landscape of trust and engagement. Ali et al. (2024) report that trust is one of the key factors influencing behavioural intention to use generative AI tools in media creation, emphasizing the role of user perception in AI adoption.

Shi and Sun (2024), while primarily focused on ethics, also highlight the shared responsibility of journalists and audiences in maintaining editorial standards when AI tools are utilized. Their analysis supports the idea that trust is not only a function of content quality, but also of audience awareness, expectations, and perceived legitimacy.

This group of papers underscores that trust is not merely a residual outcome of media content, but a structural condition that must be actively managed. Whether through transparent labelling, human-in-the-loop frameworks, or shared ethical commitments, audience trust remains a decisive factor in the future relationship between journalism and artificial intelligence.

6. Scholarly Reviews, Meta-Analysis, and Risk Discourse

This parameter collates contributions that reflect the circumstances of the broader field of AI and journalism through systematic reviews, bibliometric studies, and discursive analyses. These papers examine how AI is framed by media, how it is being studied in the academic literature, and how risk, ethics, and innovation are being conceptualized across different contexts.

González-Arias and López-García (2024) examine the way AI-related risks are constructed in the press of four European countries. Their study analyses how newspapers in Belgium, France, Portugal, and Spain represent AI's societal impact. Fourteen types of risk and seven voice categories are identified, showing that media portrayals are shaped by national contexts, institutional cultures, and professional norms.

Ioscote et al. (2024) offer a ten-year retrospective study of AI in journalism research, with the scope covering publications from 2014 to 2023. Through a combined bibliometric and content analysis, they find that themes such as automation, ethics, and the future of journalistic labour have gained increasing attention. However, they also identify a gap in research regarding education and training for journalists in AI-related competencies.

Sonni et al. (2024) present a bibliometric and content analysis of 331 Scopus-indexed articles from 2019 to 2023, highlighting major research clusters around fake news, algorithms, and automated journalism. Their paper emphasizes that ethical considerations are frequently mentioned, even in technically oriented work, indicating a shift toward more critical and reflective approaches in journalism studies.

Vicente and Burnay (2024) conduct a systematic review of AI-based recommender systems in over-the-top (OTT) media services. Although their primary focus is not on journalism per se, their analysis of algorithmic mediation in content distribution reveals important challenges related to transparency, personalization, and media diversity. These findings resonate with current debates about AI-driven editorial control in journalism.

In addition to these four primary contributions, several papers offer relevant secondary insights. Sánchez-García et al. (2025) provide a comparative synthesis of internal editorial guidelines, which functions as a quasi-review of self-regulatory practices. Alaql et al. (2023) develop a methodological tool that could support future empirical studies in media analytics. Shi and Sun (2024) engage critically with the broader implications of generative

AI and call for frameworks that integrate philosophical, ethical, and audience-centered considerations.

Together, these contributions provide a panoramic view of how AI is currently being researched, represented, and critiqued in journalism and media. They do not merely summarize the field, but rather shape it by raising new questions about accountability, governance, and the shifting boundaries of journalistic practice in the age of automation.

7. Synthesis and Reflections

The fifteen papers in this Special Issue collectively map the broad and evolving landscape at the intersection of journalism, media, and artificial intelligence. They show that AI is no longer a marginal or speculative addition to journalism, but an active agent reshaping editorial workflows, audience engagement, investigative capacity, and institutional norms. Across the five thematic parameters, several cross-cutting insights emerge.

First, ethical and governance concerns are not confined to dedicated policy discussions. Even in studies primarily focused on content production, audience behaviour, or technical innovation, questions of transparency, authorship, and editorial control repeatedly surface. This is evident in the analyses of institutional self-regulation (Sánchez-García et al., 2025), generative AI ethics (Shi & Sun, 2024), AI authorship perceptions (Lermann Henestrosa & Kimmerle, 2024), and even headline design (Gherheş et al., 2024). These works reflect an underlying consensus that innovation in journalism must remain anchored to professional values, even as tools evolve.

Second, trust and audience perceptions are central to the uptake and success of AI in journalism. The findings from multiple studies indicate that readers react differently based on how AI involvement is disclosed (Lermann Henestrosa & Kimmerle, 2024), and that the perceived credibility of content changes when the authorship is attributed to machines (Heim & Chan-Olmsted, 2023). Whether trust is reduced by the label of machine authorship (Lermann Henestrosa & Kimmerle, 2024), or maintained when it is known that humans are in control (Heim & Chan-Olmsted, 2023), the social contract between journalists and audiences is being renegotiated in real time. These responses underscore the need for transparency, meaningful human oversight, and shared ethical frameworks (Shi & Sun, 2024).

Third, the adoption of AI appears to occur through a variety of pathways. In some cases, innovation is led by major media organizations formalizing internal policies and workflows (Sánchez-García et al., 2025). In others, grassroots or small-scale initiatives use open-source tools to experiment with AI-driven reporting (Pinto & Barbosa, 2024). The divergence in adoption patterns is also visible in the regional studies presented from the Arab Gulf (Ali et al., 2024), Brazil (Pinto & Barbosa, 2024), and Spain (Albizu-Rivas et al., 2024); these cases highlight the importance of local context and institutional capacity in shaping how AI is used and what kinds of journalism it enables or displaces.

Fourth, there is a growing effort to critically assess the state of the field of AI in journalism itself. Bibliometric reviews (Ioscote et al., 2024; Sonni et al., 2024), discourse studies (González-Arias & López-García, 2024), and systematic reflections (Vicente & Burnay, 2024) contribute to a more grounded understanding of the academic landscape. These studies suggest that while research on AI in journalism has expanded significantly, there remain gaps in education, interdisciplinary collaboration, and geographic representation.

Finally, the use of AI for investigative purposes points to a promising future for deep journalism. By automating aspects of the discovery process and enabling new forms of data analysis, AI can help to highlight issues that were previously difficult to investigate (Alaql et al., 2023; Santos, 2023). However, realizing this potential will depend on the availability

of ethical, transparent, and user-friendly tools that serve public-interest-related objectives rather than institutional or commercial agendas.

This Special Issue does not claim to offer a complete roadmap. Instead, it presents a set of grounded, situated explorations that help to define the journey ahead. What emerges is not a single trajectory, but rather a pluralistic and dynamic field where questions of ethics, utility, trust, and responsibility must be addressed at every stage of technological integration.

8. A Framework for Future Research

Building on the five parameters and the cross-cutting themes identified in this Special Issue, we outline a conceptual framework that can guide future research at the intersection of journalism, media, and artificial intelligence (see Figure 2). The diversity of the papers published herein does not only reveal multiple areas of inquiry, but also a set of shared concerns that demand a coherent and responsive research agenda. Rather than proposing a fixed model or linear roadmap, we suggest thinking in terms of a dynamic cycle that reflects how journalism and AI interact across different layers of media practice and responsibility.

Guiding Future Research in AI and Journalism

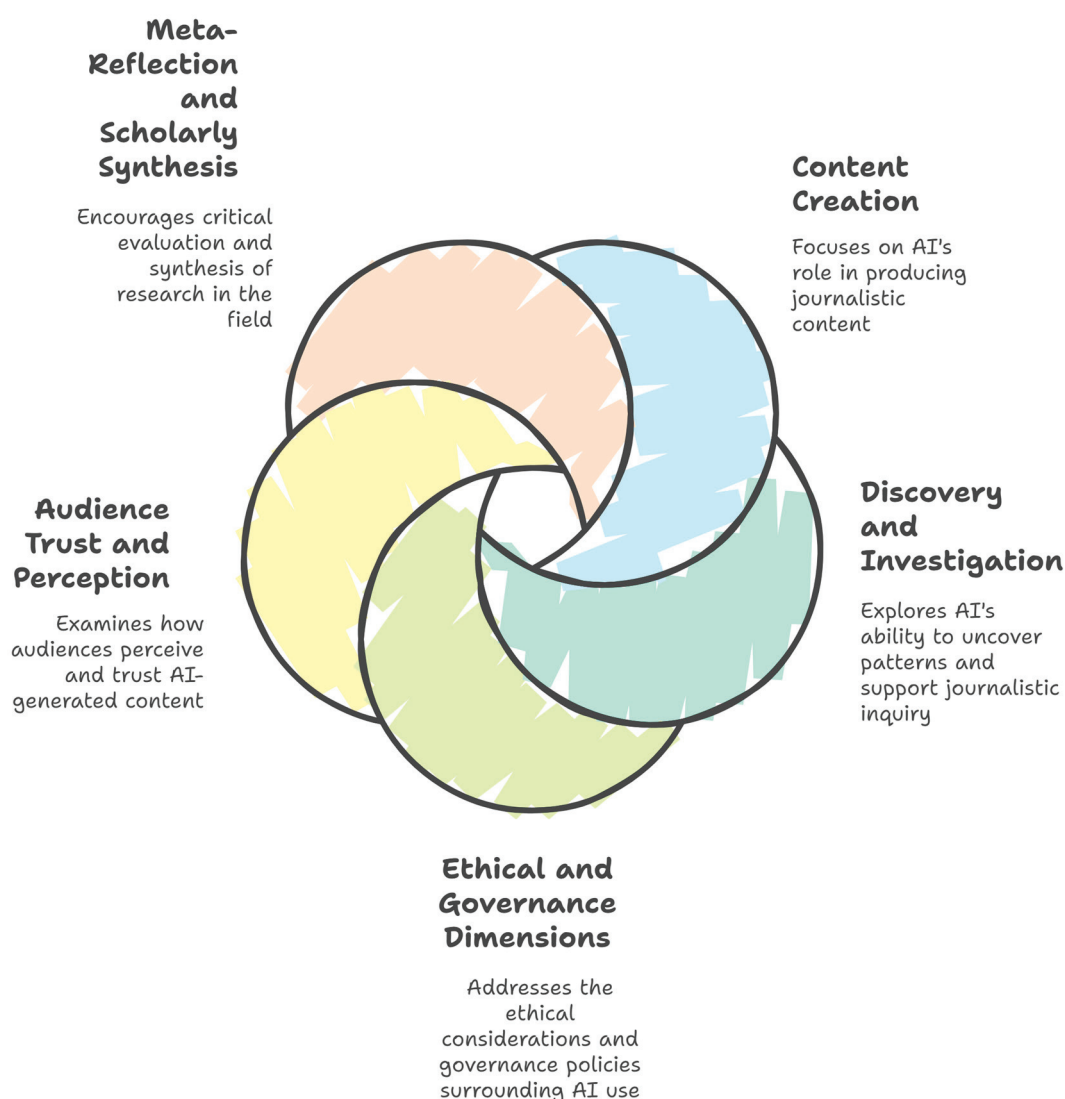


Figure 2. A framework to guide future research in journalism, media, and AI.

At the heart of this framework is the recognition that AI is now embedded across the journalism lifecycle. The papers included in this issue have shown how AI is used in the creation of content through writing tools, in personalization engines, and in workflow automation (Albizu-Rivas et al., 2024; Ali et al., 2024; Binlibdah, 2024; Gherheş et al., 2024; Pinto & Barbosa, 2024). These studies emphasize that the focus of content production is not only output, but also editorial judgement, communicative intent, and audience reception. As such, future research must address both the technological performance of AI systems and the epistemological foundations of the content they help to produce.

Equally important is the role of AI in discovery and investigation. As demonstrated by the studies on disinformation detection and labour market analysis (Alaql et al., 2023; Santos, 2023), AI has the capacity to highlight patterns, classify themes, and support journalistic inquiry into socially relevant issues. Future research in this area should continue to explore how machine learning and natural language processing can enhance the depth and breadth of journalistic investigations, particularly in domains where public data is underused or inaccessible. The challenge lies not only in developing AI's technical capacity, but in ensuring that such tools are usable, interpretable, and aligned with the goals of public-interest journalism.

Ethical and governance dimensions must also remain central in future studies. Papers in this issue have shown that media organizations are beginning to formalize internal policies on AI use (Sánchez-García et al., 2025), and that scholars are articulating normative frameworks for responsible innovation (Shi & Sun, 2024). These efforts should be extended to include comparative studies of regulatory regimes, institutional accountability mechanisms, and the newsroom-level implementation of ethical AI practices. As the influence of generative and algorithmic systems grows, so too does the urgency of embedding ethics and governance into everyday journalistic practices.

Audience trust and perception have emerged as critical variables mediating how AI-generated or AI-assisted content is received (Heim & Chan-Olmsted, 2023; Lermann Henestrosa & Kimmerle, 2024). Several contributions show that users evaluate content differently depending on its presentation, authorship disclosure, and perceived authenticity (Ali et al., 2024; Gherheş et al., 2024; Shi & Sun, 2024). Future research must investigate how trust is built, lost, and potentially restored in environments where automation plays an increasingly visible role. This includes drawing attention toward transparency practices, co-authorship models, and audience expectations across different cultures and media systems.

Finally, continued investment in meta-reflection and scholarly synthesis is required. The bibliometric and discursive studies included in this issue (González-Arias & López-García, 2024; Ioscote et al., 2024; Sonni et al., 2024; Vicente & Burnay, 2024) not only chart the past progress of this field, but also reveal areas of underdevelopment, such as media education, regional disparities, and methodological diversity. Future work should not only track academic output, but critically evaluate the assumptions, vocabularies, and frameworks used to structure research on AI and journalism.

This emerging framework proposes that future research engage with AI in journalism not only as a set of tools or topics, but as a system of responsibilities. These responsibilities span the technical, editorial, institutional, and civic dimensions of journalistic work. A sustainable research agenda must therefore be interdisciplinary, reflexive, and explicitly committed to preserving journalism's democratic and public-serving functions in an increasingly automated world.

9. Conclusions

This Special Issue began with a call to critically examine and proactively shape the evolving relationship between journalism and artificial intelligence. At its core, the call

emphasized the urgent need to improve public access to unbiased information in a media landscape marked by structural inequalities, rapid technological shifts, and growing public distrust. Drawing inspiration from the propaganda model articulated by Herman and Chomsky, and reaffirmed by international voices such as UN Secretary-General António Guterres, we asked how journalism could reclaim its public-serving mission in an increasingly algorithmic environment. The proposed answer lay in exploring AI not simply as a disruptive force, but as a possible enabler of next-generation journalism, a form of journalism that is rigorous, inclusive, data-informed, and transparent.

The fifteen papers included in this issue offer rich, multidimensional responses to this challenge. Across five thematic parameters (AI in content production, AI for investigative journalism, ethical and governance frameworks, audience trust and perception, and scholarly reviews and risk discourse), these contributions collectively chart a field which is in motion. They show that AI is used to write headlines, streamline workflows, detect disinformation, map labour market trends, and personalize content delivery. At the same time, they reveal that journalists, audiences, and institutions are grappling with deep questions about authorship, credibility, professional responsibility, and public trust.

The contributions to this editorial are organized using a two-level classification system. Each paper has been assigned to one primary parameter, where it is discussed in detail, and may also be referenced as a secondary contribution to another parameter where thematically relevant. This structure reflects the inherently interdisciplinary nature of the field, while maintaining clarity and coherence in thematic analysis.

In reflecting on the insights generated across these parameters, we have proposed a conceptual framework for future research, the Journalism–AI Responsibility Cycle, which emphasizes the interdependence of technological innovation, ethical governance, audience engagement, and institutional accountability. This model invites researchers to move beyond narrow application studies and engage with AI in journalism as a system of responsibilities that span creation, investigation, trust, and critical reflection.

The title of this Special Issue, “Let Us Define the Journey”, is not rhetorical. It is a call for a collaborative agenda-setting process, one that recognizes the urgency of the current moment and the opportunity that AI offers to transform journalism not only technologically, but institutionally and ethically. The journey defined in these pages is still unfolding, but the contributions presented herein offer strong foundations and critical guideposts for the path ahead.

Funding: This article is derived from a research grant funded by the Research, Development, and Innovation Authority (RDIA), Kingdom of Saudi Arabia, with grant number 12615-iu-2023-IU-R-2-1-EI.

Conflicts of Interest: The author declares no conflicts of interest.

References

- Ahmad, I., AlQurashi, F., & Mehmood, R. (2022). Potrika: Raw and balanced newspaper datasets in the bangla language with eight topics and five attributes. *arXiv*, arXiv:2210.09389.
- Alaql, A. A., AlQurashi, F., & Mehmood, R. (2023). Data-driven deep journalism to discover age dynamics in multi-generational labour markets from linkedin media. *Journalism and Media*, 4(1), 120–145. [CrossRef]
- Albizu-Rivas, I., Parratt-Fernández, S., & Mera-Fernández, M. (2024). Artificial intelligence in slow journalism: Journalists’ uses, perceptions, and attitudes. *Journalism and Media*, 5(4), 1836–1850. [CrossRef]
- Ali, M. S. M., Wasel, K. Z. A., & Abdelhamid, A. M. M. (2024). Generative AI and media content creation: Investigating the factors shaping user acceptance in the arab gulf states. *Journalism and Media*, 5(4), 1624–1645. [CrossRef]
- Beckett, C. (2019). *New powers, new responsibilities. A global survey of journalism and artificial intelligence*. Polis. Available online: <https://blogs.lse.ac.uk/polis/2019/11/18/new-powers-new-responsibilities/> (accessed on 20 July 2025).
- Binlibdah, S. (2024). Investigating the role of artificial intelligence to measure consumer efficiency: The use of strategic communication and personalized media content. *Journalism and Media*, 5(3), 1142–1161. [CrossRef]

- Canavilhas, J. (2022). Artificial intelligence and journalism: Current situation and expectations in the portuguese sports media. *Journalism and Media*, 3(3), 510–520. [CrossRef]
- Gherheș, V., Fărcașiu, M. A., & Cernicova-Buca, M. (2024). Are ChatGPT-generated headlines better attention grabbers than human-authored ones? An assessment of salient features driving engagement with online media. *Journalism and Media*, 5(4), 1817–1835. [CrossRef]
- González-Arias, C., & López-García, X. (2024). Rethinking the relation between media and their audience: The discursive construction of the risk of artificial intelligence in the press of Belgium, France, Portugal, and Spain. *Journalism and Media*, 5(3), 1023–1037. [CrossRef]
- Heim, S., & Chan-Olmsted, S. (2023). Consumer trust in AI-human news collaborative continuum: Preferences and influencing factors by news production phases. *Journalism and Media*, 4(3), 946–965. [CrossRef]
- Herman, E., & Chomsky, N. (1988). *Manufacturing consent: The political economy of the mass media*. Pantheon Books.
- Ioscote, F., Gonçalves, A., & Quadros, C. (2024). Artificial intelligence in journalism: A ten-year retrospective of scientific articles (2014–2023). *Journalism and Media*, 5(3), 873–891. [CrossRef]
- Lermann Henestrosa, A., & Kimmerle, J. (2024). The effects of assumed AI vs. human authorship on the perception of a GPT-generated text. *Journalism and Media*, 5(3), 1085–1097. [CrossRef]
- Mehmood, R. (2022). ‘Deep journalism’ driven by AI can aid better government. *The Mandarin*. Available online: <https://www.themandarin.com.au/201467-deep-journalism-driven-by-ai-can-aid-better-government/> (accessed on 20 July 2025).
- Pinto, M. C., & Barbosa, S. O. (2024). Artificial Intelligence (AI) in Brazilian digital journalism: Historical context and innovative processes. *Journalism and Media*, 5(1), 325–341. [CrossRef]
- Santos, F. C. C. (2023). Artificial Intelligence in automated detection of disinformation: A thematic analysis. *Journalism and Media*, 4(2), 679–687. [CrossRef]
- Sánchez-García, P., Diez-Gracia, A., Mayorga, I. R., & Jerónimo, P. (2025). Media self-regulation in the use of AI: Limitation of multimodal generative content and ethical commitments to transparency and verification. *Journalism and Media*, 6(1). [CrossRef]
- Shi, Y., & Sun, L. (2024). How Generative AI Is transforming journalism: Development, application and ethics. *Journalism and Media*, 5(2), 582–594. [CrossRef]
- Sonni, A. F., Putri, V. C. C., & Irwanto, I. (2024). Bibliometric and content analysis of the scientific work on artificial intelligence in journalism. *Journalism and Media*, 5(2), 787–798. [CrossRef]
- UN News. (2019). *A free press is ‘cornerstone’ for accountability and ‘speaking truth to power’*: Guterres. Available online: <https://news.un.org/en/story/2019/05/1037741> (accessed on 20 July 2025).
- Vicente, P. N., & Burnay, C. D. (2024). Recommender systems and over-the-top services: A systematic review study (2010–2022). *Journalism and Media*, 5(3), 1259–1278. [CrossRef]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.

Article

Artificial Intelligence in Slow Journalism: Journalists' Uses, Perceptions, and Attitudes

Iban Albizu-Rivas, Sonia Parratt-Fernández * and Montse Mera-Fernández

Department of Journalism and Global Communication, Faculty of Information Sciences, Complutense University of Madrid, 28040 Madrid, Spain; ialbizu@ucm.es (I.A.-R.); mmera@ucm.es (M.M.-F.)

* Correspondence: sonifern@ucm.es

Abstract: Through long-form, creative, high-quality stories, slow journalism seeks to counteract the effects of speed and immediacy in news production and consumption primarily driven by technological advancements. The advantages of artificial intelligence (AI) in journalism include generating and enhancing content, reducing workloads, and consequently giving journalists more time for non-routine and creative tasks. This raises the question of where AI fits into slow journalism. Twenty-one semi-structured interviews were conducted with practitioners of slow journalism in Spain to explore their use, attitudes, and perceptions of AI in their work. The findings indicate that the interviewees make rudimentary use of AI tools, and their attitudes range from a slight lack of interest to a willingness to learn more about them, alongside concerns regarding ethical boundaries and the potential for job losses. They assert that they have a moral and human responsibility when producing stories that AI cannot enhance in terms of quality, creativity, and emotional depth. It can be concluded that AI offers little to 'slow' journalists due to the significant limitations in enhancing long-form reporting. At most, it may enable them to streamline repetitive and non-creative work, thereby allowing the depth required in slow journalism, at least in its current state of development.

Keywords: slow journalism; narrative journalism; in-depth journalism; artificial intelligence; journalists; Spain

1. Introduction

The fast pace at which information is produced and consumed in a constantly changing digital world causes information overload, which in turn leads to continuous updates, fewer sources being consulted, poorly verified facts, and increasingly standardized journalistic narratives (Soliyeva 2024). In response to this, the concept of 'slowness' has gained traction across various media and communication practices in recent years, including slow communication, slow reading, slow blogging, slow television, slow news, and slow media (Craig 2020). Slow journalism, in particular, aims to counteract the effects of speed and immediacy in news production and consumption by using technology and media in a more mindful, critical, and reflective way (Barranquero-Carretero 2023). Ultimately, it takes deeper approaches that result in long-form, creative, good-quality stories (Greenberg 2012).

On the other hand, technological development has seen the rise in artificial intelligence (AI) in the media. From content creation to broadcasting and audience engagement, AI entails a major shift in journalism. It poses challenges, such as a range of ethical issues (Shi and Sun 2024) related to automated news writing, as well as broader societal concerns (Thurman et al. 2017), and potential threats to the profession (Peña-Fernández et al. 2023). Benefits include helping to generate and improve content, reducing workload and, consequently—and presumably—giving journalists more time for non-routine and creative tasks (DalBen and Jurno 2021; Simon 2024). The latter raises the question of where AI fits into slow journalism, a new perspective within the academic output on

journalists' perceptions on AI (e.g., Cools and Diakopoulos 2024; de Haan et al. 2022; DeLara-González et al. 2022; Mayoral-Sánchez et al. 2023; Noain-Sánchez 2022; among others), which is addressed in this study.

1.1. Slow Journalism: Concept and Academic Approach

The US manifesto *Not So Fast*, published in *The Wall Street Journal* in 2009, and the German *Slow Media*, published online in 2010, lay the foundations for slow journalism. These documents were calls against the culture of superficiality and rush in the media and they advocated quality over quantity, diversity of voices, sustainability, transparency and active user participation (Greenberg 2007). Slow journalism is more a promoter of reflection that enhances journalism's core mission in society (Min 2021) than just a term with a set of established characteristics (Le Masurier 2015). It is often known as in-depth and narrative journalism, and it shares similarities with other reform movements that came before it, such as New Journalism, which was an attempt to reconsider what good journalism is using long-form, personal, and narrative styles (Min 2021).

Most of the emerging slow journalism outlets have assumed an 'alternative' journalism role, taking time to investigate more focused issues, and using narrative storytelling (Le Masurier 2015). News magazines and book-length journalism, for instance, "do not only function at different speeds from more daily forms of journalism but they can also claim authority and prestige within the journalistic field because of their slower, more analytical approaches" (Craig 2020, p. 468). Other outlets diversify revenues without relying only on advertising. They adapt formats to each platform and develop communities of readers who identify with their product (Albalad Aiguabella 2018). An example of this is *The Washington Post* launching Deep Reads, a home for immersive and narrative reporting where stories are labelled at the top of the article for readers to easily access them and pieces are accompanied by human-read narration (WashPostPR 2023). In Spain, the newspaper *El Periódico de España* launched a special newsletter, offering more in-depth narrative stories and revealing how they were created with a view to, they claim, achieving higher quality journalism and strengthening links with the audience (Laboratorio de Periodismo 2023).

In academic terms, it was in 2007 that Susan Greenberg, a professor at the University of Roehampton, first adopted the term 'slow journalism'. Founded on 'the end of the middle' concept of marketing, she argued that people obtain basic news cheaply on air and online, whereas in the middle is traditional print journalism. At the other end is slow journalism, which is composed of "essays, features and other non-fiction writing and takes the time to find things out, looks at stories that others miss, and communicates it all with the highest quality" (Greenberg 2007) as well as telling readers where the information comes from and how it was gathered. From then on, the idea of slow journalism began to have a space in scholarly research (Craig 2020; Greenberg 2012; Le Masurier 2015, 2016; Neveu 2016; Rauch 2011; Rosique-Cedillo and Barranquero-Carretero 2015).

Many studies have addressed the effects of speed and use the concept of 'slow' to refer to a way some emerging media outlets are producing journalism and experimenting with new business models (Le Masurier 2016). Journalistic handicaps like haste, lack of sources, simplistic and stereotyped language, and lack of context and time prevent journalists from reflecting on the facts, length to explain the events, depth, and time to elaborate quality narratives (Gómez-Mompart 2021). Hence, some newsroom innovators are pausing to consider what producing good journalism means (Min 2021, p. 89). They conclude that slowness helps journalists respond to the complexities of modern public life (Craig 2020) and fulfil their social function. They stress the need for less 'fast food journalism' and more slow journalism. That is, a more relaxed, elaborated, contrasted, better oral-written-audiovisual and infographically narrated (Gómez-Mompart 2021), and teamwork journalism (Gómez-Mompart 2021; Le Masurier 2016).

There is a growing consensus that only two types of media that move at different speeds will survive in the future. On the one hand, the mass producers of short news. On the other hand, the minority 'alternative' media that focus on delivering hard-earned

information (Boynton 2015; Craig 2020) to an audience that has time and money and values quality, as opposed to fast-moving consumer journalism aimed at massive audiences. Although less common, slow and fast journalism could even co-exist within one publication. *The Guardian's* introduction of in-depth reporting, essays, and profiles under The Long Read section is “an example of a commitment by a major, mainstream news company to cater to different temporalities of news production and consumption” (Craig 2020).

1.2. Intersection of AI and Journalism

Studies have highlighted the efficiency gains that AI can bring to newsrooms as well as the ethical and quality challenges it poses in an evolving media environment (Clerwall 2014; Diakopoulos 2019; Túniz-López et al. 2019; Parratt-Fernández et al. 2021). AI can be used for generating basic news stories, particularly in sectors with structured data, such as finance, sports, and weather; and to assist with journalistic tasks like research, selection, verification, composition, finding connections in large datasets, and the presentation and distribution of news (Graefe 2016; Simon 2024; Thurman 2019). News executives and managers underscore the use of AI for back-end automation tasks (56%) such as transcription and copyediting as a top priority, followed by recommender systems (37%), content creation (28%) with human oversight, and commercial uses (27%) (Newman 2024, p. 27). However, the positive side of these applications is not so clear among editors, who remain wary of the potential job losses to which the implementation of AI in media outlets could lead (Mayoral-Sánchez et al. 2023).

In fact, the fear of job cuts is pointed out as the main reason for rejection of AI among practitioners across the world (Beckett 2019), who also express a desire to retain control at all stages of news production (Wu et al. 2019). AI can reduce the time journalists spend on repetitive tasks—such as fact-checking and data analysis—and they will have more time to spend on work that cannot be automated (DalBen and Jurno 2021; Wu et al. 2019; Young and Hermida 2014). But it also raises the potential threat of journalists being replaced by AI as it becomes increasingly proficient at tasks once handled by humans (Marconi and Siegman 2017). In the efficiency discussion, there are those who believe that AI will allow journalists to focus on more creative and strategic functions while technology takes care of grunt work. Others are more skeptical, arguing that AI's impact on productivity is likely to be more limited and varies depending on what is being automated (Simon 2024). In the debate on whether to see AI as a competitor or a partner, journalists generally choose the latter (Peña-Fernández et al. 2023), although recent studies have claimed that there are no guarantees that this will remain the case (Simon 2024).

Furthermore, journalists' role has undergone a profound metamorphosis, and they are now expected to be proficient in the use of AI tools in addition to traditional investigative journalism skills. This convergence of abilities results in more hybrid jobs (Deuze and Beckett 2022) and close collaboration between journalists, data scientists, information designers, and computer programmers (De-Lara-González et al. 2022). However, while data streams can offer historical context, static facts, and sentiment analysis, they are unlikely to grasp the full complexity of human expression, which shapes how events are reported or identifies the most crucial angle of a story. As a result, automation might actually heighten the demand for the essential human qualities that define good journalists—news judgment, curiosity, and skepticism (Thurman et al. 2017).

1.3. AI and In-Depth Journalism

As mentioned above, automated content production has mainly been used for algorithm-generated news articles (Dörr 2016), for which interpretation and explanation are not required (Diakopoulos 2019). But many authors argue that AI can now offer benefits for other types of journalism as well. Among them, enabling deeper investigation (Schapals and Porlezza 2020), contributing to add more complexity and meaning to texts (Brennen 2018), and enhancing creativity, listening, and sourcing (Guzman and Lewis 2019). They say it can also generate news stories according to the style of news organizations and even

semantically reframe them for different audiences (Shi and Sun 2024). This could not only increase journalists' productivity, but also improve the quality of news reporting (Shi and Sun 2024), while addressing information issues like overload or loss of credibility (Ali and Hassoun 2019).

Despite the potential benefits, AI still has significant limitations in improving some long-form reporting (Nishal and Diakopoulos 2024). Its ability to contribute to better quality is disputed (Simon 2024) because, according to Gómez-Mompart (2021), the long-term sustainability of quality journalism will depend on those who have creativity and intelligence, among other abilities. AI cannot offer any of this to an audience (Graefe 2016) that particularly values the narrative quality and context of human-written articles. The rise in AI in journalism also entails ethical and professional concerns. One of the most pressing is the potential erosion of journalistic integrity and human touch in news reporting, since AI systems lack the nuanced understanding of context and ethical judgement that journalists bring to their work (Diakopoulos 2019).

It is also questioned whether robots will be able to fully replace journalists (Lindén 2017), considering that journalists' professional craft is not just ordering or adding specific data (Gómez-Mompart 2021) but is a most human endeavor, as is reporting (Anderson 2013). Moreover, some wonder if the efficiencies gained from AI will lead to an expectation that journalists will produce more content. In essence, the point is whether AI will bring an increase in the quality of journalism or simply in its quantity (Simon 2024). Gómez-Mompart (2021) argues for the recovery of the best in-depth journalism, narrative and/or investigative, "relying more on competent humans than AI machines in terms of quality and emotion". Others, such as Graefe (2016), believe that a hybrid approach may be the most effective.

In this context, in this study, the aim is to explore the place of AI in slow journalism in Spain. The following questions are raised:

RQ1. How are journalists using AI in slow journalism?

RQ2. Do journalists see AI as an efficiency gain in the production of slow content, or as a threat to creativity and quality?

RQ3. How do journalists see AI affecting the future of slow journalism?

As for the theoretical basis for this study, according to Ayyad et al. (2023), the technology acceptance model (TAM) has two primary factors that influence users' perceptions and attitudes towards using a technology. Firstly, "perceived ease of use" refers to the degree to which someone believes that using a particular technology would be effortless. Secondly, "perceived usefulness" refers to the degree to which a person believes that using a particular system would improve his or her job performance. In addition, TAM has been theoretically extended to include "job relevance", which refers to an individual's perception of the degree to which the system is applicable to his or her job, and "output quality", which refers to the quality of the result produced by the system.

Additionally, Wu et al. (2019) draw the following three theories of how AI will change the news business: (1) AI replaces journalism, (2) AI swallows journalism, and (3) AI improves journalism. The latter believes that AI tools, such as GPT, will simply make certain journalistic operations more productive, partially automating processes and addressing concerns about accuracy, bias, and plagiarism by emphasizing the final role of the human writer.

2. Materials and Methods

This research is based on the qualitative method. The technique used was the semi-structured interview, specifically interviews with slow journalism practitioners. In line with Guion et al. (2011), the interviews seek to understand phenomena from the point of view of the protagonist, and they are used for collecting data based on opinions, feelings, emotions, and experiences that "need to be explored in depth and in detail rather than simply reported in a word or two" (Denscombe 2010, p. 174). Before identifying the interviewees, a purposive sampling (Krippendorff 1990) of representative slow journalism

publications in Spain was carried out, taking into account the following criteria established by Rosique-Cedillo and Barranquero-Carretero (2015): (a) non-daily reference publications that set their own news agenda independently from mainstream media, prioritizing slow forms of investigative and/or narrative journalism; (b) the average length of their pieces is over 2000 words; (c) they either describe themselves as slow journalism or call for quality journalism amid the dominance of fast culture.

The supplement *El País Semanal*, *Jot Down* quarterly magazine, and the publisher Libros del K. O. were chosen because of their different formats—and speeds—and their well-established reputations. Since 1976, *El País Semanal*, the Sunday supplement of the *El País* newspaper, deals with current affairs, culture, and society in an in-depth way. Its debate generation has made it one of the most prestigious publications in Spain. *Jot Down*, a magazine born in 2011 in digital form before moving to paper, stands out for its timeless, in-depth, analytical and slow, reflective journalistic approach, and for its interviews with well-known personalities (Rosique-Cedillo and Barranquero-Carretero 2015). Its distinctive style, editorial excellence, quality writing and visuals, have turned it into a reference in the Spanish cultural scene with international recognition. As for Libros del K. O., it publishes different literary genres, as well as slow journalism both by renowned and emerging authors and journalists and stands out for its literary quality and careful book design. It supports independent voices and commits to unconventional topics at national and international levels (Libros del K. O. n.d.).

An intentional selection of professionals was then made according to three criteria. Firstly, the journalists with leading positions in the three media mentioned above. Secondly, the periodicity of the publications was considered. Thirdly, the aim was to achieve as much parity as possible. In some cases, after initial contact by email, it was not possible to arrange an interview, and it was necessary to contact another professional. Thus, nine journalists from the supplement *El País Semanal*, five from *Jot Down* magazine and four from the publisher Libros del K. O. were interviewed. Ultimately, a total of 21 respondents—three leaders, three staff editors and fifteen occasional contributors, of whom nine were women and twelve were men—were interviewed (Table 1).

Table 1. Slow journalism professionals interviewed.

No.	Gender	Position	Publication	Code
1	Female	Journalist in leadership position	<i>El País Semanal</i>	L1
2	Male	Journalist in leadership position	<i>Jot Down</i>	L2
3	Male	Journalist in leadership position	Libros del K. O.	L3
4	Female	Staff editor	<i>El País Semanal</i>	S1
5	Female	Staff editor	<i>El País Semanal</i>	S2
6	Male	Staff editor	<i>El País Semanal</i>	S3
7	Male	Occasional contributor	<i>El País Semanal</i>	C1
8	Male	Occasional contributor	<i>El País Semanal</i>	C2
9	Male	Occasional contributor	<i>El País Semanal</i>	C3
10	Female	Occasional contributor	<i>El País Semanal</i>	C4
11	Male	Occasional contributor	<i>El País Semanal</i>	C5
12	Male	Occasional contributor	<i>El País Semanal</i>	C6
13	Male	Occasional contributor	<i>Jot Down</i>	C7
14	Male	Occasional contributor	<i>Jot Down</i>	C8
15	Female	Occasional contributor	<i>Jot Down</i>	C9
16	Female	Occasional contributor	<i>Jot Down</i>	C10
17	Female	Occasional contributor	<i>Jot Down</i>	C11

Table 1. *Cont.*

No.	Gender	Position	Publication	Code
18	Male	Occasional contributor	Libros del K. O.	C12
19	Female	Occasional contributor	Libros del K. O.	C13
20	Female	Occasional contributor	Libros del K. O.	C14
21	Male	Occasional contributor	Libros del K. O.	C15

Conducting semi-structured interviews requires prior elaboration and flexibility, where the sequence and formulation can be adapted to each interviewee (Rubin and Rubin 2011). For this reason, seven dynamic questions (Appendix A) in a friendly language and closer to the interviewees (Kvale 1996) were developed. Some were shared with all participants, while others were adapted to the specificities of each one. The interviewees were asked, among other things, about their use of AI tools, their perceptions about AI in slow journalism, and how AI affects their work. The interviews were conducted between March and July 2024 via the Zoom platform, lasting between 30 min and 4.5 h, in most cases over two days. All interviews were recorded with the consent of the participants and then transcribed using Converterapp software (<https://converter.app/es/>, accessed on 28 November 2024). As for the qualitative data analysis method, the transcripts were manually edited and coded to organize the responses according to thematic patterns.

3. Results

The results are shown below according to the thematic criteria used to analyze the interviews.

3.1. Integration of AI into ‘Slow’ Journalistic Work

Among the 21 slow journalism practitioners interviewed—three journalists with leading positions (L), three staff editors (S), and fifteen contributors (C)—eleven reported that they used AI tools in their work. Leaders—two out of three—and contributors—eight out of fifteen—were the most inclined to integrate AI into their daily tasks. In contrast, only one staff editor did so (Table 2).

Table 2. Slow journalism practitioners who use AI in their work.

Journalists	Use of AI
L1	Yes
L2	No
L3	Yes
S1	No
S2	Yes
S3	No
C1	No
C2	No
C3	Yes
C4	Yes
C5	Yes
C6	Yes
C7	No
C8	No
C9	No

Table 2. Cont.

Journalists	Use of AI
C10	Yes
C11	Yes
C12	Yes
C13	No
C14	Yes
C15	No

Although slightly more than half of respondents said that they frequently used AI in their work, most of them were cautious about the changes brought about by the advent of these tools. In fact, many of the responses contained phrases such as “for the time being” and “up until now”. This caution is also found in the ways they described their use of AI, “People tinker a lot, they try it out, but it isn’t very reliable at the moment” (L1); “I did some tests” (S1); “I just experimented with it” (C6); “I tried several” (C7); “I tried ChatGPT, but it was disappointing” (C9); “I started playing with Midjourney” (C13).

Practitioners’ awareness of the rapid development and adoption of AI technologies supports the idea that the technologies have great potential and, like it or not, they will eventually become part of the daily practice of journalism. For C2, “AI tools will be standardised, and this will benefit journalism, as has happened with many technological developments”. C1, on the other hand, believes that “they’ll end up complementing and benefiting not only basic news writing, but also deep reporting”. C7 has a similar opinion, “Maybe in a few years they’ll improve to the point where they can write good reports, slow journalism and novels”. However, the evidence suggests that the use of AI tools is currently limited to a few very specific tasks and the outcomes do not consistently meet quality standards. For example, eight of the eleven professionals who used AI do so to transcribe interviews, and four to translate texts. Suggesting keywords and headlines, proofreading, and creating illustrations and layout are performed by one out of eleven. The most sophisticated application, the writing of press releases, is a task also performed by just one (Figure 1).

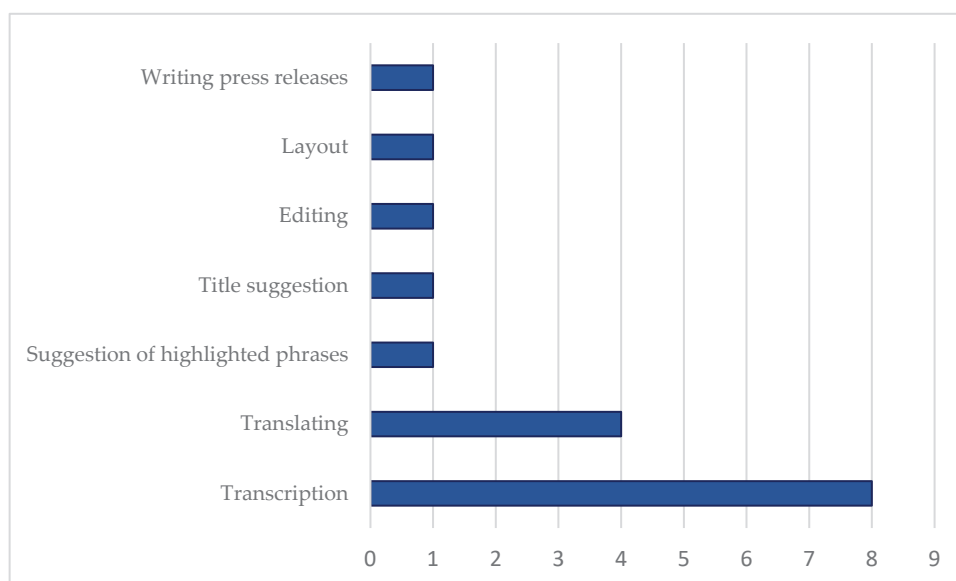


Figure 1. Tasks for which AI is being used by ‘slow’ journalists.

Transcribing interviews is therefore the task that most professionals entrust to AI, mainly for two reasons, that it frees them from tedious labor, and it saves time. “I used to hate interviews just because I had to transcribe them, so these tools help me a lot”, says S2. C6 agrees: “It’s invaluable for transcribing interviews because it saves time and speeds up work”. The most remarkable aspect for C11 is that “you only have to check for errors in the transcription, you don’t have to do it all from scratch”. It is precisely these errors that C7 highlights as the reason why, despite having tried AI tools, they do not use them, “It produces a text full of typos and misunderstandings. Having to listen to the recording again and revise the text doesn’t really save much time. I haven’t found it useful at the moment”.

Not all professionals who choose not to use AI for transcription cite the poor quality mentioned before. Some point out reasons related to the very nature of storytelling and the purpose of journalism, especially when it comes to slow journalism. For example, C2 is categorical, “I wouldn’t even think of using a transcription and translation app for interviews. I have hundreds of hours of transcriptions that take up a lot of time and it’s horrendous. Still, in no way would I use an AI for that, because I lose information that can be used to build scenes. I lose hesitation, a cough, the sound of birds or a coffee machine. All that is fundamental to the story”. The same goes for S3, “I’ve used it a few times, but I didn’t like it. Only if I was in an extreme situation or felt very lazy, I’d use it. It’s more work transcribing myself, but it’s a kind of ceremony. Having an AI do this is like a filmmaker having a film edited by a machine. Transcribing and listening are part of the story, they put me into it, it’s like warming up before a game”. C4, although more flexible, also highlights the advantages of listening to the recording and transcribing it themselves, “I like to transcribe manually sometimes because that way I remember things”.

Following interview transcription, text translation is the task most frequently performed by interviewees with the help of AI. AI’s usefulness is associated with functions considered supplementary to journalistic work, such as reading documents and information, and checking specific expressions. For instance, C5 mentions using AI to verify “certain details” when writing texts in English, though they note: “I haven’t yet made it part of my regular work process”. S2 found AI translation particularly valuable while working as a foreign correspondent and needing to read information in unfamiliar languages, “When I first arrived in the country, I didn’t know the language, so translation apps were essential to start reading local newspapers. I still use them to translate words, in addition to the dictionaries I turn to all the time. The translations might not be perfect, but they give you a general idea”.

Regarding other tools, L1 confirms that their newsroom does not generate text with AI, but it is used to generate illustrations “only when the subject requires it”. L3 makes it clear that they turn to AI “rarely, only to carry out tasks that are repetitive and tedious”, such as “suggesting highlighted phrases”. Generating titles for audiovisual pieces is something that C11 has occasionally asked the AI to do, “I do it because it is the hardest thing for me”. C10 uses it to layout texts and C6 to correct them, “For grammatical corrections I use Grammarly, which immediately detects errors or suggests a comma. I don’t use it in a sophisticated way, just to facilitate time-consuming tasks”. Finally, C14 says they have used ChatGPT for press releases, “I think it’s a fantasy that this can be done”.

3.2. Changes Brought About by Integrating AI into Slow Journalism

Except for two journalists (C6 and C11) who noted time savings in transcription, all interviewees agreed that AI has not changed their work so far. However, they have no doubt that substantial changes will come in the near future, when the tools improve. Two of the three professionals with leading positions believe that it is important to have a document to regulate the use of AI in newsrooms. L1 says, “Although AI is just beginning, it would be ridiculous not to consider it. We have a team working on how we should use it, and we want to include a section on it in our style guide”. L3’s newsroom has already published a guide “stating that we’ll use AI as a tool that’ll always be supervised

by humans and won't replace anyone's work". But this is not a priority for L2, "We don't intend to create a regulation now; I don't think people are very interested in that. If we were going to use it, we'd say so [...]. We have 180 different writers, and AI has hardly changed how they work. I'm not saying they don't use it, but they're still going to places, talking, documenting, contextualizing, choosing the beginning of a sentence or a metaphor... I have the feeling that although it's an extremely important tool, it still doesn't have the weight that it's given in public conversation".

According to the testimonies collected, neither the way of investigating nor the way of presenting information has been affected by the use of AI yet, and the changes in journalists' routines are minimal. These new technologies are still recent, and it will take time to get to know them and integrate them into journalism. This is what L1 thinks, "There's always a lot of confusion and fear at first when there are big technological leaps". C1: "The point is to learn to live with them and to handle the advances". And S2 says, "We have to see where it goes and what we want to make of it. There is a part of collective responsibility and an individual part. We have to adapt it to our needs so that it serves the best journalism we do".

As reported by most interviewees, their contact with AI does not go beyond the individual use of free tools with which they fiddle. Only two (C7 and S2) claim to have paid versions, "We've built a number of very useful tools into the editing platform that help. For example, they provide alternatives to more clickbait-friendly headlines, or 600-word agency press releases" (C7). The majority of those who use the more limited free versions are aware of the errors they can generate, "My experience is that they're not entirely reliable. You have to use the paid ones to be sure the data they provide is correct and not misleading" (S1); "I haven't paid for any yet, I've just been experimenting, but if I ever needed to, I'd definitely pay" (C6); "I've been changing tools, but I always try to use the free ones" (C4).

The impact of AI on daily work not yet being noticeable also has to do with the lack of quality and the limitations of AI tools. Again, leaders (L1: "Maybe in five years we'll forget about the original recording when automatically transcribing, but we're not there yet), editors (S1: "At the moment, AI is not developed enough"), and contributors (C14: "The challenge is that you need a critical perspective to use these tools") agree. Only C7 seems more convinced that journalists will eventually be replaced by AI, even in their work as copywriters and in in-depth news stories and long interviews, "According to technology experts, these machines may well be able to replace humans in ten years' time. Maybe not completely, but I've no doubt that with a good AI, an editor-in-chief could go from having ten editors to none".

Is there any aspect that they feel will not change? Except for one of the interviewees who claims to use AI to write press releases (C14), most only use it for tasks that do not involve text writing. Some are even clearly against doing so in the future, "Using tools that make your job easier is one thing and having an AI writing news articles is very different. I don't think that'll ever happen in my newsroom. I can ask the AI to draw three ideas from a human-written text for a Twitter version, but by no means can the mother piece be written by AI. A quality newspaper wouldn't do that because it'd be anti-journalistic" (L1). Leader L3 agrees, "We decided that our use of AI would be ethical—it says so in our guide—, which means it'll help us do repetitive work, but it'll never replace anyone's work". For C10, using it for copywriting is "absolute nonsense". If it comes to the point where copywriting is no longer journalists' regular activity, C14 says that "we'll still need professionals to think, to find stories, to find clever approaches. Only a human can do that".

3.3. AI in Slow Journalism: Increased Efficiency or a Threat to Creativity and Quality?

As seen, most interviewees are still reluctant to use AI for news writing, but they do believe that it will become the norm in the not-too-distant future. It is a different matter when they are asked about AI in slow journalism. To write 'slow' texts, which are more in-depth, time-consuming, in a freer and more creative narrative style, and not always

linked to breaking news, most of them do not currently use AI tools neither do they believe that they will do so in the short term. The reasons given have to do with the very nature of slow journalism, “One of the premises of our magazine is to report from where news events take place. That’s why you can’t have AI in long-form stories”, C13 asserts. Similarly, L1 says: “Journalism consists of going to a place, being with people, interviewing them and reporting. That cannot change because it’s the essence of respectable media”.

Another stumbling block is the belief that AI cannot replace observation and the human point of view, “Narrative journalism is by definition humanistic. In principle, we journalists are the ones who have the privilege of being able to pursue it” (C12). Likewise, S1 says “AI can help with certain slow journalism issues, but not all. What I appreciate about renowned professionals is their ability to connect emotionally. I don’t think AI can do that”. The human element, people’s sensitivity and their emotional ability, is again an argument when it comes to distinguishing between the tasks that an AI can do and those that journalists will still have to undertake in slow journalism. In this sense, C15 underlines professionals’ aims when approaching certain issues, “You can use AI tools for mundane things like searching for documents or transcribing interviews. But at the end of the day, it is the journalist who has to write the text and decide what the intention is. You can write a guideline for a washing machine with AI, but a long piece like Leila Guerriero’s, I very much doubt it”.

Interviewees C7, S2, and S1 refer to the ability to connect with other people and build a relationship with them taking into account their circumstances, “When it comes to slow journalism, to in-depth reporting, AI isn’t able to write or find the right sources. I wish it could interview people, but that’s a long way off” (C7); “I find it hard to imagine asking an AI to produce a long story. I’m one of those who still look for people, I interview them, I ask them to suggest other people. . . I would use AI to search large databases, but once I had that, I’d do journalism like in the 19th century, like in the Crimean War” (S2). S1 does not rule out the possibility that AI tools will eventually generate narrative writing but does not think they will ever behave like humans, “It can be a threat, but it hasn’t developed the ability to understand 100% of individual’s complexity yet. I’d like to believe it’ll make life easier for us and that instead of working sixteen hours a day we’ll work eight, which is what we should be doing”.

According to L1, creativity being inherent to slow journalism makes it impossible for an AI to replace it, “Readers aren’t stupid and want to read a story and be surprised, they want to see a new dimension that they may not have seen before. AI cannot go somewhere and describe what it smelled like or what the temperature was or how a character behaved. Summarising is a different thing altogether”. This is why L1’s newspaper backs the idea that slow journalism must be accomplished by humans, “You have to discover something new—a person, a place, a fact, or an approach. Our reporting isn’t a rehash of existing information. It’s very creative work that AI can’t do”. Even C11, who believes that AI tools are capable of producing original work, thinks they will not be able to replicate human qualities, “A machine has a different conception of creativity from an author’s voice”. C15 goes a step further and questions how readers would react to a story whose authorship and intentions are unknown, “I’d find AI writing an interview or a feature story strange for two reasons: I’d find it odd that it captures the atmosphere and the details; and when I read a text I often wonder who’s written it, why and who the writer serves. I don’t know who AI serves, and since there’s no signature, I’ll think something is being hidden”.

However, some respondents are confident that when AI tools become commonplace, they will have more to offer. This is the view of C14 and C9, “AI will encourage more and more creativity. It’ll be able to write texts, but we’ll still need to think, to find stories and ingenious approaches. It won’t do that” (C14); “ChatGPT lacks creativity, but it can enhance yours. If you have a fantastic idea, it’ll give you a summary. It’s amazing for that. Then you adapt it to your style” (C9). C1 is the only interviewee optimistic enough to imagine an AI capable of describing places, contextualizing situations, and even describing smells, “I’m convinced that AI will allow for better reports. It may not be able to describe

the smell in Gaza now, but we have to give it time. In fifty years, it'll be able to perfectly describe the environment and the context. In a century's time all the data, the atmosphere and the details of a story, will be supplied by a small device".

3.4. Perceptions About AI Among Practitioners Who Have Not Used It

As seen above, not all journalists are adapting to AI in the same way. Ten of the twenty-one respondents say they have never used it in their work for various reasons. For C5—who does use it—"journalists are afraid because all new technology has taken its toll. There've been many overlapping crises, and this one looks bad too". In the same vein, C1 says that "Journalists tend to be reticent to any kind of progress. They always see it from a negative perspective. But in modern journalism, especially in big newsrooms, many employees aren't journalists. It's important to have engineers, statisticians, illustrators, philosophers". Indeed, the implementation of AI in newsrooms has led to building multidisciplinary teams that include professionals from outside the field of communication. For C2, these are the ones who use it the most, whereas journalists are still reluctant, "Some people use AI for everything. But journalists don't. I cannot see my colleagues using AI against their profession in 2024".

One interviewee (C10) who has integrated AI into their work, notices "quite a lot of doom and gloom" among colleagues, "If someone thinks your job can be done by a machine, we're off to a bad start. Some people don't admit they use it, because it's frowned upon right now. Thinking it's going to eliminate jobs is something that's happened whenever there's been technological change". The fear of significant job destruction lies behind the reluctance of some professionals to embrace AI tools. 'Fear' and 'vertigo' are the most common words used. "It makes me dizzy. I think journalists, like translators and illustrators, could disappear. They'll have to defend their work a lot to convince their bosses that they can do it better than a machine" (C8).

In addition to the concern about the potential effects in the workplace, some professionals—as seen in point 4.3.—believe that AI is not (yet) applicable to the storytelling of slow journalism. C13 explains that "Many are afraid of the unknown, of what might happen. It moves very fast, and the first reaction is rejection. But I don't use it because one of the premises of our magazine is to report from where facts take place, which makes the use of AI unfeasible". Another interviewee (C15) does not believe that AI can help with 'slow' writing yet either, "I don't use it because I think I can do it much better. If one day it's the other way round, I won't say a word. With the current state of these tools, if you write with AI and it's accepted, something has gone wrong along the way". This refusal also shows that there is still mistrust, "I don't use them to avoid feeding the dragon, because it grows with the work of others. I have no rational justification; I just don't like them". Still, this attitude does not mean that the interviewees are unaware of the future of journalism being linked to the development of AI, "If you bring up what I said in fifteen years' time, I'll look like a fool".

As C1 states, the point does not seem to be whether AI tools will be used by journalists in the coming years, but how they will be used, "We need to see how we can integrate them to improve our stories. It's not about us journalists writing them, it's about making better content so that readers get better quality and better material. And if the stories are better with the help of AI, then go ahead, the reader will appreciate it. I'll be sorry it's not done by humans, but that's not the point".

3.5. Do 'Slow' Journalists Think Readers Recognize AI-Generated Content?

According to most of the professionals interviewed, readers can distinguish AI-generated texts from those written by journalists because AI tools are not sophisticated enough to produce quality content. However, when using expressions such as "for the time being" or "still", they also show their belief that this will change. "Readers are aware of it today, but the outcome may be perfected and indistinguishable in two or four years", states C3. L3 agrees, saying that "what's been done with AI so far is quite primitive, it still lacks

narrative and that's why it's noticeable. We'll see how it develops in the coming years". C1 assures that "It can be distinguished because it's untrained. But considering the tool learns and feeds back every day, if it can write a simple article now, imagine what it'll be able to write in five, ten, or fifty years' time". C5 goes one step further, pointing to what will happen when readers can't see the difference between automated and non-automated content, "When that time comes, we'll have an issue of ethics, not of quality".

The difference between automatically generated texts and human-written ones is particularly clear when it comes to slow journalism. This is what S1 believes, "So far it seems to me that readers of this kind of journalism, who are assumed to have a certain taste for literature, can notice the difference". C14 ("In narrative reporting, of course they do") is of the same view. C12 points out where the differences are, "At the moment it's noticeable in linguistic proficiency, the choice of words, the rhythm, the lack of purpose, the impersonal language. There'll come a time when it won't make a difference, but it does now". As for who readers look at when encountering a poorly written text, opinions differ. C7 thinks they blame an underdeveloped AI, "When they notice lack of quality, they think AI did it. We get a lot of feedback from our readers; after 600 words, it's very noticeable". But C15 says that "readers can see it's badly written—there are very bad texts published every day—, but I don't believe they think it's written by an AI". It remains to be seen whether, as C7 predicts, "in ten years' time, if a piece is well done, people won't care if it's done by a human or a machine".

4. Discussion and Conclusions

In this study, the increasing body of literature on the integration of AI in journalism is extended by eliciting and analyzing slow journalism professionals' experiences, attitudes, and opinions about the use of AI tools in their work. To this end, semi-structured interviews of twenty-one slow journalism practitioners in Spain were carried out.

The results of the research suggest that just over half of the professionals surveyed use AI in their work as 'slow' journalists. The most common uses are transcribing interviews and, to a lesser extent, translating texts (RQ1), similar to what recent studies on the adoption of AI in journalism (Newman 2024, p. 27) show. The role of journalists has changed significantly, and they are increasingly expected to master the use of AI tools in addition to traditional journalistic skills. As a result, more hybrid jobs and collaboration between journalists, data scientists, information designers, and computer programmers emerge (Deuze and Beckett 2022; De-Lara-González et al. 2022). According to interviewees, the latter are less reluctant to adopt AI than journalists themselves.

When journalists do use AI, it is often limited to individual experiences with free tools that do not provide the desired quality, so a thorough review of the content they generate is needed. This suggests that while news organizations are training in the use of AI in newsrooms, they do not yet have high-quality (paid) tools available to their journalists. Hence AI's ability to contribute to better quality—one of the factors that, according to the TAM, influence an individual's intention to use new technology—is questioned by the interviewees (RQ2). This contradicts some who claim that AI not only increases journalists' productivity but also improves the quality of news reporting (Shi and Sun 2024). Curiously, however, two of the three leading journalists interviewed ensure they have already drafted documents to guide the appropriate use of this new technology, presumably reflecting on what good journalism means (Min 2021, p. 89), or anticipating what is to come.

Despite their limited use of AI, all the journalists are aware that changes will arrive in the not-too-distant future, and they will be profound. Most believe that generative AI will be able to produce simple news articles in a few years' time, although they doubt that it will go as far as writing narrative pieces and thus doing slow journalism (RQ3). In particular, the majority doubt that it can bring creativity to this type of text (RQ2) (in line with Graefe 2016; Gómez-Mompart 2021). Nor do they seem to agree with the idea (supported by Brennen 2018; Schapals and Porlezza 2020) that it offers benefits, such as allowing for deeper investigation and helping to add more complexity and meaning to texts—TAM's

factor of “perceived usefulness”. On the contrary, it is precisely the human qualities that characterize journalism—and to a greater extent slow journalism—that automation lacks, such as identifying the most important angle of a story, news judgment, curiosity, and skepticism (Thurman et al. 2017).

It is not surprising, therefore, that most respondents claim that their way of working has not changed since the introduction of AI in journalism. According to them, neither the way they research nor the way they present content has changed. They do not even seem to have benefited enough to say that they have more time to spend on work that cannot be automated—TAM’s factor of “ease of use”—as claimed by some authors (e.g., DalBen and Jurno 2021; Wu et al. 2019; Young and Hermida 2014). They tend to agree with the more skeptical, arguing that AI’s impact on productivity is likely to be more limited (Shi and Sun 2024), and that it varies depending on what is specifically automated (Simon 2024). In sum, practitioners believe that AI’s contribution to slow journalism will be limited to freeing journalists from routine and less creative tasks—TAM’s factor of “job relevance”—(RQ2).

In terms of how AI could affect the journalistic labor market, fear of job destruction is cited as the main reason for rejection of AI among professionals around the world (Beckett 2019). In the present case, respondents are also aware that AI could lead to significant job losses, although they do not currently seem to believe it could affect slow journalism practitioners that much (RQ3). According to their statements, it is not so much a question of seeing AI as a competitor or partner (a debate pointed out by Peña-Fernández et al. 2023), but rather as a useful support tool—in line with Wu et al.’s (2019) theory about how AI will change the news business—that as yet produces more quantity than the quality content (as suggested by Simon 2024) expected from slow journalists (Greenberg 2007, 2012).

In short, it can be concluded that according to the responses of the twenty-one slow journalism practitioners in Spain, AI has little to offer these minority-media (Boynton 2015; Craig 2020; Le Masurier 2015) professionals due to the notable limitations in improving long-form reporting (recently highlighted by authors such as Nishal and Diakopoulos 2024; Simon 2024). At most, it will allow them to streamline repetitive and non-creative tasks and thus better engage in in-depth journalism without it significantly threatening their jobs, at least in its current state of development. Still, it must be acknowledged that this study is not without limitations. While the sample of interviewees encompasses a diverse range of slow journalism formats in Spain, it does not represent all of slow journalism. Furthermore, future research could investigate whether there are variations between countries, given that the implementation of AI in journalism varies globally.

Author Contributions: Conceptualization, I.A.-R.; methodology, I.A.-R.; software, I.A.-R.; validation, S.P.-F.; formal analysis, I.A.-R. and M.M.-F.; investigation, I.A.-R.; resources, I.A.-R.; data curation, I.A.-R.; writing—original draft preparation, S.P.-F. and M.M.-F.; writing—review and editing, S.P.-F. and M.M.-F.; visualization, M.M.-F.; supervision, S.P.-F.; project administration, S.P.-F. and M.M.-F.; funding acquisition, S.P.-F. All authors have read and agreed to the published version of the manuscript.

Funding: This study was funded by the Spanish Ministry of Innovation, Science and Universities as part of project PID2023-146913NB-I00.

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of Complutense University of Madrid (protocol code CE_20240912_SOC_09, approved 12 September 2024) for studies involving humans.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author to respect the ethical principle of anonymity of respondents.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Appendix A

1. Do you use artificial intelligence tools in your work?
2. If so, for what type of tasks?
3. How has it changed your work?
4. Does its use affect the way you research or present information?
5. Does it make you more efficient in producing slow content, or is it a threat to creativity and quality?
6. If you don't use it, does anyone in the team collaborating on your work use it, and what for?
7. Why aren't you using it?

References

- Albalad Aiguabella, José María. 2018. *Periodismo slow. O cómo se cuecen las historias en los fogones de Anfibia, Narratively y FronteraD*. Madrid: Fragua.
- Ali, Waleed, and Mohamed Hassoun. 2019. Artificial Intelligence and Automated Journalism: Contemporary Challenges and New Opportunities. *International Journal of Media, Journalism and Mass Communications* 5: 40–49. [CrossRef]
- Anderson, Christopher W. 2013. Towards a sociology of computational and algorithmic journalism. *New Media & Society* 15: 1005–21. [CrossRef]
- Ayyad, Khayrat, Mohamed Ben Moussa, and Bouziane Zaid. 2023. Journalists' Perception of the Adoption of New Communication Technologies in the UAE's Media Organizations. *Journalism Practice*, 1–21. [CrossRef]
- Barranquero-Carretero, Alejandro. 2023. Slow Media, Media Disconnection, and Slow Journalism. A Critical Balance of the First Decade of Research. *Palabra Clave* 26: e2642. [CrossRef]
- Beckett, Charlie. 2019. *New Powers, New Responsibilities. A Global Survey of Journalism and Artificial Intelligence*; The London School of Economics and Political Science. Available online: <https://bit.ly/3HKYefy> (accessed on 12 September 2024).
- Boynton, Robert S. 2015. *El nuevo Nuevo Periodismo. Conversaciones sobre el oficio con los mejores escritores estadounidenses de no ficción*. Barcelona: UB.
- Brennen, J. Scott. 2018. *An Industry-Led Debate: How UK Media Cover Artificial Intelligence*. Oxford: Reuters Institute for the Study of Journalism.
- Clerwall, Christer. 2014. Enter the robot journalist. *Journalism Practice* 8: 519–31. [CrossRef]
- Cools, Hannes, and Nicholas Diakopoulos. 2024. Uses of Generative AI in the Newsroom: Mapping Journalists' Perceptions of Perils and Possibilities. *Journalism Practice*, 1–19. [CrossRef]
- Craig, Geoffrey. 2020. Reclaiming slowness in journalism: Critique, complexity and difference. In *Slow Journalism*. Edited by Megan Le Masurier. New York: Routledge, pp. 23–37.
- DalBen, Silvia, and Amanda Jurno. 2021. More than code: The complex network that involves journalism production in five Brazilian robot initiatives. *ISOJ Journal* 11: 111–37.
- de Haan, Yael, Eric van den Berg, Nele Goutier, Sanne Kruikemeier, and Sophie Lecheler. 2022. Invisible friend or foe? How journalists use and perceive algorithmic-driven tools in their research process. *Digital Journalism* 10: 1775–93. [CrossRef]
- De-Lara-González, Alicia, José Alberto García-Avilés, and Félix Arias-Robles. 2022. Implantación de la Inteligencia Artificial en los medios españoles: Análisis de las percepciones de los profesionales. *Textual & Visual Media* 1. [CrossRef]
- Denscombe, Martyn. 2010. *The Good Research Guide: For Small-Scale Research Projects*. London: Buckingham Open University Press.
- Deuze, Mark, and Charlie Beckett. 2022. Imagination, algorithms and news: Developing AI literacy for journalism. *Digital Journalism* 10: 1913–18. [CrossRef]
- Diakopoulos, Nicholas. 2019. *Automating the News: How Algorithms Are Rewriting the Media*. Cambridge: Harvard University Press.
- Dörr, Konstantin Nicholas. 2016. Mapping the field of Algorithmic Journalism. *Digital Journalism* 4: 700–22. [CrossRef]
- Gómez-Mompарт, Josep Lluís. 2021. Periodismo reposado para civilizar la información en la sociedad de conocimiento. In *Nuevos modelos y paradigmas de la información. Desafíos y oportunidades en el periodismo*. Edited by Carmen Peñafiel and Carmen Gurrutxaga. Madrid: Dykinson, pp. 55–62. [CrossRef]
- Graefe, Andreas. 2016. *Guide to Automated Journalism*; Columbia Journalism School. Tow Center for Digital Journalism. Available online: https://www.cjr.org/tow_center_reports/guide_to_automated_journalism.php (accessed on 30 September 2024).
- Greenberg, Susan. 2007. Slow Journalism. *Prospect*, February. pp. 15–16.
- Greenberg, Susan. 2012. Slow Journalism in the Digital Fast Lane. In *Global Literary Journalism: Exploring the Journalistic Imagination*. Edited by Robert Lance Keeble and John Tulloch. New York: Peter Lang, pp. 381–93.
- Guion, Lisa A., David C. Diehl, and Debra McDonald. 2011. *Conducting and in-Depth Interview*. Gainesville: University of Florida Institute of Food and Agricultural Sciences.
- Guzman, Andrea L., and Seth C. Lewis. 2019. Artificial Intelligence and Communication: A Human–Machine Communication Research Agenda. *New Media & Society* 20: 1–18. [CrossRef]
- Krippendorff, Klaus. 1990. *Metodología de análisis de contenido*. Barcelona: Paidós.
- Kvale, Steinar. 1996. *Interviews. An Introduction to Qualitative Research Interviewing*. Thousand Oaks: Sage.

- Laboratorio de Periodismo. 2023. La nueva newsletter de El Periódico de España desvela los procesos de creación de los reportajes. June 9. Available online: <https://lc.cx/HAhD8T> (accessed on 12 September 2024).
- Le Masurier, Megan. 2015. What is Slow Journalism? *Journalism Practice* 9: 138–52. [CrossRef]
- Le Masurier, Megan. 2016. Slow Journalism: An introduction to a new research paradigm. *Journalism Practice* 10: 439–47. [CrossRef]
- Libros del K. O. n.d. ¿Quiénes Somos? Available online: <https://www.librosdelko.com/pages/quienes-somos> (accessed on 13 September 2024).
- Lindén, Carl-Gustav. 2017. Algorithms for journalism: The future of news work. *The Journal of Media Innovations* 4: 60–76. [CrossRef]
- Marconi, Francesco, and Alex Siegman. 2017. *The Future of Augmented Journalism: A Guide for Newsrooms in the Age of Smart Machines*. New York: Associated Press.
- Mayoral-Sánchez, Javier, Sonia Parratt-Fernández, and Montse Mera-Fernández. 2023. Uso periodístico de la IA en medios de comunicación españoles: Mapa actual y perspectivas para un futuro inmediato. *Estudios sobre el Mensaje Periodístico* 29: 821–32. [CrossRef]
- Min, Seong Jae. 2021. *Rethinking the New Technology of Journalism: How Slowing Down Will Save the News*. University Park: The Pennsylvania State University Press. [CrossRef]
- Neveu, Erik. 2016. On not going too fast with slow journalism. *Journalism Practice* 10: 448–60. [CrossRef]
- Newman, Nic. 2024. *Journalism, Media, and Technology Trends and Predictions 2024*; Reuters Institute, January 9. Available online: <https://reutersinstitute.politics.ox.ac.uk/journalism-media-and-technology-trends-and-predictions-2024> (accessed on 12 September 2024).
- Nishal, Sachita, and Nicholas Diakopoulos. 2024. Envisioning the Applications and Implications of Generative AI for News Media. *arXiv arXiv:2402.18835*.
- Noain-Sánchez, Amaya. 2022. Addressing the Impact of Artificial Intelligence on Journalism: The perception of experts, journalists and academics. *Communication & Society* 35: 105–21. [CrossRef]
- Parratt-Fernández, Sonia, Javier Mayoral-Sánchez, and Montse Mera-Fernández. 2021. The application of artificial intelligence to journalism: An analysis of academic production. *Profesional de la Información* 30: e300317. [CrossRef]
- Peña-Fernández, Simón, Koldo Meso-Ayerdi, Ainara Larrondo-Ureta, and Javier Díaz-Noci. 2023. Without journalists, there is no journalism: The social dimension of generative artificial intelligence in the media. *Profesional de la Información* 32: e320227. [CrossRef]
- Rauch, Jennifer. 2011. The Origin of Slow Media: Early Diffusion of a Cultural Innovation through Popular and Press Discourse, 2002–10. *Transformations* 20. Available online: <http://www.transformationsjournal.org/issue-20/> (accessed on 28 September 2024).
- Rosique-Cedillo, Gloria, and Alejandro Barranquero-Carretero. 2015. Periodismo lento (slow journalism) en la era de la inmediatez. Experiencias en Iberoamérica. *Profesional de la Información* 24: 451–62. [CrossRef]
- Rubin, Herbert J., and Irene S. Rubin. 2011. *Qualitative Interviewing: The Art of Hearing Data*. Thousand Oaks: Sage.
- Schapals, Alhosha Karim, and Colin Porlezza. 2020. Assistance or resistance? Evaluating the intersection of automated journalism and journalistic role conceptions. *Media and Communication* 8: 16–26. [CrossRef]
- Shi, Yi, and Lin Sun. 2024. How Generative AI Is Transforming Journalism: Development, Application and Ethics. *Journalism and Media* 5: 582–94. [CrossRef]
- Simon, Felix M. 2024. Artificial Intelligence in the News: How AI Retools, Rationalizes, and Reshapes Journalism and the Public Arena. Tow Center for Digital Journalism. Available online: https://www.cjr.org/tow_center_reports/artificial-intelligence-in-the-news.php (accessed on 14 September 2024).
- Soliyeva, Soxibaxon. 2024. Slow Journalism as an Alternative Economic Model in New Media. *Excellencia: International Multi-Disciplinary Journal of Education (1994–9521)* 2: 356–58.
- Thurman, Neil. 2019. Computational Journalism. In *The Handbook of Journalism Studies*. Edited by Karin Wahl-Jorgensen and Thomas Hanitzsch. New York: Routledge.
- Thurman, Neil, Konstantin Dörr, and Jessica Kunert. 2017. When reporters get hands-on with robo-writing. *Digital Journalism* 5: 1240–59. [CrossRef]
- Túñez-López, Miguel, Carlos Toural-Bran, and Cesibel Valdiviezo-Abad. 2019. Automatización, bots y algoritmos en la redacción de noticias. Impacto y calidad del periodismo artificial. *Revista Latina de Comunicación Social* 74: 1411–33. [CrossRef]
- WashPostPR. 2023. Introducing Deep Reads, The Washington Post's Home for Longform and Narrative Journalism. May 14. Available online: <https://www.washingtonpost.com/pr/2023/05/14/introducing-deep-reads-washington-posts-home-longform-narrative-journalism/> (accessed on 25 September 2024).
- Wu, Shangyuan, Edson Tandoc, and Charles T. Salmon. 2019. When Journalism and Automation Intersect: Assessing the Influence of the Technological Field on Contemporary Newsrooms. *Journalism Practice* 13: 1238–54. [CrossRef]
- Young, Mary Lynn, and Alfred Hermida. 2014. From Mr. and Mrs. Outlier to Central Tendencies: Computational journalism and crime reporting at the *Los Angeles Times*. *Digital Journalism* 3: 381–97. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.

Article

Are ChatGPT-Generated Headlines Better Attention Grabbers than Human-Authored Ones? An Assessment of Salient Features Driving Engagement with Online Media

Vasile Gherheș ^{1,*}, Marcela Alina Fărcașiu ² and Mariana Cernicova-Buca ¹

¹ Department of Communication and Foreign Languages, Interdisciplinary Research Center for Communication and Sustainability, Politehnica University of Timisoara, 300006 Timisoara, Romania; mariana.cernicova@upt.ro

² Department of Communication and Foreign Languages, Faculty of Communication Sciences, Politehnica University of Timisoara, 300006 Timisoara, Romania; marcela.farcasiu@upt.ro

* Correspondence: vasile.gherhes@upt.ro

Abstract: This study focuses on the case of news headlines in current online journalism, looking into the current possibilities opened by ChatGPT to generate such texts in an attention-grabbing manner. To assess the reaction of online readers to headlines (clickbait or click-worthy), an online survey was applied, involving Romanian students. A total of 100 original human-authored articles with clickbait headlines were extracted from a relevant Romanian database. ChatGPT was used to generate alternative headlines (one clickbait and one informative) based on the original texts. The resulting corpus of 100 headline triplets was offered to students for evaluation. More than 70% of the 600 participants in the survey preferred AI-generated headlines over the human-authored ones, indicating their experiences and behaviors in media consumption. The preferred headlines were further analyzed along lexical and grammatical characteristics, and stylistically, to pinpoint the features sparking readers' curiosity and engagement. While on a cognitive level the investigated audience rejected clickbait headlines as being deceitful and frustrating, in practice less than 34% favored neutral and objective headlines. Also, the linguistic analysis provided insights into the mechanics of reader engagement and the effectiveness of various headline strategies. The results are useful to anticipate the adoption of AI as a creative partner in Romanian media practice.

Keywords: AI (artificial intelligence); headline; clickbait; click-worthiness; attention grabber; ChatGPT; linguistic analysis; headline features

1. Introduction

The highly dense technological environment of modern life in the 21st century imprints all activities and dramatically changes all sectors of society. As Marshall McLuhan so aptly foretold, the technological extensions of man expand the possibilities of action beyond imagination (McLuhan 1964), although not without cost. The debate over such extensions is relaunched with the multiplication of technologies capable of imitating human intellect, summed up under the generous term 'artificial intelligence' (Prasad and Makesh 2024). The media industry, by its very nature, could not and did not make an exception in making use of the tremendous range of applications that can optimize the collection, creation, editing, distribution, and promotion of media content (Chan-Olmsted 2019). As Sylvia Chan-Olmsted states, in her comprehensive overview of AI use in the journalism and entertainment industries, digital audiences have enhanced expectations regarding the tailoring of news, the speed of delivery of content, capable services providing on-demand 'smart' products, etc. (Chan-Olmsted 2019). AI changes the journalistic workflow, the delivery and the promotion of media content, the pricing structure, and the marketing strategies (Chan-Olmsted 2019; Ioscote et al. 2024; Prasad and Makesh 2024). As Fabia

Ioscote et al. state, the advent of generative AI took steps further than digital or automated journalism, forcing the news industry to reflect upon the possibility of maintaining competitiveness and quality. At the same time, the journalistic profession has to face the challenges brought by the increasingly more intrusive use of AI in the journalistic workflow, where routine activities can be optimized, but human touch still must be maintained to convey trustworthy, quality, ethically attested media content (Ioscote et al. 2024; Amponsah and Atianashie 2024). Major prestigious news agencies such as Associated Press and Reuters already use integrated AI as tools to extract well-documented and timely stories from large data sets (Amponsah and Atianashie 2024). However, despite some examples of successful use of AI in journalism practices and praised advantages such as modernity, speed, and the capability to handle enormous amounts of data, the literature cautions that it is too soon to give up human control over journalistic practices. Ethical and professional values are to be instilled into automated tools before spreading AI use to a larger extent (Amponsah and Atianashie 2024; Aydın and İnce 2024; Beckett and Mira n.d.; Dragomir et al. 2024; Graefe and Bohlken 2020; Helberger et al. 2020; Ioscote et al. 2024). Limitations acknowledged in the larger-scale use of AI in journalism are, besides ethical considerations, the danger of spreading misinformation, the peril of creating echo chambers, and the threat of reducing exposure to a diversity of viewpoints for the media consumers allowed to tailor the received media content to their taste and preference (Breazu and Katsos 2024; Chan-Olmsted 2019; Siitonen et al. 2024; Amponsah and Atianashie 2024; Prasad and Makesh 2024). As Siitonen and colleagues concluded, from analyzing ten years of studies dedicated to the influence of AI on journalism and journalistic practices, attitudes towards AI oscillate “between hype and fear”. However, new technologies are here to stay and it is important to inquire into how this development changes journalism and media in the long run (Siitonen et al. 2024; Sonni et al. 2024). Studies dedicated to scrutinizing the actual use of AI in newsrooms show that, at least in Central Europe, the spread of these newly developed tools is not so large as debated in the USA or China, for example (Dragomir et al. 2024; Siitonen et al. 2024; Zheng et al. 2018). For Central Europe, a region that Romania is neighboring, studies indicate that the average percentage of AI usage in media outlets does not exceed 15% (Dragomir et al. 2024). The report mapping the use of AI by newsrooms in the Czech Republic, Hungary, Poland, and Slovakia revealed that AI is primarily used for simple tasks such as gathering information, writing basic news based on existing data, editing, and moderating texts in newsrooms, but that the adoption of AI is progressing slowly and cautiously.

Given the fact that the field of journalism is so vast and that the impact of automated tools is growing at a rapid pace, the research team authoring the present study narrows down the topic of AI use, with pros and cons, to a very specific activity in the media industry: the creation of headlines, capable of attracting readers to engage with the content. The interest in headlines is manifold. In the digital age, the way in which audiences consume news is changing. Increasingly larger number of people access media content online, instead of the traditional channels (Kuiken et al. 2017). Such consumption allows for the abandonment of linear reading, listening or watching, since audiences pick and choose content according to the attractiveness of the promise or the content formulated in the headline. In traditional media, the headline functioned as a summary or informative text regarding the content of an article or news piece, meant to inform and persuade. Studies show that headlines are also the most read part of the media, receiving around five times more attention than the content they refer to (Isani 2011). Headlines also served as an attention grabber, typically requiring the skills of the best writers in the newsroom to produce such texts (Isani 2011; Ifantidou 2009; Scacco and Muddiman 2015; Iarovici and Amel 1989). The digital environment created an additional function for the headlines: that of luring the audiences towards the news and triggering engagement (Feng 2024). Experiments in reformulating headlines showed that headlines carry framing functions, tipping audiences to adopt a position and an interpretative standing prior to accessing the main media content (León 1997; Leung and Strumpf 2023). As Van Dalen concludes, from the analysis of journalists’ re-examination of their professional skills, under the

pressure of technological innovation and machine-written texts, “what can be automated will be automated” and headline production is a forerunner in the quest for journalistic productivity (Van Dalen 2012).

Among the newest topics of debate concerning the functions of headlines is the clickbait phenomenon. This function refers to the capacity of clickbait headlines to keep the reader in the webpage for as long as possible, but not to inform (Potthast et al. 2016). Perceived as deceitful and capable of propagating misleading or even false information, clickbait is actively combated both via automated tools, and by discursive strategies aimed at persuading the media to drop the practice (Blom and Hansen 2015; Chakraborty et al. 2016; Broscoteanu and Ionescu 2023; Blom and Hansen 2015; Chakraborty et al. 2016; Broscoteanu and Ionescu 2023). Despite the warnings that clickbait erodes the credibility of the media and can alienate audiences, many news outlets still use clickbait headlines. To appeal to audiences, even traditionally ‘serious’ media outlets resort to the tabloidization of titles and playing upon the curiosity gap of online readers (Ifantidou 2009; Setälä 2014), underpinning the viralization of news (Bazaco et al. 2019). The literature on clickbait headlines focuses both on the linguistic strategies and vocabulary used to entice readers’ engagement (Blom and Hansen 2015; Fărcașiu and Gherheș 2024), and on the effects and typology of such texts (Molyneux and Coddington 2020).

However, while research of English-language material is abundant in the scientific world, other, so-called “low resource” languages are covered by less than a quarter of the research (Fatima et al. 2023). It is also interesting to note that research on the contrastive man- vs. machine-produced media content indicate a skeptical reception of the latter on the part of the public (Altay and Gilardi 2024; Berber Sardinha 2024).

For the Romanian media landscape, studies on headlines (clickbait or click-worthy), journalistic practices involving AI, and reflections on the specificity of journalism in the very dense technological and digital environment are scarce. A notable exception is represented by Broscoteanu and Ionescu (Broscoteanu and Ionescu 2023) who created a vast corpus of clickbait headlines from the most popular media outlets, Păcurar and Oprișă, interested in automated affordances to fight clickbait in Romanian articles (Păcurar and Oprișă 2023), and some ethical considerations regarding AI in journalism (Stănescu 2023). To catch up with the state of research on headline status, as described by Scacco and Muddiman (2015), and enrich knowledge on non-English practices, the research team authoring the present study embarked on a scientific journey to understand human reactions to headlines, human-authored or AI-generated, to deepen the knowledge on the features of effective headlines and to reflect upon the future of journalistic practices in Romanian newsrooms.

The objectives of this study were the following:

- O1. To analyze the media consumption behavior of online readers.
- O2. To assess the features of the headlines leading to the decision of audiences to engage with the content of online media, highlighting the possible effect of such texts.
- O3. To compare ChatGPT-generated headlines with human-authored ones, from the point of view of their function as attention grabbers for online audiences, in an educational environment.
- O4. To identify the linguistic and stylistic characteristics of ChatGPT-generated headlines that effectively pique readers’ curiosity and motivate them to read the articles.

2. Materials and Methods

This research aimed to investigate readers’ consumption behavior concerning online articles, to assess how headlines influence their reading decisions, and to examine the reactions of readers to misleading headlines. In addition, it sought to compare the impact of human-authored clickbait headlines with that of clickbait and informative headlines generated by the ChatGPT model to assess their effectiveness in capturing the readers’ attention. To address the initial objectives, the questionnaire included four closed-ended, scale-type questions. For the final objective, the selection of the articles was based on the findings of Broscoteanu and Ionescu, who conducted research on detecting clickbait

headlines in Romanian and developed the first Romanian corpus for this topic, called RoCliCo (Broscoteanu and Ionescu 2023).

Corpus

To analyze the impact of headlines (O4), 100 articles were extracted from RoCliCo. This database contains 8.313 headlines selected from six media sources. Almost half of the headlines are of a clickbait nature. For the purpose of the present research, only five media outlets were considered, since one of the sources present in RoCliCo did not have a format allowing for statistical analysis. The five Romanian online media sources include the *Digi24* TV station, the *Libertatea* newspaper, the *ProTV* TV station, the *WOWBiz* newspaper, and the *Viva* magazine. To maintain a balance in the corpus, 20 articles with clickbait headlines were chosen from each source.

The selection of the 20 headlines per media outlet followed a systematic and objective approach. First, only articles identified as having clickbait headlines were included in the selection pool. For each media source, the total number of clickbait articles was divided by 20, establishing a fixed selection interval. Headlines were then chosen systematically at these intervals, ensuring an even distribution across the dataset. This method provided a representative and unbiased sample of 20 clickbait headlines per outlet, balancing the contribution of each source to the overall corpus.

These articles were used to compare the original human-authored clickbait headlines with their ChatGPT-generated versions. For each of the 100 articles, the ChatGPT language model has produced two alternative headline versions:

1. A clickbait-style headline generated by ChatGPT: Based on the existing news article, the model was instructed to generate a clickbait headline that would grab attention and entice the reader to click on the article.
2. An informative headline generated by ChatGPT: Based on the existing news article, the model was instructed to generate a headline in a clear and objective manner, accurately representing the article's content and avoiding speculative or sensationalist language.

It is essential to emphasize the fact that the two variant headlines produced by ChatGPT were based exclusively on the articles' content, without the model accessing the original headlines. This method ensured that the alternative headlines were independently generated and not influenced by the original phrasing, allowing for an objective evaluation of how different types of headlines affect reader perception. Consequently, each article was accompanied by triplet headlines: the original, human-authored headline, a clickbait ChatGPT-generated headline, and an informative ChatGPT-generated headline. Thus, a corpus of 100 triplet headlines was created, allowing for the next stage of research.

Questionnaire

The measures in the questionnaire were specifically developed for this study and did not come from previous research. They were designed to align with the study's objectives of understanding reading habits, perceptions of headlines, and preferences for different types of headlines.

Ten distinct variants of the questionnaire were created. The first part was identical and included questions about reading habits, perceptions of headlines, and features of headlines appealing to them on a cognitive level. The second part of the questionnaire featured 10 sets of headline triplets, which included the original (human-authored) headline, the clickbait-style headline generated by ChatGPT, and the informative headline generated by the model. Each participant rated one set of 10 headlines, which were randomly distributed to minimize order effects and ensure a balanced representation of headline types among participants. In total, participants evaluated 100 sets of headlines.

A separate, smaller group of 10 university students participated in the pretest of the questionnaire. This pretest group was not part of the main sample of 624 participants. The purpose of the pretest was to verify the clarity of the questions and the validity of the research instrument before full implementation. Feedback from these students was instrumental in refining the questionnaire to ensure comprehensibility and alignment with the study's goals.

To assess the internal consistency of the instrument used, Cronbach's Alpha coefficient was calculated (Howitt and Cramer 2008; Tabachnick and Fidell 2012). The analysis indicated a value of 0.786, which suggests a good level of internal reliability as per the general guidelines (George and Mallery 2003) (Table 1). The 14 items are correlated with each other and contribute to measuring the same variable.

Table 1. Reliability statistics.

Cronbach's Alpha	N of Items
0.786	14

The participants completed the questionnaires via an online specialized platform. Invitations were sent out by the research team and responses were collected in the timeframe 25 September–20 October 2024.

Sample

The participants in this study were exclusively university students, enrolled in higher education institutions in Timișoara, the largest city in the Western part of Romania. The sample of 624 respondents was carefully selected to represent young consumers of online media, a group highly relevant to the research objectives. No members of the general community were included in the study. For this sample of respondents, aged 18–24, the margin of error was estimated at $\pm 4\%$. Participation was voluntary, with individuals being informed in advance about the study's purpose and assured of the confidentiality of their responses. No incentives were provided and participants were free to withdraw from the questionnaire at any time. All data collected were anonymized and used solely for research purposes.

The collected data were analyzed using statistical methods and quantitative analysis tools to assess the impact of headlines on the students' reading behavior.

3. Results

The first aspect that was analyzed was the frequency with which the study participants read online articles. As shown in the graph below (Figure 1), reading habits among the respondents vary, which may influence how they are impacted by article headlines. The largest group, 31.5% of the students, read online articles several times a week, followed by 27.5%, who read them daily. These two groups are the most active in consuming online content. Meanwhile, 20.2% of the participants rarely read online articles, indicating a lower exposure to online content. Additionally, 14.2% of them read articles weekly, reflecting a moderate level of content consumption, while 6.6% read articles monthly, indicating minimal exposure to online content.

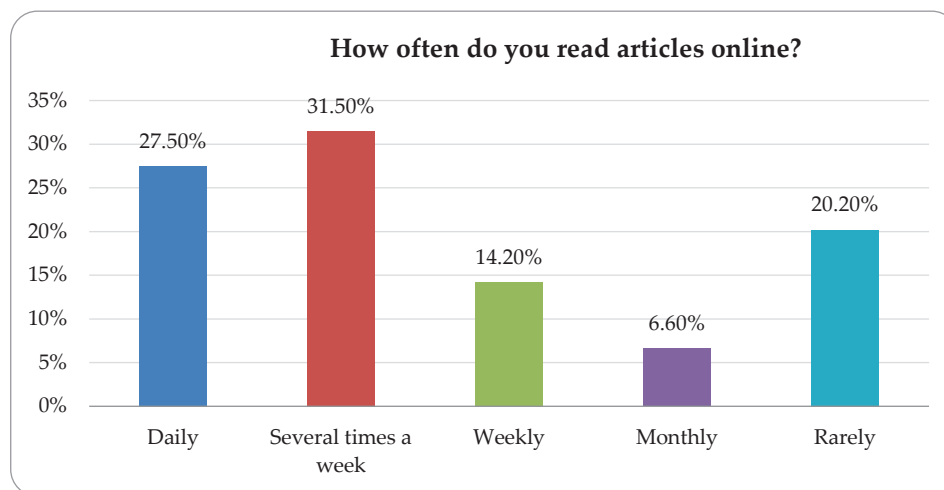


Figure 1. Frequency of reading articles online.

Another aspect examined was the way in which participants perceive the influence of headlines on their decision to read an article. As illustrated in the graph below (Figure 2), the largest portion of subjects (43.9%) believes that the appeal of a headline significantly impacts their decision to click on an article, suggesting that, for some readers, the headline is a key factor in their choice to further explore the content. This category also includes 40.2% of the respondents who state that headlines have a strong influence on their decision, further emphasizing the fact that headlines play a crucial role in attracting readers. Thus, more than 80% of the students report that headlines have a significant impact on their reading behavior, emphasizing the crucial role of effective headline writing in an article's success. In contrast, 11.3% of the participants are neutral about the influence of headlines, indicating a group for whom headlines play a smaller role in their decision to read. At the other end of the spectrum, 3.7% of the respondents believe that headlines have little influence, while 1.0% state that headlines have no impact at all on their decision to read an article.

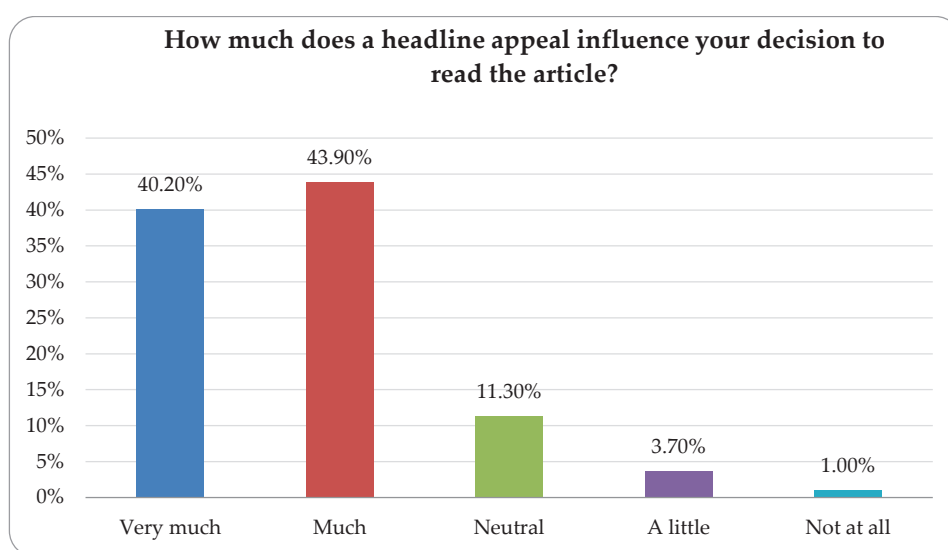


Figure 2. Impact of headline appeal on reading choices.

To better understand the features that readers consider important in a headline, a group of students was invited to participate in this study. They were asked to identify the aspects they find crucial when deciding whether to read an article or not. The collected responses were analyzed and summarized, while the similar characteristics were grouped together to create a list of key factors in headline assessment. As a result, 14 categories were identified, reflecting the preferences and priorities of students regarding the main attributes of an appealing headline. The participants were then asked to rate the importance of these headline characteristics. The analysis of their responses offers a detailed view of the elements that readers prioritize when deciding to click to read an article, highlighting the factors that most influence their decision to read online content. The results are summarized in Table 2 below.

The first aspect that emerges from the collected data is *the clarity of the headline and its ability to accurately represent the content*. Approximately 54.9% of the students view this factor as very important, while 30.2% rate it as important, indicating that the transparency and relevance of the headline in relation to the content are essential criteria for most readers. Only a small percentage (2.9%) of the participants consider this aspect to be of little or very little importance. Additionally, headlines that convey *important information* are regarded as very important by 40.9% of the survey participants, while 34.9% rate it as important. Following this, *creativity and the headline's ability to be engaging* rank third, receiving strong appreciation, with 30.9% of the respondents considering it very important and 36.3% agreeing that it is important.

Table 2. Assessment of the significance of various headline features for readers.

	To a Very Small Extent	To a Small Extent	To Some Extent	To a Large Extent	To a Very Large Extent
To be clear and accurately reflect the content	0.8	2.1	12.0	30.2	54.9
To contain important information	1.4	2.6	20.2	34.9	40.9
To be creative and engaging	1.1	6.2	25.4	36.3	30.9
To pique interest and stimulate curiosity	0.8	4.8	19.7	42.4	32.3
To include keywords relevant to the topic	1.9	6.2	29.1	35.8	26.9
To be short and concise	1.9	6.6	38.0	36.5	17.0
To provide a summary of the content	3.4	13.4	34.9	28.0	20.3
To be shocking or surprising	5.9	17.0	38.6	22.9	15.5
To promise new or exclusive information	5.3	14.3	36.5	26.8	17.1
To have an optimistic or positive tone	4.5	10.6	45.7	26.7	12.5
To be neutral and objective	6.4	22.1	38.7	19.4	13.4
To evoke strong emotions	7.6	20.1	44.2	17.5	10.6
To suggest an unusual situation	8.5	26.1	42.5	15.1	7.9
To contain figures or statistics	12.0	26.1	39.7	14.9	7.2

Another valued aspect is the ability of headlines to *pique interest and stimulate curiosity*, with 32.3% of the interviewees deeming this feature very important and 42.4% considering it important to a large extent. Following this, *the inclusion of relevant keywords* ranks next on the list of preferences, being deemed very important by 26.9% of the respondents and important to a large extent by 35.8%. Most respondents favor *short and concise headlines*; 38.0% consider them somewhat important, 36.5% view them as very important, and 17.0% rate them as extremely important, indicating that readers generally prefer concise titles. Additionally, 20.3% of the respondents highly value headlines that *provide a summary of the content*, while 28.0% consider them very important. This indicates the fact that many readers appreciate headlines that give a clear preview of the article's content, although this feature is not considered the most important one as compared to others. *Shocking or surprising headlines* are not seen as a priority. Only 15.5% of the respondents regard them as very important, while 22.9% consider them significantly important. However, a larger portion (38.6%) consider them as somewhat important, indicating that while such headlines may catch attention, they are not a priority for most readers. On the other hand, headlines that promise *new or exclusive information* are considered very important by 17.1% of the respondents, while 36.5% find them somewhat important. This suggests that, for a significant number of readers, novelty and exclusivity can be key factors in deciding whether to read an article or not. Headlines with *an optimistic or positive tone* are highly valued by 12.5% of the respondents and considered important by 26.7%, while 45.7% view them as somewhat important. This indicates that while a positive tone is appreciated, it is not necessarily a decisive factor in the decision to read an article.

The neutral and objective tone of the headline is appreciated by 19.4% of the participants in the survey, with 13.4% of them rating it very highly. Additionally, a significant portion of readers (38.7%) views this aspect as moderately important.

Headlines that *evoke strong emotions* are rated very highly by 10.6% of the respondents and highly by 17.5% of them. However, for the majority (44.2%), this aspect holds only moderate importance, suggesting that while emotional headlines can draw attention, they are not always a decisive factor in choosing to read.

Headlines *suggesting an unusual situation* are rated as very important by just 7.9% of the survey participants and important by 15.1%, reflecting a lower preference for this style. With 42.5% of the respondents finding this aspect moderately important, it appears that

unusual headlines are generally not a primary factor for most readers when deciding to read an article.

The *inclusion of figures or statistics* in a headline is highly valued by only 7.2% of the respondents and moderately valued by 14.9% of them, with 39.7% considering it somewhat important. This suggests that while headlines featuring figures and statistics are useful to some readers, they are not a decisive factor for most.

To understand how often the study participants have encountered situations where headlines do not accurately reflect the content of the articles, the questionnaire has also included the question, “How often do you come across titles that do not reflect the content of the article?”. The chart below (Figure 3) illustrates the readers’ perceptions of this discrepancy between headlines and content, a common issue in online media.

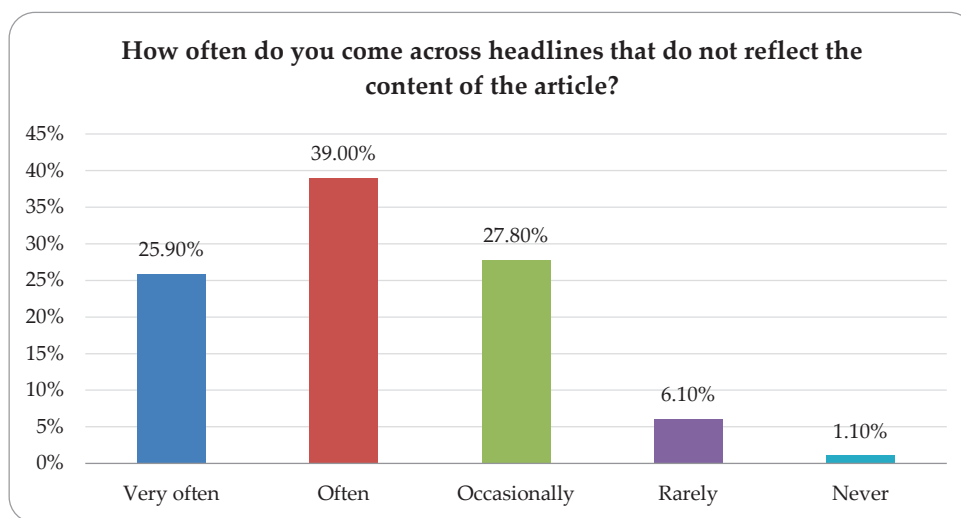


Figure 3. Frequency of encountering misleading headlines.

The largest portion of the respondents (39%) reports frequently encountering headlines that do not accurately reflect the content of the article, indicating a common experience with such discrepancies among readers. Following this, 27.8% of the respondents state that they encounter such headlines occasionally, representing those who experience the issue often enough to notice, but not consistently. Additionally, 25.9% indicate that they very often come across misleading headlines, suggesting that over a quarter of readers are regularly exposed to such headlines, potentially undermining trust in information sources. A smaller group (6.1%) say they rarely encounter such headlines, while only 1% claim that they have never encountered headlines that misrepresent the article’s content.

The question “How frustrated would you feel if you read an article whose headline did not accurately reflect the content?” explores the level of frustration respondents feel towards misleading headlines, offering insight into their emotional responses when an article’s content fails to meet the expectations set by its headline. The results indicate that most respondents (44%) experience moderate frustration, suggesting a significant, though not overwhelming, reaction to discrepancies between the promise of the headline and the content of the actual news piece (Figure 4).

About 36.2% of the study participants report feeling very frustrated, showing that over a third of the sample experiences a high level of frustration in these situations. This suggests that misleading headlines can create a negative experience, potentially undermining trust in the information source. Meanwhile, 18.1% of the respondents maintain a neutral attitude, indicating that they are not significantly impacted by discrepancies between the headline and its content. Only 1.8% of the respondents are not bothered by such headlines, suggesting that a very small portion of the sample feels that misleading headlines do not affect their reading experience.

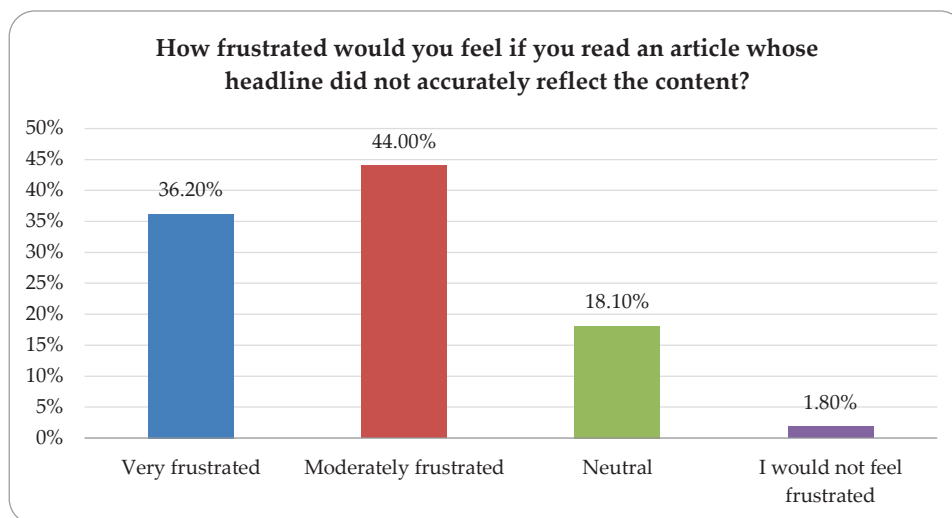


Figure 4. Reader frustration with misleading headlines.

Linguistic and stylistic characteristics of ChatGPT-generated clickbait headlines

This study also explored how various headline types influence the readers' curiosity to engage with an article. The primary goal was to compare original headlines with both clickbait and informative versions generated by ChatGPT to gauge their effectiveness in drawing attention. The data collected (see Figure 5) offer insight into the readers' preferences, showing that ChatGPT-generated clickbait headlines lead, with a top score of 37.5%. This suggests that clickbait headlines are the most successful at capturing attention and arousing curiosity. *The informative headline* by ChatGPT followed closely with a score of 33.4%, indicating that clear and factual headlines also appeal to readers, though somewhat less strongly than clickbait. The small margin between these scores suggests that many readers still value the transparency and accuracy found in informative headlines.

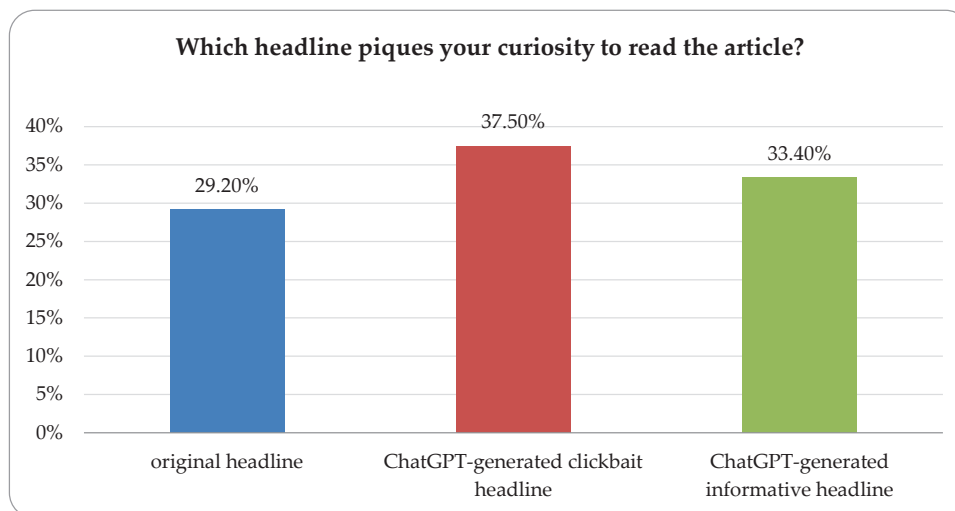


Figure 5. Most engaging headlines for readers.

The article's original headline received the lowest interest score, gathering only 29.2% of responses. This result indicates that the original headlines are less effective at capturing readers' attention as compared to those generated by ChatGPT, whether clickbait or informative.

As clickbait headlines are intricately linked to curiosity through their wording, being crafted to tap into the readers' natural desire to uncover answers and explore the unknown,

it has become clear that studying clickbait headlines from a linguistic perspective is important because it allows for an understanding of the specific linguistic strategies that capture readers' attention, shape perceptions, and influence reader engagement. Moreover, linguistic research on clickbait can reveal how language manipulates information, potentially impacting public perception and trust in the media. It also helps understand how digital communication has evolved with the influence of social media algorithms, which reward engagement, thereby encouraging language use that maximizes clicks.

Therefore, the selected headlines were further analyzed through a qualitative linguistic lens to uncover the features that spark the readers' curiosity and emotional engagement. The analysis first focused on the lexical and grammatical characteristics, followed by the analysis of the stylistic elements, and continued by comparing the human-authored clickbait headlines and the ChatGPT-generated ones to uncover what makes certain headlines more compelling, providing insights into the mechanics of reader engagement and the effectiveness of various headline strategies.

The decision to analyze clickbait through lexis, grammar, and stylistics provides a nuanced framework for understanding the specific linguistic strategies that engage and influence readers. Each level of analysis sheds light on how language is deliberately structured to capture attention in the digital media landscape.

The effectiveness of clickbait relies heavily on its vocabulary choices, which evoke curiosity, emotion, and urgency. The foundational work of Biber et al. (Biber et al. 1999) on lexical patterns highlights the strategic selection of verbs, nouns, and adjectives to create dramatic effects. The psychological dimension of emotionally charged vocabulary is supported by Pennebaker et al. (Pennebaker et al. 2003), who emphasize that words with strong emotional valence increase engagement. In the context of clickbait, this aligns with the use of high-arousal words to stimulate curiosity and anticipation.

In terms of grammar, grammatical structures in clickbait headlines are meticulously designed to draw readers into the narrative. The analysis by Biber et al. (Biber et al. 1999) on tense and aspect could inform how the present tense, commonly used in clickbait, creates a sense of immediacy and relevance. The work of Beaugrande and Dressler (De Beaugrande and Dressler 1981) focuses on principles of cohesion and coherence in texts, which can be directly applied to understanding the use of ellipsis and interrogative structures in clickbait headlines. An ellipsis creates a gap that engages the reader's cognitive processes, requiring them to "fill in the blanks" with information implied by the surrounding text. In the same line, Halliday and Matthiessen (Halliday and Matthiessen 2013) offer a comprehensive framework for analyzing language through its ideational, interpersonal, and textual metafunctions, which can serve as a foundation for studying clickbait. The ideational metafunction helps identify how dynamic verbs, noun phrases, and lexical choices in headlines convey curiosity and emotional engagement. The interpersonal metafunction examines how imperatives, direct address, or rhetorical questions establish a connection with readers. Finally, the textual metafunction reveals how features such as ellipsis or thematic structure enhance cohesion and intrigue, effectively capturing audience attention.

Lastly, stylistics enhances clickbait's appeal by making it more vivid, memorable, and emotionally engaging. For instance, Lakoff and Johnson (Lakoff and Johnson 1980) offer a foundational understanding of how metaphor shapes perception, cognition, and communication. Their insights are particularly relevant to the study of clickbait headlines, which frequently use metaphorical language to evoke emotional responses, create intrigue, and frame information in a compelling way. Similarly, the stylistic principles of Tannen (Tannen 1989), particularly her analysis of involvement strategies in discourse, align with the use of direct address and pseudo-conversational tone in clickbait. Furthermore, Jeffries and McIntyre (Jeffries and McIntyre 2010) provide tools for analyzing how linguistic choices shape meaning and impact, making them highly relevant for studying clickbait. Their focus on the interaction between form and function in texts aligns with examining how stylistic elements like metaphors, lexical emphasis, and structural patterns create intrigue and emotional resonance in headlines. Their discussion of reader interpretation and narrative

engagement helps understanding how clickbait strategically employs stylistic devices to capture attention, evoke curiosity, and manipulate reader expectations.

The analysis of the linguistic and stylistic features of the clickbait headlines is detailed in the following section.

Lexical and grammatical level

At the lexical–grammatical level, verbs and verbal structures play an essential role in creating a sense of urgency and drama.

➤ Verbs and verbal structures

The dynamic verbs found in the clickbait headlines in the analyzed corpus (such as “amenință” (“threatens”), “explodează” (“are exploding”), and “dezvăluie” (“reveals”) imply swift, dramatic, or perilous actions, evoking a sense of intrigue. These verbs indicate that something significant is currently occurring, motivating the reader to seek further information.

E.g.,

“Putin *amenință* cu atacuri preventive! Rusia ar putea lansa prima lovitură nucleară, schimbând doctrina militară!” [“Putin *threatens* with preventive attacks! Russia could launch the first nuclear strike, changing the military doctrine!”]

“Extremiștii proruși din Bulgaria *explodează* în popularitate!” [“Bulgaria’s pro-Russian extremists *are exploding* in popularity!”]

“Olaf Scholz *dezvăluie*: Rusia a renunțat la planul nuclear!” [Olaf Scholz *reveals*: Russia has given up its nuclear plan!”]

Modal verbs such as “ar putea lansa” (“could launch”) introduce uncertainty and possibility, encouraging speculation and enhancing curiosity. They imply a catastrophic scenario that captures attention and drives the reader to delve into potential details.

E.g.,

“Putin *amenință* cu atacuri preventive! Rusia *ar putea lansa* prima lovitură nucleară, schimbând doctrina militară!” [“Putin *threatens* with preventive attacks! Russia *could launch* the first nuclear strike, changing the military doctrine!”]

Likewise, the use of phrases such as “a trasa o linie roșie” (“to draw a red line”) or “a da în judecată” (“to take to court”) creates a framework of tension and mystery, drawing attention to seemingly suspenseful events. “Drawing a red line” or “taking to court” are associated with conflict and tense situations, which can stimulate interest in the development of these events.

E.g.,

“Olaf Scholz *dezvăluie*: Rusia a renunțat la planul nuclear! Află cum comunitatea internațională *a trasat o linie roșie*!” [“Olaf Scholz *reveals*: Russia has abandoned the nuclear plan! Find out how the international community *has drawn a red line*!”]

“Șoc în Elveția! Mii de femei senior *dau în judecată* guvernul din cauza schimbărilor climatice—Europa așteaptă o decizie istorică” [“Shock in Switzerland! Thousands of senior women *take* the government *to court* over climate change—Europe awaits historic decision”]

➤ Nouns

Nouns are strategically selected to heighten emotions. Words such as “bombă” (“bomb”) and “dezastru” (“disaster”) exaggerate the scenarios, making them appear more dramatic. These terms emphasize sensationalism and capture attention, as seen in the following headlines.

E.g.,

“*Bombă* la vama Siret! Vameșii români, complici într-o rețea internațională de fraudă cu tutun, *dezvăluită* de Kovesi!” [“*Bomb* at the Siret customs! Romanian

customs officials, accomplices in an international tobacco fraud network, revealed by Kovesi!”]

“Dezastru în București! Zeci de copaci prăbușiți de furtună din cauza nepăsării autorităților!” [“Disaster in Bucharest! Dozens of trees collapsed by the storm due to the carelessness of the authorities!”]

Other nouns suggest mystery and revelations. Nouns such as “adevărul” (“the truth”), “secretul” (“the secret”), and “povestea nespusă” (“the untold story”) attract attention because they suggest information that is not known to the general public.

E.g.,

“Secretul din spatele numelor Kira și Ianis Hagi! Află povestea nespusă a copiilor lui Gică Hagi care i-a adus succesul!” [“The secret behind the names Kira and Ianis Hagi! Learn the untold story of the children of Gică Hagi who brought him success!”]

“Marian Godină dezvăluie ADEVĂRUL despre dosarul penal al Liei Bugnar: Ce nu știe publicul despre lege!” [“Marian Godină reveals the TRUTH about Lia Bugnar’s criminal case: What the public does not know about the law!”]

➤ Adjectives and adverbs

Adjectives and adverbs enhance the emotional weight of headlines. Words such as “șocantă” (“shocking”) or “incendiară” (“incendiary”) are employed to heighten the headline’s impact, implying that the information presented is highly surprising or even extraordinary.

E.g.,

“Gigi Becali, donație șocantă de 800.000 de euro pentru o biserică în Africa! Află de ce a ales Rwanda!” [“Gigi Becali, shocking donation of 800,000 euros for a church in Africa! Find out why he chose Rwanda!”]

“Bătălia incendiară de la Vocea României! Iulian Nunucă a lăsat juriul fără cuvinte, iar Bogdan Jeler surprinde cu o decizie șocantă!” [“The incendiary battle from the Voice of Romania! Iulian Nunucă has left the jury speechless, and Bogdan Jeler surprises with a shocking decision!”]

Superlatives in the corpus emphasize the uniqueness or intensity of certain elements, creating a heightened sense of drama. They are instrumental in capturing readers’ attention by implying that the event or person being described is extraordinary or uncommon.

E.g.,

“Cel mai murdar om din lume a murit la 94 de ani! Vei fi șocat de motivul pentru care nu s-a spălat timp de 65 de ani!” [“The dirtiest man in the world has died at the age of 94! You’ll be shocked to find out why he hasn’t washed for 65 years!”]

“Incredibil! La 106 ani, Apo Whang-Od devine cel mai bătrân model pe coperta Vogue—povestea care a uimit lumea!” [“Unbelievable! At 106 years old, Apo Whang-Od becomes the oldest model on the cover of Vogue—the story that has stunned the world!”]

Likewise, adverbs of manner such as “brusc” (“suddenly”) or “incredibil” (“unbelievable”) are employed to highlight the novelty or intensity of the events. These words imply an unexpected shift, sparking curiosity about the reasons behind this decision.

E.g.,

“Șoc în junglă! Alex Bogdan părăsește brusc competiția “Sunt celebru, scoate-mă de aici”! Colegii sunt revoltați!” [“Shock in the jungle! Alex Bogdan suddenly leaves the competition “I’m famous, get me out of here”! His colleagues are outraged”]

“Incredibil! La 106 ani, Apo Whang-Od devine cel mai bătrân model pe coperta Vogue—povestea care a uimit lumea!” [“Unbelievable! At 106 years old, Apo Whang-Od becomes the oldest model on the cover of Vogue—the story that has stunned the world!”]

➤ Using numbers

Numbers in clickbait headlines are highly effective in grabbing readers' attention and arousing curiosity. They provide a sense of clarity, specificity, and sometimes an element of surprise, lending the content an appearance of credibility and concreteness.

E.g.,

"Fața ascunsă a lui Tutankhamon dezvăluită după 3.300 de ani! Nu o să crezi cum arată legendarul faraon!" ["Tutankhamun's hidden face revealed after 3,300 years! You won't believe what the legendary pharaoh looks like!"]

"Dezastrul falimentelor din asigurări: Peste 1,6 miliarde de lei pierduți și riscuri uriașe pentru clienți! Află care companie este cea mai afectată!" ["The disaster of insurance bankruptcies: Over 1.6 billion lei lost and huge risks for customers! Find out which company is most affected!"]

➤ Using exclamation marks

Exclamation marks signal a shocking event, giving the impression of urgency and piquing curiosity.

E.g.,

"Bebeto Yildirim, milionarul viral pe TikTok! Află secretul care l-a transformat în cel mai urmărit 'Sugar Daddy' din România!" ["Bebeto Yildirim, the viral millionaire on TikTok! Find out the secret that turned him into the most followed 'Sugar Daddy' in Romania!"]

"România trădată în aderarea la Schengen! Manfred Weber, revoltat: "Nu este corect!" ["Romania betrayed in joining Schengen! Manfred Weber, outraged: "It's not fair!"]

Stylistic level

Beyond the linguistic features previously mentioned, clickbait headlines often employ additional stylistic effects to spark the readers' curiosity. These techniques make the information appear more enticing, provocative, and deserving of attention, as detailed in the following examples.

One of the stylistic techniques employed by ChatGPT was *the use of metaphors and vivid images*. Metaphors create vivid mental images, making headlines more memorable and dramatic. They invite readers to interpret the situation figuratively, which can heighten interest. For instance, "își întinde tentaculele" ("spreading its tentacles") implies aggressive expansion, vividly depicting the Chinese influence, while "bătălia incendiară" ("incendiary battle") evokes a heated confrontation, drawing attention through the intensity of the emotions portrayed.

E.g.,

"China își întinde tentaculele în Orientul Mijlociu! SUA avertizează: Ordinea internațională este în pericol!" ["China is spreading its tentacles in the Middle East! The US warns: international order is in danger!"]

"Bătălia incendiară de la Vocea României! Iulian Nunucă a lăsat juriul fără cuvinte, iar Bogdan Jeler surprinde cu o decizie șocantă!" ["The incendiary battle from the Voice of Romania! Iulian Nunucă has left the jury speechless, and Bogdan Jeler surprises with a shocking decision!"]

Another technique found in the analyzed corpus is *direct questioning and the use of conversational terms*. In Romanian, the T-V distinction to convey politeness plays a key role in communication, reflecting how we relate to the other person based on context formality and the level of respect we intend to show. Phrasings such as "nu o să crezi" ("you won't believe it") or "află cum" ("find out how") directly address the reader, creating the impression that the headline is speaking to them personally. This direct approach is designed to arouse curiosity through a friendly, inviting tone.

E.g.,

“Fața ascunsă a lui Tutankhamon dezvăluită după 3.300 de ani! *Nu o să crezi cum arată legendarul faraon!*” [“Tutankhamun’s hidden face revealed after 3300 years! *You won’t believe what the legendary pharaoh looks like!*”]

“Celine Dion, diagnosticul care îi devastează cariera! *Află cum îi afectează boala concertul din România!*” [“Celine Dion, the diagnosis that devastates her career! *Find out how the disease affects her concert in Romania!*”]

Other headlines use *contrasts and antitheses* to suggest a sudden change or unusual situation, which makes them appealing. For example, the headline below shows a strong contrast between the idea of “eurodeputat” (“MEP”), a respectable civil servant, and “arestat cu 600.000 de euro cash” (“arrested with €600,000 cash”), suggesting corruption or irregularities. This brings an element of surprise and intrigue, making the reader want to know more.

“Scandal uluitor în Parlamentul European! *Fost eurodeputat arestat cu 600.000 de euro cash* ascunși acasă!” [“Amazing scandal in the European Parliament! Former MEP arrested with 600,000 euros in cash hidden at home!”]

Together, lexis, grammar, and stylistics reveal how clickbait operates on multiple linguistic levels to engage readers. Lexical choices set the tone and evoke emotion and grammatical structures establish immediacy and suspense, while stylistic elements ensure vividness and memorability. This multi-layered linguistic approach not only shapes reader behavior but also provides insights into how digital media manipulate language to drive consumption.

Human-authored clickbait headlines vs. ChatGPT-generated clickbait headlines

In examining the respondents’ preferences regarding the clickbait headlines, a notable distinction emerged between human-authored headlines and those generated by ChatGPT. While 29.20% of the participants favored the clickbait headlines crafted by humans, a more significant 37.50% expressed a preference for the ChatGPT-generated headlines. The analysis delves into the characteristics that set these two types apart, seeking to understand why the AI-generated titles resonated more effectively with readers. Key differences may lie in the linguistic features, emotional engagement, and stylistic choices employed in the headlines.

Human-authored headlines have a more sober and informative tone, often focused on facts and analysis, even if they are meant to be clickbait. In the examples below, besides the clickbait element expressed through the interrogative form and the surprise “declarant mort” (“declared dead”) and drama (through EXCLUSIVE NEWS in capitals) elements, the headlines also promise to offer specific answers, e.g., when to read the Akathist or the artist’s answer to the blunder involving irony.

E.g.,

“Când este bine să citești Acatistul Nașterii Domnului. Este considerată cea mai puternică rugăciune pentru Crăciun” [“When is it advisable to read the Nativity Akathist. It is considered the most powerful prayer for Christmas”]

“Cornel Constantiniu a fost declarat mort, la Festivalul Mamaia. Ce replică a avut artistul după gafa Corinei Chiriac: “Bășcălia asta ce este?”/EXCLUSIV” [Cornel Constantiniu was declared dead at the Mamaia Festival. What was the artist’s response after Corina Chiriac’s blunder: “Are you making fun of me?”/EXCLUSIVE NEWS]

In contrast, the ChatGPT-generated headlines often leverage a more sensationalist and provocative tone, employing dynamic verbs, vivid adjectives, with exclamations and wording that suggest urgency or scandal. Headlines are designed to evoke intense emotions and curiosity. The examples below are very suggestive in this respect, especially when

compared to the human-authored headlines; they use exclamations, hyperbolic words (shock), a conversational tone and shorter and more to-the-point sentences.

E.g.,

“Cea mai puternică rugăciune de Crăciun care îți aduce sănătate și pace! Află când trebuie să citești Acatistul Nașterii Domnului!” [“The most powerful Christmas prayer that brings you health and peace! Find out when to read the Nativity Akathist!”]

“ȘOC la Festivalul Mamaia! Cornel Constantiniu, declarat mort din greșeală! Adevărul despre gafa monumentală a Corinei Chiriac!” [“SHOCK at the Mamaia Festival! Cornel Constantiniu, declared dead by mistake! The truth about Corina Chiriac’s monumental blunder!”]

The presented examples illustrate the complex art of combining lexical–grammatical affordances with stylistic strategies to create attention-grabbing headlines, appealing to young audiences.

4. Discussion

The results of this study underscore the significant influence of headlines on readers’ decisions to engage with an article, confirming that headlines are among the main factors driving interaction with media content. About 80% of participants indicated that headlines play a critical role in their reading choices, highlighting the need for strategic headline creation in content production. Additionally, the importance of specific headline characteristics—such as clarity and relevance—was emphasized by most respondents, underscoring that these elements are fundamental in engaging audiences effectively.

In light of this, the study also explores the evolving role of AI in journalism, focusing on its potential to enhance the creation of attention-grabbing headlines within an increasingly competitive digital landscape. As AI technologies become integrated into media production, they offer new efficiencies in headline generation while simultaneously introducing concerns around authenticity and credibility—key pillars of journalistic integrity.

The findings reveal that AI has become a valuable tool in the newsroom, helping to streamline tasks such as data analysis and basic content generation. Yet, despite its convenience, AI brings with it a crucial dilemma. On the one hand, it can quickly generate content that is catchy and tailored to audience preferences; on the other, it risks eroding the very standards of ethical and diverse reporting that foster trust among readers. While sensationalist headlines are effective in drawing readers in, there is a growing discontent when these “clickbait” headlines do not deliver the promised content, ultimately leading readers to view such practices skeptically.

The analysis of the differences between human-authored and AI-generated clickbait headlines offers a valuable window into what truly engages readers and the ethical implications behind these attention-grabbing techniques. By studying how people respond to the subtle linguistic choices that distinguish these headlines, the power behind certain phrasing or structures can be better understood. For content creators, this knowledge is of utmost importance, as it helps pinpoint what drives reader curiosity—insights that can lead to more compelling yet responsible content creation strategies.

Ethics come to the forefront in such an analysis, given the often-controversial nature of clickbait. Headlines that use sensationalism run the risk of misleading or manipulating readers, which raises questions about their transparency. Comparing human and AI-crafted headlines allows creators to assess whether AI might unintentionally reinforce these concerns, or alternatively, if it can be trained to use engaging tactics responsibly.

Furthermore, these results also present the evolution of language models such as ChatGPT. By understanding why certain AI-generated headlines resonate with readers, developers can refine the model to better align with human preferences for authenticity,

effectiveness, and ethical standards. This kind of analysis therefore supports the creation of tools that produce impactful yet trustworthy language—a priority for responsible AI.

Equally important, this analysis can also help readers in recognizing the methods that media use to grab their attention. Developing an awareness of these techniques supports media literacy, empowering audiences to critically assess the headlines and content they encounter.

Ultimately, exploring these differences between human-authored and AI-generated headlines sheds light on AI's potential as a creative partner. It allows us to examine how AI might complement or even extend human intuition and creativity, particularly in fields such as journalism, where headline effectiveness is key. By combining effectiveness, ethics, and audience trust, this analysis reveals a thoughtful approach to using AI as a tool in modern content creation.

5. Limitations and Further Directions

The study presents several limitations that may influence the generalizability and applicability of its conclusions. Firstly, all research participants were Romanian students, which restricts the demographic and cultural diversity of the sample. Their preferences for AI-generated headlines over human-crafted ones may reflect the particularities of the Romanian cultural and educational context, limiting the applicability of the results to other cultural contexts. Additionally, the study does not include participants from other countries or with different media consumption habits, which could lead to varied reactions to AI-generated headlines. This lack of diversity among participants makes it challenging to extrapolate the results to a global level.

At the same time, it is to be acknowledged that further research is necessary in order to fully understand the rationale behind the respondents' choices for a certain type of headline. Understanding why respondents prefer certain types of headlines—whether clickbait or informative—requires deeper exploration of the psychological, cultural, and contextual factors influencing their choices. Investigating these dynamics through behavioral studies, cross-platform analyses, and cultural comparisons can provide valuable insights into how headlines shape digital media engagement while balancing ethical journalism with audience expectations.

Moreover, the AI-generated headlines were produced using only a single ChatGPT model, without investigating the variability offered by other versions or alternative models. This approach reduces the ability to fully understand the potential of various AI models in generating engaging headlines. Participant preferences were evaluated through a questionnaire, a method that introduces a degree of subjectivity in assessing the headlines. In the absence of objective measures, such as click-through rates in real media contexts, conclusions regarding headline appeal are limited to participants' reported perceptions.

These limitations highlight the need for future studies with more diverse samples and objective measures, allowing for a more comprehensive evaluation of AI-generated headlines.

This study serves as a catalyst for further exploration into the complex role of AI in media and journalism, offering a springboard for a range of investigative paths that delve deeper into both the opportunities and challenges AI presents. Its findings reveal how AI-generated headlines influence reader behavior, paving the way for nuanced research on AI's impact on public trust in the news. As AI becomes increasingly embedded in newsrooms, one essential question for future studies could be posed: can AI be trained to create headlines that maintain or even enhance trust, while still captivating readers? This would be especially relevant in light of growing concerns over clickbait and sensationalism in digital media. Moreover, this research could ignite a new wave of longitudinal studies. By tracking the evolution of AI in journalism across regions and cultures, future research could shed light on the long-term impacts of AI on media quality, reader engagement, and even societal trust in journalism. Such comparative studies could uncover the cultural and regulatory factors that shape AI's role in different contexts, revealing both commonalities and unique challenges.

It also highlights readers' appreciation for clarity, relevance, and conciseness, pointing to fertile ground for research into how audience preferences adapt to repeated exposure to both AI-generated and human-created content. A possible area of focus could be the behavioral shifts in readers over time, exploring how continuous interaction with clickbait and straightforward headlines might alter trust in news sources.

Additionally, by comparing human versus AI-generated headlines, this study hints at the potential for effective human–AI collaboration in journalism. Instead of AI replacing human creativity, future research could explore how humans and AI might co-create content, balancing engagement with trustworthiness. This research could identify ways to preserve the human touch in journalism while utilizing AI to enhance productivity and reach.

Lastly, this study brings attention to the ongoing challenges posed by clickbait. While some see clickbait as a necessary evil in digital media, others view it as detrimental to credibility. This study could guide future research into policies that regulate clickbait, investigating the balance between crafting engaging headlines and upholding the ethical standards of journalism.

Author Contributions: Conceptualization, V.G., M.A.F. and M.C.-B.; formal analysis, V.G., M.A.F. and M.C.-B.; investigation, V.G., M.A.F. and M.C.-B.; methodology, V.G., M.A.F. and M.C.-B.; software, V.G., M.A.F. and M.C.-B.; supervision, V.G., M.A.F. and M.C.-B.; visualization, V.G., M.A.F. and M.C.-B.; writing—original draft, V.G., M.A.F. and M.C.-B.; writing—review and editing, V.G., M.A.F. and M.C.-B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available upon request from the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

References

- Altay, Sacha, and Fabrizio Gilardi. 2024. People are skeptical of headlines labeled as AI-generated, even if true or human-made, because they assume full AI automation. *PNAS Nexus* 3: pgae403. [CrossRef]
- Amponsah, Peter N., and Miracle Atianashie. 2024. Navigating the New Frontier: A Comprehensive Review of AI in Journalism. *Advances in Journalism and Communication* 12: 1. [CrossRef]
- Aydın, Begüm, and Mustafa İnce. 2024. Can Artificial Intelligence Write News: A Research on Determining The Effect of Artificial Intelligence on News Writing Practice. *Intermedia International E-Journal* 11: 20. [CrossRef]
- Bazaco, Ángela, Marta Redondo, and Pilar Sánchez-García. 2019. Clickbait as a Strategy of Viral Journalism: Conceptualisation and Methods. *Revista Latina de Comunicación Social* 74: 94–115. [CrossRef]
- Beckett, Charles, and Yaseen Mira. n.d. *Generating Change: A Global Survey of What News Organizations are Doing with AI*. JournalismAI, Polis, Department of Media and Communications, The London School of Economics and Political Science. Available online: <https://www.journalismai.info/research/2023-generating-change> (accessed on 31 October 2024).
- Berber Sardinha, Tony. 2024. AI-generated vs. human-authored texts: A multidimensional comparison. *Applied Corpus Linguistics* 4: 100083. [CrossRef]
- Biber, Douglas, Stig Johansson, Geoffrey N. Leech, Susan Conrad, and Edward Finegan. 1999. *Longman Grammar of Spoken and Written English*. London: Longman.
- Blom, Jonas Nygaard, and Kenneth Reinecke Hansen. 2015. Click bait: Forward-reference as lure in online news headlines. *Journal of Pragmatics* 76: 87–100. [CrossRef]
- Breazu, Petre, and Napoleon Katsos. 2024. ChatGPT-4 as a journalist: Whose perspectives is it reproducing? *Discourse & Society* 35: 687–707. [CrossRef]
- Broscoteanu, Daria-Mihaela, and Radu Tudor Ionescu. 2023. A Novel Contrastive Learning Method for Clickbait Detection on RoCliCo: A Romanian Clickbait Corpus of News Articles. *arXiv* arXiv:2310.06540. [CrossRef]
- Chakraborty, Abhijnan, Bhargavi Paranjape, Sourya Kakarla, and Niloy Ganguly. 2016. Stop Clickbait: Detecting and preventing clickbaits in online news media. Paper presented at the 2016 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM), San Francisco, CA, USA, August 18–21; pp. 9–16. [CrossRef]

- Chan-Olmsted, Sylvia M. 2019. A Review of Artificial Intelligence Adoptions in the Media Industry. *International Journal on Media Management* 21: 193–215. [CrossRef]
- De Beaugrande, Robert-Alain, and Wolfgang U. Dressler. 1981. *Introduction to Text Linguistics*. London: Longman.
- Dragomir, Marius, Davor Marko, Bojan Klačar, and Ivo Čolo. 2024. *How Artificial Intelligence Is Changing Media and Journalism in Central Europe. A Study Mapping the Use of AI by Newsrooms in the Czech Republic, Hungary, Poland and Slovakia*. Thomson Foundation and Media and Journalism Research Center. Available online: <https://journalift.org/resources/how-artificial-intelligence-is-changing-media-and-journalism-in-central-europe/> (accessed on 15 September 2024).
- Fărcașiu, Marcela Alina, and Vasile Gherheș. 2024. *Exploring Linguistic Strategies in Romanian Clickbait Headlines: Communication Tactics in Online Media*. | EBSCOhost. Available online: <https://openurl.ebsco.com/contentitem/gcd:179861731?sid=ebsco:plink:crawler&id=ebsco:gcd:179861731> (accessed on 11 September 2024).
- Fatima, Noureen, Sher Muhammad Daudpota, Zenun Kastrati, Ali Shariq Imran, Saif Hassan, and Nouh Sabri Elmitwally. 2023. Improving news headline text generation quality through frequent POS-Tag patterns analysis. *Engineering Applications of Artificial Intelligence* 125: 106718. [CrossRef]
- Feng, Guangchao Charles. 2024. Effects of narratives and information valence in digital headlines on user responses. *Asian Journal of Communication* 34: 156–77. [CrossRef]
- George, Darren, and Paul Mallery. 2003. *SPSS for Windows Step by Step: A Simple Guide and Reference, 11.0 Update*. Boston: Allyn and Bacon.
- Graefe, Andreas, and Nina Bohlken. 2020. Automated Journalism: A Meta-Analysis of Readers' Perceptions of Human-Written in Comparison to Automated News. *Media and Communication* 8: 50–59. [CrossRef]
- Halliday, Michael Alexander Kirkwood, and Christian M.I.M. Matthiessen. 2013. *Halliday's Introduction to Functional Grammar*, 4th ed. London: Routledge. [CrossRef]
- Helberger, N., S.J. Eskens, M.Z. van Drunen, M.B. Bastian, and J.E. Möller. 2020. *Implications of AI-Driven Tools in the Media for Freedom of Expression: Artificial Intelligence—Intelligent Politics: Challenges and Opportunities for Media and Democracy*. Strasbourg: Council of Europe.
- Howitt, Dennis, and Duncan Cramer. 2008. *Introduction to Statistics in Psychology*. Harlow: Pearson Education.
- Iarovici, Edith, and Rodica Amel. 1989. The strategy of the headline. *Semiotica* 77: 441–60. [CrossRef]
- Ifantidou, Elly. 2009. Newspaper headlines and relevance: Ad hoc concepts in ad hoc contexts. *Journal of Pragmatics* 41: 699–720. [CrossRef]
- Ioscote, Fabia, Adriana Gonçalves, and Claudia Quadros. 2024. Artificial Intelligence in Journalism: A Ten-Year Retrospective of Scientific Articles (2014–2023). *Journalism and Media* 5: 3. [CrossRef]
- Isani, Shaeda. 2011. Of headlines & headlines: Towards distinctive linguistic and pragmatic genericity. *ASp. La Revue Du GERAS* 60: s1–s102. [CrossRef]
- Jeffries, Lesley, and Daniel McIntyre. 2010. *Stylistics*. Cambridge: Cambridge University Press, Cambridge Core. [CrossRef]
- Kuiken, Jeffrey, Anne Schuth, Martijn Spitters, and Maarten Marx. 2017. Effective Headlines of Newspaper Articles in a Digital Environment. *Digital Journalism* 5: 1300–14. [CrossRef]
- Lakoff, George, and Mark Johnson. 1980. *Metaphors We Live by*. Chicago: University of Chicago Press, vol. 40.
- León, Jose A. 1997. The effects of headlines and summaries on news comprehension and recall. *Reading and Writing* 9: 85–106. [CrossRef]
- Leung, Tin Cheuk, and K Coleman S. Strumpf. 2023. *All the Headlines that Are Fit to Change*. SSRN Scholarly Paper 4075398. Rochester: Social Science Research Network. [CrossRef]
- McLuhan, Marshall. 1964. *Understanding Media: The Extensions of Man*. New York: McGraw-Hill.
- Molyneux, Logan, and Mark Coddington. 2020. Aggregation, Clickbait and Their Effect on Perceptions of Journalistic Credibility and Quality. *Journalism Practice* 14: 429–46. [CrossRef]
- Păcurar, Aralda, and Ciprian Oprea. 2023. Using Artificial Intelligence to Fight Clickbait in Romanian News Articles. Paper presented at the 2023 IEEE 19th International Conference on Intelligent Computer Communication and Processing (ICCP), Cluj-Napoca, Romania, October 26–28; pp. 397–404. [CrossRef]
- Pennebaker, James W., Matthias R. Mehl, and Kate G. Niederhoffer. 2003. Psychological aspects of natural language use: Our words, our selves. *Annual Review of Psychology* 54: 547–77. [CrossRef]
- Potthast, Martin, Sebastian Köpsel, Benno Stein, and Matthias Hagen. 2016. Clickbait Detection. In *Advances in Information Retrieval*. Edited by Ferro Nicola, Fabio Crestani, Marie-Francine Moens, Josiane Mothe, Fabrizio Silvestri, Giorgio Maria Di Nunzio, Claudia Hauff and Gianmaria Silvello. Berlin/Heidelberg: Springer International Publishing, pp. 810–17. [CrossRef]
- Prasad, Ramya, and Deepa Makesh. 2024. Impact of AI on Media & Entertainment Industry. In *Media & Journalism Transformations-Emerging Trends and Paradigm Shifts*. Bingley: Emerald Publications, pp. 41–71.
- Scacco, Joshua, and Ashley Muddiman. 2015. The Current State of News Headlines. *Centre for Media Engagement*. Available online: <https://mediaengagement.org/research/the-current-state-of-news-headlines/> (accessed on 15 September 2024).
- Setälä, Sini. 2014. *Tabloid Headlines in Mind: A Frame for Research*. Doctoral dissertation, University of Jyväskylä, Jyväskylä, Finland. Available online: <https://jyx.jyu.fi/handle/123456789/44750> (accessed on 28 August 2024).
- Siitonen, Marko, Anne Laajalahti, and Päivi Venäläinen. 2024. Mapping Automation in Journalism Studies 2010–2019: A Literature Review. *Journalism Studies* 25: 299–318. [CrossRef]

- Sonni, Alem Febri, Hasdiyanto Hafied, Irwanto Irwanto, and Rido Latuheru. 2024. Digital Newsroom Transformation: A Systematic Review of the Impact of Artificial Intelligence on Journalistic Practices, News Narratives, and Ethical Challenges. *Journalism and Media* 5: 1554–70. [CrossRef]
- Stănescu, Georgiana Camelia. 2023. The impact of artificial intelligence on journalism. Adverse effects vs. Benefits. *Social Sciences and Education Research Review* 10: 258–62. [CrossRef]
- Tabachnick, Barbara G., and Linda S. Fidell. 2012. *Using Multivariate Statistics*, 6th ed. Harlow: Pearson.
- Tannen, Deborah. 1989. *Talking Voices: Repetition, Dialogue and Imagery in Conversational Discourse*. Cambridge: Cambridge University Press.
- Van Dalen, Arjen. 2012. The Algorithms Behind the Headlines: How machine-written news redefines the core skills of human journalists. *Journalism Practice* 6: 648–58. [CrossRef]
- Zheng, Yue, Bu Zhong, and Fan Yang. 2018. When algorithms meet journalism: The user perception to automated news in a cross-cultural context. *Computers in Human Behavior* 86: 266–75. [CrossRef]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.

Article

Generative AI and Media Content Creation: Investigating the Factors Shaping User Acceptance in the Arab Gulf States

Mahmoud Sayed Mohamed Ali ^{1,2,*}, Khaled Zaki AbuElkhair Wasel ^{3,4}
and Amr Mohamed Mahmoud Abdelhamid ^{5,6}

¹ Mass Communication Department, College of Arts and Sciences, Abu Dhabi University, Abu Dhabi P.O. Box 59911, United Arab Emirates

² Public Relations and Advertising Department, Faculty of Mass Communication, Beni-Suef University, Beni-Suef P.O. Box 62511, Egypt

³ Communication and Multimedia Department, University College of Bahrain, Manama P.O. Box 55040, Bahrain; kwasel@ucb.edu.bh

⁴ Journalism Department, Faculty of Mass Communication, Cairo University, Giza P.O. Box 12613, Egypt

⁵ Mass Communication Department, College of Communication, Al Qasimia University, Sharjah P.O. Box 63000, United Arab Emirates; aabdelhamid@alqasimia.ac.ae

⁶ Radio and Television Department, Faculty of Mass Communication, Beni-Suef University, Beni-Suef P.O. Box 62511, Egypt

* Correspondence: mahmoud.ali@adu.ac.ae

Abstract: This article aims to investigate the factors that affect behavioural intention (BI) and user behaviour (UB) among Arabian users of generative artificial intelligence (GenAI) applications in the context of media content creation. The study's theoretical framework is grounded in the unified theory of acceptance and use of technology (UTAUT2). A sample of 496 users was analysed using the partial least squares structural equation modelling technique (PLS-SEM). The results revealed that BI is significantly influenced by performance expectancy, effort expectancy, social influence, hedonic motivation, habit, and user trust, with hedonic motivation having the greatest impact. In terms of UB, facilitation conditions, habit, user trust, and BI were all found to have a positive and significant impact. This study contributes to the existing theory on the utilisation of GenAI applications by organising findings pertaining to the use of AI technology for media content creation.

Keywords: generative AI; media content; Arabian Gulf; UTAUT2; technology acceptance

1. Introduction

Information technology has undergone rapid advancement in recent years, driven in part by artificial intelligence (AI) and related technologies and applications. This progress has been particularly notable since the rise of generative AI (GenAI), which uses advanced algorithms to analyse data patterns and use that information to create various types of new content, including text, images, sounds, videos, and code (Michel-Villarreal et al. 2023).

Major technology companies, such as Microsoft and Google, have begun to compete in launching GenAI applications. OpenAI, supported by Microsoft, announced the interactive chatbot ChatGPT in November 2022; Google launched the Google Bard application, and other applications have since appeared, such as Midjourney AI for photos, which is also owned by OpenAI (Feuerriegel et al. 2023).

Technology companies are intensifying their efforts to not only release new apps but also enhance existing ones, elevating them to a professional level of content creation utilising four cutting-edge technologies: natural language, machine learning, computer vision, and artificial neural networks. These technologies simulate the functions of the human brain and are highly effective at learning from large volumes of data (Fui-Hoon Nah et al. 2023).

In the context of the recent developments in generative artificial intelligence during the current year, OpenAI launched ChatGPT 4o with Canvas, which features performance

and efficiency improvements that allow users to edit texts and codes and develop ideas (OpenAI 2024). Google also introduced a new update to its Gemini 1.5 Pro model, which supports text, image, and video analysis with multimedia capabilities (Google AI 2024).

Microsoft launched Copilot Vision, which enables users to analyse texts and images on web pages in real-time while maintaining privacy and security while browsing (Microsoft 2024). It also launched MidJourney version 6.1, which offers significant improvements in image quality and accuracy while reducing visual defects and enhancing details of small elements (MidJourney 2024).

GenAI represents significant monetary potential, with global corporate profits projected to range from \$2.6 and \$4.4 trillion per year. According to World Economic Forum forecasts, GenAI is projected to contribute around \$16 trillion to the worldwide economy by the year 2030 (Paige et al. 2023).

One of the key ethical challenges posed by AI in creative fields is the blurring of the lines between human-generated and AI-generated content. This raises crucial questions about authenticity and plagiarism, as the distinction between inspiration and imitation becomes increasingly blurred (Kanont et al. 2024).

Additionally, the incorporation of AI into creative workflows has raised apprehensions regarding the possible displacement of creative professionals in fields like media and film, with AI's ability to generate texts and compositions raising fears of job losses among writers (Cheng 2024). Others argue that AI can act as a valuable collaborator, enhancing rather than replacing human creativity (Lai 2023).

Arab countries, especially those in the Gulf region, have made numerous efforts to adopt GenAI and benefit from its applications. The United Arab Emirates has created the position of Minister of State for Artificial Intelligence and the Digital Economy and developed the National Strategy for Artificial Intelligence 2031, which aims to achieve global leadership in the field of AI. It has also launched the Artificial Intelligence Programme and established the Artificial Intelligence and Digital Transactions Council with the aim of creating a stimulating environment for the application of AI technologies and developing guidelines for GenAI (Artificial Intelligence Office, UAE 2024).

The Kingdom of Saudi Arabia established the Saudi Data and Artificial Intelligence Authority (SDAIA), issued two guides on using GenAI, created the National Center for Artificial Intelligence, and strengthened the research and innovation system. AI is expected to contribute 58.8 trillion Saudi riyals to the domestic product by 2030 (Saudi Authority for Data and Artificial Intelligence 2024).

Qatar launched a project called The Arab Model for Generative Artificial Intelligence Fanar to develop Arabic content using GenAI, aiming to improve both accuracy and understanding. In the Kingdom of Bahrain, the Labor Fund "Tamkeen" launched the Artificial Intelligence Academy, a training platform that helps young people enhance their innovative and creative abilities. It also created the Sheikh Nasser Center for Research and Development in Artificial Intelligence and designed a guide to help governments use AI technologies in a responsible and sustainable manner (Nasser Vocational Training Center 2023).

Trust in AI applications among users in Gulf countries is influenced by several factors, including the level of awareness of potential concerns, misuse and its impact on psychological security, and cultural factors (Aldossary et al. 2024; Pashentsev et al. 2024; Alshamsi et al. 2024). Concerns about the impact of AI on the labour market make users anxious about their professional future, especially among workers in media institutions (Al Adwan et al. 2024).

In the Arab Gulf states, efforts are underway to localise GenAI technology and raise awareness about its applications. Various studies have analysed the challenges and ethical issues problems associated with AI and its applications and investigated the impact of AI on professions and opportunities while failing to address user acceptance and motivation for using these technologies. This study aims to explore the factors influencing user behavioural intention (BI) and user behaviour (UB) regarding GenAI in the Arab Gulf states. The following four questions will be explored:

Q1: What factors influence the acceptance of GenAI applications among users in the Arabian Gulf states?

Q2: What are the most widely used applications of GenAI among users in the Arabian Gulf states?

Q3: What are the uses of GenAI applications among users in the Arabian Gulf states?

Q4: To what extent are users in the Arabian Gulf region aware of the differences between human-generated content and GenAI applications?

1.1. Literature Review

Factors Affecting Acceptance of Generative Artificial Intelligence Applications

GenAI applications, which integrate deep learning with natural language processing to enable human-like interactions, represent a significant advance over traditional AI systems (Markovič 2024). These applications, such as ChatGPT, Copilot, Gemini, and others, are changing how we communicate and engage with technology (Victor et al. 2023).

Studying the acceptance of GenAI applications is essential to grasp the elements that motivate both individuals and organizations to adopt this technology (Ho et al. 2022). Studies have investigated various factors influencing GenAI adoption, highlighting the perceptions, benefits, challenges, and levels of acceptance among different user groups, as well as technology acceptance, UB, technological progress, and ethical considerations (Ling et al. 2021).

Yin et al. (2023) highlighted the underlying factors predicting professionals' acceptance of and intention to use GenAI, focusing on the anxiety about AI among professionals working in creative industries. The study indicated that factors such as performance expectancy (PE), social influence (SI), pleasure motives (hedonic motivation, HM), and habit (HT) significantly influenced user intentions and acceptance. In contrast, expected effort (EE), facilitating conditions (FC), and price value (PV) had no significant impact.

A study by Kim and Kim (2020), which surveyed media professionals who produce news using GenAI, found that media reliability was the most significant influencing factor for the acceptance of GenAI content. Readers prioritised the reliability of the media source over technical aspects, indicating that in the media, trust is crucial in the acceptance and use of GenAI applications.

In the context of the academic community, Strzelecki et al. (2024) examined the factors affecting the intention to use ChatGPT for research and teaching among academics in Poland. They found that HT, PE, and HM were key factors shaping teachers' and researchers' intentions to adopt ChatGPT, with both personal innovation and SI also positively influencing its acceptance. EE and ease of adoption did not significantly affect academics' acceptance of this tool, suggesting that academics are willing to invest more effort in technology if they perceive it as valuable to their work. The study identified age as the sole variable influencing academics' acceptance and adoption of AI applications.

Lavidas et al. (2024) came to a different conclusion. In exploring students' use of GenAI at the Greek University of Patras, it found that acceptance and adoption were unaffected by gender, age, and experience. Instead, the study confirmed that PE, HT, BI, FC, and HM significantly influenced students' intentions to use GenAI applications. Furthermore, Salama (2023) found that gender and specialisation had no effect on students' acceptance of GenAI applications, with students considering them valuable tools capable of enhancing their creative work and abilities. The study also identified that expected benefits, ease of use, attitudes towards use, and BI influenced their acceptance and use of GenAI applications.

Some studies have identified obstacles limiting the wider adoption of GenAI in the academic context (Abdullah and Zaid 2023; Kshetri 2024), such as lack of relevance; excessive reliance; inadequate support, training, and resources; and, most importantly, ethical issues.

Vo and Nguyen (2024) examined how English major students perceive the use of ChatGPT for language development and identified the factors influencing their acceptance of GenAI applications. They discovered that while the students found ChatGPT easy to

use and considered it useful for language learning, they were neutral about its overall usefulness. The study also confirmed that gender had no effect on students' acceptance and perceptions of GenAI applications. This finding was confirmed by Nja et al. (2023), who examined the factors influencing the use of AI applications by science teachers and found that behaviour and intention to use GenAI applications were unaffected by gender, age, and place of residence.

In the engineering field, Russo (2024) found that social factors had no significant influence on GenAI usage intention. Additionally, while personal and environmental factors shaped technology perceptions, they did not directly affect their usage intention. Bernal and Maligaya (2024) investigated the levels of awareness and acceptance of GenAI among airline engineers and its application in problem-solving. They observed significant acceptance among the airline engineers, with expected usefulness and ease of use playing key roles in their acceptance and adoption of GenAI applications.

When it comes to user trust (UT), the relationship between humans and AI is complex. Studies indicate that although people may forgive human errors, they quickly lose trust in AI, which confirms the importance of the trust factor in accepting GenAI (Wirtz et al. 2018). Individuals' demographic characteristics and attitudes towards the efficiency of GenAI applications significantly influence their trust in them (Yakar et al. 2022).

The use of GenAI applications also brings up numerous ethical issues about authorship, academic integrity, trust, misinformation, deepfakes, algorithmic bias, transparency, accountability, and impact on human creativity (Al-kfairy et al. 2024; Wakunuma and Eke 2024; Porsdam Mann et al. 2023; Bautista et al. 2024; Fui-Hoon Nah et al. 2023). Privacy concerns are another critical area for ethical scrutiny. The gathering and utilization of personal information for training AI models brings forth numerous significant inquiries regarding consent, data ownership, and the right to privacy (Oladoyinbo et al. 2024; Hastuti and Syafruddin 2023).

1.2. Theoretical Framework

The UTAUT2 model, introduced in 2012, swiftly gained widespread recognition due to its capacity to elucidate the factors impacting technology adoption. Its efficacy has been demonstrated across various contexts, technologies, cultures, and nationalities. Venkatesh (2022) considered UTAUT a powerful general theoretical model that could be integrated with other models to enhance the comprehension of technology adoption behaviour. PE, SI, and FCs emerged as primary influencers directly affecting the intention to use.

The internet and smartphones have become crucial components of daily life. Numerous scholars have endeavoured to identify the determinants shaping individuals' acceptance and comprehension of new technology (Hughes et al. 2019), exploring myriad theories, contexts, units of analysis, and research methodologies (Choudrie and Dwivedi 2005; Dwivedi and Williams 2008). These encompass, among others, the diffusion of innovation (DoI) by Rogers (1962), the technology acceptance model (TAM) by Davis (1989), the theory of planned behaviour (TPB) by Ajzen (1991), and the theory of task-technology fit (TTF) by Goodhue and Thompson (1995).

The TAM has significantly contributed to developing frameworks to explain and anticipate the acceptance and adoption of novel technologies. The TAM suggests that the perception of a new technology's usefulness, as well as its ease of use, significantly influence its acceptance. Extending the TAM framework, Venkatesh et al. (2012) introduced the UTAUT, amalgamating prior studies and introducing the effects of new variables, including PE, effort expectancy (EE), SI, FC, HM, PV, and HT, on BI.

Several extensions have emerged that include additional variables and are collectively referred to as (TAM++). The technology acceptance model (TAM) has been widely validated as a leading scientific model and a reliable model for explaining, predicting, and improving user acceptance across a range of technology applications (Davis et al. 2024).

In previous studies related to AI usage, UTAUT has been empirically tested for its validity and reliability (Lin and Lee 2023; Venkatesh 2022; Zhang 2020) and has proven effective in assessing the acceptance of new technologies like GenAI. De Graaf et al. (2017) used UTAUT as a framework for evaluating the acceptability of social robots, while Terblanche and Kidd (2022) scrutinised adoption determinants for AI and the Internet of Things (IoT) AI. Kuberkar and Singhal (2020) and Ho and Cheung (2024) found that trust in AI influences the public's perceptions of autonomous drones.

Ho and Cheung (2024) augmented the UTAUT2 model to enhance the understanding of public trust and intention to utilise AI. Upadhyay et al. (2022) found that factors like PE, openness, SI, HM, and creative motives positively impact entrepreneurs' inclination to use AI. Ahmed et al. (2023) conducted a comprehensive meta-analysis, revealing that PE, perceived usefulness, UT, and HT were the most accurate predictors of consumer BI for mobile app adoption.

Alkhwaldi and Abdulmuhsin (2022) enriched UTAUT2 by incorporating contextual factors such as trust and autonomy as key predictors of remote learning acceptance. Maican et al. (2023) utilised structural equation modelling (SEM) to analyse how UTAUT2 factors affect BI towards GenAI, noting the influences of language proficiency and gender. Wang and Zhang (2023) evaluated factors driving Generation Z's embrace of GenAI-assisted design, finding positive effects of EE, PV, and HM but no significant effect of PE. Zhu et al. (2024) extended the UTAUT2 model with ethical influencing factors, while Yin et al. (2023) explored the adoption of GenAI, identifying predictors including PE, SI, HM, HT, and AI anxiety.

In this study, the UTAUT model is critical for explaining and analysing factors affecting the acceptance of GenAI applications among users in the Arab Gulf states.

1.3. Research Hypotheses

The UTAUT2 model was used to investigate 12 hypotheses (see Figure 1) that centre on the key influences related to GenAI:

- H1.** *PE has a positive direct influence on the BI to use GenAI in media content creation.*
- H2.** *EE has a positive direct influence on the BI to use GenAI in media content creation.*
- H3.** *SI has a positive direct influence on the BI to use GenAI in media content creation.*
- H4.** *FCs have a positive direct influence on the BI to use GenAI in media content creation.*
- H5.** *FCs have a positive direct influence on GenAI UB in media content creation.*
- H6.** *HM has a positive direct influence on the BI to use GenAI in media content creation.*
- H7.** *PV has a positive direct influence on the BI to use GenAI in media content creation.*
- H8.** *HT has a positive direct influence on the BI to use GenAI in media content creation.*
- H9.** *HT has a positive direct influence on GenAI UB in media content creation.*
- H10.** *UT has a positive direct influence on the BI to use GenAI in media content creation.*
- H11.** *UT has a positive direct influence on GenAI UB in media content creation.*
- H12.** *BI has a positive direct influence on GenAI UB in media content creation.*

This figure illustrates the proposed conceptual model, showing the relationships between key constructs influencing user behaviour and behavioural intention. The constructs include social influence, performance expectancy (PE), effort expectancy (EE), facilitating

conditions (FCs), user trust (UT), hedonic motivation (HM), habit (HT), and price value (PV). Arrows represent hypothesised relationships, labelled as H1 through H12, indicating the proposed hypotheses tested in the study.

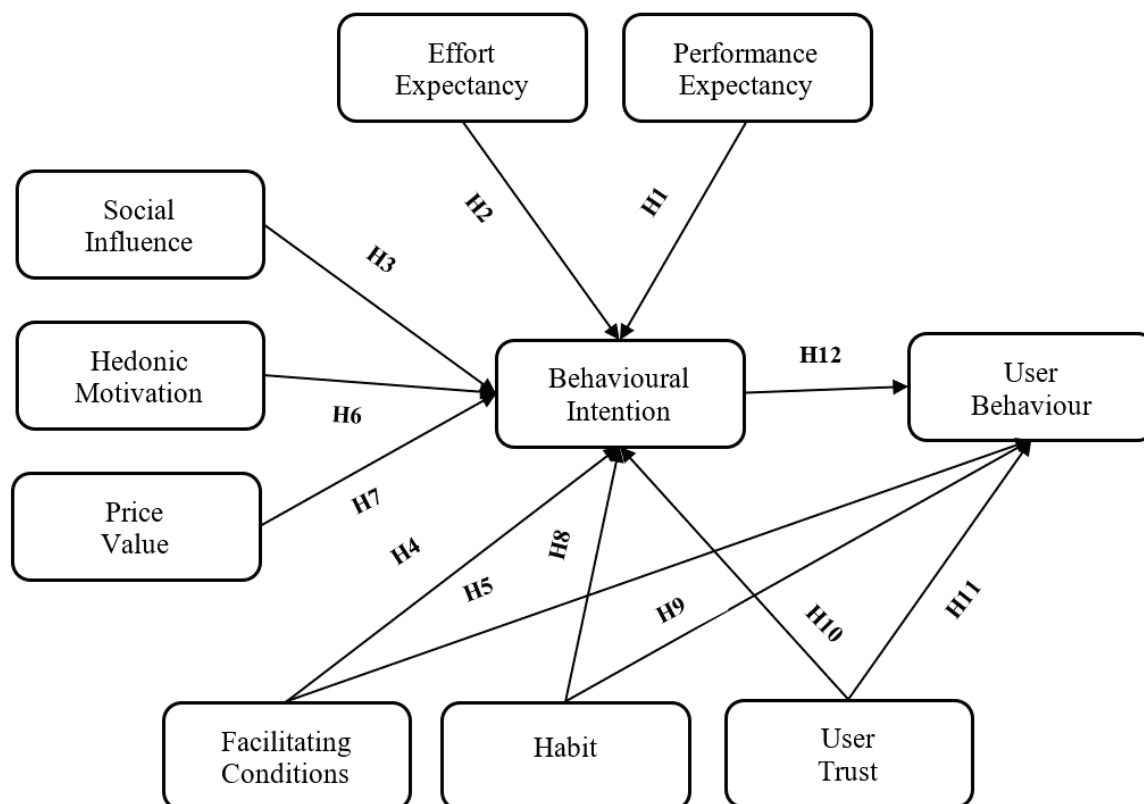


Figure 1. Hypothesised model (adopted from the UTAUT2 model).

Table 1 presents an overview of measurement scales, factor loadings, means, and standard deviations (SD) for each construct of the UTAUT2 model. The table outlines specific items for each construct, including item descriptions, average scores, and SD, illustrating the respondents' average agreement and consistency (or lack thereof) among each construct. This structure is useful in evaluating the model's constructs, is backed by clearly defined measures and trustworthy sources, and guarantees clarity and consistency in interpretation.

Table 1. Measurement scale and factor loadings, means, and standard deviation (SD).

Constructs	Items	Description	Mean	SD	Measure Definition and Source
Performance expectancy (PE)	PE1	I expect generative AI applications to provide new and innovative ideas.	4.16	0.89	PE "refers to the extent to which individuals believe that using a system will help them attain gains in job performance or enhance their performance in learning processes" (Venkatesh et al. 2003).
	PE2	These applications help me accomplish tasks quickly.	4.17	0.82	
	PE3	Using generative AI applications increases my work performance.	4.03	0.91	
	PE4	The use of generative AI applications brings about positive change.	3.99	0.91	
	PE5	Using generative AI applications enhances my chances of solving the problems I encounter.	4.01	0.95	
	PE6	Generative AI applications help me create content in a short time without affecting quality.	3.93	0.98	
	PE7	I expect these apps to produce diverse content that meets my needs.	4.00	0.94	

Table 1. Cont.

Constructs	Items	Description	Mean	SD	Measure Definition and Source
Effort expectancy (EE)	EE1	Applications are capable of completing tasks autonomously without the need for constant human intervention.	3.79	0.98	EE is defined “as the degree of ease or effort associated with the use of technology” (Venkatesh et al. 2003).
	EE2	Generative AI applications are easy to use.	4.01	0.87	
	EE3	I can be good at using applications without needing much technical experience.	3.97	0.89	
	EE4	My interaction with generative AI applications is clear and understandable.	3.99	0.86	
Facilitating conditions (FCs)	FC1	Generative AI applications align with other technologies I use.	3.98	0.88	FC is defined as “the degree to which an individual believes that an organisational and technical infrastructure exists to support use of the system” (Venkatesh et al. 2003).
	FC2	I can get help from others when I have difficulty using apps.	3.99	0.92	
	FC3	If I encounter any problems while using generative AI applications, I have access to the necessary information and technical support to resolve them.	3.92	0.96	
	FC4	Subscription to generative AI applications matches the systems and software I use.	3.91	0.93	
	FC5	The information needed to use the apps is available and easy to access.	4.01	0.90	
Social influence (SI)	SI1	People who are important to me think I should use generative AI applications.	3.84	0.94	SI is defined “as the extent to which important others, such as family and friends, believe that an individual should use a particular technology” (Venkatesh et al. 2003).
	SI2	People whose opinions I value prefer that I use generative AI applications.	3.85	0.97	
	SI3	The organisations I work with allow me to use the apps.	3.80	0.96	
	SI4	My use of generative AI applications increases other people’s interactions with me.	3.79	1.01	
	SI5	Users of generative AI applications are better placed in their organisations.	3.86	0.95	
Hedonic motivation (HM)	HM1	Using generative AI applications is fun.	4.15	0.82	HM is “the fun or pleasure derived from using a technology” (Venkatesh et al. 2012).
	HM2	Generative AI applications provide an impressive experience.	4.17	0.81	
Price value (PV)	PV1	Companies offer generative AI applications at affordable prices.	3.70	1.04	PV is “an individual’s trade-off between the perceived benefits of using the system and its monetary cost” (Venkatesh et al. 2012).
	PV2	I consider subscription prices for generative AI applications to be good value for the money.	3.73	1.00	
Habit (HT)	HT1	Using generative AI applications has become a habit for me.	3.66	1.14	HT is defined “as the extent to which an individual tends to perform behaviours automatically because of prior learning and experiences with the technology” (Venkatesh et al. 2012).
	HT2	Using generative AI applications has become natural for me.	3.97	1.10	
User Trust (UT)	UT1	I trust the accuracy of content produced using generative AI.	3.70	0.99	UT is “users’ confidence in the security and reliability of the technology” (Gefen and Straub 2003).
	UT2	I trust the realism of images produced using generative AI.	3.62	0.99	
	UT3	The video produced by generative AI is as close to the truth as possible.	3.73	1.01	
	UT4	The sounds produced by generative AI approximate natural sounds.	3.84	1.01	
Behavioural intention (BI)	BI1	I intend to continue using generative AI applications in the future.	4.16	0.88	BI refers to “individuals’ willingness and intention to use a particular technology for a specific task or purpose” (Venkatesh et al. 2012).
	BI2	I will always try to use generative AI applications in my life.	4.01	0.95	
	BI3	I plan to continue using generative AI applications frequently.	4.04	0.89	

Table 1. Cont.

Constructs	Items	Description	Mean	SD	Measure Definition and Source
User behaviour (UB)	UB1	I use generative AI applications regularly in my work.	3.88	0.97	UB “aims to explain user technology acceptance and usage behaviour. According to the model, actual use refers to the extent to which users actually use a technology for a specific task or purpose” (Strzelecki et al. 2024).
	UB2	I use generative AI applications on various devices I own.	3.93	0.98	
	UB3	I spend a lot of time using generative AI applications.	3.65	1.09	

2. Method

2.1. Research Design

Using the UTAUT2 model as its foundation, this study utilised a quantitative research design and survey methodology to examine the factors influencing the acceptance of GenAI by users in the Arabian Gulf for content production.

2.2. Sample Description

The study targeted users in the Arabian Gulf region, focusing on users of GenAI applications in the UAE, Saudi Arabia, and Bahrain, whether citizens or residents, who varied by gender, age, nationality, and years of experience using GenAI applications. The sample was selected using a non-random, purposive sampling method, chosen to ensure relevance to the research objectives.

G*power (v3.1.9.4), as described by Faul et al. (2009), was utilised to calculate the minimum necessary sample size according to statistical power. The sample consisted of 526 respondents, with 30 participants excluded for unsuitability. Thus, 496 cases were valid for data analysis, which was considered sufficient for SEM analysis.

The Arab Gulf states were chosen based on their efforts to localise GenAI technology and spread awareness of its applications, which enabled the respondents to answer the questionnaire accurately. These countries also include many nationalities with diverse cultural and social backgrounds, which contributes to enriching the results of the field study.

Using a non-random sample in this study is justified for several reasons. It enables researchers to select a specific target relevant to the research objectives, especially when comprehensive databases for random sampling are unavailable (Shaliha and Marsasi 2024; Schnuerch and Erdfelder 2023).

This approach is appropriate in terms of selecting eligible respondents for the study, ensuring that they have knowledge and experience in dealing with GenAI applications, which makes the data collected more relevant to the study objectives. This is vital in the Gulf region due to its wide geographical and demographic diversity, as the use of a random sample requires large financial resources and logistical difficulties related to collecting comprehensive data on all citizens and residents in the target countries.

This study’s exploratory nature focuses on examining how specific user groups interact with GenAI technology. Therefore, the primary aim is not absolute generalisation but rather an understanding of behavioural patterns and user trends within this newly emerging technological context.

As shown in Table 2, 50.4% of the respondents were male and 49.6% were female. Most respondents were aged 18–37 (79.7%), with only 20.3% over 38 years old. This may be due to younger people having greater familiarity with AI. Most respondents (73.2%) had less than one year of experience using GenAI. In terms of the level of interest in GenAI applications, 20.8% reported a constant interest, 44.2% expressed occasional curiosity, and 35.1% said they rarely use it.

Table 2. Respondents' profile.

Variables	Categories	Frequency	Percent
Gender	Male	250	50.4
	Female	246	49.6
Age	18–27 years	289	58.3
	28–37 years	106	21.4
	38–47	77	15.5
	48 years and over	24	4.8
status	Citizen	265	53.4
	Resident	231	46.6
Experience with GenAI	Less than one year	363	73.2
	More than one year	133	26.8
Interest in GenAI applications	Always	103	20.8
	Sometimes	219	44.2
	Rarely	174	35.1

2.3. Data Collection

Using a web survey created in Google Docs, data were collected via social media platforms, email lists, and professional networks. The online responses were collected from mid-April until the end of May 2024. Participation was voluntary.

2.4. Survey Instrument

UTAUT2 was utilised to develop the survey instrument, which included five main sections: level of experience with GenAI applications, everyday use of GenAI applications, level of awareness of the distinction between GenAI-generated and human-produced content, confidence in the content produced using GenAI, and factors affecting the acceptance of GenAI applications, including PE, EE, SI, FC, HM, PV, HT, and UT. To test the instrument, we ran a trial with a small user sample. Feedback from this test led to adjustments to improve clarity and reliability.

2.5. Data Analysis

In this investigation, researchers applied two types of statistical software, SPSS (v22) and SmartPLS (3.2.9), to analyse the research dataset. The researchers chose the PLS-SEM technique due to the numerous constructs related to the number of items and the model's complexity. In addition, PLS-SEM can be applied to non-normal datasets (Al-Sharafi et al. 2022) and is a non-parametric statistical method that performs exceptionally well on small sample sizes (Roy et al. 2024).

A bootstrapping technique with 5000 subsamples, along with the path coefficient of the constructs, was used to assess the statistical significance of the findings (Kashyap and Agrawal 2020). There are two primary steps for analysing data with PLS-SEM: the measurement model and the structural model.

2.6. Normality Test

The multivariate normality of the dataset was also checked using a web-based calculator (Zhang and Yuan 2018). Following Mardia (1970), we obtained multivariate skewness ($\beta = 992.4121$, p -value < 0.001) and multivariate kurtosis ($\beta = 4942.3441$, p -value < 0.001). This implies that the data are not in multivariate normal distribution. PLS-SEM is a highly effective approach for handling non-normal datasets in such scenarios (Hair et al. 2019), which provides further support for the use of PLS-SEM.

2.7. Measurement Model Assessment

Initially, the measurement model was verified for accuracy and reliability. To accomplish this, we comprehensively analysed multiple facets of the variables. For the internal consistency and reliability of the constructs, we tested factor loadings (λ), composite reliability (CR), and Cronbach's alpha (α) values. The cut off value for the measures was

at least 0.70 (Roy 2022). All λ , CR, and α values exceeded the threshold value. We then employed average variance extracted (AVE) values to evaluate the convergent validity of the constructs. Normally, an AVE value of more than 0.50 is acceptable (Hair et al. 2019). All our AVE values were over 0.50, confirming convergent validity. Table 3 presents the outcomes.

Table 3. Measurement model results.

Factors	Items	Loadings (λ)	α	CR	AVE
Behavioural intention (BI)	BI1	0.894	0.881	0.927	0.808
	BI2	0.894			
	BI3	0.909			
Effort expectancy (EE)	EE1	0.734	0.904	0.904	0.904
	EE2	0.859			
	EE3	0.874			
	EE4	0.881			
Facilitating conditions (FCs)	FC1	0.783	0.877	0.911	0.672
	FC2	0.773			
	FC3	0.854			
	FC4	0.833			
	FC5	0.851			
Hedonic motivation (HM)	HM1	0.921	0.800	0.909	0.833
	HM2	0.904			
Habit (HT)	HT1	0.934	0.731	0.876	0.780
	HT2	0.829			
Performance expectancy (PE)	PE1	0.765	0.919	0.935	0.674
	PE2	0.825			
	PE3	0.835			
	PE4	0.828			
	PE5	0.835			
	PE6	0.824			
	PE7	0.834			
Price value (PV)	PV1	0.898	0.812	0.913	0.840
	PV2	0.935			
Social influence (SI)	SI1	0.816	0.889	0.918	0.693
	SI2	0.854			
	SI3	0.813			
	SI4	0.828			
	SI5	0.849			
User behaviour (UB)	UB1	0.862	0.828	0.897	0.744
	UB2	0.853			
	UB3	0.872			
User trust (UT)	UT1	0.848	0.862	0.906	0.707
	UT2	0.858			
	UT3	0.843			
	UT4	0.815			

Subsequently, discriminant validity was assessed in PLS-SEM using the Fornell and Larcker characteristics (1981) and the heterotrait–monotrait ratio (HTMT) (Henseler et al. 2015). According to Fornell and Larcker’s criteria, the square root of the AVE values must be more than the construct correlations. As shown in Table 4, all the square roots of the AVE values exceeded the correlations of the constructs. All the HTMT scores were below the expected standard of 0.80 (Kline 2023), revealing no discriminant validity issues. Table 4 displays the outcomes. All the HTMT scores were below the expected standard, indicating no issues with discriminant validity.

Table 4. Discriminant validity results.

Fornell–Larcker Results										
	BI	EE	FC	HM	HT	PE	PV	SI	UB	UT
BI	0.899									
EE	0.611	0.839								
FC	0.554	0.659	0.819							
HM	0.657	0.586	0.565	0.913						
HT	0.433	0.365	0.386	0.368	0.883					
PE	0.646	0.659	0.618	0.634	0.429	0.821				
PV	0.244	0.354	0.407	0.273	0.161	0.287	0.917			
SI	0.592	0.606	0.643	0.543	0.432	0.525	0.396	0.832		
UB	0.633	0.503	0.545	0.521	0.564	0.509	0.317	0.626	0.862	
UT	0.524	0.519	0.494	0.474	0.345	0.537	0.268	0.432	0.482	0.841
HTMT results										
	BI	EE	FC	HM	HT	PE	PV	SI	UB	UT
BI										
EE	0.698									
FC	0.625	0.758								
HM	0.781	0.699	0.669							
HT	0.533	0.473	0.483	0.493						
PE	0.716	0.737	0.685	0.737	0.547					
PV	0.285	0.426	0.479	0.334	0.201	0.328				
SI	0.664	0.693	0.725	0.642	0.526	0.577	0.467			
UB	0.741	0.601	0.638	0.639	0.682	0.583	0.389	0.731		
UT	0.597	0.609	0.565	0.565	0.429	0.599	0.321	0.487	0.565	

The diagonal and bold values indicate the square roots of the AVEs. The off-diagonal values indicate correlations between the various constructs.

3. Results

Table 5 shows that ChatGPT is the most used among respondents (79.8%). This high usage is expected, given that ChatGPT was the first GenAI application introduced by OpenAI. Its popularity in the Gulf countries can be attributed to its ease of access; diversity of uses; early entry into the market, which helped it gain wide fame; continuous updates; integration with many platforms; and extensive media coverage at the beginning of its appearance, which created social momentum that encouraged more people to try it.

Table 5. The most widely used GenAI applications among Arab Gulf state users.

GenAI Applications	Frequency	Percent
Chat GPT	396	79.8
Gemini	127	25.6
Copilot	95	19.2
Midjourney	75	15.1
DALL·E 3	45	9.1
Snapchat (My AI)	16	3.2
Others	12	2.4

Note: Respondents were allowed to choose more than one alternative for the GenAI applications they use.

Gemini was the second most-used application (25.6%), followed by Copilot (19.2%), Midjourney (15.1%), DALL·E 3 (9.1%), Snapchat's My AI (3.2%), and others (2.4%). The results show that respondents in the Arab Gulf states use a variety of GenAI applications. These applications range from those used to generate and produce text, like ChatGPT and Gemini, to those used to generate images, like Midjourney. These findings align with Victor et al. (2023), Yin et al. (2023), and Upadhyay and Khandelwal (2018), demonstrating the widespread use of GenAI applications in fields including education, media, and entrepreneurship.

Table 6 shows the diverse utilisation of GenAI apps in everyday activities. For composing and editing text, 16.7% consistently utilise GenAI, 44.8% use it occasionally, and 38.5% rarely employ it. For editing and processing photographs, 24.4% always use it, 37.9% use it sometimes, and 37.7% rarely use it. The utilisation of GenAI is consistently highest in the animation production and film and visual programmes industries, with 48.8% of individuals in these fields always using it. Just 14.1% consistently use GenAI to interpret text, while 48.0% rarely do. For ad and poster design, 34.3% consistently utilise GenAI, whereas 23.6% always use it for spell-checking and grammar verification. The utilisation rate for creating engineering designs is consistently the highest, at 49.0%.

Table 6. Uses for GenAI applications in everyday activities.

Questions	Categories	Frequency	Percent
Writing and editing text	Always	83	16.7
	Sometimes	222	44.8
	Rarely	191	38.5
Editing and processing images	Always	121	24.4
	Sometimes	188	37.9
	Rarely	187	37.7
Animation production	Always	242	48.8
	Sometimes	144	29.0
	Rarely	110	22.2
Film and visual programmes industry	Always	242	48.8
	Sometimes	148	29.8
	Rarely	106	21.4
Translating text into other languages	Always	70	14.1
	Sometimes	188	37.9
	Rarely	238	48.0
Designing ads and posters	Always	170	34.3
	Sometimes	174	35.1
	Rarely	152	30.6
Checking spelling and grammar	Always	117	23.6
	Sometimes	188	37.9
	Rarely	191	38.5
Creating engineering designs	Always	243	49.0
	Sometimes	135	27.2
	Rarely	118	23.8

The results indicate a variety of areas in which respondents use GenAI applications. Yilmaz et al. (2023) found that GenAI is frequently used in artistic and technical domains but is less prevalent in translation and text editing. This is understandable given the ongoing criticism of the writing and translation accuracy of these apps. GenAI apps have made it easy for users to create designs in seconds, which has led to its widespread use in the arts and sciences.

Table 7 illustrates the different degrees of awareness regarding the distinction between GenAI-generated text and human-created content. Specifically, 15.1% of the participants consistently find it challenging to differentiate the two, 59.5% occasionally have difficulties, and 25.4% rarely experience difficulty. For images, 15.3% of people consistently find it effortless to identify AI-generated photos, 42.7% sometimes find it effortless, and 41.9% rarely find it effortless. For video, 15.7% of individuals consistently find it effortless to distinguish, 44.4% occasionally, and 39.9% rarely. With respect to advertisements, 16.5% of individuals consistently find ads created by humans more noticeable, 50.8% find them more noticeable at times, and 32.7% rarely find them more noticeable. Clearly, a considerable percentage of respondents had difficulty regularly differentiating between GenAI information and content produced by humans. However, a large portion of users find this difficult only occasionally or not at all.

Table 7. Awareness of the distinction between content produced using GenAI and content produced by humans.

Questions	Categories	Frequency	Percent
It is difficult for me to differentiate between texts produced using generative AI and those written by humans.	Always	75.00	15.1
	Sometimes	295.00	59.5
	Rarely	126.00	25.4
I can easily differentiate between images produced via generative AI and regular images.	Always	76.00	15.3
	Sometimes	212.00	42.7
	Rarely	208.00	41.9
I can distinguish between videos produced through generative AI and those created by humans.	Always	78.00	15.7
	Sometimes	220.00	44.4
	Rarely	198.00	39.9
Ads produced by humans are easier to spot than ads produced using generative AI.	Always	82.00	16.5
	Sometimes	252.00	50.8
	Rarely	162.00	32.7

These results confirm the findings of Tiernan et al. (2023) in providing users with digital media literacy skills that enable them to distinguish between human content and GenAI content.

3.1. Structural Model Assessment

The investigators employed PLS-SEM techniques to determine how the predictor variables influence BI and UB. To assess the structural model, we evaluated the path coefficient (β) of the variables. We found that 10 out of 12 hypotheses were supported. Table 8 represents the output of the structural model evaluation.

Table 8. The results of the structural model's path coefficients.

Hypotheses	Relationships	Path Coefficients (β)	t-Values	p-Values	Decisions
H1	PE→BI	0.203	3.406	0.001	Supported
H2	EE→BI	0.127	2.058	0.040	Supported
H3	SI→BI	0.196	3.036	0.002	Supported
H4	FC→BI	−0.009	0.156	0.876	Not supported
H5	FC→UB	0.185	3.890	0.000	Supported
H6	HM→BI	0.279	3.876	0.000	Supported
H7	PV→BI	−0.056	1.554	0.121	Not supported
H8	HT→BI	0.082	1.997	0.046	Supported
H9	HT→UB	0.308	6.069	0.000	Supported
H10	UT→BI	0.124	2.487	0.013	Supported
H11	UT→UB	0.105	2.406	0.016	Supported
H12	BI→UB	0.343	6.391	0.000	Supported

Note: PE = performance expectancy, EE = effort expectancy, SI = social influence, HM = hedonic motivation, PV = price value, FC = facilitating condition, HA = habit, UT = user trust, BI = behavioural intention, UB = user behaviour.

We found that PE has a statistically significant and favourable effect on BI, with a beta coefficient (β) of 0.203 and a p -value of less than 0.05. Therefore, H1 is supported. BI is significantly and positively correlated with EE ($\beta = 0.127, p < 0.05$), SI ($\beta = 0.196, p < 0.05$), HM ($\beta = 0.279, p < 0.05$), HT ($\beta = 0.082, p < 0.05$), and UT ($\beta = 0.124, p < 0.05$). Therefore, H2, H3, H6, H8, and H10 are supported. Among these independent variables, HM has the highest impact on BI, with a beta coefficient of 0.279 ($p < 0.05$). The findings revealed that FCs ($\beta = -0.009, p > 0.05$) and PV ($\beta = -0.056, p > 0.05$) have no significant impact on BI. Therefore, H4 and H7 are not supported.

The findings demonstrate that FCs ($\beta = 0.185, p < 0.05$), HT ($\beta = 0.308, p < 0.05$), UT ($\beta = 0.105, p < 0.05$), and BI ($\beta = 0.343, p < 0.05$) significantly affect UB. Therefore, H5, H9,

H11, and H12 are supported. The findings confirm that BI is the most impactful factor for respondents in the context of UB, since $\beta = 0.343$ ($p < 0.001$). See Figure 2.

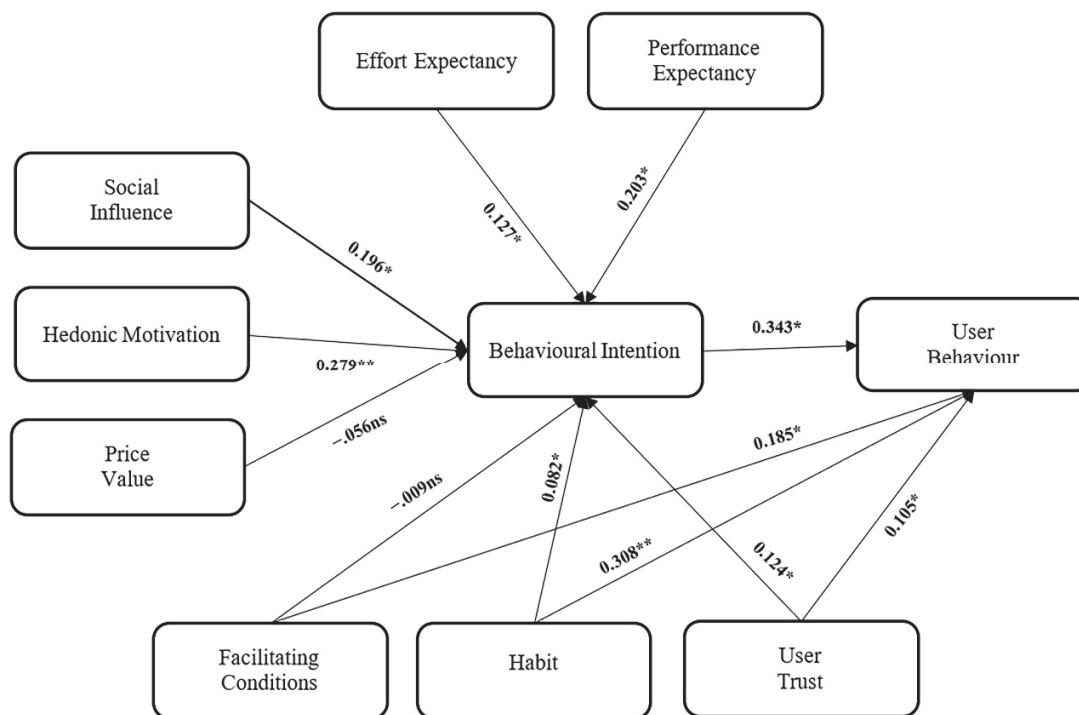


Figure 2. Results of the structural model. Note: * $p < 0.05$, ** $p < 0.01$, ns = non-significant.

This figure presents the results of the structural model analysis, indicating the relationships between various constructs such as social influence, performance expectancy, effort expectancy, facilitating conditions, user trust, hedonic motivation, habit, price value, user behaviour, and behavioural intention. The paths are annotated with standardised coefficients, where significant paths are marked with * ($p < 0.05$), ** ($p < 0.01$), and non-significant paths are denoted as “ns”. The model depicts the strength and direction of these relationships, providing insights into the factors influencing user behaviour and intentions.

3.2. Assessment of the Explanatory Power

Finally, we evaluated the explanatory power of the structural model by determining the coefficient of determination (R^2) of the model. For BI, the R^2 value was 0.589. Based on the R^2 value, we can infer that 58.9% of the variation in the BI construct was explained by the independent variables (PE, EE, SI, HM, HT, and UT). In the same vein, FC, HT, UT, and BI explained 54.2% of the variation in UB. According to Hair et al. (2019), R^2 values of 0.25, 0.50, and 0.75 indicate weak, moderate, and strong explanatory power of the model, respectively. Therefore, we can conclude that the model has moderate explanatory power for prediction.

4. Discussion

In this study, we examined the factors affecting BI and UB among users in Arab Gulf states who adopt GenAI apps, using the modified UTAUT2 model. The findings enhance our understanding of the interconnections between different components of the UTAUT2 and their impact on BI and UB.

The study proposed 12 hypotheses, 8 addressing how GenAI apps affect respondents' BI to use them and 4 focusing on the consequences of GenAI applications on UB. Only 2 hypotheses were found to be insignificant, while 10 were supported by the analysis.

The component with the greatest influence on BI is HM ($\beta = 0.279$). This supports the results of Tseng et al. (2019), who demonstrated that HM significantly affected platforms

and learning management systems in terms of BI. Additionally, Tian et al. (2024) observed the utilisation of ChatGPT in relation to HM. HM is not associated with the tangible outcomes of utilising GenAI technologies but rather with the subjective experience of pleasure and satisfaction that individuals may derive from using this technology and achieving important outcomes.

Studies have indicated that HM has a large and favourable impact on BI. Gunadi et al. (2023) emphasises that hedonic drive plays an important role in shaping BI, particularly among younger users such as Generation Z. Given their great preference for technology that delivers amusement and pleasure, HM is a crucial factor in their acceptance of generative AI. Similarly, Sudirjo et al. (2023) claim that hedonic incentive has a major influence on users' behavioural intentions, implying that the pleasure gained from utilising technology can increase acceptance rates. Suyanto et al. (2024) also suggests that the regular use of technology can improve BI, particularly when users like their interactions. This habitual involvement might be especially noticeable in generative AI systems, where users may build habits for creating and sharing content, which increases their willingness to continue using the device.

PE, with a coefficient of 0.203, is the second most influential aspect for BI. Studies have found that PE significantly motivates users to adopt innovative educational tools such as ChatGPT (Strzelecki et al. 2024) and Google Classroom (Kumar and Bervell 2019). This study found that PE significantly influences respondents, motivating them to adopt a new technology that facilitates both learning and content creation. Their motivation increases if they believe that GenAI applications will enhance their expertise.

These findings are supported by Biloš and Budimir (2024), and Wang and Zhang (2023). When users believe that the benefits of utilising AI tools outweigh the costs, their acceptance and interaction with these technologies increases, which has a significant impact on their behavioural intentions and the overall acceptability of these applications.

The EE of GenAI systems directly affects the BI of respondents to utilise them, which suggests that participants are willing to invest time in learning new technology, provided they perceive it as beneficial. The findings of this study corroborate EE's influence on shaping BI in various educational institutions, such as the adoption of software engineering technologies (Wrycza et al. 2016), mobile technologies (Hu et al. 2020), and Learning Management System (LMS) software (Raza et al. 2021). In contrast, several researchers found non-significant results (Strzelecki and ElArabawy 2024; Strzelecki et al. 2024; Zacharis and Nikolopoulou 2022).

SI also positively influences BI. Previous research has demonstrated that SI positively influences technology acceptance (Oye et al. 2012) and learning tools (Tseng et al. 2019), as well as the utilisation of ChatGPT (Strzelecki et al. 2024). For GenAI applications, SI encompasses the perspective of the modern environment, which may include family, friends, and colleagues, among others. The likelihood of an Arabic Gulf state user adopting GenAI applications is directly proportional to the extent to which their environment actively encourages them to do so.

Various studies have found that HT positively and significantly influences BI, including those of Tamilmani et al. (2019) for technology in general, Alotumi (2022) in education and learning, and Strzelecki et al. (2024) for ChatGPT. This suggests that as Arab Gulf state users become more familiar with GenAI applications, they will use them more regularly, eventually coming to see them as standard, much like using a search engine or online translator.

Lastly, the study found a strong positive association between BI and UT, confirming the findings of Hooda et al. (2022). When users perceive that GenAI applications offer tangible benefits for content creation, they are more likely to use them to enhance their productivity and skills. This research produced a theoretical model that integrated trust into the underlying UTAUT framework. The investigation posited that trust, a variable that has not been explored in previous models of technology adoption, is essential in the adoption of GenAI applications.

In contrast, FCs—which refer to whether sufficient resources exist for GenAI applications to be used effectively—have no significant impact on BI. This demonstrates that Arab Gulf state users do not solely prioritise the ease of use or accessibility when selecting a GenAI application. Instead, they consider the implications of using these tools, which implies that addressing concerns about these impacts may be a strategic approach to increase adoption. This is supported by previous studies by Alowayr (2021), Strzelecki and ElArabawy (2024), and Strzelecki et al. (2024) on the acceptance of ChatGPT in the academic realm.

Furthermore, the intricacy and novelty of generative AI applications may raise scepticism among potential users, reducing the influence of facilitating conditions. This is supported by the findings of Eamon's study on AI adoption among business professionals, which found that trust and views towards AI greatly influenced behavioural intention more frequently than facilitating conditions (Emon et al. 2023). This scepticism may originate from concerns about the reliability and ethical consequences of AI technologies, causing users to prioritise their own judgements of the technology over the external support available to them.

Facilitating conditions may have less effect on environments with extensive digital infrastructure, such as Gulf countries like the UAE, Saudi Arabia, and Bahrain, which have heavily invested in smart technologies and digital services. Users may not view these factors as important to GenAI adoption because they already have easy access to the technology.

Like FCs, PV, which represents the belief that the benefits of using technology outweigh its expenses, did not exhibit a significant correlation with BI. Prior technology adoption studies have demonstrated that PV has a significant impact on BI (Tamilmani et al. 2019) and, more specifically, technology for learning (Azizi et al. 2020). However, this study found that PV is not the primary factor Arab Gulf state users consider when deciding whether to utilise GenAI applications. This result is consistent with that of Strzelecki et al. (2024). This may be due to the simple reason that several apps for GenAI, such as ChatGPT, provide a free version with substantial capability. In contexts where generative AI tools are available at no cost, the importance of price value is often overlooked, suggesting that users may not take cost into account when making adoption decisions (Biloš and Budimir 2024).

According to Romero-Rodríguez et al. (2023) and Kanont et al. (2024), free access to tools such as ChatGPT may initially encourage adoption. However, the potential introduction of costs could significantly alter users' perceptions of equity and accessibility, thereby influencing their behavioural intentions to adopt such technologies. Furthermore, other motivational factors, such as perceived usefulness and ease of use, may override price value perceptions. Gupta (2024) suggests that entrepreneurs are more motivated by the perceived enjoyment and benefits derived from generative AI technologies than by their cost implications.

After testing the BI hypotheses, we proceeded to test the four UB hypotheses. The primary determinant of UB in relation to GenAI applications is BI, with a coefficient of 0.343. UB measures how extensively a user engages with a specific technology to complete a task, whereas BI reflects their preparedness and desire to apply the technology for the activity. Consequently, a stronger intention to use GenAI apps leads to more active engagement with them. An important observation arises—respondents will only actively engage with GenAI applications if they feel prepared and eager to utilise them. The willingness to act (BI) is acquired through the influence of several other circumstances. Many academics have emphasised the pivotal significance of BI in the utilisation of AI applications (Gansser and Reich 2021; Strzelecki et al. 2024).

Notably, FCs ($\beta = 0.185$) statistically significantly and positively influence UB. This confirms the findings of Strzelecki et al. (2024). However, FCs only have a direct effect on UB. As a result, the availability of assistance and resources for GenAI applications (FCs) will not affect the preparedness of learners to utilise GenAI applications. However, it may have an impact on the level of involvement they maintain with the platform.

Additionally, HT has a tremendous influence on UB in the context of GenAI applications. If consumers become accustomed to these applications, they are more likely to use them to enhance content. All these findings have been corroborated by earlier research (Gansser and Reich 2021; Strzelecki et al. 2024).

In conclusion, the UT variable has a considerable positive influence on the UB variable. When it comes to GenAI applications, if consumers perceive them as trustworthy, they are more likely to continue using them.

5. Implications

5.1. Practical Implications

The findings enhance our comprehension of the pivotal elements that impact the acceptance and assimilation of GenAI systems across numerous organisations for content creation. The findings suggest that the HM (human-machine interaction) and PE (perceived ease of use) variables significantly impact Arabian users' intent to embrace and deploy GenAI systems. As users become increasingly proficient in GenAI and witness the positive outcomes of their collaboration with this technology, they will develop a sense of enjoyment. HM will also enhance their inclination to utilise GenAI in the future.

Furthermore, it is important to emphasise the significance of the SI factor. After a user has discussed the benefits and drawbacks of utilising GenAI applications, it is recommended that they disseminate their expertise and experience to their acquaintances, relatives, and coworkers. When evaluating GenAI systems, users should consider both positive and negative practices rather than solely basing their opinion on someone's negative experience. EE, which pertains to the perceived level of ease in utilising a technology, significantly influences BI in the context of GenAI. The probability of consumers adopting and incorporating GenAI apps into their daily routines is higher when they perceive these tools as intuitive and user-friendly. A greater EE decreases the cognitive burden associated with acquiring and utilising the technology, hence enhancing its attractiveness.

UT is a crucial factor in influencing the desire to utilise GenAI for content development. Users' faith in the accuracy, reliability, and ethical production of GenAI content increases their likelihood of adopting and depending on these technologies in their creative processes. On the other hand, if users have reservations regarding the trustworthiness or honesty of AI-generated content, or if they are worried about possible biases or ethical consequences, their desire to use such technology decreases. It is crucial to establish and uphold UT in GenAI for content production by being transparent, accountable, and demonstrating high quality.

5.2. Theoretical Implications

This study's main conceptual contribution is in the comprehensive literature assessment undertaken on the application of GenAI for content production. It facilitates the organisation of information regarding the utilisation of GenAI systems in content creation, scientific research, and text composition, catering to users from numerous organisations. We suggest that our work serves as an exemplar of SI and can help users better understand the capabilities of GenAI systems for content generation and other functions. This paper highlights the significance of exercising caution when utilising GenAI applications for content creation and didactics. It also underscores the need to carefully examine all text and materials generated by AI tools before incorporating them into further use. This study developed a conceptual framework that incorporated the trust factor into the foundational UTAUT framework within the specific context of GenAI applications for the Arab region. The analysis asserted that trust is crucial in the context of GenAI applications, and it had not been utilised in earlier models of technology deployment.

The findings contribute to helping decision-makers, stakeholders, and social media influencers in the Gulf countries to direct their strategies to improve the understanding of the factors influencing the adoption of GenAI technologies in the media content industry. This can be achieved by, first, improving the productivity and quality of content through

accelerating reporting, editing, and idea generation. Second, government entities, media outlets, and technology developers should cooperate to create tools that meet the needs of the local market. Third, establishing regulatory and ethical guidelines should ensure the handling of data privacy issues and reducing bias in AI-generated content. Finally, the launch of training programs for media content creators to develop their skills in using artificial intelligence is essential in light of the contribution of strong technological infrastructure and government support through initiatives such as the UAE Artificial Intelligence Strategy 2031 and Saudi Vision 2030 in providing a conducive environment to enhance the adoption of these technologies.

6. Limitations and Future Research

The current study's sample of 496 users does not represent the entire population of the Arab Gulf countries, and demographic variations in age, gender, education, occupation, and socioeconomic status can affect the generalisability of the results.

The cultural context of the Arab Gulf states may restrict the generalisability of the findings, given that cultural norms, values, and attitudes towards technology adoption can vary significantly worldwide.

Although the UTAUT2 model is comprehensive, it may not cover all the factors that influence GenAI acceptance and use, such as ethical concerns, the level of technological proficiency, data privacy issues, and AI creativity.

The authors propose several future studies to address the gaps in GenAI and user acceptance research.

1. Ethical challenges of using generative AI in media content production.
2. Journalists' acceptance of GenAI applications in the Arabian Gulf states.

Author Contributions: Supervision, M.S.M.A.; writing—original draft preparation, M.S.M.A. and A.M.M.A.; conceptualization, M.S.M.A., K.Z.A.W. and A.M.M.A.; methodology, M.S.M.A. and A.M.M.A.; data curation, M.S.M.A. and A.M.M.A.; formal analysis, M.S.M.A. and A.M.M.A.; investigation, K.Z.A.W.; editing, K.Z.A.W.; resources, K.Z.A.W. and A.M.M.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Ethical approval has been obtained from the Institutional Review Board (IRB) Committee of Abu Dhabi University, with reference number CAS-0000031.

Informed Consent Statement: All participants gave their informed consent before participating in the online survey. They received detailed information about the study objectives, procedures, potential risks, and benefits. They were made clear that their participation was completely voluntary, with the freedom to withdraw at any time. In addition, the consent process ensured that participants' responses were confidential and anonymous.

Data Availability Statement: A study includes the original contributions provided in the article; for further information, please contact the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

References

- Abdullah, Zaleha, and Norasykin Mohd Zaid. 2023. Perception of Generative Artificial Intelligence in Higher Education Research. *Innovative Teaching and Learning Journal* 7: 84–95. [CrossRef]
- Ahmed, Mazharuddin Syed, John Everatt, Wendy Fox-Turnbull, and Fahad Alkhezzi. 2023. Systematic Review of Literature for Smartphones Technology Acceptance Using Unified Theory of Acceptance and Use of Technology Model (UTAUT). *Social Networking* 12: 29–44. [CrossRef]
- Ajzen, Icek. 1991. The theory of planned behavior. *Organizational Behavior and Human Decision Processes* 50: 179–211. [CrossRef]
- Al Adwan, Muhammad Noor, Mohmad El Hajji, and Hossam Fayez. 2024. Future anxiety among media professionals and its relationship to utilizing artificial intelligence techniques: The case of Egypt, France, and UAE. *Online Journal of Communication and Media Technologies* 14: e202425. [CrossRef]

- Aldossary, Aminah Saad, Alia Abdullah Aljindi, and Jamilah Mohammed Alamri. 2024. The role of generative AI in education: Perceptions of Saudi students. *Contemporary Educational Technology* 16: 10–11. [CrossRef]
- Al-kfairy, Mousa, Dheya Mustafa, Nir Kshetri, Mazen Insiew, and Omar Alfandi. 2024. Ethical Challenges and Solutions of Generative AI: An Interdisciplinary Perspective. *Informatics* 11: 58. [CrossRef]
- Alkhwaldi, Abeer F., and Amir A. Abdulmuhsin. 2022. Crisis-centric distance learning model in Jordanian higher education sector: Factors influencing the continuous use of distance learning platforms during COVID-19 pandemic. *Journal of International Education in Business* 15: 250–72. [CrossRef]
- Alotumi, Mohialdeen. 2022. Factors influencing graduate students' behavioral intention to use Google Classroom: Case study-mixed methods research. *Education and Information Technologies* 27: 10035–63. [CrossRef]
- Alowayr, Ali. 2021. Determinants of mobile learning adoption: Extending the unified theory of acceptance and use of technology (UTAUT). *The International Journal of Information and Learning Technology* 39: 1–12. [CrossRef]
- Alshamsi, Ibrahim, Kaneez Fatima Sadriwala, Fouad Jameel Ibrahim Alazzawi, and Boumedyen Shannaq. 2024. Exploring the impact of generative AI technologies on education: Academic expert perspectives, trends, and implications for sustainable development goals. *Journal of Infrastructure, Policy and Development* 8: 8532. [CrossRef]
- Al-Sharafi, Mohammed A., Mostafa Al-Emran, Mohammad Iranmanesh, Noor Al-Qaysi, Noorminshah A. Iahad, and Ibrahim Arpaci. 2022. Understanding the Impact of Knowledge Management Factors on the Sustainable Use of AI-Based Chatbots for Educational Purposes Using a Hybrid SEM-ANN Approach. *Interactive Learning Environments* 31: 7491–510. [CrossRef]
- Artificial Intelligence Office, UAE. 2024. Available online: <https://ai.gov.ae/ar/> (accessed on 12 April 2024).
- Azizi, Seyyed Mohsen, Nasrin Roozbahani, and Alireza Khatony. 2020. Factors affecting the acceptance of blended learning in medical education: Application of UTAUT2 model. *BMC Medical Education* 20: 367. [CrossRef]
- Bautista, Yohn Jairo Parra, Carlos Thera, and Richard Aló. 2024. Ethical Considerations of Generative AI: A Survey Exploring the Role of Decision Makers in the Loop. *Proceedings of the AAAI Symposium Series* 3: 391–98. [CrossRef]
- Bernal, Ena A., and Jonald L. Maligaya. 2024. Examining the Levels of Awareness and Acceptance of Generative Artificial Intelligence to Supplement Problem Solving Analysis in an Aerospace Company. *Ignatian International Journal for Multidisciplinary Research* 2: 1739–49. [CrossRef]
- Biloš, Antun, and Bruno Budimir. 2024. Understanding the adoption dynamics of chatgpt among generation z: Insights from a modified utaut2 model. *Journal of Theoretical and Applied Electronic Commerce Research* 19: 863–79. [CrossRef]
- Cheng, Guo. 2024. Research on the Displacement Impact of Artificial Intelligence on the Film Industry. *Highlights in Business Economics and Management* 28: 48–53. [CrossRef]
- Choudrie, Jyoti, and Yogesh Kumar Dwivedi. 2005. Investigating the research approaches for examining technology adoption issues. *Journal of Research Practice* 1: D1.
- Davis, Fred D. 1989. Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *Management Information Systems Quarterly* 13: 319. [CrossRef]
- Davis, Fred D., Andrina Granić, and Nikola Marangunić. 2024. *The Technology Acceptance Model: 30 Years of TAM*. Cham: Springer International Publishing AG.
- De Graaf, Maartje M. A., Somaya Ben Allouch, and Jan AGM Van Dijk. 2017. Why Would I Use This in My Home? A Model of Domestic Social Robot Acceptance. *Human-Computer Interaction* 34: 115–73. [CrossRef]
- Dwivedi, Yogesh K., and Michael D. Williams. 2008. Demographic influence on UK citizens' e-government adoption. *Electronic Government* 5: 261. [CrossRef]
- Emon, Md Mehedi Hasan, Farheen Hassan, Mehzabul Hoque Nahid, and Vichayan Rattanawiboonsom. 2023. Predicting Adoption Intention of Artificial Intelligence ChatGPT. *AIUB Journal of Science and Engineering (AJSE)* 22: 189–99. [CrossRef]
- Faul, Franz, Edgar Erdfelder, Axel Buchner, and Albert-Georg Lang. 2009. Statistical power analyses using G* Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods* 41: 1149–60. [CrossRef] [PubMed]
- Feuerriegel, Stefan, Jochen Hartmann, Christian Janiesch, and Patrick Zschech. 2023. "Generative AI". *Business & Information Systems Engineering* 66: 111–26. [CrossRef]
- Fui-Hoon Nah, Fiona, Ruilin Zheng, Jingyuan Cai, Keng Siau, and Langtao Chen. 2023. Generative AI and ChatGPT: Applications, challenges, and AI-human collaboration. *Journal of Information Technology Case and Application Research* 25: 277–304. [CrossRef]
- Gansser, Oliver Alexander, and Christina Stefanie Reich. 2021. A new acceptance model for artificial intelligence with extensions to UTAUT2: An empirical study in three segments of application. *Technology in Society* 65: 101535. [CrossRef]
- Gefen, David, and Detmar Straub. 2003. Managing User Trust in B2C e-Services. *E-Service Journal/E-Service Journal* 2: 7. [CrossRef]
- Goodhue, Dale L., and Ronald L. Thompson. 1995. Task-Technology Fit and Individual Performance. *Management Information Systems Quarterly* 19: 213. [CrossRef]
- Google AI. 2024. Gemini 1.5 Pro Model Updates and Capabilities. Available online: <https://ai.google.dev> (accessed on 25 October 2024).
- Gunadi, Valentino, Nur Indah Septyani, Riyadh Annafi, and Robertus Nugroho Perwiro Atmojo. 2023. The effect of live streaming methods in online sales on behavioral intention in generation z. *E3s Web of Conferences* 426: 02127. [CrossRef]
- Gupta, Varun. 2024. An empirical evaluation of a generative artificial intelligence technology adoption model from entrepreneurs' perspectives. *Systems* 12: 103. [CrossRef]

- Hair, Joseph F., Jeffrey J. Risher, Marko Sarstedt, and Christian M. Ringle. 2019. When to use and how to report the results of PLS-SEM. *European Business Review* 31: 2–24. [CrossRef]
- Hastuti, Rochmi, and None Syafruddin. 2023. Ethical Considerations in the Age of Artificial Intelligence: Balancing Innovation and Social Values. *West Science Social and Humanities Studies* 1: 76–87. [CrossRef]
- Henseler, Jörg, Christian M. Ringle, and Marko Sarstedt. 2015. A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science* 43: 115–35. [CrossRef]
- Ho, Shirley S., and Justin C. Cheung. 2024. Trust in artificial intelligence, trust in engineers, and news media: Factors shaping public perceptions of autonomous drones through UTAUT2. *Technology in Society* 77: 102533. [CrossRef]
- Ho, Yi-Hui, Syed Shah Alam, Mohammad Masukujaman, Chieh-Yu Lin, Samiha Susmit, and Sumaiya Susmit. 2022. Intention to adopt AI-powered online service among tourism and hospitality companies. *International Journal of Technology and Human Interaction* 18: 1–19. [CrossRef]
- Hooda, Apeksha, Parul Gupta, Anand Jeyaraj, Mihalis Giannakis, and Yogesh K. Dwivedi. 2022. The effects of trust on behavioral intention and use behavior within e-government contexts. *International Journal of Information Management* 67: 102553. [CrossRef]
- Hu, Sailong, Kumar Laxman, and Kerry Lee. 2020. Exploring factors affecting academics' adoption of emerging mobile technologies-an extended UTAUT perspective. *Education and Information Technologies* 25: 4615–35. [CrossRef]
- Hughes, D. Laurie, Nripendra P. Rana, and Yogesh K. Dwivedi. 2019. Elucidation of IS project success factors: An interpretive structural modelling approach. *Annals of Operation Research/Annals of Operations Research* 285: 35–66. [CrossRef]
- Kanont, Kraisola, Pawarit Pingmuang, Thewawuth Simasathien, Suchaya Wisnuwong, Benz Wiwatsiripong, Kanitta Poonpirome, Noawanit Songkram, and Jintavee Khlaisang. 2024. Generative-AI, a Learning Assistant? Factors Influencing Higher-Ed Students' Technology Acceptance. *The Electronic Journal of e-Learning* 22: 18–33. [CrossRef]
- Kashyap, Ankur, and Rajat Agrawal. 2020. Scale development and modeling of intellectual property creation capability in higher education. *Journal of Intellectual Capital* 21: 115–38. [CrossRef]
- Kim, Soyoung, and Boyoung Kim. 2020. A decision-making model for adopting ai-generated news articles: Preliminary results. *Sustainability* 12: 7418. [CrossRef]
- Kline, Rex B. 2023. *Principles and Practice of Structural Equation Modeling*, 5th ed. New York: Guilford Publications.
- Kshetri, Nir. 2024. The academic industry's response to generative artificial intelligence: An institutional analysis of large language models. *Telecommunications Policy* 48: 102760. [CrossRef]
- Kuberkar, Sachin, and Tarun Kumar Singhal. 2020. Factors influencing adoption intention of AI powered chatbot for public transport services within a smart city. *International Journal of Emerging Technologies in Learning* 11: 948–58.
- Kumar, Jeya Amantha, and Brandford Bervell. 2019. Google Classroom for mobile learning in higher education: Modelling the initial perceptions of students. *Education and Information Technologies* 24: 1793–817. [CrossRef]
- Lai, Yuehua. 2023. The Impact of AI-Driven Narrative Generation, Exemplified by ChatGPT, on the Preservation of Human Creative Originality and Uniqueness. *Lecture Notes in Education Psychology and Public Media* 26: 121–24. [CrossRef]
- Lavidas, Konstantinos, Iro Voulgari, Stamatis Papadakis, Stavros Athanassopoulos, Antigoni Anastasiou, Andromachi Filippidi, Vassilis Komis, and Nikos Karacapilidis. 2024. Determinants of Humanities and Social Sciences Students' Intentions to Use Artificial Intelligence Applications for Academic Purposes. *Information* 15: 314. [CrossRef]
- Lin, Rong-Rong, and Jung-Chieh Lee. 2023. The supports provided by artificial intelligence to continuous usage intention of mobile banking: Evidence from China. *Aslib Journal of Information Management* 76: 293–310. [CrossRef]
- Ling, Erin Chao, Iis Tussyadiah, Aarni Tuomi, Jason Stienmetz, and Athina Ioannou. 2021. Factors influencing users' adoption and use of conversational agents: A systematic review. *Psychology & Marketing* 38: 1031–51. [CrossRef]
- Maican, Catalin Ioan, Silvia Sumedrea, Alina Tecau, Eliza Nichifor, Ioana Bianca Chitu, Radu Lixandroi, and Gabriel Bratucu. 2023. Factors influencing the behavioural intention to use AI-Generated images in business: A UTAUT2 perspective with moderators. *Journal of Organizational and End User Computing* 35: 1–32. [CrossRef]
- Mardia, Kanti V. 1970. Measures of multivariate skewness and kurtosis with applications. *Biometrika* 57: 519–30. [CrossRef]
- Markovič, Daniel. 2024. Current options and limits of digital technologies and artificial intelligence in social work. *SHS Web of Conferences* 184: 05003. [CrossRef]
- Michel-Villarreal, Rosario, Eliseo Vilalta-Perdomo, David Ernesto Salinas-Navarro, Ricardo Thierry-Aguilera, and Flor Silvestre Gerardou. 2023. Challenges and Opportunities of Generative AI for Higher Education as Explained by ChatGPT. *Education Sciences* 13: 856. [CrossRef]
- Microsoft. 2024. An AI Companion for Everyone. Microsoft Blog. Available online: <https://blogs.microsoft.com/blog/2024/10/01/an-ai-companion-for-everyone/> (accessed on 25 October 2024).
- MidJourney. 2024. Version 6.1 Release Notes and Updates. Available online: <https://updates.midjourney.com/version-6-1/> (accessed on 25 October 2024).
- Nasser Vocational Training Center. 2023. Available online: <https://rb.gy/4hc5kc> (accessed on 18 April 2024).
- Nja, Cecilia Obi, Kimson Joseph Idiege, Uduak Edet Uwe, Anne Ndidi Meremikwu, Esther Etop Ekon, Costly Manyo Erim, Julius Ukah Ukah, Eneyo Okon Eyo, Mary Ideba Anari, and Bernedette Umalili Cornelius-Ukpepi. 2023. Adoption of artificial intelligence in science teaching: From the vantage point of the African science teachers. *Smart Learning Environments* 10: 42. [CrossRef]

- Oladoyinbo, Tunboson Oyewale, Samuel Oladiipo Olabanji, Oluwaseun Oladeji Olaniyi, Olubukola Omolara Adebisi, Olalekan J. Okunleye, and Adegbeniga Ismaila Alao. 2024. Exploring the Challenges of Artificial Intelligence in Data Integrity and its Influence on Social Dynamics. *Asian Journal of Advanced Research and Reports* 18: 1–23. [CrossRef]
- OpenAI. 2024. Introducing Canvas: A New Way to Collaborate with AI. Available online: <https://openai.com/index/introducing-canvas/> (accessed on 25 October 2024).
- Oye, N. D., N. A. Iahad, and N. Ab. Rahim. 2012. The history of UTAUT model and its impact on ICT acceptance and usage by academicians. *Education and Information Technologies* 19: 251–70. [CrossRef]
- Paige, Amer, Sven Blomberg, Eva Lee, Megha Sinha, Douglas Merrill, Adi Pradhan, Steven Shaw, and Alexander Sukharevsky. 2023. The Golden Age of Technology Powered by Generative AI: A Comprehensive Guide for CIOs and CTOs. McKinsey & Company. Available online: <https://www.mckinsey.com/featured-insights/highlights-in-arabic/technologys-generational-moment-with-generative-ai-a-cio-and-cto-guide-arabic/ar> (accessed on 22 April 2024).
- Pashentsev, Evgeny, Vladilena Chebykina, and Ruslan Nikiforov. 2024. The Malicious Use of AI: Challenges to Psychological Security in the United Arab Emirates. *BBK 16.6 M21* 94: 8–9.
- Porsdam Mann, Sebastian, Brian D. Earp, Sven Nyholm, John Danaher, Nikolaj Møller, Hilary Bowman-Smart, Joshua Hatherley, Julian Koplin, Monika Plozza, Daniel Rodger, and et al. 2023. Generative ai entails a credit-blame asymmetry. *Nature Machine Intelligence* 5: 472–75. [CrossRef]
- Raza, Syed Ali, Zubaida Qazi, Wasim Qazi, and Maiyra Ahmed. 2021. E-learning in higher education during COVID-19: Evidence from blackboard learning system. *Journal of Applied Research in Higher Education* 14: 1603–22. [CrossRef]
- Rogers, Everett M. 1962. *Diffusion of Innovations*, 3rd ed. New York: Free Press.
- Romero-Rodríguez, José-María, María-Soledad Ramírez-Montoya, Mariana Buenestado-Fernández, and Fernando Lara-Lara. 2023. Use of chatgpt at university as a tool for complex thinking: Students' perceived usefulness. *Journal of New Approaches in Educational Research* 12: 323–39. [CrossRef]
- Roy, Sanjoy Kumar. 2022. The impact of age, gender, and ethnic diversity on organizational performance: An empirical study of Bangladesh's banking sector. *International Journal of Financial, Accounting, and Management* 4: 145–61. [CrossRef]
- Roy, Sanjoy Kumar, Mst Musfika, and Ummey Habiba. 2024. Moderated Mediating Effect on Undergraduates' Mobile Social Media Addiction: A Three-Stage Analytical Approach. *Journal of Technology in Behavioral Science*, 1–20. [CrossRef]
- Russo, Daniel. 2024. Navigating the Complexity of Generative AI Adoption in Software Engineering. *ACM Transactions on Software Engineering and Methodology* 33: 1–50. [CrossRef]
- Salama, Hossam. 2023. Employing Artificial Intelligence Techniques in Developing the Productions of Media Students in Gulf Universities. *The Union of Arab Universities for Media & Communication Technology Research* 11: 62–63. [CrossRef]
- Saudi Authority for Data and Artificial Intelligence. 2024. Available online: <https://sdaia.gov.sa/en/default.aspx> (accessed on 7 April 2024).
- Schnuerch, Martin, and Edgar Erdfelder. 2023. *Building the Study*. Cambridge: Cambridge University Press, pp. 103–24. [CrossRef]
- Shaliha, Alifia Indah Putri, and Endy Gunanto Marsasi. 2024. The influence of attitude and perceived risk to optimize intention to adopt based on theory of planned behavior in generation z. *Ekombis Review Jurnal Ilmiah Ekonomi Dan Bisnis* 12: 1679–94. [CrossRef]
- Strzelecki, Artur, and Sara ElArabawy. 2024. Investigation of the moderation effect of gender and study level on the acceptance and use of generative AI by higher education students: Comparative evidence from Poland and Egypt. *British Journal of Educational Technology* 55: 1209–30. [CrossRef]
- Strzelecki, Artur, Karina Cicha, Mariia Rizun, and Paulina Rutecka. 2024. Acceptance and use of ChatGPT in the academic community. *Education and Information Technologies*, 1–26. [CrossRef]
- Sudirjo, Frans, David Ahmad Yani, Amat Suroso, and Aulia Ar Rakhman Awaludin. 2023. Comparative analysis of customer acceptance of digital wallet gopay, dana and ovo using unified theory of acceptance and use of technology. *Jurnal Sistim Informasi Dan Teknologi* 5: 38–43. [CrossRef]
- Suyanto, Mohamad Afan, Luh Komang Candra Dewi, Donny Dharmawan, Dadang Suhardi, and Silvia Ekasari. 2024. Analysis of the influence of behavior intention, technology effort expectancy and digitalization performance expectancy on behavior to use of qris users in small medium enterprises sector. *Jurnal Informasi Dan Teknologi* 6: 57–63. [CrossRef]
- Tamilmani, Kuttimani, Nripendra P. Rana, and Yogesh K. Dwivedi. 2019. Use of 'habit' is not a habit in understanding individual technology adoption: A review of UTAUT2 based empirical studies. In *Smart Working, Living and Organising: IFIP WG 8.6 International Conference on Transfer and Diffusion of IT, TDIT 2018, Portsmouth, UK, June 25, 2018, Proceedings*. Cham: Springer International Publishing, pp. 277–94.
- Terblanche, Nicky, and Martin Kidd. 2022. Adoption Factors and Moderating Effects of Age and Gender That Influence the Intention to Use a Non-Directive Reflective Coaching Chatbot. *SAGE Open* 12: 215824402210961. [CrossRef]
- Tian, Weiqi, Jingshen Ge, Yu Zhao, and Xu Zheng. 2024. AI Chatbots in Chinese Higher Education: Adoption, Perception, and Influence Among Graduate Students—An Integrated Analysis Utilizing UTAUT and ECM Models. *Frontiers in Psychology* 15: 1268549. [CrossRef]
- Tiernan, Peter, Eamon Costello, Enda Donlon, Maria Parysz, and Michael Scriney. 2023. Information and Media Literacy in the Age of AI: Options for the Future. *Education Sciences* 13: 906. [CrossRef]

- Tseng, Timmy H., Shinjeng Lin, Yi-Shun Wang, and Hui-Xuan Liu. 2019. Investigating teachers' adoption of MOOCs: The perspective of UTAUT2. *Interactive Learning Environments* 30: 635–50. [CrossRef]
- Upadhyay, Ashwani Kumar, and Komal Khandelwal. 2018. Applying artificial intelligence: Implications for recruitment. *Strategic HR Review* 17: 255–58. [CrossRef]
- Upadhyay, Nitin, Shalini Upadhyay, Salma S. Abed, and Yogesh K. Dwivedi. 2022. Consumer adoption of mobile payment services during COVID-19: Extending meta-UTAUT with perceived severity and self-efficacy. *International Journal of Bank Marketing* 40: 960–91. [CrossRef]
- Venkatesh, Viswanath. 2022. Adoption and use of AI tools: A research agenda grounded in UTAUT. *Annals of Operation Research/Annals of Operations Research* 308: 641–52. [CrossRef]
- Venkatesh, Viswanath, James Y. L. Thong, and Xin Xu. 2012. Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *Management Information Systems Quarterly* 36: 157. [CrossRef]
- Venkatesh, Viswanath, Michael G. Morris, Gordon B. Davis, and Fred D. Davis. 2003. User Acceptance of Information Technology: Toward a Unified View. *Management Information Systems Quarterly* 27: 425. [CrossRef]
- Victor, Bryan G., Sheryl Kubiak, Beth Angell, and Brian E. Perron. 2023. Time to Move Beyond the ASWB Licensing Exams: Can Generative Artificial Intelligence Offer a Way Forward for Social Work? *Research on Social Work Practice* 33: 511–17. [CrossRef]
- Vo, Anh, and Huong Nguyen. 2024. Generative Artificial Intelligence and ChatGPT in Language Learning: EFL Students' Perceptions of Technology Acceptance. *Journal of University Teaching & Learning Practice* 21: 199–218. [CrossRef]
- Wakunuma, Kutoma, and Damian Eke. 2024. Africa, ChatGPT, and Generative AI Systems: Ethical Benefits, Concerns, and the Need for Governance. *Philosophies* 9: 80. [CrossRef]
- Wang, Yiyang, and Weining Zhang. 2023. Factors Influencing the Adoption of Generative AI for Art Designing among Chinese Generation Z: A structural equation modeling approach. *IEEE Access* 11: 143272–84. [CrossRef]
- Wirtz, Bernd W., Jan C. Weyerer, and Carolin Geyer. 2018. Artificial Intelligence and the Public Sector—Applications and Challenges. *International Journal of Public Administration* 42: 596–615. [CrossRef]
- Wrycza, Stanislaw, Bartosz Marcinkowski, and Damian Gajda. 2016. The Enriched UTAUT Model for the Acceptance of Software Engineering Tools in Academic Education. *Information Systems Management* 34: 38–49. [CrossRef]
- Yakar, Derya, Yfke P. Ongena, Thomas C. Kwee, and Marieke Haan. 2022. Do People Favor Artificial Intelligence Over Physicians? A Survey Among the General Population and Their View on Artificial Intelligence in Medicine. *Value in Health* 25: 374–81. [CrossRef] [PubMed]
- Yilmaz, Fatma Gizem Karaoglan, Ramazan Yilmaz, and Mehmet Ceylan. 2023. Generative Artificial Intelligence Acceptance Scale: A Validity and Reliability Study. *International Journal of Human-computer Interaction*, 1–13. [CrossRef]
- Yin, Ming, Bingxu Han, Sunghan Ryu, and Min Hua. 2023. Acceptance of Generative AI in the Creative Industry: Examining the Role of AI Anxiety in the UTAUT2 Model. In *Lecture Notes in Computer Science*. Cham: Springer Nature Switzerland, pp. 288–310. [CrossRef]
- Zacharis, Georgios, and Kleopatra Nikolopoulou. 2022. Factors predicting University students' behavioral intention to use eLearning platforms in the post-pandemic normal: An UTAUT2 approach with 'Learning Value'. *Education and Information Technologies* 27: 12065–82. [CrossRef]
- Zhang, Weiwei. 2020. A Study on the User Acceptance Model of Artificial Intelligence Music Based on UTAUT. *Han-guk Keompyuteo Jeongbo Hakoe Nonmunji/Han'gug Keompyuteo Jeongbo Haghoe Nonmunji* 25: 25–33. [CrossRef]
- Zhang, Zhiyong, and Ke-Hai Yuan. 2018. *Practical Statistical Power Analysis Using Webpower and R*. Granger: ISDSA Press. [CrossRef]
- Zhu, Wenjuan, Lei Huang, Xinni Zhou, Xiaoya Li, Gaojun Shi, Jingxin Ying, and Chaoyue Wang. 2024. Could AI Ethical Anxiety, Perceived Ethical Risks and Ethical Awareness About AI Influence University Students' Use of Generative AI Products? An Ethical Perspective. *International Journal of Human-Computer Interaction*, 1–23. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.



Article

Investigating the Role of Artificial Intelligence to Measure Consumer Efficiency: The Use of Strategic Communication and Personalized Media Content

Saud Binlibdah

Mass Communication Department, College of Humanities and Social Sciences, King Saud University, Riyadh 12372, Saudi Arabia; bhaylan@ksu.edu.sa

Abstract: This study examines the relationships between strategic communication, personalized media content, AI, and consumer service efficiency in social marketing companies in Saudi Arabia. The study used a cluster sampling technique with a quantitative research design. The study targeted 498 responses via distributing the survey links on social media platforms. Using the SEM analysis in Smart PLS 4, this research tested the research hypotheses. The findings showed that strategic communication significantly improves personalized media content and consumer service efficiency, confirming its importance in business customer interactions and outcomes. Customized media content does not significantly improve consumer service efficiency, suggesting other mediating factors may be involved. AI mediates this relationship, bridging strategic inputs and service outcomes. AI boosts strategic communication and personalized content, improving consumer service efficiency. The results showed that AI fully mediates strategic communication and personalized media content into improved service efficiency, demonstrating its transformative potential in business communications and operations. The study shows that AI supports and improves digital marketing communication strategies. It is statistical evidence and confidence intervals that exclude zero, AI-enabled the application of personalized content and strategic directives to improve service efficiency in the mediation analysis.

Keywords: strategic communication; personalized media content; consumer service efficiency; AI; social media companies

1. Introduction

The use of strategic communication and personalized media content to improve customer service in the Saudi Arabian market has greatly influenced the evolution of e-commerce in the digital age. Al-Jehani et al. (2021) examine how AI-assisted social media marketing affects Saudi Arabian SMEs and how AI improves business management through targeted intelligent marketing. Alqahtani and Alqahtani (2022) examine AI techniques in e-commerce and how they could improve consumer interactions and business processes in Saudi Arabia. AlGosaibi et al. (2020) propose an intelligent framework to improve service quality in government organizations, showing how AI can improve service delivery and customer satisfaction through smart, adaptive communication. Al-Baity (2023) proposes a comprehensive framework that highlights AI's transformative impact on digital finance, highlighting its role in improving customer interactions and service efficiency through advanced analytics and personalized content.

Personalization is crucial in email marketing and health campaigns to improve relevance and impact by tailoring content to individual traits (Dijkstra 2008; Pfiffelmann et al. 2020; Upadhyaya 2024). Personalization is the incorporation of recognizable personal aspects into content (Al-Jehani et al. 2021). It can include personally identifying information, past behaviors, or group characteristics such as gender. Marketing often uses cue-based personalization, such as a consumer's name or location, to draw attention and

improve message relevance (Hawkins et al. 2008). Some studies show that such strategies increase consumer engagement (Maslowska et al. 2016), while others note potential negative reactions, primarily when privacy concerns are raised. AI-enabled personalization has advanced and become more subtle (Boerman et al. 2017). AI role in personalization, especially in consumer service and strategic communication, is a promising area of research for efficiency and engagement (Cheng and Jiang 2022; Huang and Rust 2021a, 2021b). Strategic communication using AI involves planning and implementing communication methods and tools to achieve organizational goals. This involves using AI to analyze, optimize, and implement communication strategies to improve engagement, understanding, and effectiveness across platforms and audiences. The goal is to streamline, personalize, and improve communications using AI.

Despite extensive research on personalization, strategic communication's effects on personalized media content are still unclear. Strategic communication, which involves an organization using communication to achieve its mission (Coombs 2015), shapes personalized content. However, strategic communication and personalization in digital and social media contexts should be studied more. Previous studies have focused on the direct effects of personalization cues (Pfiffelmann et al. 2020) without addressing how strategic communication strategies affect personalization. The digital age expects immediate and personalized responses, so consumer service efficiency—the effectiveness and promptness of service delivery (Gursoy et al. 2019)—is crucial. AI-driven personalization improves service efficiency and customer satisfaction (Bag et al. 2022; Buhalis and Moldavska 2022), but little is known about how it affects media content perception. The impact of consumer service efficiency on the reception and effectiveness of personalized media content needs further study to understand AI potential to improve consumer experiences fully.

Another research gap is how AI mediates strategic communication, consumer service efficiency, and personalized media content. AI can analyze massive amounts of data and create personalized content (Ameen et al. 2022; Hawkins et al. 2008). The mechanisms by which AI improves strategic communication and personalization or service efficiency and personalization are unclear. This mediating role can illuminate how AI can optimize personalization strategies. Since the personalization-privacy paradox shows the conflict between personalization benefits and privacy concerns (Awad and Krishnan 2006), strategic communication and service efficiency may help mitigate privacy concerns when using AI for personalization. Data show that privacy concerns can reduce the effectiveness of personalized advertising (Gurau et al. 2003), but ways to address these concerns through better communication and service delivery are scarce.

Finally, AI's personalization effects need further study. Many overlook AI's ethical and practical implications despite its potential to improve personalized media content (Huang and Rust 2021a; Mustak et al. 2021). Sustainable and consumer-friendly personalization strategies that balance technological capabilities with user expectations and privacy rights must address these issues. Based on the research gaps and problem statement, the study offers the following research objectives:

1. To examine the effect of strategic communication on consumer service efficiency;
2. To investigate the effect of personalized media content on consumer service efficiency;
3. To explore the mediating role of artificial intelligence between strategic communication, personalized media content and consumer service efficiency.

2. Literature Review

2.1. What Is Personalized Media Content?

Social media marketing and campaigns have extensively studied personalization. Dijkstra (2008, p. 768) defines personalization as “incorporating recognizable aspects of a person in the content information.” Personal details such as a person's name or picture, past behaviors such as websites visited or movies watched, or group characteristics such as gender may be considered. These traits describe many people, but their combination may identify one person (Basri 2020). Social media marketing often uses cue-based per-

sonalization to include a consumer's name, employer, or town in the header or body. This approach keeps the persuasive message generic for all recipients and adds personal cues to grab attention (Hawkins et al. 2008).

Research shows that people process information with their names (Tacikowski and Nowicka 2010) and pay more attention to first-name ads than non-personalized ads (Bang and Wojdynski 2016). Despite being less noticeable or visited, Pfiffelmann et al. (2020) found that personalized ads capture more frequent and prolonged visual attention. Cue-based personalization may also increase self-referencing and heuristic or central processing (De Keyser et al. 2015). This personalization enhances message development (Maslowska et al. 2016). Many studies have used cue-based personalization (Sahni 2016), but some studies have shown no effect or even negative effects.

Other studies indicate that personalization has limited benefits. Maslowska et al. (2011) found that personalization improves communication evaluations, not behaviors. Negative effects may result from involvement and relevance (Kalyanaraman and Sundar 2006). Simola et al. (2013) found that personalized ads on social media, which consumers use for information and socializing, disrupt these experiences and cause negative reactions. The recipient may perceive the message as personalized, which may increase persuasion knowledge and decrease effectiveness (Pfiffelmann et al. 2020). Personalized ads can be seen as intrusive in social spaces, significantly when personal information is misused or collected without consent (Aguirre et al. 2015; De Keyser et al. 2015; Pfiffelmann et al. 2020). Increased privacy concerns may reduce the impact of personalized advertising (Gurau et al. 2003). The "*personalization-privacy paradox*" shows how delicate personalization strategies are (Awad and Krishnan 2006).

While cue-based personalization uses simple elements such as demographics or past behaviors, it can backfire, especially when privacy concerns arise. More advanced personalization strategies, such as trait-based personalization, have garnered attention for their use in recent political campaigns. This method, called microtargeting (Pfiffelmann et al. 2020) or online behavioral advertising (Boerman et al. 2017), subtly tailors messages to recipient characteristics.

2.2. Role of Technologies in Social Media Marketing

Companies use Facebook, Snapchat, and Twitter for social media marketing. Their choice depends on the audience and marketing strategy. Chen and Lee (2018) examined Snapchat's role in youth-targeted social media marketing. Snapchat is an intimate, casual, and dynamic platform for information, socialization, and entertainment, according to their findings. The study found that young consumers like Snapchat, which affects their purchase intentions and brand perceptions of Snapchat-advertised products. In addition, Tafesse and Wien (2018) examined company-advertising strategies. Transformational, which associates the brand with positive psychological traits; informational, which clearly communicates product or service details; and interactional, which encourages customer interaction through social media advertising. Interactive brand posts were more engaging than informative ones (Kusumasondjaja 2018). The study found that Twitter worked best for informative content, Facebook for interactive entertainment, and Instagram for informative entertainment posts. Interactive posts with mixed appeals received the most Facebook and Instagram engagement, while informative messages received the least (Kusumasondjaja 2018).

Content marketing is essential for marketing communications, and some research suggests that emotional messaging influences consumer behavior. Hutchins and Rodriguez (2018) examined eleven B2B companies' content marketing and found that using emotions can boost brand equity and competitiveness. According to Ang et al. (2018), consumers view livestreaming as more authentic, increasing their search and subscription intentions. A scenario-based experiment with 462 participants used social impact theory to reach this conclusion. Advertisers need social media message characteristics. Hwang et al. (2018) applied motivation theory to tourism and found that argument completeness, relevance, flexibility, timeliness, and source credibility increase user satisfaction, which influences

their intention to return to websites and buy tourism products. Seo et al. (2020) found that message structure—interactivity, formality, and immediacy—significantly impacts consumer behavior, including brand attitudes, corporate trust, and purchase intentions. Companies face many challenges when creating social media marketing strategies. Parsons and Lepkowska-White (2018) proposed a framework to help managers market via social media.

2.3. Media Richness Theory

Media Richness Theory (MRT) states how AI can enrich media interactions, making it relevant to the study of AI in media personalization (Dennis and Kinney 1998). MRT founders Daft and Lengel (Hutchins and Rodriguez 2018) argue that richer media provide immediate feedback, multiple cues, personalization, and language variety, which are essential for effective communication. AI can improve media richness and communication by tailoring content to individual preferences (Daft and Lengel 1986). Studies have found that AI-enabled personalized content matches MRT principles. Dennis and Kinney (1998) found that feedback- and customization-rich media improve user engagement and understanding. This personalized approach makes content more relevant and engaging, improving user satisfaction and communication (Dennis and Kinney 1998).

AI in strategic communication enriches interactions by making them more dynamic and interactive. Carlson and Zmud (1999) found that real-time user input makes interactive media richer and more effective. AI-powered tools can adjust content and make personalized recommendations in real time, improving communication. These real-time adaptations and responses to user needs align with MRT emphasis on immediacy and feedback, making it applicable to AI-driven personalized media content (Carlson and Zmud 1999). AI also improves media richness and consumer service efficiency. According to Kock (2004), richer media helps customers understand and resolve issues faster, improving service efficiency. AI can reduce customer service time by providing personalized responses and solutions. AI-enhanced media richness allows for more nuanced and effective consumer communication, improving efficiency. Therefore, MRT provides a solid theoretical foundation for understanding how AI can improve media personalization and consumer service efficiency (Kock 2004).

2.4. Strategic Communication and Personalized Media Content

Strategic communication helps create and deliver personalized media content for consumer engagement. For example, Schivinski et al. (2016) found that strategically tailoring brand-related social media content to audience preferences and expectations increases consumer engagement. This suggests that strategic communication-produced personalized media content can boost user engagement and satisfaction. Coombs (2015) also emphasizes strategic communication during crises, showing how well-crafted messages can change public opinion. This suggests that strategic communication improves media personalization by tailoring messages to individual users.

AI enhances strategic communication's impact on personalized media content. Basri (2020) finds that AI-assisted social media marketing improves SME performance by creating more personalized and engaging content. Bag et al. (2022) discuss how AI technologies personalize the digital customer journey to increase user engagement and conversion. Effective media personalization requires real-time adjustments and personalized interactions, which AI can provide. A systematic review of strategic AI use by Borges et al. (2020) shows that AI can personalize and respond to digital communication. In hospitality, AI-driven voice assistants improve customer service by providing personalized responses based on user data, according to Buhalis and Moldavska (2022). AI-supported strategic communication personalizes media content to meet users' needs and preferences, improving their experience and engagement. Thus, a research hypothesis is proposed:

H1. *Strategic communication has a significant impact on personalized media content.*

2.5. Strategic Communication and Consumer Service Efficiency

Strategic communication helps companies improve customer service by facilitating clear, effective, and timely interactions. For example, Coombs (2015) shows how well-structured and transparent crisis communication can reduce damage and maintain customer trust. Consumer efficiency refers to the degree to which consumers can achieve their desired outcomes with minimal effort, time, and resources (Gursoy et al. 2019; Maslowska et al. 2016). Optimizing consumer decision-making, using information effectively, and integrating consumer activities into daily routines improves satisfaction and reduces cognitive load. In daily consumer interactions, strategic communication ensures accurate and prompt responses to customer queries, improving service efficiency. When combined with strategic communication practices, AI-enhanced communication enhances customer experience and service efficiency (Daqar and Smoudy 2019). AI personalized and immediate responses boost strategic communication's impact on consumer service efficiency. Gursoy et al. (2019) examined consumer acceptance of AI devices in service delivery and found that AI handles routine inquiries, freeing up human agents to handle more complex issues. Strategic communication guides this division of labor to streamline and improve customer service. Huang and Rust (2021a) discuss a marketing AI strategic framework, noting that AI-scaled personalized communication enhances service quality and efficiency. Thus, AI in strategic communication improves customer service by streamlining interactions.

AI in communication improves customer engagement and satisfaction. Chan-Olmsted (2019) examined media industry AI adoptions and found that chatbots and personalized messaging improve consumer engagement by providing timely and relevant information. Nguyen and Malik (2021) found that AI-enabled knowledge sharing enhances service quality. Effective strategic communication optimizes tools to provide consistent, high-quality service, increasing consumer service efficiency. Communication improves consumer service efficiency, according to empirical evidence from various industries. By providing personalized and efficient service, predictive modeling and AI-driven customer support can increase customer loyalty (Patel and Trivedi 2020). Song et al. (2022) found that AI-powered communication improves response times and service quality, increasing customer satisfaction. These studies emphasize the importance of strategic communication in using AI to improve service processes and efficiency.

Strategic communication encourages proactive consumer service that anticipates and resolves issues before they escalate. Wamba-Taguimdje et al. (2020) note that strategic communication improves firm performance, including customer service efficiency, in AI-based transformation projects. Marti et al. (2024) suggest that AI in online customer communities can anticipate and resolve customer issues, improving service efficiency. Thus, a research hypothesis is proposed:

H2. *Strategic communication has a significant impact on consumer service efficiency.*

2.6. Personalized Media Content and Consumer Service Efficiency

Customized media content improves consumer service efficiency by meeting consumer needs and preferences. For example, Schivinski et al. (2016) developed and validated a scale to measure consumer engagement with brand-related social media content, finding that personalized and relevant content increases engagement. Engagement increases customer service efficiency because customers who feel understood and valued are more likely to have their needs met quickly. Gorla et al. (2010) found that high-quality, personalized information systems improve organizational service quality and customer service. AI helps create and deliver personalized media content, improving consumer service. Chatterjee and Bhattacharjee (2020) used structural equation modeling to analyze higher education AI adoption, highlighting AI's ability to personalize content and enhance learning outcomes. Ameen et al. (2022) advanced creativity in marketing and AI theory by showing that AI-driven personalization strategies improve consumer engagement and service efficiency.

Strategic communication using AI, personalized media content, and consumer service efficiency are linked by AI ability to tailor interactions to user data and preferences, improving relevance and engagement (Pfiffelmann et al. 2020). AI-driven personalization improves customer service by tailoring content to consumer behaviors and needs (Bang and Wojdowski 2016; De Keyser et al. 2015). In addition, Maslowska et al. (2011) found that personalized AI communications improve efficiency by predicting and responding to consumer queries faster and more accurately. These capabilities strategically support organizational goals to improve customer service. AI-based marketing studies show that personalized media content improves customer service. Babatunde et al. (2024) found that AI-driven personalized content boosts consumer satisfaction and loyalty. Bag et al. (2022) showed how AI technologies personalize the customer journey to increase engagement, conversion, and service efficiency. The hospitality and service industries demonstrate how personalized media content improves service efficiency. Buhalis and Moldavska (2022) found that AI-driven voice assistants improve customer service by providing timely and relevant responses. This is consistent with Nguyen and Malik (2021), who found that AI-facilitated knowledge sharing enhances service quality, especially when content is personalized to customer needs.

Strategic AI integration in personalized media content creation improves consumer experiences and service efficiency. Kolasani (2023) mentioned how natural language processing and large language models improve customer service and hyper-personalization. Kshetri et al. (2024) found that AI-generated personalized content boosts consumer engagement and service efficiency in marketing. Thus, a research hypothesis is proposed:

H3. *Personalized media content has a significant impact on consumer service efficiency.*

2.7. Mediating Role of Artificial Intelligence between Strategic Communication and Consumer Service Efficiency

AI mediates strategic communication, improving consumer service efficiency. Media Richness Theory states that richer communication media reduce ambiguity and improve understanding (Dennis and Kinney 1998). AI technologies enhance consumer media by providing personalized, real-time, and contextually relevant communication. Chatterjee and Bhattacharjee (2020) found that AI adoption in higher education improves communication personalization and effectiveness, improving outcomes. Strategic AI in communication improves service efficiency by providing timely and relevant customer-specific responses. Buhalis and Moldavska (2022) noted that AI-driven voice assistants improved hospitality customer service through personalized interactions. This suggests that AI can mediate strategic communication and consumer service efficiency by enabling more personalized and responsive interactions. Bag et al. (2022) found that AI technologies improve service efficiency by customizing customer journeys to user preferences, increasing user engagement and conversion.

High-quality information systems deliver accurate and relevant information to customers, improving service quality, according to Gorla et al. (2010). AI systems can analyze massive amounts of data and generate insights, making strategic communication accurate and contextually relevant. Patel and Trivedi (2020) agreed, arguing that AI-driven customer support using predictive modeling and natural language processing boosts customer loyalty by providing efficient and personalized service. AI also mediates strategic communication into actionable insights that improve service efficiency. Babatunde et al. (2024) found that AI-driven personalized content boosts consumer satisfaction and loyalty. Wamba-Taguimdje et al. (2020) found that AI-based transformation projects boost firm performance, including customer service. AI improves consumer interactions by turning strategic communication into personalized and actionable content, mediating the relationship between communication strategies and service outcomes.

Finally, AI provides real-time feedback and adapts communication strategies to consumer behavior, strengthening its mediating role. Personalized and interactive brand-related social media content increases consumer engagement (2016). Through continuous

consumer behavior analysis and communication strategy adjustments, AI technologies enable personalization and interactivity. According to Nguyen and Malik (2021), AI-enhanced knowledge sharing improves service quality, so real-time adaptability is essential for efficient and effective consumer service. Thus, a research hypothesis is proposed:

H4. *Artificial intelligence significantly mediates the relationship between strategic communication and consumer service efficiency.*

2.8. Mediating Role of Artificial Intelligence between Personalized Media Content and Consumer Service Efficiency

Media Richness Theory states that richer media can better convey complex and ambiguous messages (Dennis and Kinney 1998). AI provides personalized, real-time, contextually relevant communication and enriches media. Schivinski et al. (2016) found that personalized media content increases consumer engagement, suggesting that AI can make content more relevant and timely. By providing customized responses to customer needs, AI-generated personalized media content improves service efficiency. Buhalis and Moldavska (2022) noted that AI-driven voice assistants improved hospitality customer service through personalized interactions. Babatunde et al. (2024) found that AI-driven personalized content boosts consumer satisfaction and loyalty. AI facilitates more relevant and efficient interactions between personalized media content and consumer service efficiency, according to these studies.

AI improves the quality and consistency of personalized media content, which enhances consumer service. High-quality information systems deliver accurate and relevant information to customers, improving service quality (2010). AI systems can analyze massive amounts of data and generate insights, ensuring accurate and contextually relevant personalized content. Patel and Trivedi (2020) found that AI-driven customer support using predictive modeling and natural language processing boosts customer loyalty by providing efficient and personalized service. Bag et al. (2022) found that AI technologies personalized customer journeys to increase user engagement and conversion, improving service efficiency. According to Wamba-Taguimdje et al. (2020), AI-based transformation projects boost firm performance, including customer service efficiency. AI makes consumer interactions more efficient and effective by turning personalized media content into actionable and relevant interactions, mediating the relationship between personalized content and service outcomes.

Finally, AI real-time feedback and content strategy adaptation to consumer behavior strengthens its mediating role. Nguyen and Malik (2021) showed that AI-enhanced knowledge sharing improves service quality, especially when personalized to customer needs. This adaptability is essential for efficient and effective consumer service because AI can continuously analyze consumer behavior and adjust content strategies. Thus, the study proposed a research hypothesis:

H5. *Artificial intelligence significantly mediates the relationship between personalized media content and consumer service efficiency.*

After an in-depth literature justification, the study developed the conceptual model (see Figure 1).

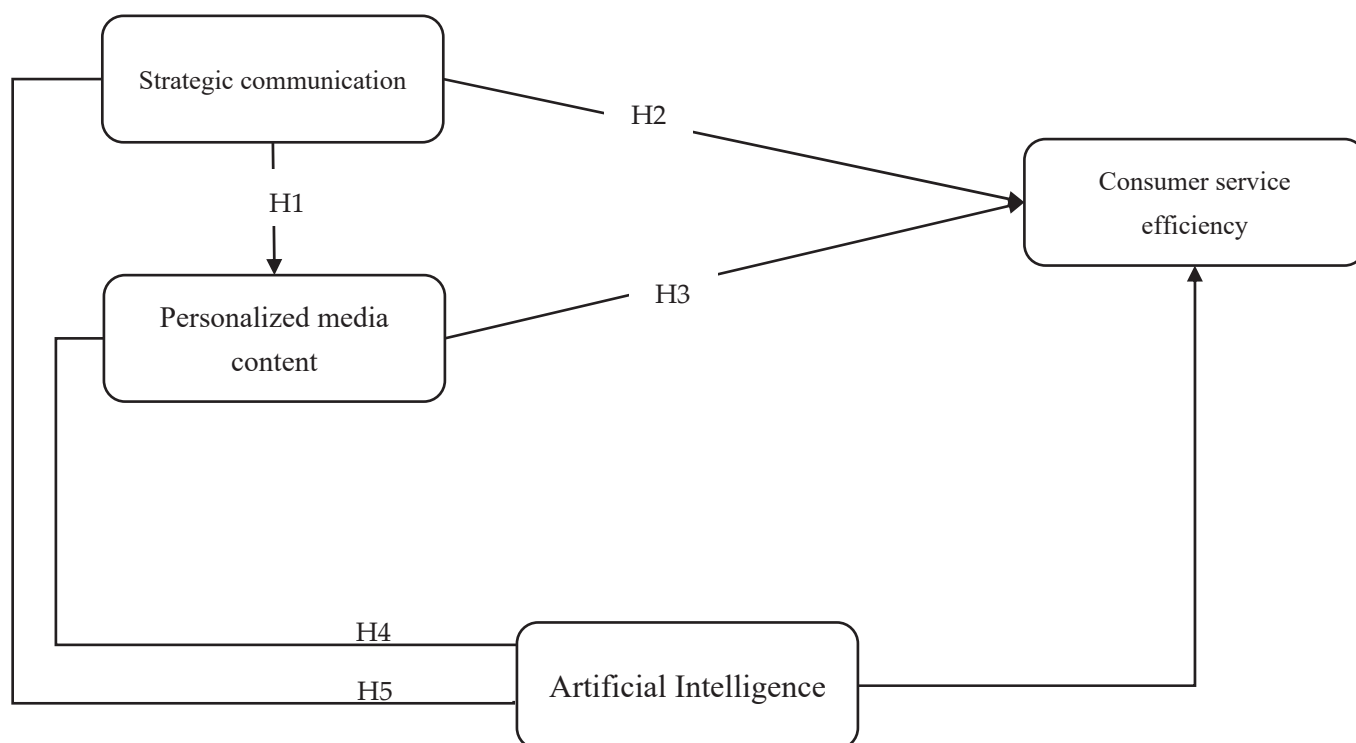


Figure 1. Conceptual framework.

3. Research Methodology

3.1. Research Design

Quantitative methods let researchers measure variables and analyze relationships statistically. Chatterjee and Bhattacharjee (2020) emphasize that quantitative analysis, including structural equation modeling, can accurately and reproducibly examine complex relationships and test hypotheses. Surveys collect large amounts of data from diverse respondents, improving generalizability. This study collected quantitative data on consumer perceptions and experiences using a survey method, providing statistically significant insights into AI-enhanced strategic communications and personalized content. Surveys allow diverse audiences to provide direct feedback, ensuring that data reflects a wide range of consumer interactions and preferences. This cost-effective and efficient method allows rapid data collection and analysis across Saudi Arabia's e-commerce demographics. Survey questionnaires (Appendix A) help quantify consumer perceptions, attitudes, and behaviors. Schivinski et al. (2016) showed that surveys measure consumer engagement with brand-related social media content. Surveys are ideal for collecting self-reported user experiences and satisfaction data to determine how AI-mediated personalized content affects service efficiency. Gorla et al. (2010) recommend surveys for assessing information system quality and organizational outcomes. Thus, a quantitative research design with survey questionnaires (Appendix A) allows for a structured and efficient test of the study's hypotheses and meaningful conclusions about AI's mediating role in improving personalized media content and consumer service efficiency.

3.2. Data Collection Procedures

The data for this study were gathered through an online survey distributed via social media platforms such as Facebook, LinkedIn, Twitter, and WhatsApp. Initially, the survey instrument, which included quartiles to capture the responses, was uploaded to Google Drive. This Google Drive survey has a shareable link that allows for easy access and distribution across various social media channels. The survey targeted Saudi consumers who are active social media users and buy and share stories online.

To ensure a diverse and representative sample, the study used a cluster sampling technique. The target population was divided into three age groups: 18–30 years, 31–45 years, and 46 years or older. This clustering method was chosen to capture potential differences in social media usage and purchasing behavior between age groups (Singh and Masuku 2014). Each cluster was represented equally in survey responses, resulting in balanced data for analysis. The study aimed to collect responses from the 18–30 years cluster, 31–45 years cluster, and the 46 years and older cluster.

The survey link was distributed on 1 January 2024, and responses were collected over a month, ending on 31 January 2024. Throughout this time, the survey link was actively shared and promoted on Facebook, LinkedIn, Twitter, and WhatsApp to reach a large portion of the target population. Periodic reminders and follow-up messages were sent to encourage participation and ensure that each cluster's response targets were met. The use of multiple social media platforms contributed to a broad reach and diverse set of respondents.

After the survey ended on 31 January 2024, the collected data were reviewed to ensure completeness and accuracy. Each cluster received the required number of responses, from the 18–30 age group, 31–45 age group, and 46+ age group. The total number of samples was 498 but the study collected and ensured 367 valid responses. The data were then cleaned and prepared for analysis, with any missing or duplicate responses removed to ensure data integrity. This thorough data collection process resulted in a robust and representative dataset for investigating the mediating role of artificial intelligence in the relationship between personalized media content and consumer service efficiency.

3.3. Measurement Scales

The study used a variety of measurement scales to evaluate the constructs of personalized media content, strategic communication, and service efficiency, adapting items from previous research to ensure reliability and validity. Schivinski et al. (2016) provided 17 items for measuring personalized media content. These items were divided into three categories: consumption (5), contributions (6), and creation (6). This comprehensive scale measures consumer engagement with personalized media content through various modes of interaction, such as passive consumption, active contributions, and content creation.

Additionally, Curtis et al. (2004) developed 12 items to assess strategic communication. These items were created to evaluate the effectiveness of communication strategies used by organizations, with a focus on clarity, responsiveness, and relevance. Service efficiency was measured using 6 items from the study of Gorla et al. (2010). Additionally, the study adapted 8 items of AI adoption from the study of Chatterjee and Bhattacharjee (2020). These items evaluated various aspects of service quality, such as system efficiency, data accuracy, and overall service performance. By adapting these well-validated scales, the study ensures that the measurement instruments are both reliable and valid, providing solid data for examining the relationships between personalized media content, strategic communication, and service efficiency.

3.4. Data Analysis

The demographic analysis of the collected data was carried out using IBM SPSS version 22. This software is well-known for its powerful statistical capabilities and user-friendly interface, making it ideal for handling large datasets and performing descriptive statistics. SPSS made it easier to examine demographic variables such as age, gender, and social media usage patterns, resulting in a better understanding of the sample's characteristics. The literature strongly supports the use of SPSS for demographic analysis. Hair et al. (2021) emphasize effectiveness in descriptive and inferential statistical analysis, which ensures that demographic data are correctly summarized and presented.

The validity, reliability, and hypotheses were tested using Smart PLS 4. Smart PLS is an effective tool for partial least squares structural equation modeling (PLS-SEM), especially for complex models that include multiple constructs and indicators. The software's

ability to deal with small to medium sample sizes, non-normal data distributions, and complex model structures makes it an excellent choice for this study. Sarstedt et al. (2020a) highlight the benefits of PLS-SEM in social science research, precisely its flexibility and robustness. Furthermore, Henseler et al. (2014) and Becker et al. (2014) show that Smart PLS is effective at evaluating both measurement and structural models, ensuring construct reliability and validity. The advanced features of the software enabled rigorous hypothesis testing, confirming artificial intelligence's role as a mediator in the relationship between personalized media content and consumer service efficiency.

4. Results

4.1. Demographic Analysis

Table 1 shows a demographic breakdown of a sample of 367 people. The gender distribution reveals a significant male dominance of 88.3% (324 males) versus 11.7% for females (43 females). In terms of age, the majority of participants are between 31 and 45 years old, accounting for 64.3% (236 individuals), followed by those aged 18 to 30 years, 25.9% (95 individuals), and a smaller proportion aged 46 and up, 9.8% (36 individuals). The purchasing experience varies, with the majority (42.2% or 155 individuals) having more than 6 years of experience, followed by those with 4–6 years at 31.6% (116 individuals), 1–3 years at 20.7% (76 individuals), and the least experienced group with less than 1 year at 5.4% (20 individuals). The educational level is predominantly high, with 66.5% (244 individuals) holding a Master's degree, followed by those with a Bachelor's degree at 19.1% (70 individuals), MS/PhD at 12.8% (47 individuals), and only a small fraction at O level at 1.6% (6 individuals). These findings show a demographic profile skewed towards male, middle-aged, highly educated individuals with extensive purchasing experience, indicating a potentially mature and professionally advanced sample.

Table 1. Demographic analysis.

Demographics	Sub-Categories	N	%
Gender	Male	324	88.3
	Female	43	11.7
Age	18–30 Years	95	25.9
	31–45 Years	236	64.3
	Over 46 Years	36	9.8
	Less than 1 Year	20	5.4
Buying Experience	1–3 Years	76	20.7
	4–6 Years	116	31.6
	More than 6 Years	155	42.2
	O level	6	1.6
Education	Bachelor's Degree	70	19.1
	Master's Degree	244	66.5
	MS/PhD	47	12.8

4.2. Assessing Measurement Model

The study runs an algorithm technique to assess the validity and reliability of the measurement constructs. For this purpose, the study used 5000 sub-samples in Smart PLS to create maximum iterations. According to Hair et al. (2021), the convergent validity and reliability assessment requires several statistical thresholds, i.e., factor loadings exceed 0.7 (see Figure 2), AVE exceeds 0.5, and Cronbach's alpha (α) and Composite reliability (CR) exceed 0.7 for convergent validity and reliability (Sarstedt et al. 2020a, 2020b; Henseler et al. 2014). A series of algorithms were performed to improve validity and reliability. Due to this, the study removed 8 items of strategic communication including SC1, SC6, SC7, SC8, SC9, SC10, SC11, and SC12, 12 items of personalized media content including PMC1, PMC2, PMC3, PMC4, PMC5, PMC6, PMC7, PMC8, PMC9, PMC10, PMC11, and PMC15, and 1 item of AI including AI1 had been deleted from the model due to lower factor loadings. Table 2 shows that the remaining items meet the thresholds, indicating

robust model constructs. All items under the scales—AI, consumer service efficiency, personalized media content, and strategic communication—have strong factor loadings, exceeding 0.7. This indicates good convergent validity because the items and constructs are strongly related. All scales have AVE values above 0.5, proving that the constructs can explain indicator variance. This is crucial to ensure that construct indicators accurately represent them.

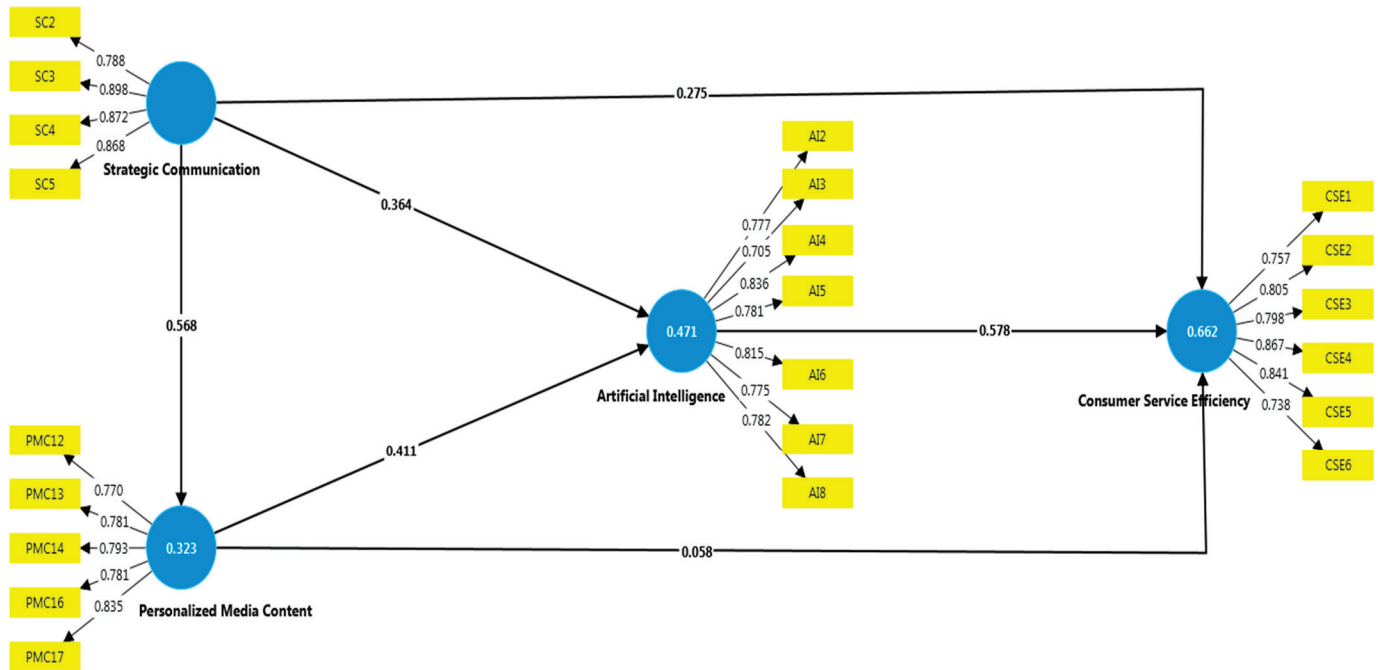


Figure 2. Confirmatory factor analysis.

Table 2. Convergent validity and reliability.

Scales	Items	Factor Loadings	α	CR	AVE	Multi-Collinearity
Artificial Intelligence	AI2	0.777	0.894	0.917	0.612	1.889
	AI3	0.705				
	AI4	0.836				
	AI5	0.781				
	AI6	0.815				
	AI7	0.775				
	AI8	0.782				
	AI9	0.781				
Consumer Service Efficiency	CSE1	0.757	0.889	0.915	0.644	1.726
	CSE2	0.805				
	CSE3	0.798				
	CSE4	0.867				
	CSE5	0.841				
	CSE6	0.738				
Personalized Media Content	PMC12	0.770	0.851	0.894	0.628	1.476
	PMC13	0.781				
	PMC14	0.793				
	PMC15	0.781				
	PMC16	0.835				
Strategic Communication	SC2	0.788	0.879	0.917	0.735	1.000
	SC3	0.898				
	SC4	0.872				
	SC5	0.868				

In terms of reliability, α and CR values are strong for all constructs. α values range from 0.851 to 0.894, and CR values from 0.894 to 0.917. These metrics easily exceed recommended thresholds, indicating construct internal consistency and reliability. This high reliability indicates that constructs are consistent across items and reliable for SEM analysis. The low multi-collinearity values for all constructs shown in Table 2 indicate that there is no issue.

Assessing discriminant validity requires analyzing cross-loadings to ensure that each item correlates more strongly with its own construct than with any other model construct (Henseler et al. 2014). The loading of each item on its designated construct is greater than its loadings on other constructs, indicating discriminant validity (Sarstedt et al. 2020a, 2020b). Table 3 shows that all items follow this principle. These results support the construct framework and the reliability and validity of this SEM analysis by showing that the constructs are distinct and measure different aspects as intended. Discriminant validity improves the model's research and field application.

Table 3. Cross-loadings.

Items	Artificial Intelligence	Consumer Service Efficiency	Personalized Media Content	Strategic Communication
AI2	0.777	0.635	0.549	0.474
AI3	0.705	0.515	0.346	0.356
AI4	0.836	0.648	0.534	0.478
AI5	0.781	0.578	0.457	0.486
AI6	0.815	0.666	0.489	0.534
AI7	0.775	0.606	0.433	0.420
AI8	0.782	0.597	0.542	0.500
CSE1	0.521	0.757	0.429	0.499
CSE2	0.654	0.805	0.558	0.553
CSE3	0.620	0.798	0.437	0.537
CSE4	0.690	0.867	0.491	0.581
CSE5	0.678	0.841	0.490	0.520
CSE6	0.562	0.738	0.321	0.445
PMC12	0.453	0.424	0.770	0.448
PMC13	0.511	0.427	0.781	0.443
PMC14	0.447	0.449	0.793	0.461
PMC16	0.475	0.458	0.781	0.431
PMC17	0.552	0.501	0.835	0.468
SC2	0.506	0.510	0.459	0.788
SC3	0.490	0.548	0.483	0.898
SC4	0.498	0.582	0.479	0.872
SC5	0.550	0.595	0.524	0.868

Contemporary methods for assessing discriminant validity in SEM models use the Heterotrait-Monotrait (HTMT) ratio of correlations, with threshold values typically not exceeding 0.90 (Henseler et al. 2014; Sarstedt et al. 2020a). This method estimates the true correlation between constructs using the geometric mean of the average correlations among indicators of the same constructs. In Table 4, all construct pairs (artificial intelligence, consumer service efficiency, personalized media content, strategic communication) have HTMT values below 0.90, ranging from 0.651 to 0.866. No construct correlations exceed 0.90, indicating good discriminant validity. This suggests that the constructs are distinct enough to be reliable and valid in the SEM model. Results showing that constructs do not overlap significantly confirm their uniqueness and suitability for structural model analysis and interpretation.

Table 4. HTMT Ratio.

Constructs	Artificial Intelligence	Consumer Service Efficiency	Personalized Media Content	Strategic Communication
Artificial Intelligence				
Consumer Service Efficiency	0.866			
Personalized Media Content	0.700	0.651		
Strategic Communication	0.669	0.736	0.656	

4.3. Assessing Model Fitness

Table 5 shows how well the model explains and predicts AI, service efficiency, and personalized media content. R^2 values, which indicate how well the model explains dependent variable variance, are telling. Consumer service efficiency has the highest R-square value, 0.662, indicating that the model explains 66.2% of its variability. Following closely are artificial intelligence (0.471) and personalized media content (0.323). The model is well-specified with minimal overfitting because the adjusted R^2 values, which account for the number of predictors, are close to the R^2 values. Positive Q^2 predictive values (0.351, 0.422, and 0.315) indicate model relevance in predicting new data. These values show that the model fits the data well and can predict all three constructs, especially Consumer Service Efficiency, which has high explanatory and predictive power.

Table 5. R^2 and Q^2 .

Constructs	R^2	R^2 Adjusted	Q^2 Predict
Artificial Intelligence	0.471	0.468	0.351
Consumer Service Efficiency	0.662	0.660	0.422
Personalized Media Content	0.323	0.321	0.315

4.4. Assessing Path Model

Table 6 shows how strategic communication and personalized media content affect outcomes. The analysis examines these direct effects' strength, significance, and practical effects on consumer service efficiency. Hypothesis H1 states that strategic communication affects personalized media. The analysis reveals a significant effect with a β value of 0.568, a high T-value of 12.868, and a p -value of 0.000. Not including zero in the confidence interval [0.479, 0.652] strengthens this effect. The large effect size ($f^2 = 0.476$) suggests that strategic communication is a strong predictor of how personalized media content is developed or used, emphasizing its importance in media content strategies. We accept Hypothesis H1.

Hypothesis H2 examines how strategic communication affects consumer service efficiency. It is supported by a significant β value of 0.275, T-value of 6.183, and p -value of 0.000. With a moderate effect size ($f^2 = 0.130$), the confidence interval [0.187, 0.362] supports the hypothesis. Strategic communication improves clarity, engagement, and service goal alignment, which may boost consumer service efficiency, so the study accepted hypothesis H2. Hypothesis H3 examines how personalized media content affects consumer service efficiency. Despite the expected positive effect, the analysis shows a β value of 0.058, a T-value of 1.302, and a non-significant p -value of 0.193. The confidence interval includes zero [−0.027, 0.150], and the effect size is negligible ($f^2 = 0.006$), suggesting that personalized media content does not affect consumer service efficiency. The model rejects Hypothesis H3, showing that while personalized media content is essential for engaging consumers, its direct effect on service efficiency may be less than expected or may require interaction with other factors not captured in this model.

Table 6. Direct effects.

No	Hypotheses Testing	β Value	T-Values	<i>p</i> -Values	Confidence Interval (C.I.) %	f^2	Decision
H1	Strategic Communication -> Personalized Media Content	0.568	12.868	0.000	[0.479, 0.652]	0.476	Accept
H2	Strategic Communication -> Consumer Service Efficiency	0.275	6.183	0.000	[0.187, 0.362]	0.130	Accept
H3	Personalized Media Content -> Consumer Service Efficiency	0.058	1.302	0.193	[-0.027, 0.150]	0.006	Reject

Strategic communication is crucial to personalizing media content and improving consumer service efficiency. However, the role of personalized media content in directly impacting service efficiency is unclear, suggesting further research or a reevaluation of media content in consumer service strategies.

Table 7 shows how AI mediates strategic communication, personalized media content, and consumer service efficiency (see Figure 3). This mediation analysis shows how AI mediates strategic initiatives into operational results. Hypothesis H4 examines whether AI mediates the relationship between personalized media content and consumer service efficiency. The β value for this pathway is 0.237, with a T-value of 6.778 and a 0.000 *p*-value. Without including zero, the confidence interval [0.173, 0.310] strongly supports mediation. Despite the lack of an effect size (f^2), AI significantly mediates this relationship, improving consumer service efficiency by integrating and applying insights from personalized media content. AI successfully implements personalized content strategies to improve service outcomes, supporting Hypothesis H4.

Table 7. Mediating effects.

No	Hypotheses Testing	β Value	T-Values	<i>p</i> -Values	Confidence Interval (C.I.) %	f^2	Decision
	Personalized media content -> Artificial intelligence	0.411	8.110	0.000	[0.315, 0.515]	0.216	-
	Strategic communication -> Artificial intelligence	0.364	6.679	0.000	[0.254, 0.467]	0.169	-
	Artificial intelligence -> Consumer service efficiency	0.578	13.070	0.000	[0.492, 0.666]	0.523	-
H4	Personalized media content -> Artificial intelligence -> Consumer service efficiency	0.237	6.778	0.000	[0.173, 0.310]	-	Accept
H5	Strategic communication -> Artificial intelligence -> Consumer service efficiency	0.210	5.672	0.000	[0.139, 0.286]	-	Accept

Hypothesis H5 examines how AI mediates strategic communication's effects on consumer service efficiency. The β value is 0.210, with a T-value of 5.672 and a *p*-value of 0.000. The confidence interval [0.139, 0.286] reinforces AI's mediating role. Strategic communication affects AI implementations, which improves consumer service efficiency. Results show that strategic communication directly affects AI and significantly improves consumer service operations through AI. We accept Hypothesis H5, emphasizing AI's crucial role in turning strategic communications into service efficiency gains.

Finally, AI mediates strategic communication and personalized media content to improve consumer service efficiency. These findings emphasize the importance of integrating advanced AI technologies to leverage strategic communications and personalized content for more efficient and effective service delivery. This integration leverages AI's analytical strengths and positions it as a key player in organizational strategic initiatives.

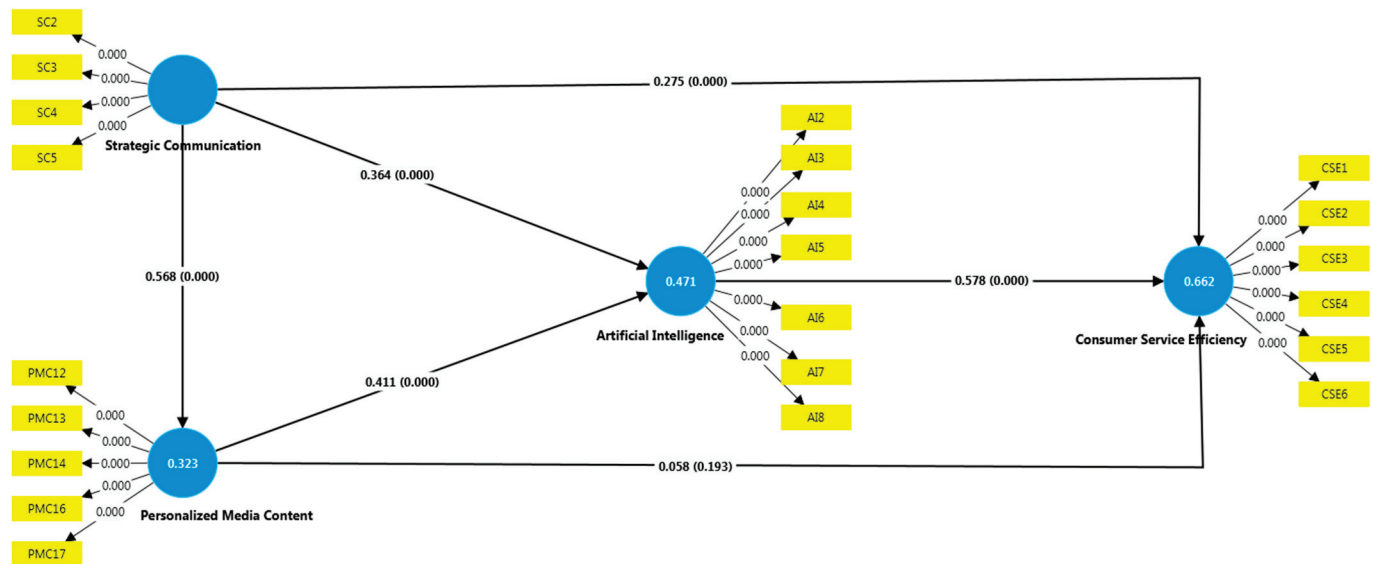


Figure 3. Structural equation modeling (SEM).

5. Discussion and Conclusions

The study is conducted in Saudi Arabia by targeting the social media marketing consumers who have shared evidence of how they perceive good efficiency via strategic communication, personalized media contents in the presence of AI as a mediator. The research respondents agreed that AI in consumer communications and personalized content management improves consumer service efficiency. This supports the literature that emphasizes AI's transformative role in personalizing user interactions and improving service delivery. Hawkins et al. (2008) and Dijkstra (2008) found that tailored communication in health-related contexts is psychologically effective, which is consistent with AI influence on optimizing personalized media content in this study.

The findings also support Pfiffelmann et al. (2020) and De Keyzer et al. (2015), which show that AI-enabled personalized advertising increases consumer engagement and response. AI ability to integrate complex consumer data and provide tailored interactions increases engagement and efficiency, as seen in the high predictive relevance (Q^2) for consumer service efficiency in this study. The high R^2 values for AI and consumer service efficiency support Ang et al.'s (2018) and Aguirre et al.'s (2015) findings that AI can navigate consumer preferences and improve service delivery through strategic communication. AI's mediating role between strategic communication and consumer service efficiency shows its ability to translate strategic inputs into improved service outputs.

In addition, Huang and Rust (2021a) and Gurau et al. (2003) also discuss the role of AI in marketing and service industries, which supports the current study's findings. Therefore, the research respondents agreed that AI has strategic value in predicting and adapting consumer behavior to optimize marketing and operations. High R^2 adjusted values indicate robust model specification and large effect sizes indicate practical significance. The consistency of the findings with prior research emphasizes the role of AI in personalizing and streamlining consumer services. The research respondents affirmed the strategic integration of AI in business processes as a tool for operational optimization and a competitive lever for consumer engagement and service excellence. These insights help

explain AI operational and strategic effects across consumer interaction points, enabling its continued adoption and integration into modern business practices.

5.1. Theoretical Implications

This study advances the theoretical understanding of strategic communication, personalized media content, and AI's role in consumer service efficiency. The research shows how strategic messaging and effective communication protocols can directly affect service outcomes by carefully analyzing the impact of strategic communication on consumer service efficiency. This empirically shows that communication strategies cause operational efficiency in service delivery, supporting strategic communication theories. The findings support the theory that well-crafted communication strategies improve consumer service responsiveness and effectiveness, strengthening the case for communication as a core business strategy.

Second, the study examined how personalized media content affects consumer service efficiency. This research contributes to the growing literature on digital marketing customization by showing how tailored content engages consumers and improves service delivery. The study suggests that strategic deployment of personalized content with advanced technological tools like AI may improve service efficiency. This observation highlights the conditional effectiveness of personalization, dependent on technological frameworks, in marketing and consumer behavior theories. The mediation of AI between strategic communication and personalized content is a major theoretical advance. The study fills a significant gap in the literature by showing that AI can use strategic communication and personalized content to improve consumer service efficiency. It portrays AI as a mediator that turns strategic inputs into service operations improvements. This finding adds nuance to AI in business process theories by showing how AI can bridge the gap between strategic intent and consumer satisfaction.

The analysis of strategic communication, personalized media content, and AI in service efficiency provides a solid foundation for future research. It expands the theoretical framework for how businesses can use AI to improve communication and content personalization. The research contributes to academic discourse and provides practical frameworks for businesses to optimize consumer engagement strategies in a digital marketplace by aligning theoretical concepts with empirical evidence.

5.2. Limitations and Future Directions

The study relies on a specific dataset and context, which may limit its generalizability across industries and cultures. Thus, the results may only be applicable to other sectors or global markets with further validation. The study also focused on AI as a mediator rather than other mediators or moderators that could affect strategic communication, personalized media content, and consumer service efficiency. Organizational culture, technology readiness, and consumer privacy concerns could affect the effectiveness of AI and personalized social media marketing strategies.

Future research should expand the study to include diverse industries and cross-cultural settings to improve robustness and applicability. Additionally, studying other mediators and moderators would help explain social media marketing and consumer engagement. Leadership styles and innovation capabilities may affect AI marketing strategy implementation, which researchers could study. Future studies could also examine how consumer privacy and data security perceptions affect AI-driven personalized marketing, which is becoming increasingly important in the digital age. These studies will fill the gaps in this study and advance the discussion on strategic AI and personalization to improve consumer relationships and business performance.

5.3. Conclusions

The hypotheses reveal how strategic communication, personalized media content, AI, and consumer service efficiency interact. Acceptance of H1 and H2 reveals significant direct

effects of strategic communication on personalized media content ($\beta = 0.568$) and consumer service efficiency ($\beta = 0.275$), with significant effect sizes (f^2 values of 0.476 and 0.130). An insignificant t-value and a confidence interval straddling zero reject H3, which tested the direct effect of personalized media content on consumer service efficiency. The accepted mediated relationships in H4 and H5 involving artificial intelligence show that AI plays a crucial mediating role, enhancing the impact of both personalized media content and strategic communication on consumer service efficiency, with effect sizes demonstrating substantial leverage. These findings show that AI is crucial to optimizing communication strategies for organizational success.

Funding: This research received no external funding.

Institutional Review Board Statement: Due to the nature of the study and the absence of personal data utilization, in accordance with the laws of Saud Arabia, the study was deemed exempt from Ethics Committee approval at King Saud University.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

Conflicts of Interest: The author declares no conflict of interest.

Appendix A Survey Questionnaire

Constructs	Items	Rating (1–5)
Personalized Media Content (Schivinski et al. 2016)	1. I read posts related to Brand X on social media.	[1] [2] [3] [4] [5]
	2. I read fan pages related to Brand X on social network sites.	[1] [2] [3] [4] [5]
	3. I watch pictures/graphics related to Brand X.	[1] [2] [3] [4] [5]
	4. I follow blogs related to Brand X.	[1] [2] [3] [4] [5]
	5. I follow Brand X on social network sites.	[1] [2] [3] [4] [5]
	6. I comment on videos related to Brand X.	[1] [2] [3] [4] [5]
	7. I comment on posts related to Brand X.	[1] [2] [3] [4] [5]
	8. I comment on pictures/graphics related to Brand X.	[1] [2] [3] [4] [5]
	9. I share posts related to Brand X.	[1] [2] [3] [4] [5]
	10. I “Like” pictures/graphics related to Brand X.	[1] [2] [3] [4] [5]
	11. I “Like” posts related to Brand X.	[1] [2] [3] [4] [5]
	12. I initiate posts related to Brand X on blogs.	[1] [2] [3] [4] [5]
	13. I initiate posts related to Brand X on social network sites.	[1] [2] [3] [4] [5]
	14. I post pictures/graphics related to Brand X.	[1] [2] [3] [4] [5]
	15. I post videos that show Brand X.	[1] [2] [3] [4] [5]
	16. I write posts related to Brand X on forums.	[1] [2] [3] [4] [5]
	17. I write reviews related to Brand X.	[1] [2] [3] [4] [5]
Strategic Communication (Curtis et al. 2004)	1. I read posts related to Brand X on social media.	[1] [2] [3] [4] [5]
	2. I look you in the eye when discussing your care.	[1] [2] [3] [4] [5]
	3. Including loved ones in treatment discussions is important.	[1] [2] [3] [4] [5]
	4. I ensure to answer all questions about your illness.	[1] [2] [3] [4] [5]
	5. Listening to what you have to say is crucial to me.	[1] [2] [3] [4] [5]
	6. I care about you as a person, not just as a patient.	[1] [2] [3] [4] [5]
	7. I give my full attention during our conversations.	[1] [2] [3] [4] [5]
	8. Talking about your feelings about getting sicker is part of our discussions.	[1] [2] [3] [4] [5]
	9. We discuss the details in case you get sicker.	[1] [2] [3] [4] [5]
	10. We discuss how long you have to live when necessary.	[1] [2] [3] [4] [5]
	11. Talking about what dying might be like is part of our conversation.	[1] [2] [3] [4] [5]
	12. Involving you in discussions about your care is fundamental.	[1] [2] [3] [4] [5]

Constructs	Items	Rating (1–5)
Consumer Service Efficiency (Gorla et al. 2010)	The company information systems apply modern technology effectively.	[1] [2] [3] [4] [5]
	The company information systems are well integrated.	[1] [2] [3] [4] [5]
	The company information systems are user-friendly.	[1] [2] [3] [4] [5]
	The company information systems have good documentation.	[1] [2] [3] [4] [5]
	The company information systems have a short response time for online inquiries.	[1] [2] [3] [4] [5]
AI Adoption (Chatterjee and Bhattacharjee 2020)	The company information systems have a short time lag between data input and output for batch processing.	[1] [2] [3] [4] [5]
	AI integration in social media marketing significantly contributes to societal progress.	[1] [2] [3] [4] [5]
	AI technologies in social media marketing help address societal challenges more effectively.	[1] [2] [3] [4] [5]
	AI facilitates more interactive and engaging learning experiences on social media platforms.	[1] [2] [3] [4] [5]
	The use of AI tools enhances student interaction with social media content.	[1] [2] [3] [4] [5]
	Implementing AI in social media marketing reduces overall marketing costs for consumers.	[1] [2] [3] [4] [5]
	AI adoption makes social media marketing more financially accessible to a broader range of consumers.	[1] [2] [3] [4] [5]
	AI technologies make learning activities on social media platforms more captivating and engaging.	[1] [2] [3] [4] [5]
	The incorporation of AI in marketing strategies increases consumer interest and participation in buying.	[1] [2] [3] [4] [5]

References

- Aguirre, Elizabeth, Dominik Mahr, Dhruv Grewal, de Ko Ruyter, and Martin Wetzels. 2015. Unraveling the Personalization Paradox: The Effect of Information Collection and Trust-Building Strategies on Online Advertisement Effectiveness. *Journal of Retailing* 91: 34–49. [CrossRef]
- Al-Baity, Heyam H. 2023. The Artificial Intelligence Revolution in Digital Finance in Saudi Arabia: A Comprehensive Review and Proposed Framework. *Sustainability* 15: 13725. [CrossRef]
- AlGosaibi, Abdullelah Abdallah, Abdul Rahaman Wahab Sait, Abdulaziz Fahad AlOthman, and Shadan AlHamed. 2020. Developing an Intelligent Framework for Improving the Quality of Service in the Government Organizations in the Kingdom of Saudi Arabia. *International Journal of Advanced Computer Science and Applications* 11: 260–68.
- Al-Jehani, Nermeen B., Zainab A. Hawsawi, N. E. Y. A. R. A. Radwan, and M. A. G. E. D. Farouk. 2021. Development of Artificial Intelligence Techniques in Saudi Arabia: The Impact on COVID-19 Pandemic. *Journal of Engineering Science and Technology* 16: 4530–47.
- Alqahtani, Maha, and Kholod Alqahtani. 2022. Artificial Intelligence Techniques in E-Commerce: The Possibility of Exploiting Them in Saudi Arabia. *International Journal of Engineering and Management Research* 12: 152–59. [CrossRef]
- Ameen, Nisreen, Gagan Deep Sharma, Shlomo Tarba, Amar Rao, and Ritika Chopra. 2022. Toward Advancing Theory on Creativity in Marketing and Artificial Intelligence. *Psychology & Marketing* 39: 1802–25. [CrossRef]
- Ang, Tyson, Shuqin Wei, and Nwamaka A. Anaza. 2018. Livestreaming vs Pre-Recorded: How Social Viewing Strategies Impact Consumers' Viewing Experiences and Behavioral Intentions. *European Journal of Marketing* 52: 2075–104.
- Awad, Naveen Farag, and Mayuram S. Krishnan. 2006. The Personalization Privacy Paradox: An Empirical Evaluation of Information Transparency and the Willingness to Be Profiled Online for Personalization. *MIS Quarterly* 30: 13–28.
- Babatunde, Sodiq Odetunde, Opeyemi Abayomi Odejide, Tolulope Esther Edunjobi, and Damilola Oluwaseun Ogundipe. 2024. The Role of AI in Marketing Personalization: A Theoretical Exploration of Consumer Engagement Strategies. *International Journal of Management & Entrepreneurship Research* 6: 936–49. [CrossRef]
- Bag, Surajit, Gautam Srivastava, Mamoon Al Bashir, Sushma Kumari, Mihalís Giannakis, and Abdul Hannan Chowdhury. 2022. Journey of Customers in This Digital Era: Understanding the Role of Artificial Intelligence Technologies in User Engagement and Conversion. *Benchmarking: An International Journal* 29: 2074–98. [CrossRef]
- Bang, Hyejin, and Bartosz W. Wojdyski. 2016. Tracking Users' Visual Attention and Responses to Personalized Advertising Based on Task Cognitive Demand. *Computers in Human Behavior* 55: 867–76. [CrossRef]
- Basri, Wael. 2020. Examining the Impact of Artificial Intelligence (AI)-Assisted Social Media Marketing on the Performance of Small and Medium Enterprises: Toward Effective Business Management in the Saudi Arabian Context. *International Journal of Computational Intelligence Systems* 13: 142–52. [CrossRef]

- Becker, Jan-Michael, Christian M. Ringle, Marko Sarstedt, and Franziska Völckner. 2014. How Collinearity Affects Mixture Regression Results. *Marketing Letters* 26: 643–59. [CrossRef]
- Boerman, Sophie C., Sanne Kruikemeier, and Frederik J. Zuiderveen Borgesius. 2017. Online Behavioral Advertising: A Literature Review and Research Agenda. *Journal of Advertising* 46: 363–76. [CrossRef]
- Borges, Aline F. S., Fernando J. B. Laurindo, Mauro M. Spínola, Rodrigo F. Gonçalves, and Claudia A. Mattos. 2020. The Strategic Use of Artificial Intelligence in the Digital Era: Systematic Literature Review and Future Research Directions. *International Journal of Information Management* 57: 102225. [CrossRef]
- Buhalis, Dimitrios, and Iuliia Moldavska. 2022. Voice Assistants in Hospitality: Using Artificial Intelligence for Customer Service. *Journal of Hospitality and Tourism Technology* 13: 386–403. [CrossRef]
- Carlson, John R., and Robert W. Zmud. 1999. Channel Expansion Theory and the Experiential Nature of Media Richness Perceptions. *Academy of Management Journal* 42: 153–70.
- Chan-Olmsted, Sylvia M. 2019. A Review of Artificial Intelligence Adoptions in the Media Industry. *International Journal on Media Management* 21: 193–215. [CrossRef]
- Chatterjee, Sheshadri, and Kalyan Kumar Bhattacharjee. 2020. Adoption of Artificial Intelligence in Higher Education: A Quantitative Analysis Using Structural Equation Modelling. *Education and Information Technologies* 25: 3443–63. [CrossRef]
- Cheng, Yang, and Hua Jiang. 2022. Customer–Brand Relationship in the Era of Artificial Intelligence: Understanding the Role of Chatbot Marketing Efforts. *Journal of Product & Brand Management* 31: 252–64. [CrossRef]
- Chen, Huan, and Yoon Joo Lee. 2018. Is Snapchat a Good Place to Advertise? How Media Characteristics Influence College-Aged Young Consumers’ Receptivity of Snapchat Advertising. *International Journal of Mobile Communications* 16: 697–714. [CrossRef]
- Coombs, W. Timothy. 2015. The Value of Communication During a Crisis: Insights from Strategic Communication Research. *Business Horizons* 58: 141–48. [CrossRef]
- Curtis, J. R., R. A. Engelberg, E. L. Nielsen, D. H. Au, and D. L. Patrick. 2004. Patient-Physician Communication about End-of-Life Care for Patients with Severe COPD. *European Respiratory Journal* 24: 200–205. [CrossRef]
- Daft, Richard L., and Robert H. Lengel. 1986. Organizational Information Requirements, Media Richness and Structural Design. *Management Science* 32: 554–71. [CrossRef]
- Daqar, Mohannad A. M. Abu, and Ahmad K. A. Smoudy. 2019. The Role of Artificial Intelligence on Enhancing Customer Experience. *International Review of Management and Marketing* 9: 22.
- De Keyser, Freya, Nathalie Dens, and Patrick De Pelsmacker. 2015. Is This for Me? How Consumers Respond to Personalized Advertising on Social Network Sites. *Journal of Interactive Advertising* 15: 124–34.
- Dennis, Alan R., and Susan T. Kinney. 1998. Testing Media Richness Theory in the New Media: The Effects of Cues, Feedback, and Task Equivocality. *Information Systems Research* 9: 256–74. [CrossRef]
- Dijkstra, Arie. 2008. The Psychology of Tailoring-Ingredients in Computer-Tailored Persuasion. *Social and Personality Psychology Compass* 2: 765–84.
- Gorla, Narasimhaiah, Toni M. Somers, and Betty Wong. 2010. Organizational Impact of System Quality, Information Quality, and Service Quality. *The Journal of Strategic Information Systems* 19: 207–28. [CrossRef]
- Gurau, Calin, Ashok Ranchhod, and Claire Gauzente. 2003. To Legislate or Not to Legislate: A Comparative Exploratory Study of Privacy/Personalisation Factors Affecting French, UK and US Web Sites. *Journal of Consumer Marketing* 20: 652–64.
- Gursoy, Dogan, Oscar Hengxuan Chi, Lu Lu, and Robin Nunkoo. 2019. Consumers Acceptance of Artificially Intelligent (AI) Device Use in Service Delivery. *International Journal of Information Management* 49: 157–69. [CrossRef]
- Hair, Joe F., Jr., Marko Sarstedt, Lucas Hopkins, and Volker G. Kuppelwieser. 2021. Partial Least Squares Structural Equation Modeling (PLS-SEM): An Emerging Tool in Business Research. *European Business Review* 26: 106–21.
- Hawkins, Robert P., Matthew Kreuter, Kenneth Resnicow, Martin Fishbein, and Arie Dijkstra. 2008. Understanding Tailoring in Communicating about Health. *Health Education Research* 23: 454–66. [CrossRef]
- Henseler, Jörg, Christian M. Ringle, and Marko Sarstedt. 2014. A New Criterion for Assessing Discriminant Validity in Variance-Based Structural Equation Modeling. *Journal of the Academy of Marketing Science* 43: 115–35. [CrossRef]
- Huang, Ming-Hui, and Roland T. Rust. 2021a. A Strategic Framework for Artificial Intelligence in Marketing. *Journal of the Academy of Marketing Science* 49: 30–50. [CrossRef]
- Huang, Ming-Hui, and Roland T. Rust. 2021b. Engaged to a Robot? The Role of AI in Service. *Journal of Service Research* 24: 30–41. [CrossRef]
- Hutchins, Jennifer, and Darlene Xiomara Rodriguez. 2018. The Soft Side of Branding: Leveraging Emotional Intelligence. *Journal of Business & Industrial Marketing* 33: 117–25. [CrossRef]
- Hwang, Jooyoung, Sangwon Park, and Mina Woo. 2018. Understanding User Experiences of Online Travel Review Websites for Hotel Booking Behaviors: An Investigation of a Dual Motivation Theory. *Asia Pacific Journal of Tourism Research* 23: 359–72. [CrossRef]
- Kalyanaraman, Sriram, and S. Shyam Sundar. 2006. The Psychological Appeal of Personalized Content in Web Portals: Does Customization Affect Attitudes and Behavior? *Journal of Communication* 56: 110–32.
- Kock, Ned. 2004. The Psychobiological Model: Towards a New Theory of Computer-Mediated Communication Based on Darwinian Evolution. *Organization Science* 15: 327–48. [CrossRef]
- Kolasani, Saydulu. 2023. Optimizing Natural Language Processing, Large Language Models (LLMs) for Efficient Customer Service, and Hyper-Personalization to Enable Sustainable Growth and Revenue. *Transactions on Latest Trends in Artificial Intelligence* 4: 936.

- Kshetri, Nir, Yogesh K. Dwivedi, Thomas H. Davenport, and Niki Panteli. 2024. Generative Artificial Intelligence in Marketing: Applications, Opportunities, Challenges, and Research Agenda. *International Journal of Information Management* 75: 102716. [CrossRef]
- Kusumasondjaja, Sony. 2018. The Roles of Message Appeals and Orientation on Social Media Brand Communication Effectiveness. *Asia Pacific Journal of Marketing and Logistics* 30: 1135–58. [CrossRef]
- Marti, Candice L., Huimin Liu, Gurpreet Kour, Anil Bilgihan, and Yu Xu. 2024. Leveraging Artificial Intelligence in Firm-Generated Online Customer Communities: A Framework and Future Research Agenda. *Journal of Service Management* 35: 438–58. [CrossRef]
- Maslowska, Ewa, Bas van Den Putte, and Edith G. Smit. 2011. The Effectiveness of Personalized E-Mail Newsletters and the Role of Personal Characteristics. *Cyberpsychology, Behavior, and Social Networking* 14: 765–70. [CrossRef] [PubMed]
- Maslowska, Ewa, Edith G. Smit, and Bas van Den Putte. 2016. It Is All in the Name: A Study of Consumers' Responses to Personalized Communication. *Journal of Interactive Advertising* 16: 74–85. [CrossRef]
- Mustak, Mekhail, Joni Salminen, Loïc Plé, and Jochen Wirtz. 2021. Artificial Intelligence in Marketing: Topic Modeling, Scientometric Analysis, and Research Agenda. *Journal of Business Research* 124: 389–404. [CrossRef]
- Nguyen, Tuyet-Mai, and Ashish Malik. 2021. Impact of Knowledge Sharing on Employees' Service Quality: The Moderating Role of Artificial Intelligence. *International Marketing Review* 39: 482–508. [CrossRef]
- Parsons, Amy L., and Elzbieta Lepkowska-White. 2018. Social Media Marketing Management: A Conceptual Framework. *Journal of Internet Commerce* 17: 81–95. [CrossRef]
- Patel, Nikhil, and Sandeep Trivedi. 2020. Leveraging Predictive Modeling, Machine Learning Personalization, NLP Customer Support, and AI Chatbots to Increase Customer Loyalty. *Empirical Quests for Management Essences* 3: 1–24.
- Pfiffelmann, Jean, Nathalie Dens, and Sébastien Soulez. 2020. Personalized Advertisements with Integration of Names and Photographs: An Eye-Tracking Experiment. *Journal of Business Research* 111: 196–207. [CrossRef]
- Sahni, Navdeep S. 2016. Advertising Spillovers: Evidence from Online Field Experiments and Implications for Returns on Advertising. *Journal of Marketing Research* 53: 459–78. [CrossRef]
- Sarstedt, Marko, Christian M. Ringle, and Joseph F. Hair. 2020a. *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 3rd ed. Thousand Oaks: SAGE Publications.
- Sarstedt, Marko, Christian M. Ringle, and Joseph F. Hair. 2020b. Partial Least Squares Structural Equation Modeling. In *Handbook of Market Research*. Edited by C. Homburg, M. Klarmann and A. Vomberg. Cham: Springer.
- Schivinski, Bruno, George Christodoulides, and Dariusz Dabrowski. 2016. Measuring Consumers' Engagement with Brand-Related Social-Media Content: Development and Validation of a Scale that Identifies Levels of Social-Media Engagement with Brands. *Journal of Advertising Research* 56: 64–80.
- Seo, Eun Ju, Jin-Woo Park, and Yu Jin Choi. 2020. The Effect of Social Media Usage Characteristics on E-WOM, Trust, and Brand Equity: Focusing on Users of Airline Social Media. *Sustainability* 12: 1691. [CrossRef]
- Simola, Jaana, Markus Kivikangas, Jarmo Kuisma, and Christina M. Krause. 2013. Attention and Memory for Newspaper Advertisements: Effects of Ad-Editorial Congruency and Location. *Applied Cognitive Psychology* 27: 429–42. [CrossRef]
- Singh, Ajay S., and Micah B. Masuku. 2014. Sampling Techniques & Determination of Sample Size in Applied Statistics Research: An Overview. *International Journal of Economics, Commerce and Management* 2: 1–22.
- Song, Mengmeng, Xinyu Xing, Yucong Duan, Jason Cohen, and Jian Mou. 2022. Will Artificial Intelligence Replace Human Customer Service? The Impact of Communication Quality and Privacy Risks on Adoption Intention. *Journal of Retailing and Consumer Services* 66: 102900. [CrossRef]
- Tacikowski, Pawel, and Anna Nowicka. 2010. Allocation of Attention to Self-Name and Self-Face: An ERP Study. *Biological Psychology* 84: 318–24. [CrossRef]
- Tafesse, Wondwesen, and Anders Wien. 2018. Using Message Strategy to Drive Consumer Behavioral Engagement on Social Media. *Journal of Consumer Marketing* 35: 241–53. [CrossRef]
- Upadhyaya, Makarand. 2024. The Role of Artificial Intelligence in Personalized Marketing. *Educational Administration: Theory and Practice* 30: 2388–97.
- Wamba-Taguimdje, Serge-Lopez, Samuel Fosso Wamba, Jean Robert Kala Kamdjoug, and Chris Emmanuel Tchatchouang Wanko. 2020. Influence of Artificial Intelligence (AI) on Firm Performance: The Business Value of AI-Based Transformation Projects. *Business Process Management Journal* 26: 1893–924. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.



Article

Artificial Intelligence (AI) in Brazilian Digital Journalism: Historical Context and Innovative Processes

Moisés Costa Pinto ^{1,2,*} and Suzana Oliveira Barbosa ¹

¹ Online Journalism Research Group (GJOL), Federal University of Bahia, Salvador 40020-160, Brazil; suzana.barbosa@ufba.br

² Communication and Design Department, Jorge Amado University, Salvador 41745-130, Brazil

* Correspondence: moisescosta@ufba.br

Abstract: This article investigates the historical uses and types of artificial intelligence (AI) systems and resources in Brazilian journalistic products. It is a work anchored in critically analyzing the literature on the subject, mapping and observing cases, seeking to identify uses and innovative processes, and analyzing AI projects for journalism. A search was carried out in web repositories, specifically Google, Google Scholar, and Scopus, using the terms: “inteligência artificial” + “jornalismo”, “bot + jornalismo”, “Geração de linguagem natural [NLG] + jornalismo”, “aprendizado de máquina [machine learning] + jornalismo”, and “algoritmos + jornalismo”. The corpus analysis (N = 45) includes the evaluation of the impacts of AI on the production and distribution of news in the context of Brazilian digital journalism. We try to answer questions about the uses of databases, approximation with platforms, uses of shared codes, connections with other AIs, and sources of funding, and whether they are backend or frontend initiatives. In a parallel investigation, we try to identify if Brazilian newsrooms are officially using ChatGPT, a generative AI. The findings point to advances in using low-cost and low-impact AI, with the predominance of bots. The great availability of this kind of AI in web repositories is believed to facilitate native digital media to incorporate innovative processes in using these technologies.

Keywords: artificial intelligence (AI); digital journalism; automated journalism; innovation; Brazil; digital media

1. Introduction

As digital technologies advance in the real world, algorithms also advance in society. The global village, alluded to by McLuhan (1963), or our information society (Castells and Espanha 1999; Burch 2005; Lemos 2015), would not be possible without the logical power of algorithms and computers. An algorithm is a conceptual sequence of steps that must be expressed in any computer language, human language, or logic (Gillespie 2014). They perform (Lemos 2021) processes of mediatization, datafication, and the consequent abundance of information (Boczkowski 2021) that leads us to the era of big data (Kitchin 2014; Siegel 2013), where bits about the most diverse aspects of everyday life are processed, stored, treated, analyzed, etc. For Lemos (2021), datafication makes it possible to convert any and all actions into traceable digital data, producing diagnoses and inferences in the most diverse domains. This datafication is only possible thanks to digital technologies, which have algorithms at their core. They are also at the heart of big tech (Birch and Bronson 2022), the so-called high-tech platforms, which foster the platformization of society (Poell et al. 2020) and, in this context of data capitalism (Fonseca 2020; Sodré 2021), they generate participatory simulacra, helping to shape behavior and attitudes (Sodré 2021), often through predictions mined from “machine learning—computers automatically developing new knowledge and capabilities by feeding furiously on modern society’s largest and most powerful unnatural resource: data” (Siegel 2013). Lemos (2021) calls

this system “algorithmic intelligence,” which should be thought of as a set of methods for collecting, processing, and treating data to make predictions. These systems use data that they help create, causing new data to be produced continuously, according to Siegel (2013), retroactively feeding big data. So, data performs. Its performativity (Blouin 2020; Lemos 2021) refers to the idea that it does not simply represent reality but plays an active role in shaping and producing certain outcomes or subjectivities. This suggests that collecting, analyzing, and using data can have performative effects, influencing the behavior and decisions of individuals and institutions.

What has brought us to this point, where we are experiencing the predominance of data in our society, is the “algorithmic turn” (Linden 2018; Napoli 2014) enhanced by the advances in digital technologies. We can say that only algorithms and artificial intelligence (AI) can deal with the performativity of the data (Lemos 2021) that we continually produce every day.

Therefore, this paper addresses the intersection between artificial intelligence (AI) and contemporary digital journalism (Salaverría 2019; Steensen et al. 2021; Alves 2006; Perreault and Ferrucci 2020; Ferrari 2007)—both journalism and artificial intelligence are actors that are transforming society. More specifically, we look at artificial intelligence initiatives in Brazilian digital journalism. We will conduct a historical survey to investigate the uses and types of artificial intelligence (AI) systems and resources in Brazilian journalistic products. Some examples include bots, chatbots, machine learning, natural language generation, visualization, image creation, text generation, and story automation. These resources are used by various media, such as G1 and Grupo Globo, UOL, Folha de S. Paulo, Estadão, Núcleo Jornalismo, Aos Fatos, Serenata de Amor, and Jota. We will also answer questions about innovation, use of databases, approach to platforms, use of shared codes, connections with others AI, source of funding, and whether they are backend or frontend initiatives. In a parallel investigation, we will analyze whether Brazilian newsrooms officially use ChatGPT, a generative AI.

2. Artificial Intelligence (AI)

But what about artificial intelligence? Is it a machine that thinks, as Turing (1950) proposed? To begin with, algorithms are at the core of AI, as they are the foundation that makes any AI system work, like any digital system, whether they have virtual or physical interfaces.

As the core of artificial intelligence, algorithms are widely used in news production and distribution by major media, and have had a significant impact on the field of news dissemination. In the field of news production, algorithms can help journalists find valuable clues and complete news reports, and provide matching news information to audiences in the field of news distribution.

(Zhang 2022)

Algorithms materialize the so-called smart media (Zhang 2022), while data are the key pieces that stand out in the high-tech journalism ecosystem (López-García and Vizoso 2021), whose scope is expanding more and more due to innovative digital resources, devices, and technologies. These range from drones, 360° video, immersive audio (binaural), virtual reality, augmented and extended reality, newsgames, holograms, 3D printers (Pavlik 2019; Silva 2022; Lima and Barbosa 2022), the use of machine learning, natural language processing (NLP), natural language generation (NLG)—which, for example, can automate the processes of producing, investigating, editing, publishing, distributing, and consuming journalistic content.

Artificial intelligence, in turn, is a technological tool that aims to mimic human actions and tasks (Cardozo et al. 2020) as they are, and, in journalism, contribute to (re)aggregating facts and data (structured or not) into information, and organizing and producing knowledge. In journalism, AI can be used for repetitive and “boring” tasks, such as systematizing financial reports and databases, as well as for searching for stories, writing, publishing,

disseminating, and interacting with audiences (Baldessar and Zandoménico 2022; Linden 2018; Diakopoulos 2019; Marconi 2020; Túnhez-López et al. 2021).

Considering the forecasts (Kunova and Granger 2022; Newman 2023), the trend for this and the next few years is exponential growth and consolidation of the use of resources, tools, and technologies based on artificial intelligence (AI) by newsrooms, whether legacy media or digital natives.

The title phrase of Bruno Latour (1994)'s book "We Have Never Been Modern" can help problematize the advances of AI in journalism. Latour, in an analysis of the Anthropocene, points out that even in a society that is widely connected and poses as a global village (McLuhan 1963), there is a huge gap in the spread of all the technological achievements and resources of so-called modernity. Many still live on the fringes of cutting-edge technological development (Latour 1994) without access to digital technologies. According to the French author, technology does not arrive equally or simultaneously in every corner of the planet. This is also true for journalism, which mirrors the problems and contexts of each location. The journalism practiced in Brazil will not necessarily be done with the same bases, processes, and resources as in the Global North (Chan 2021).

Since adapting to new technologies and digital resources requires constant financial investment, not all news organizations, even the largest ones, can balance technological, editorial, and professional innovation and their management processes. This explains the slower pace of adoption of technologies associated with artificial intelligence. Decapitalization, aggravated by cyclical economic crises, points to a probable dependence on funding allocated through projects and partnerships with large platform companies (especially Google and Meta) to continue innovating, as is already happening in several countries. While platform companies dominate the field of AI, providing services, tools, and infrastructures, news organizations lack almost all resources and depend on big tech to conduct research and development (Simon 2022). However, in the results session, we will see data about the partnerships between vehicles and platforms that use AI in their initiatives.

3. AI and Journalism in Brazil

Previous research (Canavilhas and Giacomelli 2023; Cabral 2022; Cabral and Siqueira 2022; Essenfelder and Sant'Anna 2022; Essenfelder et al. 2019; Araújo 2017; Pinto 2021; Ioscote 2021; Dalben 2020; Carreira 2017; Paganotti 2020; Oliveira and Costa 2020; Träsel 2014) has addressed and exemplified the use of artificial intelligence in Brazilian journalism, pointing out trends, ethical issues, and innovations. In this paper, we conduct a systematic review of the cases pointed out, with an expansion and survey of the history of the penetration of AI that has been and is being officially used by digital native media, legacy media sites, fact-checking agencies, and experimental academic initiatives in Brazil. We also analyzed the impacts, types of AI, their spread, and innovations in news production in Brazilian digital journalism.

Lopezosa et al. (2023) say that "innovation" is the incorporation of new technologies, methodologies, and strategies into journalism. This encompasses exploring unexplored journalistic formats, including immersive journalism, 360° video reporting, virtual reality, and AI-automated journalism. In addition, innovation involves the assimilation of new technologies, actors, and practices to address the obstacles encountered by the creative industry (Bossio and Nelson 2021) in the face of changes in society, technology, the economy, and politics. On the other hand, innovation in journalism can also be understood from Franciscato's (2014) definition as adopting technological initiatives and processes that alter the media's business positioning, ways of working, and journalists' profiles. It can also be understood as the adoption of news products (formats and narratives) and modes of consumption. Moreover, this process of incorporating innovation into journalism, especially digital journalism in recent years, is ongoing (Barbosa 2014).

The adoption of artificial intelligence (AI) by news organizations is uneven (Lima Santos et al. 2022; Simon 2022), as it is still expensive and requires high investments, limiting its use, especially by those based in the Global South. This is the case in Brazil,

where studies indicate that the use of AI by national news organizations is still sporadic (Carreira 2017; Araújo 2017; Essenfelder and Sant’Anna 2022), although there are significant cases as reported in previous research (Pase and Pellanda 2019; Essenfelder et al. 2019; Dalben 2020, 2022; Santos 2020; Pérez-Seijo et al. 2023) and verified by us in the empirical research for this article.

The reason why new systems and tools based on generative artificial intelligence (GAI) are not used in every media outlet, especially in Brazil, also lies in the transnational differences in the distribution of technology, which is based, among other things, on the distribution of capital. In this scenario, Brazilian digital journalism finds itself in a marginal location in terms of development and access to technological and financial resources. Furthermore, as we shall see, this implies how and what types of initiatives to use AI are implemented in Brazil.

4. Methodology

From a methodological point of view, to critically study the presence of artificial intelligence (AI) in Brazilian digital journalism, we broadly mapped the synergy of these technologies in national media outlets. By observing the cases, we aimed to identify innovative uses and processes and answer questions about the impacts and effects of these journalistic AI initiatives and approaches to platforms. The research was carried out in two complementary stages:

- (a) an initial search between 1 May and 30 May 2021;
- (b) a complementary search between 1 April and 20 April 2023.

The second search was necessary to complement the first once new examples, including before 2021, emerged after the first search. Both searches took place in Google Scholar, Scopus web repositories, and Google’s web search engine. First, we choose Google Scholar and Scopus for their enormous academic base, including theses and dissertations. In his turn, Google Web search was selected to fulfill the corpus with initiatives that have not yet been studied, and that are found only on websites and social media. In fact, the major initiatives that we analyzed had no place in academic studies yet, and this is one of the limitations of using academic repositories in this kind of research, whose purpose is to grab all possible uses in one particular period of time. Another limitation of the research is in the algorithms of these tools themselves, with biases in their codes written to meet companies’ objectives, in what their search methodology shows research results that best meet what these companies believe to be the most viable considering their interests—this algorithmic methodology is a black box that we cannot access, we only have clues. This brings us to another critical point in this type of research: the need to use more than one web repository to obtain the best possible results—which we did.

We used the following terms, illustrated in Table 1.

Table 1. Search terms on artificial intelligence in Brazilian digital journalism.

Search Terms
“inteligência artificial” + “jornalismo” + “Brasil”
“bot” + “jornalismo” + “Brasil”
“Geração de linguagem neural [NLG]” + “jornalismo” + “Brasil”
“aprendizado de máquina [machine learning]” + “jornalismo” + “Brasil”
“algoritmos” + “jornalismo” + “Brasil”
“jornalismo automatizado” + “Brasil”

Source: Author.

We collected information from websites, blogs, social media posts, academic articles, dissertations, and theses that pointed to examples of artificial intelligence in Brazilian digital journalism. After this first stage, in order to compose the corpus, all the initiatives

found were filtered to determine whether they were automation initiatives using artificial intelligence in at least one stage of the journalistic production process—from a perspective of collaboration between humans and non-humans (Latour 1994, 2012; Lemos 2013). This answer was made possible by reading all the publicity material, documentation, and/or repositories—if available. Once confirmed that these were automation initiatives, further reading of these materials was undertaken for subsequent categorization with the help of an online Google Forms form, one of the most used online survey tools and useful in various academic activities (Mota 2019; Raju and Harinarayana 2016). We used the research tool for its practicality in creating databases—in an online spreadsheet—based on categorization by filling out an electronic form and offering quick visualization of the data collected in graphs. This helped speed up the categorization and a fast visual analysis, which included graphs assessing the type of AI, their technology, interactions, and relationships with platforms and understanding how these technologies position themselves as innovative.

However, the 2023 research update was also concerned with advancing generative artificial intelligence (GAI), especially ChatGPT. GAI are AI systems that can generate new data or content, such as images or text, based on patterns and examples from existing data sets (Corcoran et al. 2020) by connecting and interconnecting nodes and content nodes.

Pavlik (2023) believes that GAI could usher in an era of potential transformation of journalism and media content. This type of AI could help the journalism industry to identify more carefully the potential uses of this technology, which is currently underutilized compared to other industries (Santos 2020). Therefore, we conducted a specific search on Google and Google Scholar using the terms “chatgpt + jornalismo + Brasil” to identify the official use of ChatGPT in Brazilian newsrooms. This complementary research aligns with objectives at the point that we need to obtain a better approach to the uses of AI in Brazilian newsrooms as we understand that possible official uses of the tool by news companies can be addressed as initiatives in the research mains corpus. ChatGPT was chosen because it was the first text-based GAI in the chatbot format to hit the market, and it had relatively easy access with free and pro accounts—that have a relatively low cost (USD 20 per month), with facilitated access for Brazilian journalists. Other tools of the same type, such as Google’s Bard, were not yet available in Brazil at the time of the research. In addition, Gondwe (2023) interviewed Sub-Saharan African journalists about their uses of ChatGPT and discovered that it has both positive and negative effects on journalism in developing countries. If there is a need to promote the responsible and ethical use of AI tools in journalism, it is also necessary to keep in mind that the chatbot consistently produces expected and stereotypical outputs, as:

“[...] biases becomes apparent when the chatbot provides different responses to similar questions based on one’s affiliations. Notably, ChatGPT tends to portray African countries and their leaders in a negative spotlight, with questions about them often concluding with anecdotes that connote poverty, disease, or corruption. (Gondwe 2023)

Studying how this is reproduced in the Brazilian context, similar to the African context, in the face of Global North power, but with its idiosyncrasies, is interesting for the overall context of our research. Nonetheless, the results of this research will be analyzed at the end of this article.

Finally, we used the nomenclature “initiatives” to refer to any and all appearances or uses of AI on the Brazilian journalistic websites that make up the sample. The term can better cover experimentation (López-García and Vizoso 2021) and how they can produce news with the help of “new” technologies, which until then had either been little used or not yet used in this task. Nevertheless, some initiatives are applied definitively, such as encompassing editorials. In contrast, others are undertaken on an ad hoc basis, such as producing a report that could only be carried out using AI to obtain and manage large volumes of data. In a scenario where there is still a literacy gap in the potential of AI in newsrooms, each initiative, whether it be the production of a report, the implementation of

a bot, or extensive use by an editor of a major media outlet, has similar impacts in terms of spreading the possibilities of their use in journalism.

5. Results

At the end of the searches, which began in 2021 and ended in 2023, we found 45 initiatives (N = 45), illustrated in Table 2, which applied or used artificial intelligence (AI) at some stage of the journalistic production process, from reporting, news, visualization, hyperinfographics (Cordeiro 2020; Silva 2022; scattering Harcup and O’neill 2017), curation, moderation, and interaction with the audience.

Table 2. Initiatives to use artificial intelligence in Brazilian digital journalism.

Initiatives	Websites	Year	Types of AI
Attack Detector ¹	<i>Abraji</i>	2022	Scraping, statistical, analytical intelligence (metrics)
Robotox ²	<i>Agência Pública, Repórter Brasil</i>	2019	Bot
Malu Bot ³	<i>Agência Tatu</i>	2018	NLG/text production, scraping, data structuring, bot
Dandara ⁴	<i>Agência Tatu</i>	2022	NLG/text production, bot
Fátima ⁵	<i>Aos Fatos</i>	2018	NLG/text production, bot, chatbot/audience interaction, word processing, content curation
Radar ⁶	<i>Aos Fatos</i>	2019	Scraping, data structuring, dashboard, visualization, statistics, content curation
Elas no Congresso ⁷	<i>AzMina</i>	2020	Scraping, data structuring, dashboard, bot
Monitor de Discurso Político Misógino ⁸	<i>AzMina</i>	2021	Scraping, data structuring, visualization, statistical
Robô Jornalista da Amazônia Azul ⁹	<i>Bots do Bem</i>	2021	NLG/text production, scraping, bot, word processing, content curation
Da Mata Repórter ¹⁰	<i>Bots do Bem</i>	2021	NLG/text production, scraping, bot, word processing, content curation
RadinhoReporter ¹¹	<i>Bots do Bem</i>	2021	NLG/text production, scraping, bot, visualization, content curation
TelinhaReporter ¹²	<i>Bots do Bem</i>	2021	NLG/text production, scraping, bot, word processing, content curation
Busca Fatos ¹³	<i>Busca Fatos</i>	2022	Bot, chatbot/audience interaction, content curation
Monitor—Newsletter Meio ¹⁴	<i>Canal Meio</i>	2016	Scraping, content curation
Colaboranet ¹⁵	<i>Colaborados</i>	2019	Scraping, bot, word processing, content curation
Corona Repórter #COVID19 ¹⁶	<i>Corona Repórter</i>	2020	NLG/text production, scraping, bot, text processing, content curation
Rosa ¹⁷	<i>Correio 24 Horas</i>	2020	Chatbot/audience interaction, content moderation/comments
Broadcast ¹⁸	<i>Estadão</i>	2010	Scraping, data structuring, dashboard, visualization, text processing, statistics, content curation, analytical intelligence (metrics)
Basômetro ¹⁹	<i>Estadão</i>	2012	Scraping, data structuring, dashboard, visualization, statistical
Análise de expressões faciais de candidatos em debate ²⁰	<i>Estadão</i>	2018	Image processing, analytical intelligence (metrics)
Estadão Infográficos ²¹	<i>Estadão</i>	2019	Visualization, statistics
Maria Capitu ²²	<i>Estadão</i>	2019	NLG/text production, scraping, bot, visualization, image production, word processing, content curation
Estadão Dados ²³	<i>Estadão</i>	2021	Scraping, data structuring, visualization, statistician
Fake Check ²⁴	<i>Fake Check</i>	2020	Bot, chatbot/audience interaction, word processing
Folha Estatística ²⁵	<i>Folha de S. Paulo</i>	2018	NLG/text production, scraping, data structuring, visualization
GPS Eleitoral ²⁶	<i>Folha de S. Paulo</i>	2018	Scraping, data structuring, text processing, statistical, analytical intelligence (metrics), video processing
Acervo Folha ²⁷	<i>Folha de S. Paulo</i>	2021	Image processing

Table 2. Cont.

Initiatives	Websites	Year	Types of AI
Eleições G1 ²⁸	G1	2020	NLG/text production, scraping, data structuring
Grupo Globo/Pixelot ^{29 30}	Grupo Globo	2019	Dashboard, video production, statistics, content curation
Ruibot ³¹	Jota	2018	Scraping, data structuring, bot
Beta ³²	NOSSAS.ORG	2017	Scraping, data structuring, bot, chatbot/audience interaction
Projeto Horus ³³	Núcleo Jornalismo	2020	Scraping, data structuring, dashboard, visualization
Weber ³⁴	Núcleo Jornalismo	2021	Bot
Monitor Nuclear/Political Pulse BR ³⁵	Núcleo Jornalismo	2021	Scraping, data structuring, dashboard, visualization
BedelBot ³⁶	Núcleo Jornalismo	2022	Scraping, data structuring, dashboard, visualization, statistician
BotPonto ³⁷	Núcleo Jornalismo	2022	Scraping, bot, video processing
Legisla Redes ³⁸	Núcleo Jornalismo	2023	Scraping, data structuring, bot, image production
Amplifica ³⁹	Núcleo Jornalismo, AzMina	2022	Scraping, data structuring, dashboard, statistics
Tramitabot ⁴⁰	Radar Legislativo	2020	Scraping, bot, chatbot/audience interaction
Ruralômetro ⁴¹	Repórter Brasil	2022	Scraping, data structuring, dashboard, visualization, statistics
Mapa dos agrotóxicos na água ⁴²	Repórter Brasil, Agência Pública	2019	Scraping, data structuring, visualization
Rosie ⁴³	Serenata de Amor	2016	Scraping, data structuring, bot
Querido Diário ⁴⁴	Serenata de Amor	2020	Scraping, data structuring, dashboard, bot, visualization
Jarbas ⁴⁵	Serenata de Amor	2020	Scraping, data structuring, dashboard, visualization
Uol Eleições ⁴⁶	Uol	2020	NLG/text production, scraping, word processing, statistical

Source: author.

Among the initiatives listed are 23 Brazilian media outlets and/or institutions (Figure 1). The startup Núcleo Jornalismo leads the number of initiatives, producing 15.55% (seven) of the sample. Estado de S. Paulo (Estadão) follows with 13.3% (six). The third-largest producer was the Bots do Bem project, which involves a partnership between the Federal University of Minas Gerais (UFMG) and the University of São Paulo (USP) and is, therefore, an experimental/academic initiative.

The initiatives were also categorized by the nature of their promoting medium/institution. Thus, it can be seen that the majority of them were conceived by digital native media, a total of 40% (18). Legacy media, on the other hand, account for 28% (13). We can also note the appearance of initiatives promoted by academic experiences, 13% (six). Fact-checking agencies accounted for 11.1% (five) of the sample. News agencies and non-governmental organizations (NGOs) accounted for 4.4% (two) each.

Regarding the timeline of these initiatives (Figure 2), which is important for understanding the evolution of adoption, the vast majority were launched from 2018 onwards, representing 13.3% of the total (six), with their peak occurring in 2020, at 22.22% (10). There was a break in the growth curve of initiatives of this type, most likely due to the COVID-19 pandemic, which began in 2020; there was a decrease in the growth curve in 2021 and 2022.

Of the 45 initiatives collected, 80% are still active. Only 20% (9) have been discontinued or are not updated. The majority of the sample was used to supply information, graphics, or automated summaries to the media outlets' websites, 66% (30). Specifically, 42% (19) are interactive web applications (chatbots, hyperinfographics (Cordeiro 2020), for example). X, in turn, was the third most used interface, comprising 37% of AI, especially bots. They also appear in newsletters (11%), Telegram (8%), WhatsApp (6%), Messenger (4%), apps (4%) and TV, print, Facebook, and Instagram (2% each).

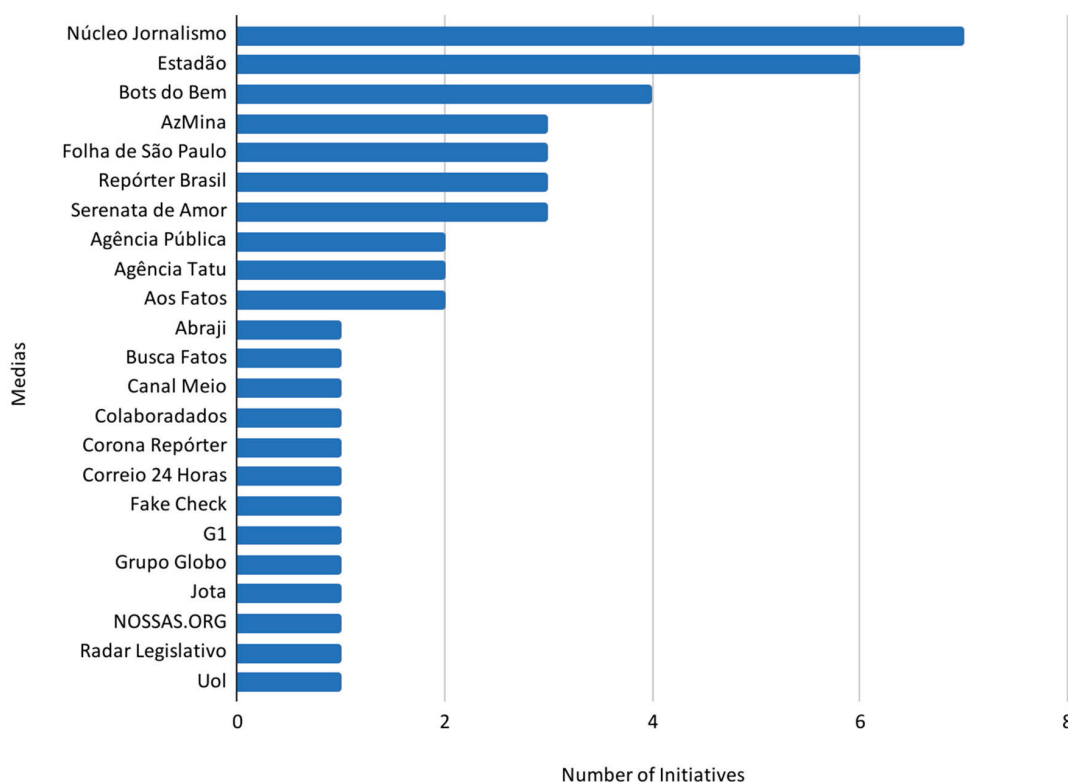


Figure 1. Number of initiatives by medium. Source: Authors.

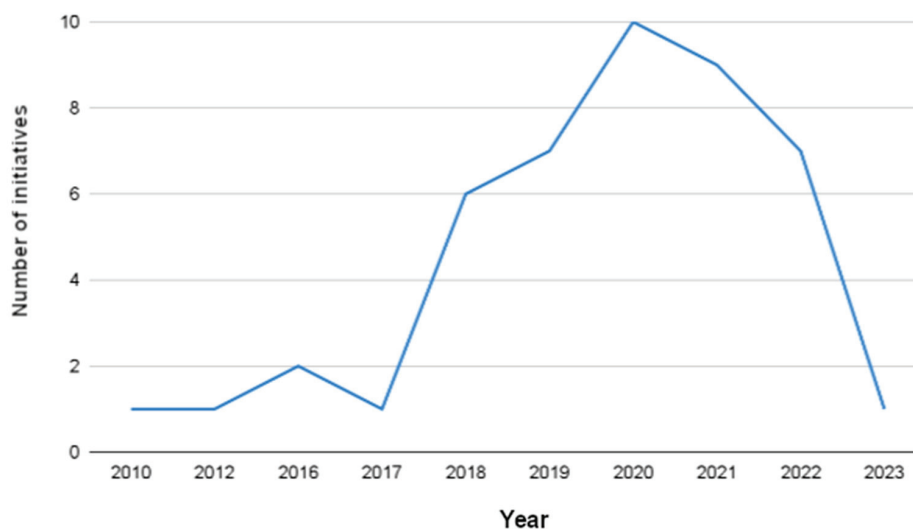


Figure 2. AI initiatives by year of launch. Source: Authors.

Regarding the technologies behind artificial intelligence, 75% (34) are based on algorithms scraped from databases (public and private), social networks, or the web. Bots and AI with data structuring account for 48% (22) each. Next is visualization AI with 35% (16) representation. AI aimed at statistical summarization and content curation is present in 28% (13) each; natural language generation (NLG) and dashboard creation are present in 26% (12) each. We also have word-processing tools, 24% (11), chatbots, 13% (six), and image production, 4% (two). Finally, video production, content moderation, and video processing complete the list with 2% (one) each.

Regarding the main objectives (Figure 3) for using AI in these initiatives, we have, in this order: data visualization, 35% (16), automated generation of statistics, 31% (14), and the creation of generative textual news (with NLG), 28% (13). This was followed

by infographics, 26% (12), push/notifications, 22% (10), political monitoring, 20% (9), and journalistic agenda generation and content curation, with 17% (8), each. Automated verification of fake news and disinformation, 13%, metrics and data insights, 8%, and audience interaction. Spreading, personalization, and environmental monitoring were 4% each. Judicial monitoring, video automation, financial market coverage, image processing, transmedia production, and video processing also appear in the sample, with 2% each.

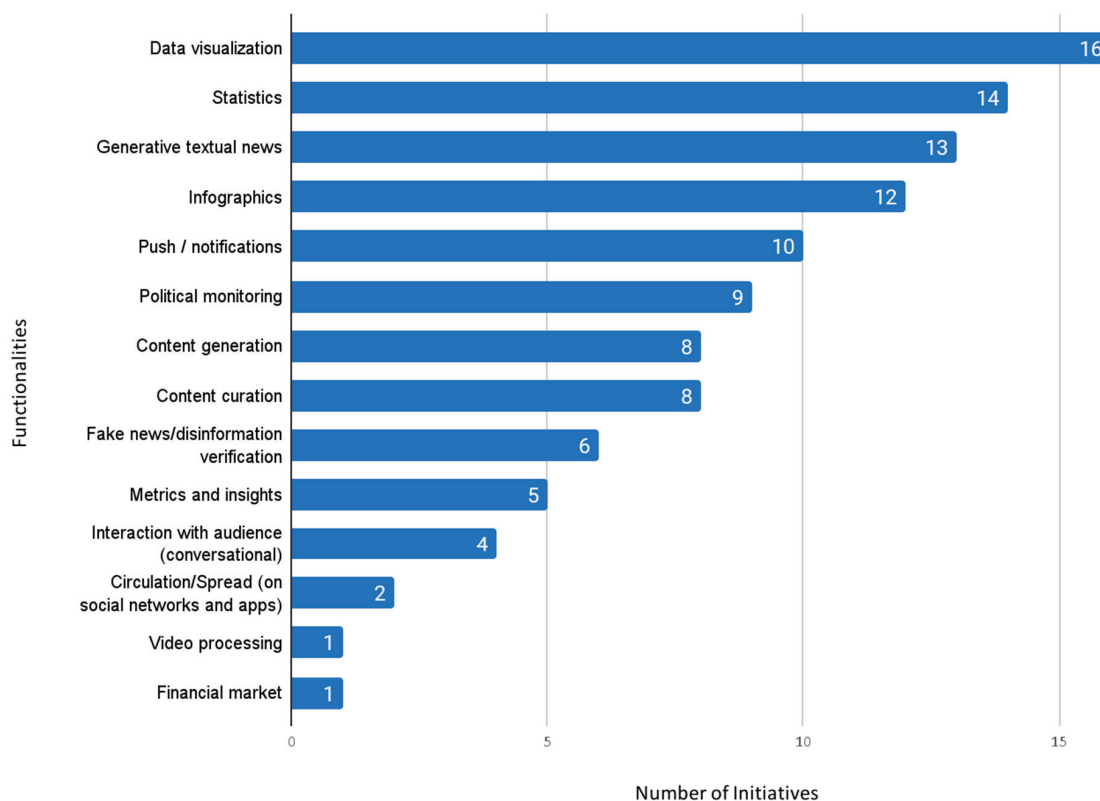


Figure 3. Objectives of the AI found. Source: author.

An interesting point is that the vast majority, 53% (24), of Brazilian initiatives cite open APIs, scripts, and codes, with licenses for unrestricted use without charge and available on the internet, often made available by previous initiatives. For example, some initiatives from Núcleo Jornalismo have codes created and made available by AzMinas. On the other hand, 17% (eight) do not use open-source codes, preferring their own or proprietary programming, and another 28% (13) do not inform or do not make it clear whether they use free codes. On the other hand, 60% (27) make their codes, APIs, and scripts available in web repositories, such as GitHub,⁴⁷ for other journalists to use in their automated journalistic projects. However, 22% (10) do not make their code available to third parties, while 17% (eight) do not report whether they make their programming available. However, it is important to note that so much availability can contribute to the spread of a broader culture of use and penetration of AI in Brazilian newsrooms, since it becomes much cheaper to produce initiatives from shared codes at no cost. This can create a culture and community of algorithmic literacy (Deuze and Beckett 2022) to spread automation technology in journalism.

When we analyze the connections between this artificial intelligence and other AI—whether used in journalism or not—it is possible to observe an integration gap: only 13% (six) of the corpus interact with other AI, such as Rosie and Jarbas, from the Serenata de Amor Project, who “talk to each other” in a process that complements their automated work. Even so, this integration is not clear in 17% (eight) of the initiatives, while the vast majority, 68% (31), have no connection reported or that could be observed in their documentation.

It is also interesting to note that the majority, 82% (37), of the AI that make up the corpus, do not use public data, such as government databases.

Most journalistic artificial intelligence (AI) still depends on some kind of supervision or editing by the human journalist in their content. Only 35% (16) publish or post automated content without the mediation of a human journalist/editor, whether on websites, messengers, newsletters, or social networks. In this respect, 33% have integrations with websites and/or web applications to enable automated publications or updates without direct human interference. AI that publishes directly to messengers without intervention represents 8% (four), and those that mediate newsletter content represents 4% (two).

As for integration with platforms, which are important for mediating journalism in contemporary times (Poell et al. 2020; Pereira 2022), we can see that X is the most used, with 58% (24) of the initiatives. Next comes Facebook, with 19% (eight), followed by Telegram, WhatsApp, Google, YouTube, and Instagram, with 7% each, and Microsoft and Spotify, with one integration each (2%). On the other hand, 14% (six) do not use any platform integration, which is unclear for another 19% (four). From this point, it is interesting to note that the vast majority, 68%, have no formal support from any platform. Even so, 13 initiatives have technological and financial support from platforms: Google, 15% (seven), Facebook, 6% (three), and Microsoft, WhatsApp, and YouTube with 2% (one) each.

In order to leverage the initiatives, the promoting media and institutions relied on a wide range of resources for financial sustainability (Figure 4). Most rely on funds from subscriptions, 53% (24), followed by crowdfunding, 40% (18), and advertisements, 31% (14). They also rely on funding from NGOs, 28%, platforms, 20% (9), governments, 13% (six), in the case of initiatives based on experiments at public universities, and direct investment, 2% (one). It is important to note that the vast majority rely on more than one funding source to support their viability (Maurício et al. 2017; Faria 2016)—a characteristic of the Brazilian journalism market. Notably, platforms such as Google, Meta, and Microsoft fund digital native initiatives. The funding projects of these big techs, roughly speaking, aim to encourage media and initiatives that bring innovation to the journalism market (Feil 2020; Jurno and d’Andréa 2020). It is a strategy aimed at developing cutting-edge innovations that can bring “news” to the field, but it is also a kind of “window shopping.” In other words, it encourages projects that marketing can use to show how they—the platforms—can be “friendly” to journalism. The search for marketing stars is also part of the interest in implementing innovations, according to Dotzel and Faggian (2019).

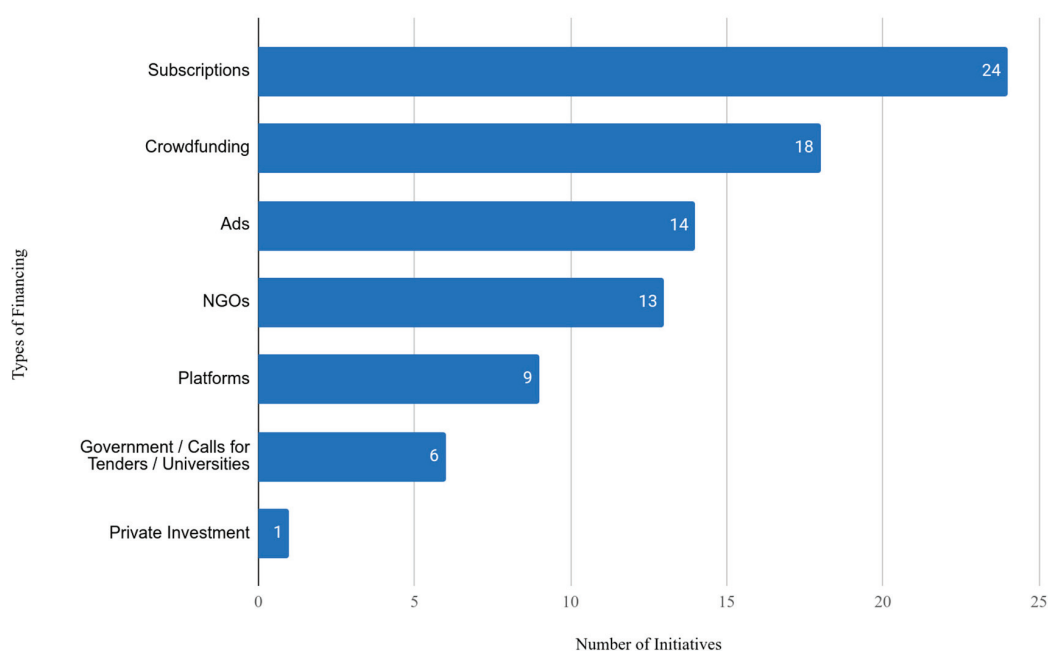


Figure 4. Website financing models. Source: Author.

However, only 35% (16) present or cite innovations in their documentation, presentation (of launches or reports published about them), or repository.

A final question analyzed dealt with how AI interacts with journalists and the public audiences. We therefore methodologically divided the categorization into two sections:

- (a) Frontend AI: In information science, a frontend program is one designed to be “seen” or interact with the end user (Abdullah and Zeki 2014; Pérez Ibarra et al. 2021); for us, bringing this concept to journalism and technology bases, a frontend AI applied to journalism is one that has direct contact, through the information it mediates or can interact with the audience, with or without human intervention, for example, the Rosie bot, which scrapes and structures data and publishes directly on X, where it can receive likes, replies, and comments from users.
- (b) Backend AI: In information science, backend programming is programming that runs behind the visible interface, with access to data (Pérez Ibarra et al. 2021) and which is not seen or perceived by end users. To work with the backend, you need to know about databases, structures, and security aspects (*ibidem*) and how the logic of the technology used works. Translated into our research, a backend AI applied to journalism would not be available to the eyes of the audience but would be available for collaborations with other human actors (Latour 1994, 2012; Lemos 2013), journalists who would produce news in partnership with these AI—knowing, at the very least, the logic of the data and algorithms that make them work—for example, the generative artificial intelligence (GAI) that collaborated with the production of electoral news, based on data from the Superior Tribunal Eleitoral (Superior Electoral Court), for the G1 and UOL portals, on all of Brazil’s more than five thousand municipalities. Thus, looking at the sample found, we can say that 77% (35) are AI with frontend interfaces, while 23% (10) focus only on the backend of journalistic production. Although they have limitations in operationalizing more acute interactions, many AI, such as bots and chatbots, open up new perspectives. They enable the audience to interact recursively, not only with the information but also with these non-human journalistic interfaces that produce news in collaboration or not with journalists.

6. Conclusions

One of the aims of this work is to help establish a historical framework for the application of AI in Brazilian digital journalism, especially given the progress made by generative artificial intelligence (GAI) at the end of 2022, such as with Midjourney and ChatGPT. Thus, this research can facilitate future comparative analyses regarding the use of AI in Brazilian digital journalism. However, one of the limits lies in the fact that the corpus was made up of AI communicated or reported by the Brazilian media—even those found in previous academic reports and studies. Thus, future research needs to extend into newsrooms to gauge the real extent and impact of the appropriation of AI by media and professionals, especially in the context of the spread of generative AI platforms.

When updating the survey in 2023, we expected significant advances in generative AI in newsrooms, such as ChatGPT. However, this was not the case. In a specific search, we noticed that journalistic organizations are still not using the OpenAI tool in an official and widespread way: we did not find any Brazilian organization that had adopted the tool and made this clear as of the closing date of this article. It is very likely that GAI applications scare professionals in the field, especially journalists, as they can be seen as “threats” to their already scarce jobs in newsrooms (Baldessar and Zandomênico 2022; Diakopoulos 2019; Marconi 2020). However, a shift induced by Generative AI (GAI) is on the way, as observed Pavlik (2023). The fast spread of GAI around our society, even with visible gaps between the global south and global north, can inevitably change how news media companies and journalists see and use it. Pavlik (2023) believes that AI tools such as ChatGPT could be used as an asset to assist a human journalist or media professional and, thereby, could be relevant to improving both the quality and efficiency of journalistic and media work.

It seems like generative AI is already a familiar technology to journalists or, at least, it is a technology that comes into the news world with a friendly interface to work with. The familiar web interface (a chatbot) and easy and cheap API integration to new tools can make technology literacy effortless for journalistic work, especially in underdeveloped countries. However, it is still necessary to amplify this research with surveys and interviews with Brazilian journalists who are using ChatGPT—even if their company does not allow it officially—to discover how it changes the way of daily work and the Brazilian journalist's perspectives with news produced.

If the media are not yet using ChatGPT and GAI platforms, the data we found, however, points to numerous initiatives aimed at solving small journalistic bottlenecks, such as, above all, accessing, managing, analyzing, and reporting from large databases. It means that there are various opportunities to use AI in journalism, especially in data journalism.

The results show a profusion of AI spread across various journalistic sites and with diverse purposes (from generating stories to producing texts and graphics). However, the same data shows that this AI is being used as a tool to overcome analytical obstacles that human reporters would not be able to overcome or would take too long to handle and produce information. This is in line with Deuze and Beckett (2022) and Marconi (2020), who believe that AI applied to journalism, now and in the coming years, will play a much greater role in assisting with routine tasks that were previously very tiring, rather than replacing journalists entirely.

Another observable point in the corpus analyzed is that many AI are present in the Brazilian scenario as interactive tools on the journalistic frontend, such as bots, chatbots, and web applications. In the case of web applications, some are also in the context of hyperinfographics (Cordeiro 2020), where the user interacts with the information. Backend AI, such as those used by G1 and UOL to write election results, are not presented or have interfaces where users do not easily recognize their collaboration. This acknowledgment is only made later, in texts publicizing journalistic innovations by each outlet—of course, to publicize their achievements. Interestingly, the main backend AI analyzed is notably positioned in the big legacy media brands (G1, UOL, Estadão, Folha de S. Paulo, for example). Frontend AI, even with many limitations, is mostly implemented by digital natives (Serenata de Amor, Aos Fatos, AzMina, Jota, Núcleo Jornalismo, Agência Tatu, etc.). In fact, it shows the use of frontend AI for digital natives is more interactive, from the audience's perspective, and it can strengthen the relationship between automated news and the public. Ultimately, this could turn out to be an important tool for valorizing automated news by the public, which could facilitate the spread of this type of technology throughout newsrooms.

It is also fascinating to note that most frontend AI is based on open codes and shared by various projects, reinforcing the construction of a collaborative community for disseminating and consequent literacy of this AI by the Brazilian journalistic market in the context of digital natives. This community is responsible for the main front in the insertion of artificial intelligence into journalism in Brazil. As noted Lewis and Usher (2013), such a community can create an open-source journalism practice as they share technology with the purpose of providing a new framework that makes journalism more relevant in a participatory digital culture. It can also improve the transparency of the news production process.

Digital platforms such as Meta, Microsoft, X, and Google also play a key role in developing and disseminating AI in Brazilian digital journalism. They fund initiatives, mainly by digital natives, through their development programs—Google News Initiative, Meta Journalism Project, and Microsoft News Center—which look for potentially “innovative” initiatives to accelerate/develop. In a scenario of scarce resources, this platform funding becomes relevant for the media, especially digital natives, to launch initiatives that attract public attention and make their existence viable. On the other hand, news companies—especially digital natives—and journalists in Global South countries, such as Brazil, with a lack of resources, may see an even greater gap in relation to resources and professionals in the Global North, further increasing the dependence on big tech for access

to AI. This could create another technological gap between journalism practiced in the Global North and the Global South.

Additionally, in this scenario, the use of AI to initiate innovations seems to be a peaceful point: the limitations of contemporary digital journalism and the limited resources in Brazil mean that AI is a feasible alternative for producing information through data and even for producing large amounts of data (Attack Detector, for example) in order to summarize it into new information finally. The Brazilian example shows how news companies struggle to surpass boundaries of financial limitations to create their own solutions and, thus, be able to stay up to date regarding what technological innovation can contribute to improving processes and products using AI.

Moreover, noteworthy is how little publicity has been given to many AI projects. A few cases have gained a lot of repercussions, such as G1, which has been featured in the press and also in academic research, while the vast majority have hardly been reported within their media, such as UOL, which, like G1, used a generative AI to produce news based on electoral data for each Brazilian municipality in the 2022 general elections. Media outlets seem reluctant to use this technology and disclose that they are using it. It appears that they are afraid of how the public can react to news produced by AI, such as noted previously Noain-Sánchez (2022), as it is a technology that is not well known. However, the exact reasons in the Brazilian context still need to be explored in future research, ideally through applications of surveys, newsmaking observations, and interviews with the professionals involved in these initiatives to better capture what they think about it and the real impact of news AI initiatives in the market.

Author Contributions: Conceptualization, M.C.P. and S.O.B.; methodology, M.C.P. and S.O.B.; software, M.C.P.; validation, M.C.P. and S.O.B.; formal analysis, M.C.P. and S.O.B.; investigation, M.C.P., S.O.B.; resources, S.O.B.; data curation, M.C.P.; writing—original draft preparation, M.C.P. and S.O.B.; writing—review and editing, M.C.P. and S.O.B.; visualization, M.C.P.; supervision, S.O.B.; project administration, S.O.B.; funding acquisition, S.O.B. All authors have read and agreed to the published version of the manuscript.

Funding: This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior—Brasil (CAPES)—Finance Code 001.

Data Availability Statement: The data used for this work can be made available to the public subject to data terms and conditions.

Conflicts of Interest: The authors declare no conflicts of interest.

Notes

- ¹ <https://github.com/JournalismAI/attackdetector> (accessed on 20 April 2023).
- ² <https://twitter.com/orobotox> (accessed on 20 April 2023).
- ³ <https://github.com/agenciatatu/malu> (accessed on 20 April 2023).
- ⁴ <https://www.agenciatatu.com.br/dandara/> (accessed on 20 April 2023).
- ⁵ <https://www.aosfatos.org/fatima/> (accessed on 20 April 2023).
- ⁶ <https://www.aosfatos.org/metodologia-radar-aos-fatos/> (accessed on 20 April 2023).
- ⁷ <https://twitter.com/elasnocongresso> (accessed on 20 April 2023).
- ⁸ <https://github.com/fer-aguirre/pmdm> (accessed on 20 April 2023).
- ⁹ https://twitter.com/BLAB_Reporters (accessed on 20 April 2023).
- ¹⁰ <https://twitter.com/DaMataReporter> (accessed on 20 April 2023).
- ¹¹ <https://twitter.com/RadinhoReporter> (accessed on 20 April 2023).
- ¹² <https://twitter.com/TelinhaReporter> (accessed on 20 April 2023).
- ¹³ <https://buscafatos.com.br/> (accessed on 20 April 2023).
- ¹⁴ <https://monitor.canalmeio.com.br/login/?next=/novidades> (accessed on 20 April 2023).
- ¹⁵ https://twitter.com/colabora_bot (accessed on 20 April 2023).
- ¹⁶ <https://twitter.com/CoronaReporter> (accessed on 20 April 2023).

- 17 <https://www.correio24horas.com.br/noticia/nid/correio-lanca-robo-que-permite-ao-leitor-sugerir-pautas/> (accessed on 20 April 2023).
- 18 <https://www.estadao.com.br/economia/broadcast-lanca-novo-aplicativo-que-se-adapta-a-cada-usuario/> (accessed on 20 April 2023).
- 19 <https://arte.estadao.com.br/politica/basometro/> (accessed on 20 April 2023).
- 20 <https://www.estadao.com.br/infograficos/politica,o-que-revela-uma-analise-das-emocoes-dos-candidatos-durante-o-debate,923037> (accessed on 20 April 2023).
- 21 <https://www.estadao.com.br/infograficos> (accessed on 20 April 2023).
- 22 <https://twitter.com/mariacapitu> (accessed on 20 April 2023).
- 23 <https://www.estadao.com.br/infograficos/saude,tratamento-precoce-perde-nas-redes-para-cpi-da-covid-e-vacina,1181660> (accessed on 20 April 2023).
- 24 <http://nilc-fakenews.herokuapp.com/> (accessed on 20 April 2023).
- 25 <https://www1.folha.uol.com.br/educacao/2018/04/estudo-inedito-indica-alta-chance-de-fraude-em-mil-provas-do-enem.shtml> (accessed on 20 April 2023).
- 26 <https://www1.folha.uol.com.br/poder/2018/10/veja-o-que-os-candidatos-mais-falaram-na-campanha-presidencial-e-em-sp.shtml> (accessed on 20 April 2023).
- 27 <https://www1.folha.uol.com.br/folha-100-anos/2021/11/video-mostra-trabalho-de-indexacao-de-25-milhoes-de-fotos-da-folha.shtml> (accessed on 20 April 2023).
- 28 <https://g1.globo.com/politica/eleicoes/2020/noticia/2020/11/12/em-iniciativa-inedita-g1-publica-textos-com-resultado-da-eleicao-em-cada-uma-das-5568-cidades-do-brasil-com-auxilio-de-inteligencia-artificial.ghml> (accessed on 20 April 2023).
- 29 https://oglobo.globo.com/economia/grupo-globo-aposta-na-inteligencia-artificial-em-transmissao-esportiva-1-24116586?utm_source=pocket_reader (accessed on 20 April 2023).
- 30 Partially acquired by Grupo Globo in a R\$13 million investment.
- 31 <https://twitter.com/ruibarbot> (accessed on 20 April 2023).
- 32 <https://www.beta.org.br/> (accessed on 20 April 2023).
- 33 <https://nucleo.jor.br/projeto-horus/> (accessed on 20 April 2023).
- 34 https://twitter.com/weber_bot (accessed on 20 April 2023).
- 35 <https://www.nucleo.jor.br/monitor/> (accessed on 20 April 2023).
- 36 <https://nucleo.jor.br/bedelbot/> (accessed on 20 April 2023).
- 37 <https://nucleo.jor.br/botponto/> (accessed on 20 April 2023).
- 38 <https://twitter.com/legislaredes> (accessed on 20 April 2023).
- 39 <https://www.nucleo.jor.br/amplifica-form/> (accessed on 20 April 2023).
- 40 <https://radarlegislativo.org/sobre/> (accessed on 20 April 2023).
- 41 <https://ruralometro2022.reporterbrasil.org.br/> (accessed on 20 April 2023).
- 42 <https://portrasdoalimento.info/agrotoxico-na-agua/#> (accessed on 20 April 2023).
- 43 <https://twitter.com/RosieDaSerenata> (accessed on 20 April 2023).
- 44 <https://queridodiario.ok.org.br/> (accessed on 20 April 2023).
- 45 <https://jarbas.serenata.ai/dashboard/> (accessed on 20 April 2023).
- 46 <https://economia.uol.com.br/noticias/redacao/2022/11/01/uol-publica-textos-de-resultados-das-eleicoes-para-mais-de-5500-cidades.htm> (accessed on 20 April 2023).
- 47 <https://github.com/> (accessed on 20 April 2023).

References

- Abdullah, Hanin M., and Ahmed M. Zeki. 2014. Frontend and backend web technologies in social networking sites: Facebook as an example. Paper presented at the 2014 3rd International Conference on Advanced Computer Science Applications and Technologies, Amman, Jordan, December 29–30; Piscataway: IEEE, pp. 85–89.
- Alves, Rosental C. 2006. Jornalismo digital: Dez anos de web... e a revolução continua. *Comunicação E Sociedade* 9: 93–102. [CrossRef]
- Araújo, Lucas Vieira. 2017. Adoção de algoritmos, NLG e inteligência artificial na imprensa brasileira em âmbito nacional e regional. *Estudos em Jornalismo e Mídia* 14: 2. [CrossRef]
- Baldessar, Maria José, and Regina Zandomênico. 2022. Os desafios da qualificação profissional do jornalista diante da inteligência artificial nas redações/The challenges of journalists' professional qualifications in the face of artificial intelligence in the newsrooms. *Brazilian Journal of Development* 8: 17959–64. [CrossRef]

- Barbosa, Suzana. 2014. Agentes de inovação, renovação e de reconfiguração para o jornalismo em tempos de convergência. *Revista de Cibercomunicación* 1: 1–8.
- Birch, Kean, and Kelly Bronson. 2022. Big tech. *Science as Culture* 31: 1–14. [CrossRef]
- Blouin, Gabriel G. 2020. Data Performativity and Health: The Politics of Health Data Practices in Europe. *Science, Technology, & Human Values* 45: 317–41. [CrossRef]
- Boczkowski, Pablo. J. 2021. *Abundance: On the Experience of Living in a World of Information Plenty*. Oxford: Oxford University Press. [CrossRef]
- Bossio, Diana, and Jacob L. Nelson. 2021. Reconsiderando a inovação: Situando e avaliando mudanças no jornalismo. *Journalism Studies* 22: 1377–81. [CrossRef]
- Burch, Sally. 2005. Sociedade da informação/sociedade do conhecimento. In *Desafios das Palavras*. Edited by Alain Ambrosi, Valérie Peugeot and Daniel Pimenta. São Paulo: Ed. VECAM 1.
- Cabral, Laura Rayssa de Andrade. 2022. Jornalismo Automatizado: Inteligência Artificial e Robôs Nas Redações das Organizações Jornalísticas. Master's thesis, Universidade Federal da Paraíba, Paraíba, Brazil. Available online: <https://repositorio.ufpb.br/jspui/handle/123456789/25273> (accessed on 12 December 2023).
- Cabral, Laura Rayssa de Andrade, and Fabiana C. Siqueira. 2022. Inteligência Artificial no jornalismo: Um estudo do robô Corona Repórter. *Revista Brasileira de Ensino de Jornalismo* 12: 3–17. [CrossRef]
- Canavilhas, João, and Fábio Giacomelli. 2023. Inteligencia artificial en el periodismo deportivo: Estudio en Brasil y Portugal. *Revista de Comunicación* 22: 53–69. [CrossRef]
- Cardozo, Missila, Poliana Ferrari, and Margareth Boarini. 2020. A inteligência artificial reconfigura a dinâmica comunicacional. *Paradoxos, Uberlândia* 5: 49–65. [CrossRef]
- Carreira, Krishma A. C. 2017. Notícias Automatizadas—A Evolução que Levou o Jornalismo a ser Feito por Não Humanos. Master's thesis, Universidade Metodista, São Paulo, Brazil. Available online: <https://feup.libguides.com/apa/tesesdissertacoes> (accessed on 1 November 2022).
- Castells, Manuel, and Rita Espanha. 1999. A Era da Informação: Economia, Sociedade e Cultura. In *Fundação Calouste Gulbenkian*. São Paulo: Paz e Terra, vol. 1.
- Chan, Anita S. 2021. Jornalismo de Dados, Universalismo Digital e Inovação na Periferia Mundial. King's Research Portal. In *Manual de Jornalismo de Dados: Rumo a Uma Prática Crítica de Dados*. São Paulo: Associação Brasileira de Jornalismo Investigativo (ABRAJI), p. 278.
- Corcoran, Peter, Hossein Javidnia, Joseph E. Lemley, and Viktor Varkarakis. 2020. Generative Augmented Dataset and Annotation Frameworks for Artificial Intelligence (GADAFI). Paper presented at the 2020 31st Irish Signals and Systems Conference (ISSC), Letterkenny, Ireland, June 11–12; Piscataway: IEEE, pp. 1–6. [CrossRef]
- Cordeiro, William. 2020. *Hiperinfografia: A Visualização da Informação Jornalística mais Sofisticada*. Florianópolis: Insular.
- Dalben, Silvia. 2020. Jornalismo Automatizado No Brasil: Análise de três robôs no Twitter. *Brazilian Journalism Research* 16: 3. [CrossRef]
- Dalben, Silvia. 2022. Uso de Inteligência Artificial nas Redações Jornalísticas na Guerra Contra a Corrupção na América Latina. In *Mobilidade e Inteligência Artificial. Os Novos Caminhos do Jornalismo*. Edited by João Canavilhas, Catarina Rodrigues and Ricardo Morais e Fábio Giacomelli. Covilhã: Livros LabCom, pp. 421–44.
- Deuze, Mark, and Charlie Beckett. 2022. Imagination, algorithms and news: Developing AI literacy for journalism. *Digital Journalism* 10: 1913–18. [CrossRef]
- Diakopoulos, Nicholas. 2019. *Automating the News: How Algorithms Are Rewriting the Media*. Cambridge: Harvard University Press.
- Dotzel, Kathryn R., and Alessandra Faggian. 2019. The impact of external knowledge sourcing on innovation outcomes in rural and urban businesses in the US. *Growth and Change* 50: 515–47. [CrossRef]
- Essenfelder, Renato, João Canavilhas, Haline C. Maia, and Ricard J. Pinto. 2019. Automatización de textos periodísticos en la televisión brasileña: Estudio de caso del sistema AIDA (Globo-Brasil). *Doxa Comunicación. Revista Interdisciplinar de Estudios de Comunicación y Ciencias Sociales* 2019: 255–74. [CrossRef]
- Essenfelder, Renato, and Emilio Sant'Anna. 2022. Inteligência Artificial Aplicada ao Jornalismo no Brasil: Experiências e Obstáculos à Adoção de Tecnologias Inteligentes. In *Mobilidade e Inteligência Artificial. Os Novos Caminhos do Jornalismo*. Edited by João Canavilhas, Catarina Rodrigues and Ricardo Morais e Fábio Giacomelli. Covilhã: Editora Livros LabCom, pp. 475–97.
- Faria, Daniel S. F. G. D. 2016. *O Crowdfunding como uma Alternativa à crise de Financiamento do Jornalismo*. Trabalho de Conclusão de Curso (Graduação em Comunicação-Habilitação em Jornalismo)—Escola de Comunicação. Rio de Janeiro: Universidade Federal do Rio de Janeiro.
- Feil, Bruna E. M. 2020. Jornalismo e Inovação: Uma Análise dos Projetos Financiados pelo Google News Initiative-Innovation Challenge em 2019. [Trabalho de Conclusão de Curso, UFMS]. Available online: <https://repositorio.ufsm.br/handle/1/24832> (accessed on 20 February 2023).
- Ferrari, Poliana. 2007. *Jornalismo Digital*. São Paulo: Contexto.
- Fonseca, Rosa A. 2020. *A Vida Mobile no Capitalismo de Dados: Narrativas de Negócios Digitais e a Constituição Do Consumidor Conectado*. São Paulo: Pimenta Cultural.
- Franciscato, Carlos E. 2014. Inovações tecnológicas e transformações no jornalismo com as redes digitais. *GEINTEC—Gestão, Inovação e Tecnologias* 4: 4.

- Gillespie, Tarleton. 2014. Algorithm [Draft] [#digitalkeyword]. Culture Digitally. Available online: <http://culturedigitally.org/2014/06/algorithm-draft-digitalkeyword/> (accessed on 13 October 2023).
- Gondwe, Gregory. 2023. CHATGPT and the Global South: How are journalists in sub-Saharan Africa engaging with generative AI? *Online Media and Global Communication* 2: 228–49. [CrossRef]
- Harcup, Tony, and Deirdre O'Neill. 2017. What is news? News values revisited (again). *Journalism Studies* 18: 1470–88. [CrossRef]
- Ioscote, Fabia C. 2021. Jornalismo e inteligência artificial: Tendências nas pesquisas brasileiras entre 2010 e 2020. *Novos Olhares* 10: 162–82. [CrossRef]
- Jurno, Amanda C., and de Carlos F. Brito d'Andréa. 2020. Between partnerships, infrastructures and products: Facebook journalism project and the platformization of journalism. *Brazilian Journalism Research* 16: 502–25. [CrossRef]
- Kitchin, Rob. 2014. The data revolution: Big data, open data, data infrastructures and their consequences. In *The Data Revolution*. London: SAGE Publications Ltd., pp. 1–240.
- Kunova, Marcela, and Jacob Granger. 2022. Predictions for Journalism in 2023: AI and Tech. Available online: <https://www.journalism.co.uk> (accessed on 13 October 2023).
- Latour, Bruno. 1994. *Jamais Fomos Modernos*. Rio de Janeiro: Editora 34.
- Latour, Bruno. 2012. *Reagregando o Social: Uma Introdução à Teoria do Ator-Rede*. Salvador: Edufba.
- Lemos, André. 2013. A Comunicação das Coisas: Teoria Ator-Rede e Cibercultura. São Paulo: Annablume, p. 310.
- Lemos, André. 2015. *Cibercultura: Tecnologia e Vida Social na Cultura Contemporânea*. Porto Alegre: Sulina.
- Lemos, André. 2021. Dataficação da vida. *Civitas-Revista de Ciências Sociais* 21: 193–202. [CrossRef]
- Lewis, Seth C., and Nikki Usher. 2013. Open source and journalism: Toward new frameworks for imagining news innovation. *Media, Culture & Society* 35: 602–19. [CrossRef]
- Lima, Luciellen, and Suzana Barbosa. 2022. Mobilidade, imersão e experiência: Entre ajustes e discordâncias conceituais no jornalismo imersivo. *Estudos em Comunicação* 34: 2–34. [CrossRef]
- Lima Santos, Mathias F., Wilson Ceron, João Canavilhas, Catarina Rodrigues, Ricardo Morais, and Fábio Giacomelli. 2022. Inteligência Artificial na mídia: Visões atuais e projeções futuras. *Mobilidade e Inteligência Artificial: Os Novos Caminhos do Jornalismo* 1: 445–74.
- Linden, Carl-Gustav. 2018. Algoritmos para Jornalismo: O futuro da produção de notícias. *LÍBERO* 41: 5–27. Available online: <https://seer.casperlibero.edu.br/index.php/libero/article/view/973> (accessed on 29 December 2023).
- Lopezosa, Carlos, Lluís Codina, Ariadna Fernández-Planells, and Pere Freixa. 2023. Journalistic innovation: How new formats of digital journalism are perceived in the academic literature. *Journalism* 24: 821–38. [CrossRef]
- López-García, Xosé, and Ángel Vizoso. 2021. Periodismo de alta tecnología: Signo de los tiempos digitales del tercer milenio. *Profesional de la Información* 30: 1–12. [CrossRef]
- Marconi, Francesco. 2020. *News-makers: Artificial Intelligence and the Future of Journalism*. New York: Columbia University Press.
- Maurício, Patrícia, Bruna Gerolis, and Maria G. Medeiros. 2017. Influenciadores digitais como parte da disrupção do modelo de negócios do jornalismo. *XL Congresso Brasileiro de Ciências da Comunicação* 1: 4–9.
- McLuhan, Marshal. 1963. *The Gutenberg Galaxy: The Making of Typographic Man*. Toronto: University of Toronto Press.
- Mota, Janine S. 2019. Utilização do Google Forms na pesquisa acadêmica. *Humanidades & Inovação* 6: 371–73.
- Napoli, Philip M. 2014. Automated media: An institutional theory perspective on algorithmic media production and consumption. *Communication Theory* 24: 340–60. [CrossRef]
- Newman, Nic. 2023. Journalism, Media, and Technology Trends and Predictions 2023. Reuters Institute for the Study of Journalism. Available online: <https://reutersinstitute.politics.ox.ac.uk/journalism-media-and-technology-trends-and-predictions-2023> (accessed on 10 October 2023).
- Noain-Sánchez, Amaya. 2022. Addressing the Impact of Artificial Intelligence on Journalism: The perception of experts, journalists and academics. *Communication & Society* 35: 105–21. [CrossRef]
- Oliveira, Daniela B., and Belarmino C. G. Costa. 2020. News Agenda Guided by Algorithms: Content and Format in Estadão Infográficos. *Brazilian Journalism Research* 16: 550–75. [CrossRef]
- Paganotti, Ivan. 2020. Refutação automatizada de notícias falsas na pandemia: Interações com o robô Fátima, da agência aos fatos. *SBPJOR—Associação Brasileira de Pesquisadores em Jornalismo* 18: 1–18.
- Pase, André F., and Eduardo C. Pellanda. 2019. Dilemas éticos do jornalismo produzido por inteligência artificial: Uma perspectiva brasileira. *Movilización ciudadana, medios sociales e Internet: Miradas latinoamericanas*. In *Cuadernos Artesanos de Comunicación*/165. Rosário: Sociedad Latina de Comunicación Social.
- Pavlik, John. 2019. *Journalism in the Age of Virtual Reality: How Experiential Media Are Transforming News*. New York: Columbia University Press.
- Pavlik, John. 2023. Collaborating with ChatGPT: Considering the implications of generative artificial intelligence for journalism and media education. *Journalism and Mass Communication Educator* 78: 84–93. [CrossRef]
- Pereira, Wanessa A. 2022. Processos de Inteligência Artificial e Parcerias Entre o Google e Jornais Brasileiros. [Trabalho de Conclusão de Curso (Bacharelado em Comunicação Social), Universidade de Brasília]. Available online: <https://bdm.unb.br/handle/10483/33429> (accessed on 12 October 2023).
- Pérez Ibarra, Susana G., José R. Quispe, Felipe F. Mullicundo, and Daniel A. Lamas. 2021. Herramientas y Tecnologías para el Desarrollo Web Desde el FrontEnd al BackEnd. Paper presented at the XXIII Workshop de Investigadores en Ciencias de la Computación, WICC 2021, Chilecito, La Rioja, Argentina, April 15–16.

- Pérez-Seijo, Sara, Suzana Barbosa, and Paulo N. Vicente. 2023. Artificial Intelligence in Journalism: Case Study of the Spanish, Portuguese and Brazilian News Media Systems. In *Blurring Boundaries of Journalism in Digital Media. Studies in Big Data*. Edited by María-Cruz Negreira-Rey, Jorge Vázquez-Herrero, José Sixto-García and Xosé López-García. Cham: Springer, vol. 140. [CrossRef]
- Perreault, Gregory P., and Patrick Ferrucci. 2020. What is digital journalism? Defining the practice and role of the digital journalist. *Digital Journalism* 8: 1298–316. [CrossRef]
- Pinto, Moisés C. 2021. Inteligências artificiais nos estudos de jornalismo da SBPJor entre 2012 e 2020. *Anais Do 19º Encontro Nacional de Pesquisadores em Jornalismo*. Available online: <https://proceedings.science/encontros-sbpjor/sbpjor-2021/trabalhos/inteligencias-artificiais-nos-estudos-de-jornalismo-da-sbpjor-entre-2012-e-2020?lang=pt-br> (accessed on 5 June 2023).
- Poell, Thomas, David Nieborg, and van José Dijck. 2020. Plataformização. *Revista Fronteiras* 22: 1. [CrossRef]
- Raju, Vasantha, and N. S. Harinarayana. 2016. Online survey tools: A case study of Google Forms. Paper presented at the National Conference on Scientific, Computational & Information Research Trends in Engineering, GSSS-IETW, Mysore, India, January 30.
- Salaverría, Ramón. 2019. Digital journalism: 25 years of research. Review article. *El Profesional de La Información* 28: e280101. [CrossRef]
- Santos, Márcio C. 2020. Data-Driven Journalistic Operation: Reshaping the Idea of News Values with Algorithms, Artificial Intelligence and Increased Personalization. *Brazilian Journalism Research* 16: 458–75. [CrossRef]
- Siegel, Eric. 2013. *Predictive Analytics: The Power to Predict Who Will Click, Buy, Lie, or Die*. Hoboken: John Wiley and Sons.
- Silva, Fernando Firmino. 2022. Áudio imersivo em narrativas jornalísticas de Realidade Virtual, Aumentada e Estendida. *Revista Eco-Pós* 25: 180–97. [CrossRef]
- Simon, Felix M. 2022. Uneasy bedfellows: AI in the news, platform companies and the issue of journalistic autonomy. *Digital Journalism* 10: 1832–54. [CrossRef]
- Sodré, Muniz. 2021. *A Sociedade Incivil: Mídia, Iliberalismo e Finanças*. Rio de Janeiro: Editora Vozes.
- Steensen, Steen, Anna M. G. Larsen, Yngve B. Hågvær, and Birgitte K. Fonn. 2021. What does digital journalism studies look like? In *Definitions of Digital Journalism (Studies)*. London: Routledge, pp. 7–29.
- Träsel, Marcelo R. 2014. Entrevistando Planilhas: Estudo das Crenças e do Ethos de Um Grupo de Profissionais de Jornalismo Guiado por Dados no Brasil. [Tese de Doutorado, UFRGS]. Available online: <https://repositorio.pucrs.br/dspace/bitstream/10923/6841/1/000461784-Texto+Completo-0.pdf> (accessed on 9 September 2023).
- Túñez-López, José-Miguel, César Fieiras-Ceide, and Martin Vaz-Álvarez. 2021. Impact of Artificial Intelligence on Journalism: Transformations in the company, products, contents and professional profile. *Communication & Society* 34: 177–93. [CrossRef]
- Turing, Alan M. 1950. Computing machinery and intelligence 1950. In *The Essential Turing: The Ideas That Gave Birth to the Computer Age*. Oxford: Clarendon Press, pp. 433–64.
- Zhang, Caixia. 2022. On the Ethical Dilemma and Countermeasures of Algorithmic Recommended News. In *Proceedings of the 3rd International Conference on Big Data and Social Sciences (ICBDSS 2022)*. Dordrecht: Atlantis Press, pp. 648–55.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.



Article

Artificial Intelligence in Automated Detection of Disinformation: A Thematic Analysis

Fátima C. Carrilho Santos

LabCom, University of Beira Interior, 6201-001 Covilhã, Portugal; fatima.catarina.santos@ubi.pt

Abstract: The increasing prevalence of disinformation has led to a growing interest in leveraging artificial intelligence (AI) for detecting and combating this phenomenon. This article presents a thematic analysis of the potential benefits of automated disinformation detection from the perspective of information sciences. The analysis covers a range of approaches, including fact checking, linguistic analysis, sentiment analysis, and the utilization of human-in-the-loop systems. Furthermore, the article explores how the combination of blockchain and AI technologies can be used to automate the process of disinformation detection. Ultimately, the article aims to consider the integration of AI into journalism and emphasizes the importance of ongoing collaboration between these fields to effectively combat the spread of disinformation. The article also addresses ethical considerations related to the use of AI in journalism, including concerns about privacy, transparency, and accountability.

Keywords: disinformation; artificial intelligence (AI); automatized detection; journalism

1. Introduction

The era of smartphones and social media has revolutionized the way content is transmitted and received, but not all of this content is accurate or truthful. The widespread use of the Internet and social media platforms has led to a significant increase in the prevalence of misleading information, known as disinformation. It is easily accessible and spreads rapidly in these digital environments.

In this article, we consider the definition of disinformation from the European Commission: “false, inaccurate, or misleading information designed, presented and promoted to intentionally cause public harm or for profit” (De Cock Buning 2018, p. 10). Disinformation, disguised as factual information, creates a distorted understanding of reality, leading to severe consequences for society by distorting people’s perceptions of various issues. Political and health matters are particularly vulnerable to disinformation, as seen during the COVID-19 pandemic, during which false information spread rapidly through social media. However, disinformation can affect various areas by disseminating false knowledge about reality.

Although the phenomenon of disinformation gained significant attention during the 2016 US election campaigns, it has taken on a new dimension since 2020. The COVID-19 pandemic highlighted the critical importance of reliable and fact-based information for decision-making across all aspects of society, emphasizing its role as a fundamental pillar of democracy (Grizzle et al. 2021).

Disinformation not only poses challenges to discerning truthful information but also undermines journalistic credibility. It represents a significant obstacle to journalism as a means of knowledge production in society. Technological advancements, especially in artificial intelligence (AI), have not only increased the spread of disinformation but have also facilitated its automated creation and distribution. Consequently, the use of AI in disinformation creation and dissemination poses a significant challenge to the reliability of information, making it increasingly difficult to distinguish between facts and falsehoods.

AI can be defined as the process of automating tasks that typically require human intelligence. In other words, it involves replicating diverse facets of human thinking and

behavior (Russell and Norvig (2013). However, Bostrom (2018) emphasized that the most significant challenge for AI lies in attaining this behavior when performing tasks that necessitate common sense and comprehension of natural language, areas in which humans instinctively excel without conscious effort.

AI systems strive to replicate human-like reasoning, learning, planning, creativity, and numerous other capabilities. Algorithms, which comprise sequences of instructions or operations, are crafted to accomplish specific objectives. Present endeavors in the development of systems to identify misleading language in disinformation have emphasized automatic classification techniques and a range of algorithms (Bhutani et al. 2019).

One notable subfield of AI is machine learning, which enables computers to autonomously identify patterns in extensive datasets through algorithms without the need for explicit programming. Machine learning plays a vital role in tasks that require machines to learn from experience (Oliveira 2018). Consequently, it focuses on creating algorithms and procedures to enhance computers' performance in executing activities.

Furthermore, while AI can be used to amplify disinformation, it also plays a crucial role in identifying disinformation. According to Singh et al. (2021), advancements in this domain involve multimodal automated detection, which incorporates both textual and visual cues to identify disinformation. Various machine learning and classification algorithms have been employed to assign categories to specific datasets based on their characteristics.

Efforts have been consistently made to develop machine learning-based systems and natural language processing (NLP) algorithms for disinformation detection. However, thus far, there have been no flawless solutions. NLP, a subfield of AI, enables machines to comprehend, interpret, and replicate human language.

One challenge associated with utilizing AI and machine learning for disinformation detection constitutes ethical concerns. Biases and prejudices can infiltrate these systems, leading to erroneous outcomes. Moreover, ethical considerations pose obstacles to the use of AI in journalism, including the lack of monitoring and transparency and the potential suppression of creativity. Nevertheless, as stated by Jamil (2021), AI has been widely employed in journalism to automate repetitive tasks, particularly in data collection and identifying relevant patterns and trends for news reporting.

While this article examines different approaches to leverage AI in combating disinformation, the main focus is on automated fact-checking, which has been supported by existing research, such as Graves and Cherubini (2016) and Kertysova (2018). As we delve into the subsequent section on the intersection of AI and blockchain technologies, automated fact-checking, especially when combined with these two technologies, can encompass the three key stages of traditional fact-checking: identification, verification, and distribution (Graves 2018; Nakov et al. 2021). While other sections discuss different approaches, they can be integrated into an automated fact-checking system. However, a separate approach was chosen since automated fact-checking does not necessarily require the inclusion of all the other alternatives described.

2. Methods and Experimental Results

The objective of this study was to synthesize the current possibilities of using AI to combat disinformation. Disinformation is currently a growing problem, and it is increasingly important to understand how we can utilize AI to help address this issue.

Thematic analysis was chosen as the methodology for this study to provide a contextual understanding of the topic from the perspective of information sciences, distinguishing it from the more prevalent approaches in the literature, which often focus on specialized areas, such as computer engineering.

Thematic analysis, as a qualitative approach, allows for a comprehensive understanding of the potential of a given issue by gathering diverse aspects and data, and it facilitates the exploration of relationships between different concepts and interpretations (Alhojailan 2012). Therefore, our objective is to provide a comprehensive understanding of the current

state of the research regarding the utilization of AI to combat disinformation using this methodology.

To collect relevant material about the topic under investigation, we initially selected multiple databases, including Web of Science, Google Scholar, and IEEE Xplore. We specifically included IEEE Xplore to comprehend the current literature in the field of computer science, although our review primarily focused on collecting studies from the perspective of the social sciences.

To search for material related to the explored topic, we utilized keywords, such as “artificial intelligence” and “disinformation”. However, due to the variety of terms used to refer to what is understood as disinformation in this context, we also included keywords such as “fake news” and “misinformation”. The collected material covered the period between 2012 and 2023, prioritizing recent studies and research articles, while also including relevant book chapters.

Subsequently, we selected the most relevant material for the topic under study, particularly contextual approaches that provided a better understanding of the subject from the perspective of the social sciences. The data analysis was conducted systematically, involving the cross-referencing of ideas from various authors on specific subtopics within the main theme and employing cross-validation methods to ensure the accuracy and consistency of the information.

Employing thematic analysis, we conducted a literature review to identify key issues related to this topic, exploring the current possibilities of utilizing AI in combating disinformation. These possibilities include automated fact-checking systems, which may or may not incorporate automated sentiment analysis and which often involve automated text analysis. Additionally, we observed that the literature frequently mentions the convergence between automated systems and human knowledge in the verification process, as well as the combination of blockchain technology and AI.

3. Automated Fact-Checking for Disinformation Detection

In the context of disinformation, fact-checking refers to the process of verifying information to confirm the accuracy of fact-based statements. Fact-checking has always been part of the journalistic production routine, but with the rise of disinformation, journalists have taken on an even greater responsibility in deepening the practice of information verification. Consequently, various fact-checking agencies have emerged, with some linked to existing newsrooms and others operating independently in the market.

Since the 2000s, the number of projects related to fact-checking has continued to increase. According to Cazetta (2018), interest was sparked with the launch in 2003 of Factcheck.org, created by the journalist Brooks Jackson in the United States, with a focus on verifying statements made by public figures. Rosenstiel, in his book *The New Ethics of Journalism: Principles for the 21st Century* Rosenstiel (2013), argued that the fact-checking movement originated after the 1988 US election, when a *Washington Post* columnist, David Broder, classified candidates' statements in debates as “lies,” “disqualified,” and “demagogic,” among other adjectives.

Some authors have also asserted that the initiative began in 1982, during the term of US President Ronald Reagan, when American journalists started to challenge inaccurate statements made by the president during press conferences (Cazetta 2018). However, in this case, it was primarily a contestation of a politician's statements and did not follow a structured methodology, unlike current fact-checking practices.

The proliferation of disinformation driven by the digital context has significantly boosted fact-checking efforts (do Nascimento 2021). In response, fact-checking projects aim to restore the credibility of journalism by exposing errors and incorrect information circulating on social media or in public figures' speeches. As Spinelli and Santos (2018) noted, what renders fact-checking a significant practice for journalism in the post-truth era is its emphasis on transparency and credibility.

Canavilhas and Ferrari (2018) pointed out that several renowned newspapers, such as the *Washington Post*, the *New York Times*, and *Le Monde*, have invested in these fact-checking formats, with the Americas and Europe being the continents with the most fact-checkers. Graves and Cherubini's study (2016) highlighted the growth of fact-checking sites throughout Europe, albeit with varying organizational forms and orientations, but with a shared commitment to publicly evaluate claims made by powerful actors, such as politicians, and in some cases information disseminated by the media.

Despite the growing interest in establishing fact-checking initiatives, it is noteworthy that the consumption of information generated by fact-checking agencies is often restricted to a specific audience, primarily journalists who rely on these verifications to validate their texts (do Nascimento 2021). According to Barrera et al. (2020), who studied the impact of content produced by fact-checking agencies compared to politicians' propaganda, there has been an absence of reaction from voters to fact-checking.

Experts and fact-checking organizations face the daunting task of investigating a vast amount of content, and AI has further intensified this workload, particularly due to the proliferation of bots deliberately generating and disseminating disinformation (Demartini et al. 2020). Due to several constraints surrounding fact-checking, such as time and resource limitations, new methods of fact-checking have been proposed, mainly based on the automatic detection of fake news. Thus, Jiang et al. (2021) argued that automated tools for detecting fake news, such as machine learning and specifically a type of machine learning algorithm, deep learning models, have become an essential requirement.

According to Kertysova's (2018) study, the initial proposals for automating online fact-checking emerged approximately a decade ago. However, the interest in research and investigation around AI-assisted fact-checking was triggered by Donald Trump's election as President of the United States, due to the large volume of erroneous information that was propagated: "The last few years have seen a wave of additional funding being earmarked for automated fact-checking initiatives that would help practitioners identify, verify, and correct social media content" (Kertysova 2018, p. 3).

One of the first challenges that had to be overcome initially in automated fact-checking was the lack of data to train the models. In 2017, online repositories with large volumes of information began to appear due to the growth of fact-checking sites. At the beginning of these developments, a database consisting of 106 fact checks from Politifact, one of the main fact-checking sites in the United States, was founded. Thus, a significant leap occurred in mid-2017 with the collection of a corpus of 12,800 checks from Politifact, and since then, the volume of databases has grown (García-Marín et al. 2022).

While creating extensive information repositories has been a significant challenge in AI-assisted fact-checking, ensuring data quality is equally crucial for designing effective algorithmic solutions to combat disinformation. Torabi Asr and Taboada (2019) argued that databases should be composed of samples of both false and true information in a balanced distribution across a range of topics. In a 2019 study, they reviewed available databases and presented a new repository called MisInfoText.

The primary objective of contemporary fact-checking endeavors is to ascertain the accuracy of information disseminated through social media channels (García-Marín et al. 2022). AI can automate the fact-checking process, especially through machine learning, NLP, and other sub-areas of AI.

There are also other automated alternatives for detecting disinformation, which can be part of fact-checking systems or exist individually. These alternatives include analyzing and verifying sources of information, cross-checking information, reviewing evidence, and more. Monitoring social media using AI-based recommendation systems, for example, can also be crucial in mitigating the spread of disinformation.

4. Detection of Disinformation through Language Analysis

Automated fact-checking can include text analysis performed by AI, which is useful in classifying news as true or false. In these cases, in addition to resources based on word

occurrences and word relationships (both semantic and syntactic), it is also necessary to have resources based on how humans perform fact-checking. That is, the automated classification of information examines human behavior in the process of manually detecting disinformation (Škol kay and Filin 2019).

In fact-checking conducted by humans, contextual factors are considered, including the historical background, individuals involved, locations, and other relevant specifics related to the event. Thus, when automated detection of disinformation includes these characteristics, it is closer to human accuracy.

According to Kertysova (2018), automated technologies have limitations in evaluating individual statements. Current AI systems excel at identifying simple statements and assertions, but they struggle with more complex ones. The same limitation applies to expressions, in which context and culture are necessary.

Despite significant advancements in NLP techniques for automated text analysis, challenges remain in understanding fundamental human concepts, such as sarcasm or irony. AI-based systems currently struggle to address disinformation that relies on subtler forms of expression beyond explicit content. Additionally, linguistic barriers and specific cultural/political environments in each country pose even greater challenges.

A common approach to managing these challenges is to involve humans in the text analysis process, especially when regarding machine learning algorithm training (Škol kay and Filin 2019). For example, in a fake news classification project, humans can flag a news story as false or true in the first phase. Then, the program can learn from these indications to assign characteristics and make classification decisions based on patterns identified in the news.

This approach, referred to as semi-supervised learning, offers the potential to enhance the accuracy of automated text analysis by combining the human ability to comprehend language nuances with the efficiency and scalability of automated text processing.

In machine learning systems, data representation greatly affects the accuracy of results, and the content shared by social media users being generally in unstructured forms makes this process difficult. Therefore, unstructured data extracted from social networks need to undergo transformation into a structured format using text mining methods. The problem of text mining can be defined as the extraction of meaningful, useful, and previously unknown information from textual data.

5. Detection of Disinformation through Sentiment Analysis

Sentiment analysis is a natural language processing technique that can also be used to detect disinformation. Although AI is not infallible, especially in the context of sentiment analysis, there have been significant improvements in this field because emotional appeal in fake news content differs from that in true news since messages with a strong emotional appeal can influence how content is consumed, processed, and shared by consumers (Paschen 2019). In fake news, the body of the news is usually more focused on specific negative emotions, such as disgust and anger, and less on positive emotions, such as joy.

In the study by Alonso et al. (2021), sentiment analysis (SA) was defined as a branch of Natural Language Processing (NLP), which is responsible for designing and implementing models, methods, and techniques to determine whether a text is composed of objective or subjective information and, in the latter case, to determine whether such information is expressed positively, neutrally, or negatively, as well as whether it is expressed strongly or weakly.

Computational techniques identify the characteristics of sentiments referred to as polarity, allowing for the classification of sentiments as positive, negative, or neutral. These techniques also identify specific emotions, such as sadness, anger, and more. While these computational techniques are applied to analyze text and images in news or content, their usage has been relatively limited in certain languages, such as Portuguese (Maia et al. 2021).

By analyzing the sentiment associated with news or content and determining whether there is emotional polarization, indications can be identified that the content is false; thus,

sentiment analysis can be a useful tool for detecting fake news, especially in automated fake news detection. Therefore, sentiment analysis, while it can exist independently, is also a tool that can be part of the automated fact-checking process.

Given that a majority of the subjective content shared by users on social media revolves around opinions, sentiment analysis is also referred to as Opinion Mining, as noted by Alonso et al. (2021). Shu et al. (2017) reported that SA should play a role in determining resource allocation based on posts since people express their emotions or opinions about fake news through social media posts, such as skeptical opinions or sensational reactions. Alonso et al. (2021) also referred to sentiment as one of the resources that can be extracted from text for fake news detection since conflicting sentiments between news disseminators can indicate a high probability of fake news.

6. Using Human-in-the-Loop AI Systems for Detecting Disinformation

As discussed throughout this article, considering the limitations of both AI and humans, it can be argued that combining the efforts of humans and AI is advantageous in combating disinformation. As Demartini et al. (2020) argued, human-in-the-loop AI (HAI) systems combine the best of both worlds, with humans filtering what will be implemented in practice by a machine that performs tasks based on databases and machine learning algorithms.

This model aims to harness AI's capability for large-scale processing, while utilizing human intelligence for complex tasks beyond AI's reach, such as language understanding and ensuring fairness and applicability within the system. One significant advantage of AI-based systems is their capacity to comprehensively analyze vast amounts of content, surpassing human capabilities (Babakar and Moy 2016).

Nevertheless, HAI systems encounter further challenges in achieving optimal functionality and generating valid results, including the inconsistency of data quality due to variations among participants involved in training the AI system. For example, using crowdsourcing, i.e., collective intelligence gathered in a complex task, to collect "labels" from online people using a platform is different from relying on experts.

Despite this limitation, since the number of available experts is usually limited, to obtain high-volume and quality labels, effective quality control mechanisms for crowdsourcing need to be developed. Another challenge that comes with HAI systems is the bias that contributing humans can create and/or amplify in the annotated data and, consequently, in the models learned with these labeled data (prejudices and stereotypes of contributing individuals can be reflected in the generated labels). As highlighted by Ghafourifar et al. (2021), if we aspire to create a potent and intelligent AI-based tool capable of detecting fake news, we must address our own biases and practice skepticism when it comes to consuming, sharing, and creating content on social media platforms and the Internet.

It is necessary to avoid biased models while leveraging human resources and filling in their gaps to better harness the scalability of AI-based methods and obtain the best of both worlds. Kertysova (2018) presented an opposite concept to human-in-the-loop AI, involving a different degree of human involvement in the decision-making process of an AI system, called humans "out of the loop" of AI systems. This approach is more common in systems that have been trained with a large volume of data and use sophisticated algorithms to make decisions, operating completely without direct human intervention.

Regarding humans being "out of the loop," the author noted that there are legal reasons why humans need to be kept informed about content moderation. According to a recent study funded by the European Science-Media Hub, limiting the automated enforcement of decisions about problems uncovered by AI is essential to ensure human agency and natural justice, including the right to appeal. This right does not prevent the suspension of bot accounts at scale, but it ensures proper auditing of the implemented system processes:

"The European data protection framework—which includes the General Data Protection Regulation (GDPR)—allows people to know how organizations are using their data as

well as to contest certain decisions made by algorithms. Because developers cannot explain how algorithms produce certain outcomes (see previous section), complaints relating to the GDPR have already been lodged, several organizations have been sanctioned, and more cases are expected to follow" (Kertysova 2018, p. 69).

7. The Application of AI Blockchain in the Automated Detection of Disinformation

In addition to AI, another technology that has been extensively discussed in the literature and could be useful in combating disinformation, especially when used in conjunction with AI, is blockchain.

Blockchain technology has been utilized for information validation and news aggregation. It is a decentralized record-keeping technology that allows for secure storage and validation of transactions to ensure that they cannot be altered. This technology, which is often used to create virtual currencies, can be leveraged to preserve and verify the integrity of news and other online content (Qayyum et al. 2019). Additionally, the authors concluded that blockchain technology, being a decentralized technology, promises to bring transparency and trust to journalism.

As do Val et al. (2021) explained, blockchain technology represents an alternative for verifying the content circulating on the Internet because, through it, users sign digital documents that are validated as true regarding a particular subject.

Therefore, technology tools based on blockchain can identify and compare false information with real facts. Several initiatives already employ blockchain to combat disinformation, including the News Provenance Project, Fake Check, and Democracy Notary. The *New York Times* also conducted a project to provide provenance metadata around news using blockchain technology to track the dissemination of news online and provide contextual information to news readers. There was also an effort to create initiatives around COVID-19, such as Hashlog.

The combination of AI and blockchain could lead to the creation of platforms with fewer limitations. Blockchain ensures secure and immutable data storage, while AI processes and analyzes large amounts of data in real time. One limitation of blockchain is its performance since it can only handle a limited number of transactions per second.

Thus, blockchain is used to store verified and trustworthy information about news sources, and AI, in turn, could be used to analyze and classify news in real time, comparing it with the information stored in the blockchain and identifying fake news.

However, in addition to detecting disinformation circulating on the Internet, Shae and Tsai (2019) pointed out that it is important to create mechanisms to minimize the impact of fake news before it is propagated; that is, it is necessary to create algorithms to predict fake news to anticipate the beginning of fake news propagation before it is actually spread.

This approach could be the most effective mechanism to combat the spread of fake news in the long run. Therefore, it is important and highly challenging to identify, label, and categorize different personal characteristics for diverse groups/communities and to develop corresponding intervention technologies. Personalized intervention technology can be developed by leveraging the AI-trustworthy news platform in blockchain.

To achieve this goal, some of the challenges include building databases of factual news, creating a trustworthy news blockchain, developing a blockchain crowdsourcing false news classification mechanism, developing scalable distributed intelligence contracting the blockchain network, and establishing a practical business model for building a trustworthy news ecosystem (Shae and Tsai 2019).

In conclusion, this study discusses a long-term strategy to develop models for predicting fake news before it spreads and to research the effectiveness of personalized intervention mechanisms. The combination of AI and blockchain technologies, such as in the practice of fact-checking, encompasses the three stages of fact-checking: identification, verification, and distribution (Graves 2018; Nakov et al. 2021). Westlund et al. (2022) pointed out that the identification stage gathers the highest concentration of technologies.

8. Discussion and Conclusions

Since the 2016 US presidential election, there has been growing interest in researching the use of new technologies, particularly AI, with a focus on automating fact-checking processes. In mid-2017, online repositories with large volumes of information started to emerge, effectively addressing the initial challenge of data scarcity for training automated fact-checking models. However, in addition to data quantity, ensuring the quality of the data used is crucial for designing effective algorithmic solutions to combat disinformation.

Currently, the main goal of fact-checking efforts is to verify the accuracy of information disseminated on social media, where AI has proved useful in automating the fact-checking process, particularly through machine learning, natural language processing, and other AI subfields.

In addition to automated fact-checking, which may also incorporate language analysis and sentiment analysis, the fight against disinformation requires a multifaceted approach that involves not only the use of AI and other technological tools but also human verification. Regarding other technologies, although this article primarily focused on artificial intelligence, it is worth mentioning that the combination of AI and blockchain technologies leads to a more efficient computer system for combating disinformation. AI can analyze and classify news in real time by comparing it with information stored on the blockchain, providing two-factor validation.

Therefore, it is important to acknowledge that automated detection of disinformation is only a part of the solution and should be complemented by other approaches that consider the complex nature of disinformation. Moreover, ethical concerns surrounding the use of AI in detecting disinformation must be addressed, including issues related to privacy, transparency, and accountability. Any use of AI in detecting disinformation must be guided by ethical principles and fundamental human values.

Efforts to combat disinformation are crucial for restoring the credibility of journalism, but a gap still exists between AI and journalistic practices. Although AI has been used to automate repetitive tasks and collect data for news, there remain ethical challenges and financial barriers that must be addressed to fully integrate AI into journalism. Hence, it is crucial to emphasize the importance of responsible implementation and the ongoing collaboration between technology and journalism.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The author declares no conflict of interest.

References

- Alhojailan, Mohammed Ibrahim. 2012. Thematic analysis: A critical review of its process and evaluation. *West east Journal of Social Sciences* 1: 39–47.
- Alonso, Miguel A., David Vilares, Carlos Gómez-Rodríguez, and Jesús Vilares. 2021. Sentiment analysis for fake news detection. *Electronics* 10: 1348. [CrossRef]
- Babakar, Mevan, and Will Moy. 2016. *The State of Automated Factchecking. How to Make Factchecking Dramatically More Effective with Technology We Have Now*. London: Full Fact.
- Barrera, Oscar, Sergei Guriev, Emeric Henry, and Ekatarina Zhuravskaya. 2020. Facts, alternative facts, and fact checking in times of post-truth politics. *Journal of Public Economics* 182: 104123. [CrossRef]
- Bhutani, Bhavika, Neha Rastogi, Priyanshu Sehgal, and Archana Purwar. 2019. Fake News Detection Using Sentiment Analysis. Paper presented at the 2019 Twelfth International Conference on Contemporary Computing (IC3), Noida, India, August 8–10; pp. 1–5.
- Bostrom, Nick. 2018. *Superinteligência*. Rio de Janeiro: DarkSide Books.
- Canavilhas, João, and Pollyana Ferrari. 2018. Fact-checking: O jornalismo regressa às origens. *Jornalismo em Tempo de Transformação: Desafios de Produção e de Ação*, 30–49.
- Cazetta, Póvoa Cazetta. 2018. *O Fact-Checking Luso-Brasileiro: Uma Análise dos Fact-Checkings Credenciados No Brasil e em Portugal pelo International Fact-Checking Network*. Porto: Faculdade de Letras da Universidade do Porto.

- do Nascimento, Flávia Lopes Sales. 2021. Entendendo o fact-checking como uma ferramenta para promoção de literacia mediática no contexto luso brasileiro. *E-Revista de Estudos Interculturais*, 3. [CrossRef]
- do Val, Ronaldo Borges, Thamirys Dias Viana, and Luis Borges Gouveia. 2021. O uso de Blockchain na identificação de Fake News: Ferramentas de apoio tecnológico para o combate à desinformação. *Brazilian Journal of Business* 3: 2726–2742. [CrossRef]
- De Cock Buning, Madeleine. 2018. *A Multi-Dimensional Approach to Disinformation: Report of the Independent High Level Group on Fake News and Online Disinformation*. Luxembourg: Publications Office of the European Union.
- Demartini, Gianluca, Stefano Mizzaro, and Damiano Spina. 2020. Human-in-the-loop Artificial Intelligence for Fighting Online Misinformation: Challenges and Opportunities. *IEEE Data Engineering Bulletin* 43: 65–74.
- García-Marín, David, Carlos Elías, and Xosé Soengas-Pérez. 2022. Big data and disinformation: Algorithm mapping for fact checking and artificial intelligence. In *Total Journalism: Models, Techniques and Challenges*. Cham: Springer International Publishing, pp. 123–35.
- Ghafourifar, P., M. Dousti, and R. Mirsaiedi. 2021. Fake news detection using a hybrid of deep learning models. *Journal of Ambient Intelligence and Humanized Computing* 12: 5841–52.
- Graves, Lucas. 2018. *Understanding the Promise and Limits of Automated Fact-Checking*. Oxford: Reuters Institute for the Study of Journalism.
- Graves, L., and F. Cherubini. 2016. *The Rise of Fact-Checking Sites in Europe*. Oxford: Reuters Institute for the Study of Journalism.
- Grizzle, Alton, Carolyb Wilson, Ramon Tuazon, Chi Kim Cheung, Jesus Lau, Rachel Fischer, Dorothy Gordon, Kwame Akyempong, Jagtar Singh, Paul R. Carr, and et al. 2021. *Media and Information Literate Citizens: Think Critically, Click Wisely!* Paris: UNESCO Publishing.
- Jamil, Sadia. 2021. Artificial intelligence and journalistic practice: The crossroads of obstacles and opportunities for the Pakistani journalists. *Journalism Practice* 15: 1400–22. [CrossRef]
- Jiang, Tao, Jian Ping Li, Amin Ul Haq, Abdus Saboor, and Amjad Ali. 2021. A novel stacking approach for accurate detection of fake news. *IEEE Access* 9: 22626–39. [CrossRef]
- Kertysova, Katarina. 2018. Artificial intelligence and disinformation: How AI changes the way disinformation is produced, disseminated, and can be countered. *Security and Human Rights* 29: 55–81. [CrossRef]
- Maia, Igor Maffei Libonati, Marcelo Pereira de Souza, Flávio Roberto Matias da Silva, Paulo Márcio Souza Freire, and Ronaldo Ribeiro Goldschmidt. 2021. A sentiment-based multimodal method to detect fake news. Paper presented at the Brazilian Symposium on Multimedia and the Web, WebMedia 21: Brazilian Symposium on Multimedia and the Web, Belo Horizonte, Brazil, November 5–12; pp. 213–16.
- Nakov, Preslav, David Corney, Maram Hasanain, Firoj Alam, Tamer Elsayed, Alberto Barrón-Cedeño, Paolo Papotti, Shaden Shaar, and Giovanni Da San Martino. 2021. Automated fact-checking for assisting human fact-checkers. *arXiv* arXiv:2103.07769.
- Oliveira, Arlindo. 2018. *Mentes Digitais*, 2nd ed. Lisboa: IST Press.
- Paschen, Jeannette. 2019. Investigating the emotional appeal of fake news using artificial intelligence and human contributions. *Journal of Product & Brand Management* 29: 223–33.
- Qayyum, Adnan, Junaid Qadir, Muhammad Umar Janjua, and Falak Sher. 2019. Using blockchain to rein in the new post-truth world and check the spread of fake news. *IT Professional* 21: 16–24. [CrossRef]
- Rosenstiel, Tom. 2013. *The New Ethics of Journalism: Principles for the 21st Century*. Thousand Oaks: CQ Press.
- Russell, Stuart, and Peter Norvig. 2013. “Parte I: Inteligência Artificial”. Em *Inteligência Artificial*. Rio de Janeiro: Elsevier, pp. 22–60.
- Shae, Zonyin, and J. Tsai. 2019. AI blockchain platform for trusting news. Paper presented at the 2019 IEEE 39th International Conference on Distributed Computing Systems (ICDCS), Dallas, TX, USA, July 7–10; pp. 1610–19.
- Shu, Kai, Amy Sliva, Suhang Wang, Jiliang Tang, and Huan Liu. 2017. Fake News Detection on Social Media: A Data Mining Perspective. *SIGKDD Explorations* 19: 22–36. [CrossRef]
- Singh, Vivek K., Isha Ghosh, and Darshan Sonagara. 2021. Detecting fake news stories via multimodal analysis. *Journal of the Association for Information Science and Technology* 72: 3–17. [CrossRef]
- Spinelli, Egle Müller, and Jéssica de Almeida Santos. 2018. Jornalismo na era da pós-verdade: Fact-checking como ferramenta de combate às fake news. *Revista Observatório* 4: 759–82. [CrossRef]
- Školkay, Andrej, and Juraj Filin. 2019. A comparison of fake news detecting and fact-checking AI based solutions. *Studia Medioznawcze* 4: 365–83. [CrossRef]
- Torabi Asr, Fatemeh, and Maite Taboada. 2019. Big Data and quality data for fake news and misinformation detection. *Big Data & Society* 6: 2053951719843310.
- Westlund, Oscar, Rebekah Larsen, Lucas Graves, Lasha Kavtaradze, and Steen Steensen. 2022. Technologies and Fact-Checking: A Sociotechnical Mapping. In *Disinformation Studies*. Covilhã: Beira Interior University, p. 193.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.



Article

Data-Driven Deep Journalism to Discover Age Dynamics in Multi-Generational Labour Markets from LinkedIn Media

Abeer Abdullah Alaql¹, Fahad AlQurashi¹ and Rashid Mehmood^{2,*}

¹ Department of Computer Science, FCIT, King Abdulaziz University, Jeddah 21589, Saudi Arabia

² High-Performance Computing Center, King Abdulaziz University, Jeddah 21589, Saudi Arabia

* Correspondence: rmehmood@kau.edu.sa

Abstract: We live in the information age and, ironically, meeting the core function of journalism—i.e., to provide people with access to unbiased information—has never been more difficult. This paper explores deep journalism, our data-driven Artificial Intelligence (AI) based journalism approach to study how the LinkedIn media could be useful for journalism. Specifically, we apply our deep journalism approach to LinkedIn to automatically extract and analyse big data to provide the public with information about labour markets; people's skills and education; and businesses and industries from multi-generational perspectives. The Great Resignation and Quiet Quitting phenomena coupled with rapidly changing generational attitudes are bringing unprecedented and uncertain changes to labour markets and our economies and societies, and hence the need for journalistic investigations into these topics is highly significant. We combine big data and machine learning to create a whole machine learning pipeline and a software tool for journalism that allows discovering parameters for age dynamics in labour markets using LinkedIn data. We collect a total of 57,000 posts from LinkedIn and use it to discover 15 parameters by Latent Dirichlet Allocation algorithm (LDA) and group them into 5 macro-parameters, namely Generations-Specific Issues, Skills and Qualifications, Employment Sectors, Consumer Industries, and Employment Issues. The journalism approach used in this paper can automatically discover and make objective, cross-sectional, and multi-perspective information available to all. It can bring rigour to journalism by making it easy to generate information using machine learning, and can make tools and information available so that anyone can uncover information about matters of public importance. This work is novel since no earlier work has reported such an approach and tool and leveraged it to use LinkedIn media for journalism and to discover multigenerational perspectives (parameters) for age dynamics in labour markets. The approach could be extended with additional AI tools and other media.

Keywords: media; journalism; deep journalism; labour markets; great resignation; quiet quitting; millennials; Generation Z; big data analytics; Natural Language Processing (NLP)

1. Introduction

1.1. The State of Journalism

We live in the information age and, ironically, meeting the core function of journalism—i.e., to provide people access to unbiased information—has never been more difficult. Perhaps the reason lies in the fact that people were never so distant from their real, physical, environments as they do now. This seems obvious given that we are connected to the virtual world that is pulled in front of our eyes by people whose intent may not be known or the intent may be to provide information that serves the business or the powerful. A perspective on this was provided by Herman and Chomsky in their book “Manufacturing Consent: The Political Economy of the Mass Media” (Herman and Chomsky 1988). They define an analytical framework called the “propaganda model” and note, “A propaganda model focuses on this inequality of wealth and power and its multilevel effects on mass-media interests and choices. It traces the routes by which money and power are able

to filter out the news fit to print, marginalize dissent, and allow the government and dominant private interests to get their messages across to the public". They further note that, normally, top-down intervention is not used to keep journalists under control, rather by "journalists' internalization of priorities and definitions of newsworthiness that conform to the institution's policy" (Herman and Chomsky 1988).

Another reason for the challenges facing journalism is the increasing complexity of the world and information, requiring new methods for journalism. Phenomena such as populism, partisanship, and kleptocracy have led societies to extremism (Goodwin 2012; Alvares and Dahlgren 2016). Consequently, public trust in governments has plummeted dramatically. The main issues are related to the perception of the public that it is the responsibility of others, not themselves, to provide impartial information and ideal or acceptable governance. The American Press Institute defines journalism's purpose as "to provide citizens with the information they need to make the best possible decisions about their lives, their communities, their societies, and their governments" (American Press Institute 2022). Traditional journalism has failed to achieve this goal for a variety of reasons, including difficulties in maintaining media organisations' freedom and impartiality, as well as funding cuts, which have led to public distrust (Carlson 2019; Allern and Pollack 2019). This is highlighted by UN News, which quotes UN Secretary-General António Guterres as saying, "at a time when disinformation and mistrust of the news media are growing, a free press is essential for peace, justice, sustainable development, and human rights" (UN News 2019).

The general public's distrust of traditional journalism, combined with the rise of the Internet, digital technologies, and digital and social media, has resulted in a rapid rise of citizen journalism, i.e., journalism by the general public, particularly through social and other digital media (Wall 2015; Raza et al. 2022; Zeng et al. 2019; Carmichael et al. 2019; Sienkiewicz 2014). Participatory journalism, democratic journalism, public journalism, and other terms were used to describe citizen journalism. Citizen journalism is difficult to understand and govern due to its very nature—i.e., it should be free—and because it is multifaceted, multidimensional, multilevel, and multimodal (Nah and Chung 2020). Citizen journalism solves some of traditional journalism's problems. However, it also introduces new ones, for example, subjectivity and, potentially, could lack responsibility, quality, standards, and regulations (Al-Ghazzi 2014; UN News 2022; Mutsvairo and Salgado 2022). Everyone bears the responsibility for upholding ideals, so everyone is accountable and must work to uphold freedom, equity, sincerity, honesty, and other ideals. Traditional and citizen journalism must collaborate, and their issues must be rectified cohesively by the people.

1.2. Labour Markets and Multi-Generation Era

We are affected by economic issues every day, such as inflation, energy, taxes, and interest rates. The global COVID-19 pandemic, environmental disasters, geopolitical situations, and wars have exacerbated the economic and social situations throughout the world, around developed and developing countries, and everywhere else. Experts, the media, politicians, and ordinary citizens are all concerned about the national and global economic situation these days. For example, Braun notes that policies of the Federal Reserve, the continuation of the COVID-19 pandemic (new variants, vaccination, and their effects), labour shortages, supply chain vulnerabilities, and US-China relations are among the top economic risks this year (Braun 2021). Kalish reported an update on the global economy for August 2022 and listed several economic concerns including global inflation, low consumer spending, effects of climate change on global economies, increase in labour costs, gas supplies for Europe, and global food security (Kalish 2022).

Moreover, our societies and workplaces are becoming more multipolar, rather than multilateral, with increased segmentation along generations, genders, races, ideologies, and several other dimensions. People are polarised and hate each other, even based on football clubs. Societies were never like this, not so complex, and not so divided.

Another current major economic issue is the Great Attrition (also called Great Resignation or Big Quit) accompanied by Quiet Quitting (Ellis and Yang 2022). People are resigning from their jobs in great numbers around the world. For example, over 24 million Americans left their jobs during the second and third quarters of 2021 (Sull et al. 2022). Based on an extensive study of over 30,000 people, Microsoft reported that more than 40% of the global workforce is considering leaving their employers in 2021 for reasons such as the need for flexible and hybrid work, the gaps between business leaders and employees, high productivity requirements causing exhaustion and burnouts in the workforce (meetings, emails, chats, etc.), Gen Z (particularly) struggling with work-life balance, and others (Microsoft 2021). According to the World Economic Forum, the Great Resignation is not over, and a fifth of workers on average plan to quit in 2022, with as many as 66% of unhappy workers in India planning to leave within the next 3–6 months, followed by Singapore, where 49% of workers plan to leave their jobs (World Economic Forum 2022). The study found that compensation, meaning (self-fulfilment), confidence or competence (allowing creativity), and autonomy (time, place, and flexibility) were the key factors when considering a job change. Quiet Quitting has aggravated the problems of Great Resignation. It is seen differently by different people. Some people see Quiet Quitting as a movement to do the minimum at work or untethering careers from identities, while others see it as a reminder to not work to the point of burnout (Ellis and Yang 2022).

The worsening and uncertain situation with the economies and labour markets globally calls for increased research in this area. For instance, research in labour markets is needed to understand the evolving nature of labour (skills, education, generation-specific trends, and preferences, etc.) and employers (industry trends, priorities, ESG (Environment, Social, and Governance), compliance to various regulations, and Triple Bottom Line (TBL), etc.). Research in labour markets is also needed to understand the role of evolving societies in labour markets and comply with national and global priorities such as UN Sustainable Development Goals (SDGs). Research in these areas is urgently needed to develop new labour economics and labour markets for sustainable economies and societies. Additionally, understanding various generations in workplaces or societies (silent generation, baby boomers, generation X, millennials, generation Z, and generation alpha) is very important in the current climate.

1.3. LinkedIn: A Trusted Professional and Business Media

Online Social Networks have continued to grow in number, quality, and significance, and with this, their influence on society is becoming more profound (Ahn et al. 2007; Tobi et al. 2013; Mislove et al. 2007). This is especially true due to the emergence of smartphones, wearables, and other smart mobile devices. This cyberspace data could be used to capture public opinion; identify communities and organisations; detect trends; obtain predictions in any area where sufficient data is available; and investigate any topics of interest, the possibilities are endless (Suma et al. 2020; Alotaibi et al. 2020; Alomari et al. 2021).

LinkedIn has 850 million subscribers and is regarded as the most popular social networking site for professionals (LinkedIn Corporation 2022). It provides users with the opportunity to display their academic achievements and form connections. LinkedIn is a key media being used for recruitment, content distribution, and building brands. It is possible to capture issues and detect trends based on the vast amount of valuable information from LinkedIn posts. We used LinkedIn media because it offers massive repositories of social media data between professionals.

The paper is organised as follows. Section 2 provides the literature review, briefly describes our work, and establishes the research gap and novelty of the work presented in this paper. In Section 3, we describe our approach, the methodology and the tool design. The implementation is discussed in Section 4. The discovered parameters are discussed in Section 5. A discussion is presented in Section 6. Conclusions and future directions are presented in Section 7.

2. Literature Review and Description of Our Work

This section discusses the works related to the research presented in this paper (Section 2.1), provides a brief description of our work (Section 2.2), and summarises the research gap and novelty of our work (Section 2.3). A comprehensive review of academic research on using artificial intelligence (AI) and data analytics for LinkedIn was conducted. We did not find any work similar to our paper. We review works within the context of data analytics using LinkedIn profiles or other related social media.

2.1. Related Works

Social media data mining is a process that involves collecting and analysing social media data. Data mining is a type of data analysis that uses machine learning and other advanced technologies to find patterns in social media data. For example, it can be used to gain knowledge about the demographics of its users (Gjurković et al. 2021). In addition, it can help companies to identify employees' skills and qualifications in the workplace. For instance, using LinkedIn as the basis for user modeling, Alruwaili and Alahmadi (2021) extracted LinkedIn profiles. Then, LinkedIn users were clustered based on their skills. Furthermore, Dai et al. (2015) scraped public profiles using a scraping technique. Then, NLP techniques are applied to the classification of educational background and the clustering of professional background in collected profiles.

Purwono and Wulandari (2021) used LinkedIn profile photos to predict face shapes. In addition, using publicly available data, Nguyen et al. (2021) explored the LinkedIn profiles of Australians. Based on facial feature extraction and analysis, K-means clustering, and Principal Component Analysis were found to be viable techniques for classification of users.

Kumalasari and Susanto (2020) used the K-Means Clustering algorithm to test whether using IT professionals' data as a reference is feasible. To classify students based on their skills and the information technology field, the Collaborative Filtering method by the K-NN algorithm is employed. Based on the collected IT student skills, the recommendation for the IT job field is generated. Furthermore, Dai et al. (2018) used Clustering methods to analyse LinkedIn profiles based on their professional backgrounds. The authors analysed the trending professional orientations of the workforce. Moreover, Domeniconi et al. (2016) used the data from LinkedIn users' public profiles to identify relationships between jobs and people skills. Giri et al. (2016) developed a hassle-free automated process that enables recruiters to select candidates who fit their organisation. Using Greedy, Hierarchical, and K Mean clustering algorithms, Garg et al. (2016) clustered LinkedIn profiles by job title, company name, and geography. On the other hand, in order to create domain-specific job understanding models, Li et al. (2020) applied deep transfer learning.

Researchers have also used other types of social media data such as Twitter data to automatically extract information using machine learning in various research fields. For example, using Twitter data, Haghighi et al. (2018) proposed a paradigm for evaluating transit riders' perceptions of service quality. For filtering tweets that are related to the real customer experiences of the transit system, the authors employ topic modeling by using an unsupervised machine learning approach. Sentiment analysis is then conducted utilising an established tweet-per-topic index to evaluate transit riders' opinions as well as investigate the root causes of their unhappiness with the service. This methodology has the potential to be very helpful to transportation authorities in terms of user-oriented analysis and investment decision-making. Moreover, Alomari et al. developed an automatic labeling approach (Alomari et al. 2021) for machine-learning-based traffic-related event identification using Twitter data in Arabic. The implemented software programme is named Iktishaf+ that uses distributed smachine learning over Spark. In addition, Karami et al. (2020) discussed topics in Twitter-based studies, to summarise the temporal trend of those topics, and to interpret their evolution over the last decade. This study utilises a productive strategy to mine many Twitter-based studies to characterise the relevant studies. Moreover, Martínez-Rojas et al. (2018) employed a research methodology based on

a systematic review of the literature to provide an overview of the current state of research on the use of Twitter in emergency management, and to identify problems and potential suggestions for further studies.

2.2. This Work

Motivated by the challenges in the journalism and labour market fields, in this paper, we explore deep journalism, our data-driven Artificial Intelligence (AI) based journalism approach to study how the LinkedIn media could be useful for journalism. Specifically, we apply our deep journalism approach to LinkedIn to automatically extract and analyse big data to provide the public with information about labour markets, people's skills and education, and businesses and industries from multi-generational perspectives. We combine big data and machine learning to create a whole machine learning pipeline and a software tool for journalism that allows discovering parameters for age dynamics in labour markets using LinkedIn data.

We collect a total of 57,000 posts from LinkedIn and use it to discover 15 parameters by the Latent Dirichlet Allocation algorithm (LDA) and group them into 5 macro-parameters. These macro-parameters represent five different views on multi-generational labour markets. (i) Generations-Specific Issues that include the relationship between unemployed young people and crimes, unemployment and drug abuse caused by family breakdown, etc., (ii) Skills and Qualifications macro-parameter includes leadership skills such as communication and effective decision making, nurturing leadership in the young generation, job-specific skills, training, and more. (iii) Employment Sectors include parameters such as changing workspaces, remote and hybrid work, recruitment sector, family businesses, entrepreneurship, and more. (iv) Consumer Industries include celebrations and events industries, the retirement industry, band marketing, energy sectors, and the entertainment industry. (v) Employment Issues include mental health and others. We also discover and elaborate on labour market-specific characteristics and preferences of the multi-generational workforce such as increased use of music consumption among Generation X and Y, a high likelihood of a criminal record among unemployed Generation Z, a focus on mental health among Generation Z, and others.

We implemented the proposed data-driven approach for age dynamics parameter discovery from labour markets data into a software tool. The tool comprises multiple software components that collect, process, discover parameters, analyse, visualize, and validate the discovered information. The details of the methodology and the software tool for parameter discovery including the data collection procedure and analysis of the parameters are provided in Sections 4–6.

The journalism approach used in this paper can make objective, cross-sectional, and multi-perspective information available to all. It can bring rigour to journalism by making it easy to generate information using machine and deep learning and can make tools and information available so that anyone can uncover information about matters of public importance. The work also contributes to an understanding of labour markets and that could be used to create awareness of important issues among the public, academics, and others, and drive future research on this topic using cutting-edge technologies. The parameters discovered and the knowledge gained could be used by the public to make informed decisions, as well as to direct labour economics research in important areas. It is expected that this work will contribute to developing the theory and practice of AI-based journalism, the use of LinkedIn media for journalism, and novel approaches toward labour economics and labour markets facilitated through the knowledge discovery and journalism approach, eventually leading to the development of sustainable societies and economies.

The work presented in this paper on journalism and media is a part of our wider work that aims to develop ICT technologies to solve pressing problems in smart cities and societies. For example, we introduced the concept of Deep Journalism in (Mehmood 2022; Ahmad et al. 2022) and discovered public, academic, and industry perspectives on transportation using The Guardian, Web of Science, and Traffic Technology International

Magazine, respectively. We have also used a similar methodology to discover parameters for smart families and homes (Alqahtani et al. 2022), healthcare services for cancer (Alahmari et al. 2022), and education and learning during the COVID-19 pandemic (Alswedani et al. 2022). Earlier we developed a range of works on AI-based event detection, such as Alomari et al. (2020).

2.3. Research Gap and Novelty

The literature review provided earlier in this section shows that the earlier work on machine learning-based analysis of LinkedIn data focused primarily on users' profiles aiming to understand people's skills and jobs and their interrelationships. None of the earlier works explored an AI-based approach to studying how LinkedIn media could be useful for journalism. None of the works has applied a journalism approach to LinkedIn to automatically extract and analyse big data to provide the public with information about labour markets; people's skills and education; and businesses and industries from multi-generational perspectives. The (deep) journalism approach and the use of LinkedIn media for journalism, the knowledge discovered on age dynamics in labour markets, the methodology of discovering parameters for labour markets, the extracted taxonomy, and the quantitative and descriptive analysis of age dynamics in labour markets, all these are novel contributions of our work. The approach could be extended with additional AI tools and other data sources.

3. Methodology

The purpose of this section is to explain the methodology and the design of the proposed architecture of the system. Figure 1 shows our software architecture, which is made up of four components, each of which will be discussed further in the following section.

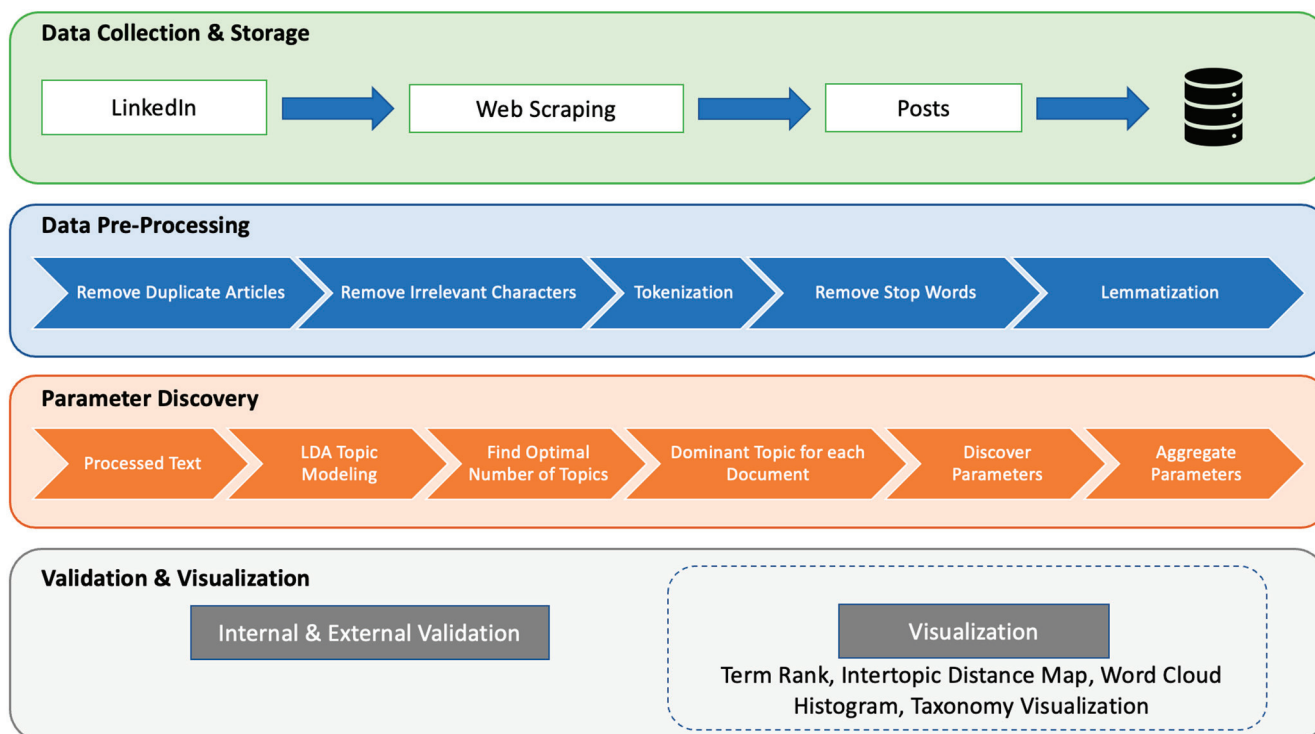


Figure 1. The System Architecture.

We first use a Web scraping technique to collect LinkedIn posts. Using a specified search query term, we collected the posts for our dataset. Post objects were collected as JSON (JavaScript Object Notation) objects. Then, we converted the JSON files into a CSV file. Afterwards, the CSV file is loaded and preprocessed with Pandas. We then

used LDA-based parameter discovery module by Gensim Python library (Řehůřek 2022). Using domain knowledge, we carried out quantitative analyses, categorised the clusters as parameters, and then grouped the parameters into macro-parameters. Finally, we visualised the parameters and macro-parameters. Additionally, internal, and external validation techniques were used to validate these parameters.

4. Implementation

The purpose of this section is to explain the implementation of the proposed architecture of the system. Sections 4.1–4.7 explain data collection, the sources of data we used in this study (LinkedIn); preprocessing; parameter modelling; parameter discovery and quantitative analysis; validation; and visualisation.

4.1. Data Collection

Since the multi-generational workforce is a topic related to multiple disciplines, an iterative process was utilised to determine the key search terms for the queries. An extensive literature review was conducted first to identify alternative synonyms used in the literature to refer to the multi-generational workforce. The final key terms used in the search query are listed in Table 1.

Table 1. Data Collection.

Source	Query	Posts
LinkedIn	Millennials, Gen Y, baby boomers, Generation Y, Generation X, Gen X, Gen Z, Generation Z, Alpha generation, multi-generation, Inter-generational, cross-generational, Employment, Unemployment, Middle Aged, Aged, Elderly, Young, Senior, Seniors, 20s, 30s, 40s, 50s, 60s, 70s, 80s, 90s, Ageism, Labourforce, Demographics, Workforce, Workplace, Workers, Retirement, Recruit, Aging, Leadership, Entrepreneur, Preschool Child, Child, Preschool, Infant, Children.	57 K

4.2. Dataset: Posts (LinkedIn)

LinkedIn (LinkedIn Corporation 2022) is one of the most widely used professional networking and social media sites in existence today. With over 850 million users, LinkedIn has become the go-to place for job seekers, businesses, and professionals to make connections, find new opportunities, and build their personal brand.

Since technologies and systems are constantly evolving, and new generations are entering the workforce, multigeneration workforce is changing the ways in which companies and organisations operate. Thus, non-personal information in LinkedIn posts could help us to make better decisions, understand, and analyse multi-generational workforces.

In this study, we collected our dataset from LinkedIn (posts). Thus, the LinkedIn website was obtained using web scraping techniques including Python (2022), BeautifulSoup (2022), Requests (2022), and Pandas (2022). The data was collected for a period of four months (March 2022–July 2022) using the search query terms listed Table 1. These posts are anonymised (aggregated) data, and we do not use personal information. Then, posts are saved in a CSV file, including around 57K posts. The CSV file includes two columns, the query term, and the post.

4.3. Data Preprocessing

The pre-processing steps are as follows: remove duplicate articles, and irrelevant characters, tokenize stop words, and lemmatize with POS tags, among other things. Pandas is a Python package that is used as the first step in reading the CSV file and saving it in a data frame (DF). A second step consisted of removing all redundant data and the third step consisted of eliminating all unnecessary characters, such as several Unicode characters. A simple preprocess function from the Python package “Gensim” was used in the fourth step to tokenize the texts. The fifth step was to eliminate the article’s stop words. Lemmatization was performed using Spacy (spaCy 2022) as the last step of data

pre-processing. As a result of preprocessing, the cleaned posts were obtained, which were then used in the LDA model.

4.4. Topic Modelling Using Unsupervised Machine Learning

In document analysis, topic modelling is a machine-learning technique for discovering topics from a set of documents (Wang et al. 2012). Topic modelling is used in various document analysis applications such as information filtering, retrieval, and semantic search. Topic modelling is also known as latent semantic analysis or latent topic analysis. This method learns the hidden themes in a body of text by analysing words and their variations appearing in different contexts.

We used Latent Dirichlet Analysis (LDA) (Maier et al. 2018), a topic modelling technique, in this research. The parameters of our LDA model were set to 15 topics, 10 passes, and 100 iterations. The number of topics is considered an essential model-building parameter. When the number of topics is great, the model must be overfitted, but when it is small, it must be under fitted. To determine the ideal topic model (optimal number of topics), we created many LDA models with varying topics (k) and chose the optimal number based on coherence measures and the visualisation of the LDA models. Passes refer to the number of times an algorithm must traverse the full corpus. The maximum number of iterations is required to determine the probability of each topic in the corpus.

4.5. Coherence Measures

Coherence scores (Röder et al. 2015) in the topic modelling are used to gauge the interpretability of a topic for humans. The topic coherence scores provide a comprehensive way to compare different topic models. It compares by capturing an optimal number of topics and assigning a number called 'Coherence Score' for the interpretability of those topics. Measuring the coherence of topics was studied recently to solve the issue of topic models not providing any guarantees about the interpretability of their output. The most widely used approaches for tuning the LDA hyperparameters are based on various topic coherence measures. In this study, we used four coherence measures: C_v measure, C_{uci} measure, C_{umass} measure, and C_{npmi} measure.

4.6. Parameter Discovery and Quantitative Analysis

We discover the parameters and macro-parameters using domain knowledge and quantitative analysis methods such as term scores, intertopic distance maps, and word clouds. The term scores for each parameter are visualised by sorting them in decreasing order. This term score visualisation greatly influences parameter identification. A two-dimensional intertopic distance map shows the parameters as parameter circles whose sizes correspond to the number of words used to describe the parameters in the dictionary. Word cloud is a graphical representation of words. Based on frequency and relevance, the famous words and phrases in the articles are highlighted through Word Cloud. It provides intuitive and quick graphical insight, which may lead to thorough analyses.

4.7. Validation and Visualization

Results can be validated internally and externally. Internal validation of a parameter involves investigating and discussing the posts related to the parameter. We discussed how we perceived the correlation between the documents and the parameters in most of the documents in our dataset. External validation is performed by comparing the knowledge and parameters gained from the analysis of the subject dataset with information from other datasets and information sources. For the visualisation, various visualisation methods are used for internal and external validation. Many visualisation methods are used to describe the datasets, the clusters of documents, and the parameters that have been discovered. These visualisations are created using several Python libraries, including LDAvis (Sievert and Shirley 2014), Plotly (2022), and Matplotlib (2022).

5. Parameter Discovery for Multi-Generational Labour Markets from LinkedIn

This section introduces and explains the parameters detected using our LDA model based on the LinkedIn dataset. These parameters are divided into five macro-parameters. Section 5.1 provides an overview of the parameters and macro-parameters. Section 5.2 gives the quantitative analysis of the parameters. The five macro-parameters are discussed in Sections 5.3–5.7.

5.1. Overview and Taxonomy

Using the LDA model, we detected 15 parameters in the LinkedIn dataset. We grouped these 15 parameters into 5 macro-parameters. We tried clustering the data with different number of clusters and decided to discover 15 clusters based on the coherence score (this will be discussed further in the next section) The LinkedIn dataset parameters and macro-parameters are listed in Table 2. In Column 1, the parameters are categorized into five macro-parameters: Generations-specific Issues, Skills and Qualifications, Employment Sectors, Consumer Industries, and Employment Issues. The second and third columns list the parameters and the cluster number, respectively. The fourth column shows the percentage of the keywords in each parameter. The fifth column displays the top keywords associated with each parameter.

Table 2. Parameters and macro-parameters of labour market from a multi-generational perspective.

Macro-Parameter	Parameter	No	%	Keywords
Generations-specific Issues	Crimes and Racism	10	3.3	Woman, Cancer, Child, Black, Abuse, State, White, Right, Skin, Cell, Legal, Body, Hospital, Police, History, Court, Japan, American, Medical, Infant.
	Leadership	2	16.1	Team, Community, Leadership, Opportunity, Event, Business, Support, Leaders, Student, Join, Future, School, Work, Programme, Great, People, Education, Young, Learn, Share.
Skills and Qualifications	Skills and Qualifications	13	2.2	Selection, Criteria, Professional, Qualifications, Relevant, Position, Work, Experience, Internships, Language, Skills, Salary, Hiring, Recruiter, Organization, Excellent, Communication, Ability Plan, Task.
	Family Business	3	12.8	Business, Company, Team, Experience, Management, Data, Customer, Skill, Work, Technology, Need, Role, Product, Client, Working, Manager, Project, Opportunity, Industry, Digital.
Business and Employment Sectors	Remote Work	7	3.5	Work, Employee, Remote, Working, LinkedIn, Podcast, Workplace, Office, Company, Culture, Worker, Comment, Week, Employer, Great, Article, Episode, Video, Hybrid, Read.
	Recruitment	8	3.3	Recruiter, Hire, Candidate, Experience, Senior, Looking, Resume, Apply, Recruitment, Manager, please, Recruit, Position, Years, Engineer, Share, Interest, Comment, Job, Year.
	Entrepreneurship	11	3.1	Startup, Founder, Investor, Tech, Web, Entrepreneur, Venture, Investment, Estate, Real, Innovation, Funding, Fintech, Capital, Ecosystem.
Consumer Industries	Brand Marketing	5	6.8	Brand, Market, Marketing, Medium, Social, Content, Consumer, Price, Growth, Rate, Product, Inflation, Increase, Year, Audience, Economy, Business, Interest, High, Generation.
	Energy Sector	9	3.3	Project, Energy, Design, Construction, Water, Engineering, Power, Plant, Space, Manufacturing, Building, Area, Production, Safety, Engineer, System, Material, Industry, Vehicle, Site.
	Celebrations and Events Industry	6	3.7	India, Award, Century, Africa, International, Food, Innovation, President, Country, Congratulations, Principal, South, City, Year, Global, National, Global, July, Holiday, Employee, Special.
	Retirement Industry	14	1.7	Retirement, Tax, Pension, Years, Old, Income, Retire, Plan, Age, Planning, Money, Insurance, Family, People, Hospital, Care, Health, Medical, Support, Physical.
	Entertainment Industry	12	2.6	Music, Game, Sport, Film, Song, Artist, Army, Play, Veteran, Fashion, Design, Player, Star, Millennial, Collection, Winner, Movie, Feature, Service.
Employment Issues	Mental Health	1	26.6	People, Time, Make, Life, Know, Like, Want, Work, Take, Would, Many, Need, Years, Love, Even, Come, Start, Help, Back, Could.
		4	9.4	Health, Care, Generation, People, Need, Population, Change, Woman, Child, Research, Mental, Aging, Boomer, Family, Increase, Impact, World, Community, Baby, Healthcare.

A taxonomy of the multigenerational workforce is shown in Figure 2. The parameters and macro-parameters found on LinkedIn posts are used to create the taxonomy. The macro-parameters are displayed on the first level branches, and the discovered parameters are displayed on the second level branches.

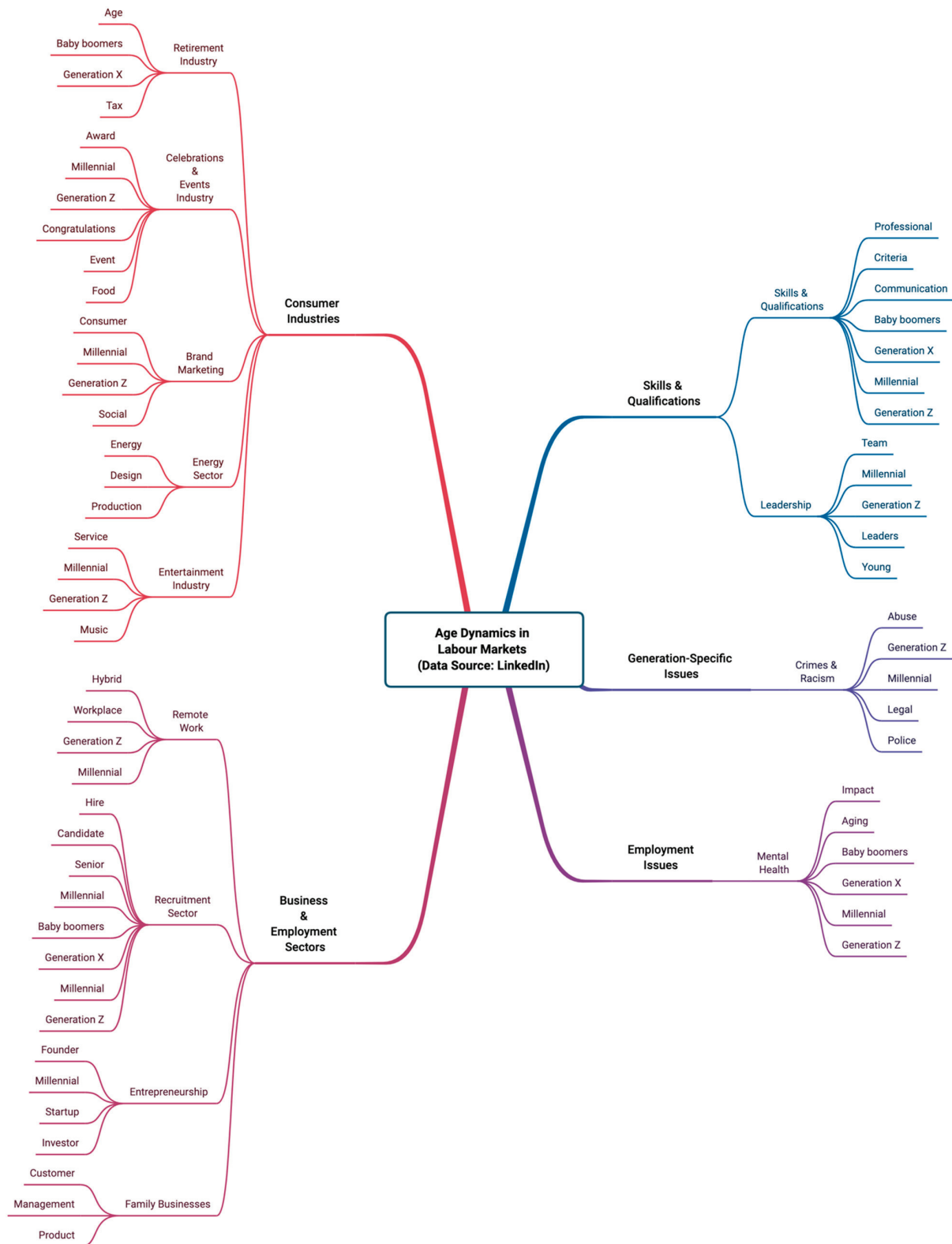


Figure 2. LinkedIn perspective taxonomy of the multi-generational labour market.

5.2. Quantitative Analysis

This Section discusses the coherence measures, intertopic distance map, and the number of posts on each topic. We have created the models using the Gensim LDA package. We have chosen different top models with the optimal number of topics based on the coherence measures. Table 2 presents the four different coherence measures employed to find the optimal number of topics. We have chosen the number of topics to be 15 since it has the best scores (highlighted in bold) in two different measures, as shown in Table 3.

Table 3. Coherence measures for selecting the optimal number of topics.

Dataset	Num Topics	Coherence Value	U_mass Value	C_uci Value	C_npmi Value
LinkedIn posts	10	0.538	−3.52	−0.23	0.049
	15	0.57	−3.204	0.067	0.071
	20	0.56	−3.939	−0.493	0.047
	25	0.582	−5.768	−1.877	−0.005
	30	0.558	−5.252	−1.494	0.008
	35	0.548	−5.83	−2.155	−0.015
	40	0.521	−7.29	−3.364	−0.077
	45	0.519	−6.643	−2.908	−0.05
	50	0.511	−7.119	−3.424	−0.076
	55	0.516	−7.796	−3.975	−0.097

Figure 3 shows the inter-topic distances and the most important words among the extracted 15 topics information. The intertopic distance map revealed the circles which represent the topics. The size of the circle is directly proportional to the topic's relevance. Generally, a good topic model will have significant, less overlapping circles throughout the chart. On the other hand, a poor topic model will have highly overlapping circles clustered in one quadrant.

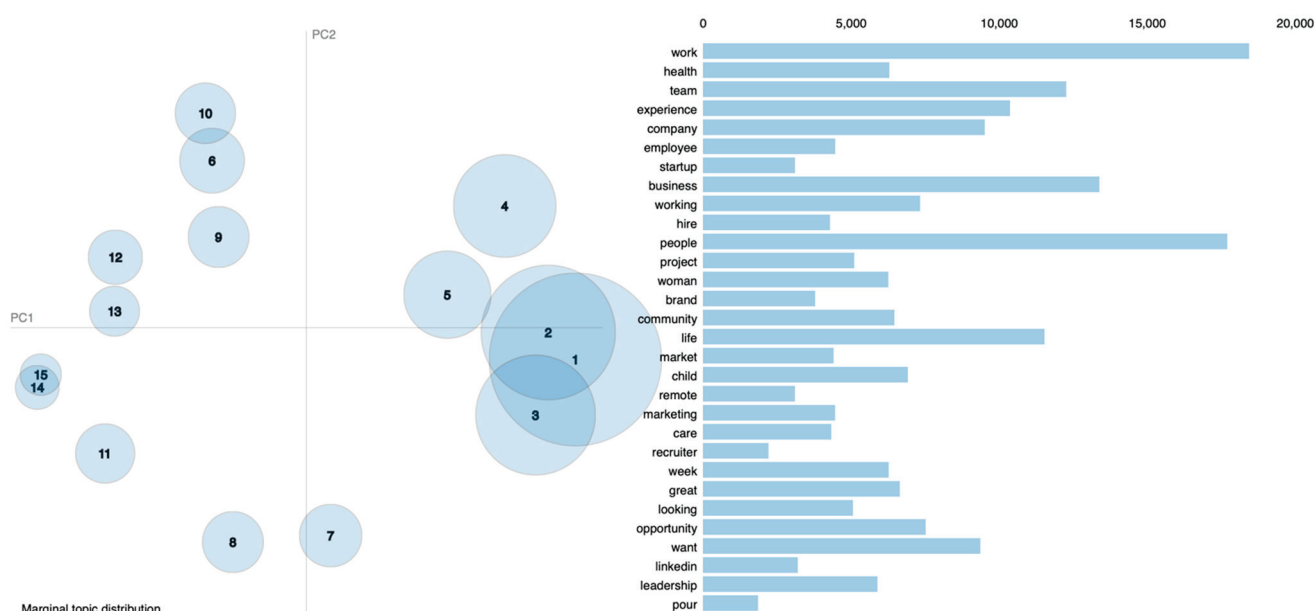


Figure 3. The intertopic distance map of the topics and the most important words.

Figure 4 shows the most relevant keywords that were detected by our LDA model in Topic 7 (Remote Work). The blue bars mean the overall term frequency while the red ones mean the estimated term frequency within the selected topic (Topic 7: Remote Work). Remote Work depicts the following keywords work, employee, remote, working, LinkedIn, podcast, workplace, office, company, culture, worker, comment, week, employer, great, article, episode, video, hybrid, and read.

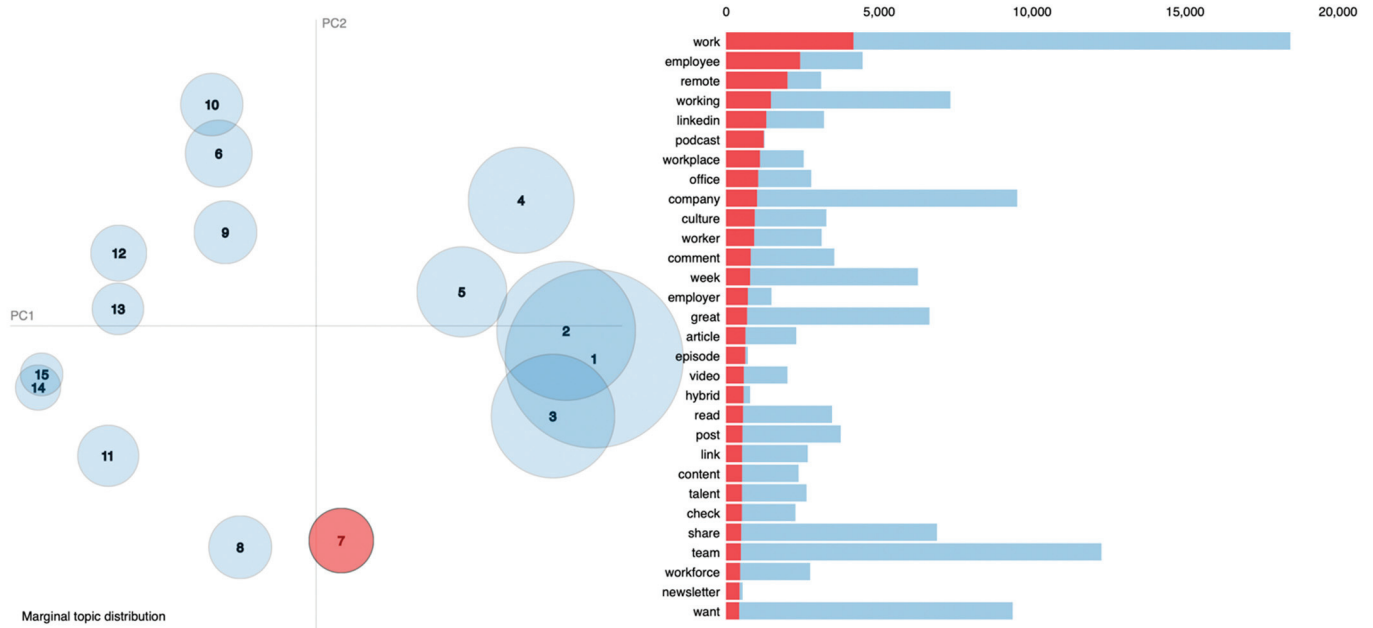


Figure 4. The top 30 relevant keywords in Topic 7 (Remote Work).

The histogram in Figure 5 shows the number of documents on each topic. The x -axis represents the number of a particular topic, while the y -axis depicts the number of documents on that topic. We have removed Topic 15 from the analysis since the majority of the posts in it are in different languages.

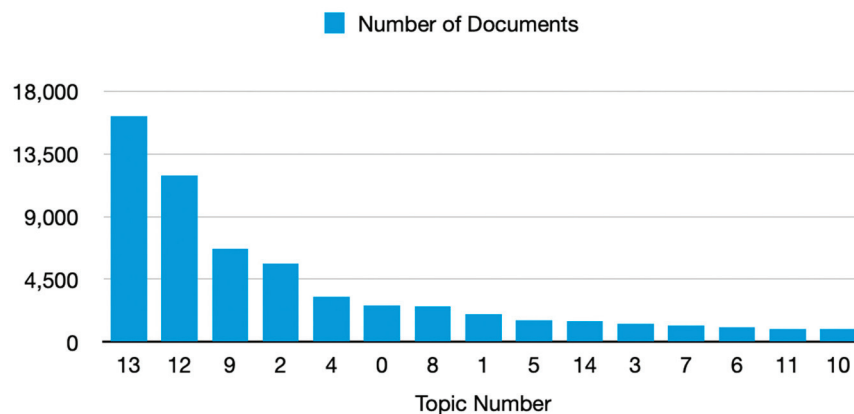


Figure 5. Number of posts in each topic (Source: LinkedIn).

Figure 6 shows the ten most important keywords for each parameter. Vertical lines indicate parameter keywords, and horizontal lines indicate importance score. The lightest blue color means the most important keyword while the darkest blue color means the least important.

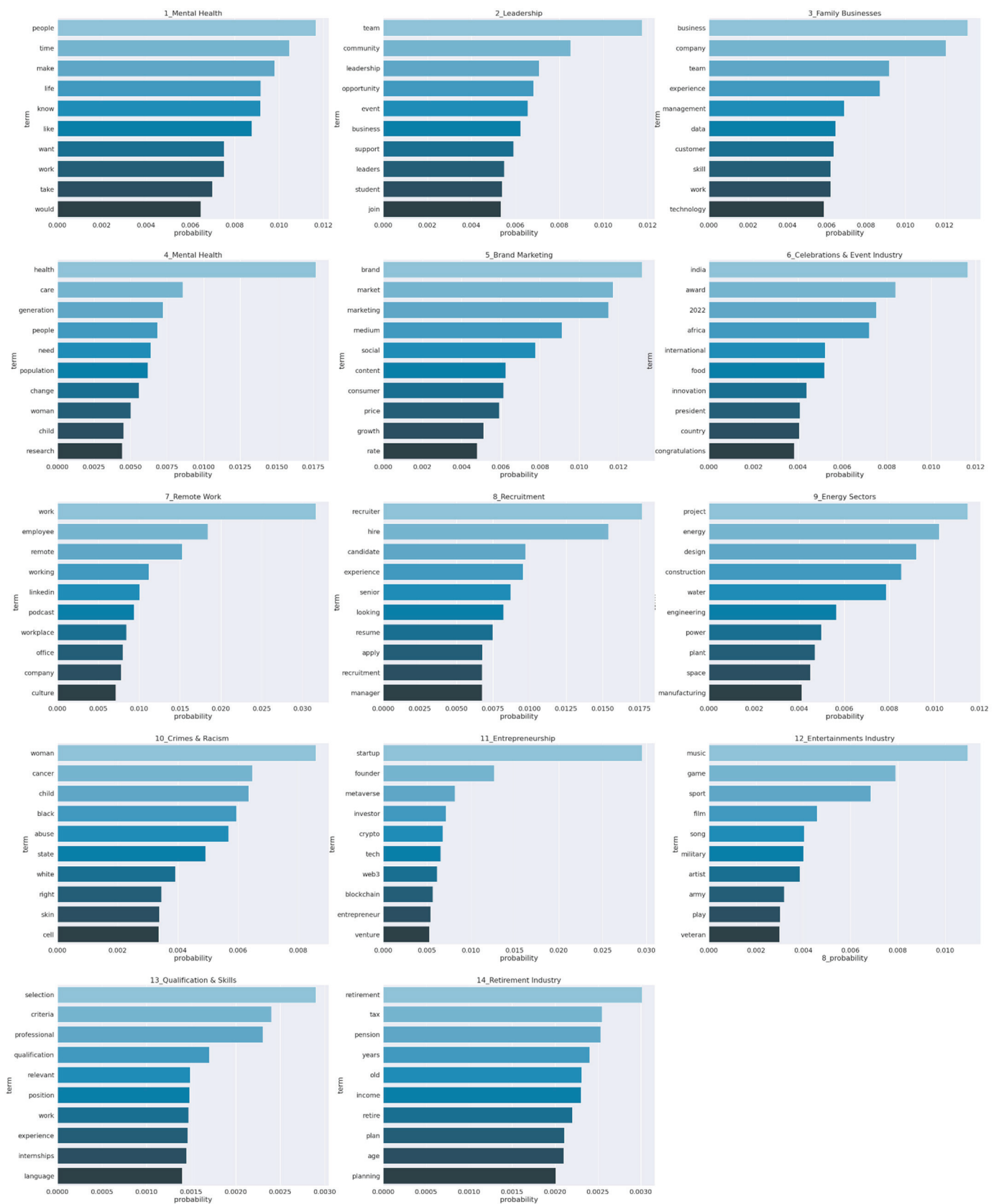


Figure 6. Term score.

5.3. Generation-Specific Issues

This macro-parameter has only one parameter; however, analysis of additional datasets in the future would likely discover additional parameters.

Crimes and Racism

The parameter Crimes and Racism contains keywords such as woman, child, black, abuse, state, white, right, skin, cell, legal, body, hospital, police, history, court, Japan, American, medical, and infant. Unemployed young people are often the victims of crimes, such as robberies and assaults. In some cases, young people are even the perpetrators of crimes. In other cases, young people may be homeless or have been evicted from their homes because they could not pay their rent or other bills.

This parameter admits a direct correlation between unemployed young people and crimes. As an example, this issue was discussed in the post *"The United States is home to more than four million , youth, young people ages 16 to 24 who are neither in education nor employment. These individuals are five times more likely to have a criminal record than their peers . . . "* (RISE 2022). Moreover, there is also a relationship between unemployment and anxiety and depression which leads to crime. The following post refers to this issue *"Long term unemployment, crime, family breakdown or homelessness usually originate from or relate to struggles with health, with anything from alcoholism to serious anxiety and depression . . . I advocated our objectives of ensuring we prevent crime and enable rehabilitation through more integrated mental health, substance misuse, help with learning needs and other support, so we can tackle the causes of crime."* (Thomas 2022).

This parameter also includes posts about racism at work which is the act of discrimination against someone based on their race. It can take many forms, including but not limited to, inappropriate racial jokes, cyberbullying, unconscious bias and prejudice, and unfair hiring practices. For instance, the following post, *" . . . ! The RARE (Racism and Racial experiences) workgroup at @Rice University has come up with this Emotional Labor Invoice . . . The next time someone micro-aggresses you based on your gender, orientation, race—feel free to drop them this invoice . . . "* (Harry 2022).

5.4. Skills and Qualifications

This macro-parameter comprises two parameters.

5.4.1. Leadership

The parameter Leadership includes keywords such as team, community, leadership, opportunity, event, business, support, leaders, student, join, future, school, work, programme, great, people, education, young, learn, and share. Leadership skills are the ability to influence others. They are a key part of success in business, and they are important for any successful person to have. One of the most important skills for a leader is being able to effectively communicate with others. That means being able to listen and understand what they are saying, and how they are feeling. For instance, a post mentioned, *"The leader's —job is to create such a space and make their employees feel free to express their opinions and ideas."* It also means being able to make decisions quickly and effectively, so that everyone feels heard and respected. Thus, our millennials and younger generations need to learn leadership skills before they supposedly "need" them. To learn about leadership, we need not wait until we become supervisors or managers. Teenagers and even younger people can be leaders. Therefore, school curriculums should include lessons on leadership and personal growth (Ong 2022).

The LinkedIn community also discussed opportunities to learn new skills through participation in workshops, team-building activities, or other programmes. For instance, a post mentioned, *"On today's episode of Being [at Work], Marketing Intern, Audrey Caron, provides a daily dose of leadership through the lens of Gen-Z."*

Multigeneration experiences through better leadership and management can create new income streams for the organisation. By creating a diverse group of workers trained

to be comfortable speaking in front of groups of people, first-time reality participants can become valuable contributors to the community through their leadership capabilities and experiences.

5.4.2. Skills and Qualifications

The parameter Skills and Qualifications includes keywords such as selection, criteria, professional, qualifications, relevant, position, work, experience, internships, language, skills, salary, hiring, recruiter, organisation, excellent, communication, ability plan, and task. The job skills and qualifications are used to identify specific job skills that are required to perform certain jobs. Skills are one of the most important factors for jobs. One of the most important skills for a job is being able to communicate with others in a way that is understandable and consistent across different generations. This is particularly important if the workplace has a multigenerational team environment where there are many people who may have different ages, skills, or experience. In addition, skills are very important for the young generations and for the future of the countries. The Education Fit for the Future in Wales report stated that “... *education and qualifications are crucial for different jobs in the future* ...” (Jones 2019). In addition, a post stated, “*Catherine Cain, Assistant Vice Principal and Careers Lead at All Saints’ Academy, Cheltenham explains how it is a priority for their curriculum and future education pathways to match the needs and skills required for the upcoming development*”. Furthermore, nowadays, programmes to provide skills to young generations become available as has been described: “... *Employment and skills for development in Africa (#E4D) have partnered to establish a landmark program to provide skills to young generations in technical training in renewable energy*” (WTS Energy 2022).

5.5. Business and Employment Sectors

5.5.1. Remote Work

The parameter Remote Work depicts the following keywords, work, employee, remote, working, LinkedIn, podcast, workplace, office, company, culture, worker, comment, week, employer, great, article, episode, video, hybrid, and read. Remote Work discusses how the workplace is changing. Many people are starting to embrace a “hybrid” or “remote” working model. This means working from home some days while also spending time in the office on other days. Others are choosing to work part-time or freelance. For instance, working and commuting from home has become a viable option for millennials and Gen Z. This is because technology is making the workday more flexible than ever. For example, someone mentioned, “... *This is the first fully remote company I have worked for, and this next chapter in my career is exciting* ...”. Moreover, according to a survey by Owl Labs (Labs 2020), “*Remote employees save an average of 40 minutes daily from commuting. Since 2020 people have been meeting by video calls 50% more since COVID-19. After COVID-19 92% of people surveyed expect to work from home at least 1 day per week and 80% expected to work at least 3 days from home per week. 23% of those surveyed would take a 10% pay cut to work from home permanently. People are saving on average close to 500 dollars per month being at home during COVID-19. Resulting in savings close to \$6000 per year. A mere 20–25% of companies are paying some of the cost for home office equipment and furnishings. 81% of those surveyed believe their employer will continue to support remote work after COVID-19. 59% of respondents said they would be more likely to choose an employer who offered remote work compared to those who didn’t* ...”.

5.5.2. Recruitment Sector

The parameter Recruitment includes keywords such as recruiter, hire, candidate, experience, senior, looking, resume, apply, recruitment, manager, please, recruit, position, years, engineer, share, interest, comment, job, and year. The recruiting world is constantly changing. Recruiters are required to possess more skills than ever before. To succeed in this competitive market, recruiters must be able to adapt and be flexible. One of the essential skills a recruiter can possess is interacting effectively with multigenerational candidates.

At the same time, the critical skills for multigenerational candidates are passion, teamwork, productivity, and commitment. Many different types of candidates make up the multi-generational workforce, including Gen Z, Millennials, Xers, and baby boomers. These candidates come from various backgrounds, but they have one thing in common: a desire to work in a team environment that allows them to be flexible and adaptable. For instance, someone mentioned the following issue: *“My role is focused on recruiting the next generation. However, I truly believe in a multi-generation workforce.”*. Furthermore, a report from the Organization for Economic Co-operation and Development (OECD) on Promoting an Age-Inclusive Workforce (OECD 2020) showcased how age inclusion can provide a competitive advantage and mentioned, *“The research projects that multi-generational workforces will be more efficient and productive, leading to a more profitable economy by raising per capita GDP by 19% over the next three decades . . . ”*.

5.5.3. Family Businesses

The parameter Family Business includes many keywords such as business, company, team, experience, management, data, and customer. The parameter includes posts about many types of businesses. Some of them are small, large, home-based, family, and franchise businesses. The most discussed type of business is family businesses. Successful, long-term family businesses are “generative” because they renew continuous luminosity across generations and have a good plan to survive. A post mentions, *“A very insightful article that highlights the importance of succession planning in family business . . . Transfer Your Family Business To The Next Generation With A Written Succession Plan”*.

Multigenerational families often initiate shared educational and philanthropic activities. Each family has a unique way of giving back to the community that reflects their family’s values and history. Family business histories and stories have been mentioned, such as *“There were so many great anecdotes to this family business story I couldn’t fit them all in . . . ”* (Roy 2022).

National Family Business Day has been mentioned too, which is a global movement that aims to raise awareness about the importance of inter-generational family in business and the importance of supporting family-run businesses. The day is celebrated on the first of January each year. A post mentions *“As four sisters running a successful inter-generational family business, we are proudly celebrating National Family Business Day 2021! Established in 1946 . . . ”* (Towbars 2022). Another post states, *“ . . . a Multi-Generation Family Business . . . learn how the family has grown, and continues to grow . . . ”* (Iron 2022).

5.5.4. Entrepreneurship

The parameter Entrepreneurship contains the following keywords: startup, founder, investor, tech, web, entrepreneur, venture, investment, estate, real, innovation, funding, fintech, capital, and ecosystem. Entrepreneurship is a broad term describing the act of starting a business. It can refer to starting a small business on one’s own, or it can refer to creating an innovative company with an idea that potential investors are willing to back. Entrepreneurship is often related to innovation, because it requires coming up with new ideas and solutions for existing problems. There are many different posts of entrepreneurship, including tech entrepreneurship, startup entrepreneurship, and venture entrepreneurship. Each type has its own set of requirements and challenges, but all entrepreneurs have one thing in common: a willingness to take risks. Entrepreneurs are also called “founders”. The Kauffman Foundation and Vivek Wadhwa (Meyers 2020) found that the average age of successful founders is 41.9. A post mentioned this report, *“ . . . Researchers found that the average age of a business founder in the United States is 41.9 years old. They discovered that older founders consistently had higher probabilities of success, at least until the age of sixty. A sixty-year-old start-up founder has a roughly three times higher chance of creating a valuable business than a thirty-year-old start-up founder . . . ”*.

Another issue that has been discussed is that talent is more important to some millennials than position. For instance, according to a recent survey conducted by the National

Venture Capital Association (NVCA 2019), the number of young people who are investing in venture capital has increased significantly in recent years. While many young people are not yet full-fledged entrepreneurs, they are beginning to see the benefits of starting their own businesses. The NVCA survey found that more than half of millennials (48%) are considering investing in their own business, compared to only 35% of baby boomers. While many people may not have the financial resources to start their own business, it is still a great way for them to start. Another issue that has been discussed is that talent is more important to some millennials than business.

On the other hand, baby boomers also have their own businesses. A post mentions, “250 k Baby Boomers own businesses . . . what is going to happen when they want to retire? . . . This provides a massive opportunity for young entrepreneurs” (Shiver 2022).

5.6. Consumer Industries

5.6.1. Brand Marketing

The parameter Brand Marketing is characterised by brand, market, marketing, medium, social, content, consumer, price, growth, rate, product, inflation, increase, year, audience, economy, business, interest, high, and generation. Digital marketing is the process of using digital platforms such as social media, blogs, and websites to communicate with customers and generate leads. The key to success for digital marketing for brands is to understand the needs of the target audience and create a brand that resonates with them. This includes understanding their demographics, interests, and likes/dislikes. Moreover, digital marketing can be a powerful tool for brands because it allows them to reach out to new audiences and engage with them through social media. By building relationships with new users, brands can build a following that drives more sales and growth. In addition, digital marketing can also help in keeping track of the customers’ progress on social media platforms like Facebook, Twitter, or Instagram. This gives businesses the opportunity to respond quickly if they need more information or updates about their products or services. Furthermore, digital marketing for the brands is the key to reaching Generation Z and future generations. These generations comprise some of the most voracious social media users. For example, someone mentioned, “ . . . *Physical advertising by billboards and banners never had the right appeal for generation Z. To market a product or service to them, digital marketing is the key. Brand marketing through platforms like Instagram, public forums, and chat groups is the new marketing strategy that works.*” (Gryffindor 2022).

5.6.2. Retirement Industry

The parameter Retirement contains keywords such as retirement, tax, pension, years, income, retire, plan, age, planning, and money. This parameter includes discussions on retirement issues and planning, which involves assessing the current financial situation, assessing future needs (financial, healthcare, etc.), and planning for an appropriate level of savings to support one’s post-work life. It also discussed the baby boomers’ situation. For instance, the number of adults over 65 will exceed the number of children in the country for the first time in 2023, according to the Bureau of Labor Statistics (U.S. Bureau of Labor Statistics 2022). Some other baby boomers’ retirement issues are mentioned below.

“Baby Boomers are moving into retirement and taking their hard-earned expertise with them, while younger workers are reluctant to even consider entering the field service industry. Those that are entering the industry face a growing skills gap that impacts costs and service . . . ”. (DeepHow 2022)

“The Boomer population is approaching retirement! You know what that means, the long-term care industry will be larger than it’s ever been. How can an already short, staffed industry provide for a growing market? Here are a few tips addressed to healthcare providers to best prepare for and effectively service this demographic . . . ”. (Leigeber 2022)

“It’s time to clear the boomers for takeoff . . . For any industry to thrive, it must value its people of all ages and generations. Beyond the friendly skies, pilots need an age-friendly

industry: one that continues to mandate safety while still valuing age and experience, retaining those pilots who have reached 65 but have still been found to be healthy enough to fly while parting ways with those who have not ... ". (Applewhite 2022)

"The baby boomers' great retirement has been forecasted for years and comes as no surprise. What makes it complicated is that the people retiring have years of experience and are typically in senior-level positions that can't be filled by new recruits. If you have a position that requires 15 years of experience, the only way to fill it is to give 15 years of experience. There's a problem that's been developing for years,". (Omar 2022)

5.6.3. Energy Sector

The parameter Energy Sector depicts keywords such as project, energy, design, construction, water, engineering, power, plant, space, manufacturing, building, area, production, safety, engineer, system, material, industry, vehicle, and site. The parameter is used to describe electricity production using a variety of technologies. Some technologies, such as steam boilers, are over 100 years old, while others, like wind turbines, are newer. There are also posts about hiring for power generation jobs. Below are some examples of posts that are related to Energy Sectors.

"Dear All, We are hiring for the below-mentioned positions with us, Apollo Power Systems is a 30-year-old company in the business of Power Generation ... ". (Kumar 2022)

"First, two facts:1. By 2030, 58.7 GW of renewables are expected to be connected to the Saudi power grid. That is approx. 50% of total installed generation capacity by then ... ". (Al-Awami 2022)

5.6.4. Celebrations and Events Industry

The Celebration parameter includes keywords detected by our LDA model such as award, international, food, innovation, president, country, congratulations, principal, south, city, year, global, national, global, and July. People share celebration posts about what they have learned with the other team or the community. Generally, these posts (Rafalski 2016; Canopus Group 2022) let everyone know about their work and achievements over the years, whether it is a new customer acquisition strategy, a product launch, or a new job promotion. Moreover, companies have a history of working with special employees and their families. For example, a company has worked with its team members to celebrate birthdays and work anniversaries. This is done by providing them with special items such as gift cards and other perks. Some companies also offer their employees a day off from work to celebrate birthdays and holidays. The company also provides employees with a day off from work during the month. Sometimes, they are offering them a free meal and other perks such as free drinks and free food at the end of the day. We list some of the posts below.

"On Friday I had the privilege of attending the 25-year anniversary party ... Although the focus was on celebration there were a few things that really resonated with me from the stories shared:—the positive impact from parents who have a strong work and family ethic and how this shapes kids from a young age- the beauty that is a business that has multi-generations of family working within it, the pride and drive that comes from a shared goal ... ". (Elouise 2022)

"... She is an instrumental part of our Benefits Eligibility & Enrollment Systems (BEES) Team, helping our clients with their eligibility needs and assisting with the training and development of the newer members of our team. She is a true team player, and we are SO lucky to have her on OUR team! Congratulations on your promotion and thanks for 8 great years ... ". (Catto 2022)

5.6.5. Entertainment Industry

The parameter Entertainment (Industry) includes keywords such as music, game, sport, film, song, millennial, artist, army, play, veteran, fashion, design, player, star, col-

lection, winner, movie, feature, and service. This parameter is related to discussions on different topics in media such as music, films, games, and movies. As an example, over the years all music has undergone tremendous changes. Thus, each generation has several songs that define it. Furthermore, a post mentions that millennials and Gen Z listen to music more than other generations *"According to data that Luminate shared with Axios. State of play: Americans born in the '90s and 2000s are listening to music from the decade they were born at higher rates than other generations listen to music from their birth decades, TikTok plays a role here. And those born in the '60s—'80s, have increased their music consumption over the past couple of years as the pandemic drove an increase in streaming . . . "* (Luminate 2022). In addition, music is a major expense for millennials and Generation Z. For instance, the Music in the Air (Ingham 2022) report discussed *"Millennials and Generation Z are spending more of their money on music than other age groups. I often say people put as much emotional value on music as just about anything and given that it remains highly undermonetized. Spending is 40% below its historical peak, but consumption grows every year. Emerging platforms (social, video games, podcasts) now represent almost 1/3 of the record industry's ad funded revenues and should grow to 40% by 2030 if not sooner . . . "* On the other hand, as a platform for influencer marketing, TikTok has quickly built a strong reputation between millennials and Gen Z. For example, someone discussed and posted *"Has the time come for me to be active on TikTok? It is clearly a dominant force in social media and marketing . . . An interesting discussion on how the ever-changing social media landscape is producing new roles and subsequent skill needs being filled by millennials."* (Wilson 2022).

5.7. Employment Issues

This macro-parameter has only one parameter; however, analysis of additional datasets in the future would likely discover additional parameters.

Mental Health

The parameter Mental Health includes keywords such as health, care, generation, people, need, population, change, woman, child, research, mental, ageing, boomer, family, increase, impact, world, community, baby, and healthcare. Mental health is a state of well-being in which an individual feels comfortable and confident. It can be affected by many factors, such as genetics, environment, age, and life experiences. The parameter has shown that mental health can be affected by various factors throughout the life cycle. For instance, how COVID affected our mental health (OX 2022). The most recognised stages of mental health are childhood, adolescence, and adulthood (Sharma 2022). However, the mental health of individuals can change throughout their lifetime. For instance, it has been mentioned that *"Young employees feel disconnected at work and home, and according to LinkedIn, 66% of Gen Z employees want a company culture built on mental health and wellness. Likewise, millennials have been pushing for better mental health benefits since joining the workforce . . . "* (Antonio 2022). In addition, someone mentioned podcasts such as *"Fitness for the Brain | On this edition of the Boomers Today podcast . . . "* which discuss how to combine brain training and physical training for better mental health after retirement (Metro 2022).

6. Discussion

Recent research on viral social networks, such as Twitter and Facebook, was intensive, and datasets are readily available. However, LinkedIn does not have a dataset gathering information (posts) perhaps because it is a design decision by the company or it is mainly for professionals and so it is not expected to grow as big as other social networks for journal public. Our study relies on LinkedIn as the data source for our study due to the nature of the study which focuses on labour markets involving professionals. The dataset was obtained using web scraping and social mining techniques.

In this paper, we applied our deep journalism approach to LinkedIn to automatically extract and analyse big data to provide the public with information about labour markets; people's skills and education; and businesses and industries from multi-generational per-

spectives. The case study focuses on a multigenerational workforce using LinkedIn posts. Specifically, we discovered 14 parameters using machine learning from LinkedIn posts using LDA algorithms and grouped them into 5 macro-parameters, namely, Generations-specific Issues, Skills and Qualifications, Employment Sectors, Consumer Industries, and Employment Issues. We developed a software tool from scratch for this work that implements a complete machine learning pipeline using the dataset.

The parameters discovered through AI-based journalism applied to LinkedIn media focused on many issues in labour markets. For instance, despite the benefits that remote work offers, it is important for millennials and future generations to understand the challenges that come with working from home and how to overcome them. One of the biggest challenges that working from home can pose is an increased risk of burnout. The nature of working in an office environment allows time for employees to decompress and recharge after a long day at work. Working from home does not offer this luxury, and as a result, employees often feel more pressure to be productive all the time. This can lead to burnout and high levels of stress, which can negatively impact health and wellbeing. To combat this, it is important to take breaks throughout the day. This will help to keep employees feeling refreshed and ready for another productive day at work. Furthermore, it is important to take care of mental health because it can affect the physical health as well as the relationships with other people. Adults and seniors should feel comfortable talking about their feelings with their friends and family members. Figure 7 shows a taxonomy of age dynamics in labour markets discovered by our tool.

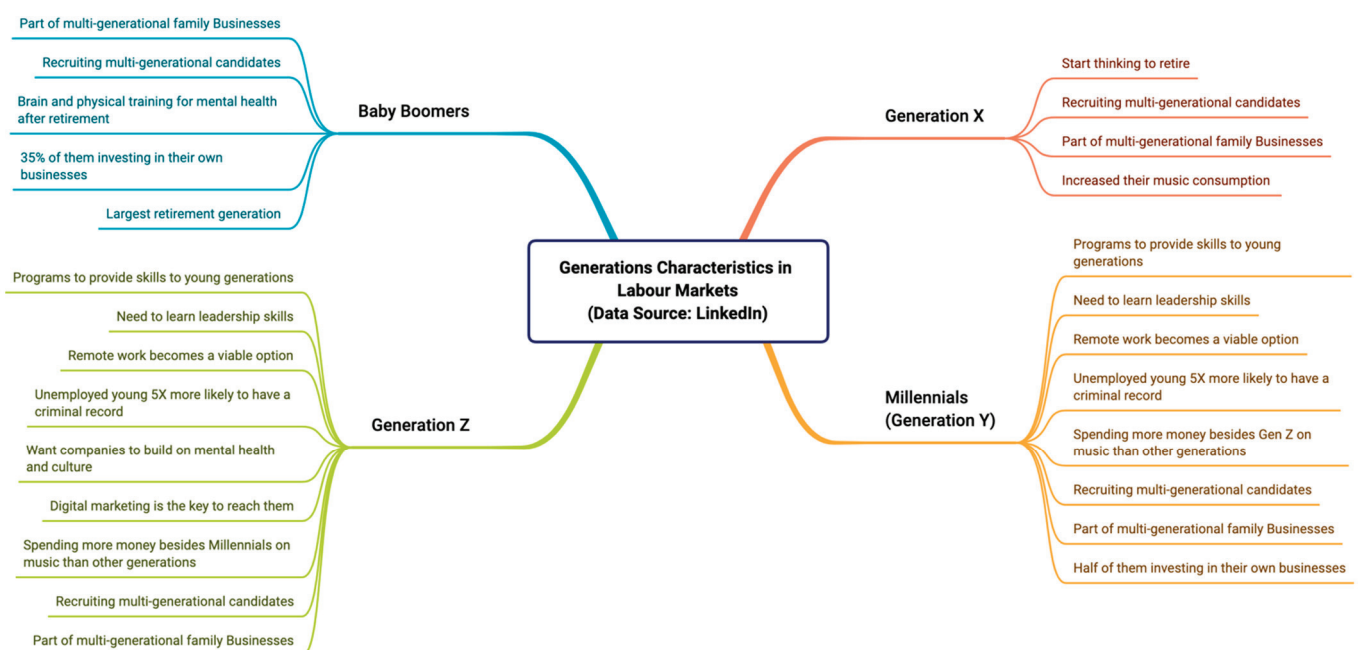


Figure 7. Different Generations in Labour Markets and Their Characteristics.

Another important issue that we discovered and discussed relates to hiring and retaining employees, which is becoming more difficult for organisations nowadays. While organisations can manage their workforce effectively, they may face challenges in hiring and retaining the right employees for their organisation. For example, multi-generational employees may be more likely to leave the organisation because of a lack of opportunities for advancement. Furthermore, it can be challenging to create a culture that is suited for all generations. To help with this situation, organisations may need to adjust their policies so that they are more inclusive of different generations in the workplace. This could include creating flexible work schedules, offering training programmes that are relevant to each employee's needs, and ensuring that communication is open between different generations.

We also discovered that baby boomers in their 50s and 60s are now retiring, and by 2023, there will be more retirees than children in the United States. This will have a huge impact on the workforce. A shrinking labour pool will drive the demand for employees higher, causing the cost of hiring and training a new worker to increase and the number of qualified applicants to decline. One solution is to bring in more retirees and offer them flexible, part-time scheduling options.

Additionally, we found that unemployed Youth (Gen Y and Gen Z) in America are five times more likely to have a criminal record. Moreover, racism issues occurring at work can have a serious impact on both the victim and the workplace. Victims may feel unwelcome or uncomfortable in their jobs, and they may lose respect for colleagues or coworkers. In addition, a racist environment can cause employees to distrust one another and discourage teamwork. In addition, racist attitudes may lead to lower productivity and turnover among employees.

Businesses are well-positioned to remain competitive in the 21st-century economy. This is because there is no specific age to become an entrepreneur. At any age, entrepreneurs can start small businesses on their own or work for established businesses. They can also look for ways to invest in startups or become involved in other types of entrepreneurial activities. However, entrepreneurs must be prepared for the many challenges that lie ahead. Furthermore, from a brand marketing perspective of the business, it was found that the new marketing theory adopted by digital marketing relies on modern digital technology and media to meet the needs of youth customers (Gen Y and Gen Z).

7. Conclusions

The social and economic situation around the world has agonized people. COVID-19, environmental disasters, geopolitical situations, and wars have exacerbated the economic and social situations throughout the world. The Great Resignation and Quiet Quitting phenomena coupled with rapidly changing generational attitudes are bringing unprecedented and uncertain changes to labour markets. In this paper, we introduced our data-driven deep journalism approach to LinkedIn media and applied it to discover age dynamics in multi-generational labour markets. We created a software tool for discovering parameters for age dynamics in labour markets using LinkedIn data. We collected a total of 57,000 posts from LinkedIn and used it to discover 15 parameters by LDA and grouped them into 5 macro-parameters, namely Generations-Specific Issues, Skills and Qualifications, Employment Sectors, Consumer Industries, and Employment Issues. We described the proposed approach and tool and discussed the discovered parameters in detail.

This work is part of our work on Deep Journalism, introduced by (Mehmood 2022; Ahmad et al. 2022), which uses machine and deep learning to gather and produce information and knowledge, design, and other parameters to provide a holistic and multi-perspective view of a sector and help bridge the knowledge and collaboration gaps that exist to reduce inefficiencies and failures. The deep journalism approach used in this paper can provide everyone with objective, cross-sectional, and multi-perspective information. It can improve the rigor of journalism by making it simple to generate information using machine and deep learning, and it can make tools and information available so that anyone can discover information about issues of public concern. The broad purpose of this work is to understand various topics of public concern and use this understanding and knowledge to create awareness of important issues and drive future research on this topic using cutting-edge technologies.

The knowledge and parameters discovered in this paper can be used to develop a better understanding of labour markets and labour economics, allowing academics, governments, industry, social enterprises, and other organisations to develop better theories and practices (policies, technologies, solutions, and industries), leading to stronger economies and labour markets, which in turn will strengthen societies around the world by embedding equality, sustainability, resilience, and opportunity.

In the future, we plan to extend the breadth and depth of this work with advanced deep-learning methods applied to different journalism problems, sectors, and media.

Author Contributions: Conceptualization, A.A.A. and R.M.; methodology, A.A.A. and R.M.; software, A.A.A.; validation, A.A.A. and R.M.; formal analysis, A.A.A. and R.M.; investigation, A.A.A., R.M. and F.A.; resources, R.M. and F.A.; data curation, A.A.A.; writing—original draft preparation, A.A.A. and R.M.; writing—review and editing, R.M. and F.A.; visualization, A.A.A.; supervision, R.M. and F.A.; project administration, R.M.; funding acquisition, R.M. All authors have read and agreed to the published version of the manuscript.

Funding: The authors acknowledge with thanks the technical and financial support from the Deanship of Scientific Research (DSR) at the King Abdulaziz University (KAU), Jeddah, Saudi Arabia, under Grant No. RG-11-611-38.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data used for this work can be made available to the public subject to data terms and conditions.

Acknowledgments: The work carried out in this paper is supported by the HPC Center at the King Abdulaziz University.

Conflicts of Interest: The authors declare no conflict of interest.

References

- Ahmad, Istiak, Fahad Alqurashi, Ehab Abozinadah, and Rashid Mehmood. 2022. Deep Journalism and DeepJournal V1.0: A Data-Driven Deep Learning Approach to Discover Parameters for Transportation. *Sustainability* 14: 5711. [CrossRef]
- Ahn, Yong Yeol, Seungyeop Han, Haewoon Kwak, Sue Moon, and Hawoong Jeong. 2007. Analysis of Topological Characteristics of Huge Online Social Networking Services. Paper presented at 16th International World Wide Web Conference, Banff, AB, Canada, May 8–12; pp. 835–44. [CrossRef]
- Alahmari, Nala, Sarah Alswedani, Ahmed Alzahrani, Iyad Katib, Aiiad Albeshri, and Rashid Mehmood. 2022. Musawah: A Data-Driven AI Approach and Tool to Co-Create Healthcare Services with a Case Study on Cancer Disease in Saudi Arabia. *Sustainability* 14: 3313. [CrossRef]
- Al-Awami, Ali. 2022. Energy Generation. Available online: https://www.linkedin.com/feed/update/urn:li:activity:6936573274046758912?updateEntityUrn=urn%3Ali%3Afs_feedUpdate%3A%28V2%2Curn%3Ali%3Aactivity%3A6936573274046758912%29 (accessed on 16 May 2022).
- Al-Ghazzi, Omar. 2014. 'Citizen Journalism' in the Syrian Uprising: Problematizing Western Narratives in a Local Context. *Communication Theory* 24: 435–54. [CrossRef]
- Allern, Sigurd, and Ester Pollack. 2019. Journalism as a Public Good: A Scandinavian Perspective. *Journalism* 20: 1423–39. [CrossRef]
- Alomari, Ebtesam, Iyad Katib, Aiiad Albeshri, Tan Yigitcanlar, and Rashid Mehmood. 2021. Iktishaf+: A Big Data Tool with Automatic Labeling for Road Traffic Social Sensing and Event Detection Using Distributed Machine Learning. *Sensors* 21: 2993. [CrossRef] [PubMed]
- Alomari, Ebtesam, Iyad Katib, and Rashid Mehmood. 2020. Iktishaf: A Big Data Road-Traffic Event Detection Tool Using Twitter and Spark Machine Learning. *Mobile Networks and Applications*. [CrossRef]
- Alotaibi, Shoayee, Rashid Mehmood, Iyad Katib, Omer Rana, and Aiiad Albeshri. 2020. Sehaa: A Big Data Analytics Tool for Healthcare Symptoms and Diseases Detection Using Twitter, Apache Spark, and Machine Learning. *Applied Sciences* 10: 1398. [CrossRef]
- Alqahtani, Eman, Nourah Janbi, Sanaa Sharaf, and Rashid Mehmood. 2022. Smart Homes and Families to Enable Sustainable Societies: A Data-Driven Approach for Multi-Perspective Parameter Discovery Using BERT Modelling. *Sustainability* 14: 13534. [CrossRef]
- Alruwaili, Fatimah, and Dimah Alahmadi. 2021. Enhanced Clustering-Based MOOC Recommendations Using LinkedIn Profiles (MR-LI). *International Journal of Advanced Computer Science and Applications* 12: 151–60. [CrossRef]
- Alswedani, Sarah, Rashid Mehmood, and Iyad Katib. 2022. Sustainable Participatory Governance: Data-Driven Discovery of Parameters for Planning Online and In-Class Education in Saudi Arabia During COVID-19. *Frontiers in Sustainable Cities* 4: 871171. [CrossRef]
- Alvares, Claudia, and Peter Dahlgren. 2016. Populism, Extremism and Media: Mapping an Uncertain Terrain. *European Journal of Communication* 31: 46–57. [CrossRef]
- American Press Institute. 2022. *What Is the Purpose of Journalism?* American Press Institute. Available online: <https://www.americanpressinstitute.org/journalism-essentials/what-is-journalism/purpose-journalism/> (accessed on 16 December 2022).
- Antonio, Vilson. 2022. Leadership Culture. Available online: https://www.linkedin.com/posts/vilsonsimonmba_leadership-culture-crestcom-activity-6950839548968939524-4uxr?utm_source=share&utm_medium=member_desktop (accessed on 1 July 2022).

- Applewhite, Ashton. 2022. Why the Number of Pilots Continues to Shrink Even as They're. Available online: <https://www.linkedin.com/feed/update/urn:li:activity:6946852778887569408?updateEntityUrn=urn%3Ali%3Afs%5Ctextunderscore%7B%7DfeedUpdate%3A%28V2%2Curn%3Ali%3Aactivity%3A6946852778887569408%29> (accessed on 16 August 2022).
- Beautifulsoup. 2022. BeautifulSoup4. Available online: <https://pypi.org/project/beautifulsoup4/> (accessed on 27 September 2022).
- Braun, Phillip. 2021. Top Economic Concerns For 2022—Growth Continues, But Risks Abound. Available online: <https://www.forbes.com/sites/phillipbraun/2021/11/30/top-economic-concerns-for-2022-growth-continues-but-risks-abound/?sh=41bc4f877179> (accessed on 15 December 2022).
- Canopus Group. 2022. Insurance. Available online: <https://www.linkedin.com/company/canopus/posts/?feedView=all> (accessed on 18 May 2022).
- Carlson, Matt. 2019. The Perpetual Failure of Journalism. *Journalism* 20: 95–97. [CrossRef]
- Carmichael, Victoria, Gavin Adamson, Kathleen C. Sitter, and Rob Whitley. 2019. Media Coverage of Mental Illness: A Comparison of Citizen Journalism vs. Professional Journalism Portrayals. *Journal of Mental Health* 28: 520–26. [CrossRef]
- Catto, Catto. 2022. Celebration. Available online: https://www.linkedin.com/posts/catto-and-catto-inc_lifethub-activity-6953691423636422657-uufg?utm_source=share&utm_medium=member_desktop (accessed on 16 July 2022).
- Dai, Kais, Ana Fernández Vilas, and Rebeca P. Díaz Redondo. 2018. The Workforce Analyzer: Group Discovery among LinkedIn Public Profiles. *Journal of Ambient Intelligence and Humanized Computing* 9: 2025–34. [CrossRef]
- Dai, Kais, Celia González Nespereira, Ana Fernández Vilas, and Rebeca P. Díaz Redondo. 2015. Scraping and Clustering Techniques for the Characterization of LinkedIn Profiles. *arXiv Preprint arXiv:1505.00989*. [CrossRef]
- DeepHow. 2022. How an AI Enabled Workforce Can Bridge The Skills Gap. Available online: https://www.linkedin.com/posts/deephow_how-an-ai-enabled-workforce-can-bridge-the-activity-6951892551498952704-QDz5/?utm_source=share&utm_medium=member_desktop (accessed on 29 August 2022).
- Domeniconi, Giacomo, Gianluca Moro, Andrea Pagliarini, Karin Pasini, and Roberto Pasolini. 2016. Job Recommendation from Semantic Similarity of LinkedIn Users' Skills. In Paper presented at ICPRAM 2016—Proceedings of the 5th International Conference on Pattern Recognition Applications and Methods, Rome, Italy, February 24–26; pp. 270–77. [CrossRef]
- Ellis, Lindsay, and Angela Yang. 2022. If Your Co-Workers Are 'Quiet Quitting,' Here's What That Means—WSJ. *The Wall Street Journal* August. Available online: <https://www.wsj.com/articles/if-your-gen-z-co-workers-are-quiet-quitting-heres-what-that-means-11660260608> (accessed on 20 November 2022).
- Elouise, Leonard-Cross Dr. 2022. Anniversary. Available online: https://www.linkedin.com/feed/update/urn:li:activity:6916486058566168576?updateEntityUrn=urn%3Ali%3Afs_feedUpdate%3A%28V2%2Curn%3Ali%3Aactivity%3A6916486058566168576%29 (accessed on 20 November 2022).
- Garg, Puneet, Rinkle Rani, and Sumit Miglani. 2016. Mining Professional's Data from LinkedIn. Paper presented at 2015 5th International Conference on Advances in Computing and Communications, ICACC, Kochi, India, September 3–5; pp. 98–101. [CrossRef]
- Giri, Animesh, Abhiram Ravikumar, Sneha Mote, and Rahul Bharadwaj. 2016. Vritthi—A Theoretical Framework for IT Recruitment Based on Machine Learning Techniques Applied over Twitter, LinkedIn, SPOJ and GitHub Profiles. Paper presented at 2016 International Conference on Data Mining and Advanced Computing, SAPIENCE, Ernakulam, India, March 16–18; pp. 1–7. [CrossRef]
- Gjurković, Matej, Mladen Karan, Iva Vukojević, Mihaela Bošnjak, and Jan Snajder. 2021. PANDORA Talks: Personality and Demographics on Reddit. Paper presented at Ninth International Workshop on Natural Language Processing for Social Media, Online, June 10; pp. 138–52. [CrossRef]
- Goodwin, Matthew J. 2012. *Right Response: Understanding and Countering Populist Extremism*. London: The Royal Institute of International Affairs, Chatham House. Available online: <https://kar.kent.ac.uk/54401/> (accessed on 29 November 2022).
- Gryffindor. 2022. Digital Marketing Academy. Available online: https://www.linkedin.com/posts/gryffindor-academy_gryffindor-gryffindordigitalmarketin-digitalacademy-activity-6813709201924251648-tn6N/?trk=public_profile_like_view&originalSubdomain=in (accessed on 20 November 2022).
- Haghighi, N. Nima, Xiaoyue Cathy Liu, Ran Wei, Wenwen Li, and Hu Shao. 2018. Using Twitter Data for Transit Performance Assessment: A Framework for Evaluating Transit Riders' Opinions about Quality of Service. *Public Transport* 10: 363–77. [CrossRef]
- Harry, Ven. 2022. Racism. Available online: https://www.linkedin.com/posts/harryven_race-microaggression-racism-activity-6871294625328455680-BNic/?utm_source=share&utm_medium=member_desktop (accessed on 4 January 2022).
- Herman, Edward S., and Noam Chomsky. 1988. *Manufacturing Consent: The Political Economy of the Mass Media*. New York: Pantheon Books. Available online: <https://worldcat.org/title/17877574> (accessed on 26 October 2022).
- Ingham, Tim. 2022. The Global Music Industry Is Going to Be Worth Even MORE than We Thought. Available online: <https://www.musicbusinessworldwide.com/goldman-sachs-global-music-industry-is-going-to-be-worth-even-more-than-we-thought/> (accessed on 13 June 2022).
- Iron, Maguire. 2022. Multi-Generation Family Business. Available online: https://www.linkedin.com/posts/maguire-iron_httpsmaguireironcom20220623multi-generation-family-business-activity-6946122394247843841-O5wj?utm_source=share&utm_medium=member_desktop (accessed on 20 November 2022).
- Jones, Calvin. 2019. Fit for the Future Education in Wales. *Journal of Physics A: Mathematical and Theoretical* 44: 8.

- Kalish, Ira. 2022. Global Weekly Economic Update | Deloitte Insights. Available online: <https://www2.deloitte.com/us/en/insights/economy/global-economic-outlook/weekly-update.html> (accessed on 20 November 2022).
- Karami, Amir, Morgan Lundy, Frank Webb, and Yogesh K. Dwivedi. 2020. Twitter and Research: A Systematic Literature Review through Text Mining. *IEEE Access* 8: 67698–717. [CrossRef]
- Kumalasari, Latifah Diah, and Ajib Susanto. 2020. Recommendation System of Information Technology Jobs Using Collaborative Filtering Method Based on LinkedIn Skills Endorsement. *Sisforma* 6: 63. [CrossRef]
- Kumar, Sunil. 2022. Hiring for the Positions. Available online: https://www.linkedin.com/posts/sunil-kumar-a-319b9338_dear-all-we-are-hiring-for-the-below-mentioned-activity-6944903705229950977-YXgj/?utm_source=share&utm_medium=member_desktop (accessed on 20 November 2022).
- Labs, Owl. 2020. State of Remote Work 2020. Available online: <https://resources.owl Labs.com/state-of-remote-work/2020> (accessed on 20 November 2022).
- Leigeber, Alex. 2022. Healthcare. Available online: https://www.linkedin.com/posts/alex-leigeber-798876a2%5Ctextunderscore%7B%7Dltc-healthcare-postacute-activity-6943573833635311616-44BN/?utm_source=share&utm_medium=member_desktop (accessed on 20 November 2022).
- Li, Shan, Baoxu Shi, Jaewon Yang, Ji Yan, Shuai Wang, Fei Chen, and Qi He. 2020. Deep Job Understanding at LinkedIn. In Paper presented at SIGIR 2020—Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval, Xi'an, China, July 25–30; pp. 2145–48. [CrossRef]
- LinkedIn Corporation. 2022. LinkedIn HomePage. Available online: www.linkedin.com (accessed on 20 December 2022).
- Luminate. 2022. 90s Is the Most Popular Decade for Music Right Now across Generations. Available online: https://www.linkedin.com/posts/luminatedata_90s-is-the-most-popular-decade-for-music-activity-6952627624011546624-fKX3?utm_source=share&utm_medium=member_desktop (accessed on 20 November 2022).
- Maier, Daniel, A. Waldherr, P. Miltner, G. Wiedemann, A. Niekler, A. Keinert, B. Pfetsch, G. Heyer, U. Reber, T. Häussler, and et al. 2018. Applying LDA Topic Modeling in Communication Research: Toward a Valid and Reliable Methodology. *Communication Methods and Measures* 12: 93–118. [CrossRef]
- Martínez-Rojas, María, María del Carmen Pardo-Ferreira, and Juan Carlos Rubio-Romero. 2018. Twitter as a Tool for the Management and Analysis of Emergency Situations: A Systematic Literature Review. *International Journal of Information Management* 43: 196–208. [CrossRef]
- Matplotlib. 2022. Matplotlib—Visualization with Python. Available online: <https://matplotlib.org> (accessed on 13 May 2022).
- Mehmood, Rashid. 2022. ‘Deep Journalism’ Driven by AI Can Aid Better Government. *The Mandarin*. Available online: <https://www.themandarin.com.au/201467-deep-journalism-driven-by-ai-can-aid-better-government/> (accessed on 20 December 2022).
- Metro, Boise. 2022. Senior Care Authority. Available online: <https://www.linkedin.com/company/senior-care-authority-boise-metro-area/> (accessed on 20 June 2022).
- Meyers, Kerby. 2020. Entrepreneurs of a Certain Age, in This Uncertain Time. Available online: <https://www.kauffman.org/currents/entrepreneurs-of-a-certain-age-uncertain-time/> (accessed on 5 August 2020).
- Microsoft. 2021. The Next Great Disruption Is Hybrid Work—Are We Ready? Available online: <https://www.microsoft.com/en-us/worklab/work-trend-index/hybrid-work> (accessed on 15 January 2022).
- Mislove, Alan, Massimiliano Marcon, Krishna P. Gummadi, Peter Druschel, and Bobby Bhattacharjee. 2007. Measurement and Analysis of Online Social Networks. Paper presented at ACM SIGCOMM Internet Measurement Conference, IMC’07, San Diego, CA, USA, October 24–26; pp. 29–42. [CrossRef]
- Mutsavairo, Bruce, and Susana Salgado. 2022. Is Citizen Journalism Dead? An Examination of Recent Developments in the Field. *Journalism* 23: 354–71. [CrossRef]
- Nah, Seungahn, and Deborah S. Chung. 2020. *Understanding Citizen Journalism as Civic Participation*. New York: Imprint Routledge. [CrossRef]
- Nguyen, Quynh T., Raouf N. G. Naguib, and Michael Loo. 2021. Towards Emotional Intelligence: Analysis of Static Facial Features in LinkedIn Profile Pictures. Paper presented at 2021 International Conference on Computational Performance Evaluation, ComPE, Shillong, India, December 1–3; pp. 399–403. [CrossRef]
- NVCA. 2019. NVCA-Deloitte Human Capital Survey Report. pp. 1–23. Available online: <https://nvca.org/research/nvca-deloitte-human-capital-survey/> (accessed on 22 December 2022).
- OECD. 2020. Promoting an Age-Inclusive Workforce: Living, Learning and Earning Longer. pp. 1–159. Available online: <https://www.oecd.org/els/promoting-an-age-inclusive-workforce-59752153-en.htm> (accessed on 16 December 2022).
- Omar, Mohamed. 2022. Baby Boomers: Labour Shortages and Recruitment. Available online: https://www.linkedin.com/posts/mohameadomar_babyboomers-labourshortages-recruitment-activity-6934818879529521152-vOHZ/?utm_source=share&utm_medium=member_desktop (accessed on 20 November 2022).
- Ong, Kian-Ming. 2022. Leadership. Available online: https://www.linkedin.com/posts/imokman_earlier-this-year-when-i-thought-that-i-activity-6835423815410040832-G0uC/?utm_source=share&utm_medium=member_desktop (accessed on 20 November 2022).
- OX (University of Oxford). 2022. *We Studied How COVID Affects Mental Health and Brain Disorders Up*. Oxford: University of Oxford.
- Pandas. 2022. Python Data Analysis Library. Available online: <https://pandas.pydata.org/> (accessed on 20 November 2022).
- Plotly. 2022. Low-Code Data App Development. Available online: <https://plotly.com/> (accessed on 20 December 2022).

- Purwono, Alfian Ma'Arif, and Amanah Wulandari. 2021. Face Shape-Based Physiognomy in LinkedIn Profiles with Cascade Classifier and K-Means Clustering. Paper presented at International Conference on Electrical Engineering, Computer Science and Informatics (EECSI), Banda Aceh, Indonesia, October 20–21; pp. 347–53. [CrossRef]
- Python. 2022. Welcome to Python.Org. Available online: <https://www.python.org> (accessed on 20 December 2022).
- Rafalski, Natacha. 2016. Disney CastLife Celebration. Available online: https://www.linkedin.com/posts/natacha-rafalski-0093735_castlifeday-castlifeday-disneycastlife-activity-6967786790728433665-vcEy/?utm_source=share&utm_medium=member_desktop (accessed on 17 August 2022).
- Raza, Syed Hassan, Ogadimma C. Emenyeonu, Muhammad Yousaf, and Moneeba Iftikhar. 2022. Citizen Journalism Practices during COVID-19 in Spotlight: Influence of User-Generated Contents about Economic Policies in Perceiving Government Performance. *Information Discovery and Delivery* 50: 142–54. [CrossRef]
- Řehůřek, Radim. 2022. Gensim. Available online: <https://radimrehurek.com/project/gensim/> (accessed on 20 May 2022).
- Requests. 2022. Requests. Available online: <https://pypi.org/project/requests/> (accessed on 20 December 2022).
- RISE. 2022. Employers like Ben & Jerry. Available online: <https://www.linkedin.com/feed/update/urn:li:activity:6938504786598117377?updateEntityUrn=urn%3Ali%3Afs%5Ctextunderscore%7B%7DfeedUpdate%3A%28V2%2Curn%3Ali%3Aactivity%3A6938504786598117377%29> (accessed on 20 December 2022).
- Röder, Michael, Andreas Both, and Alexander Hinneburg. 2015. Exploring the Space of Topic Coherence Measures. In Paper presented at WSDM 2015—Proceedings of the 8th ACM International Conference on Web Search and Data Mining, Shanghai, China, January 31–February 6; pp. 399–408. [CrossRef]
- Roy, Furchgott. 2022. The Pralines, Pecan Log Rolls and Nostalgia Fueling the Stuckey. Available online: https://www.linkedin.com/posts/roy-furchgott-3a31261_the-pralines-pecan-log-rolls-and-nostalgia-activity-6941375348957724672-vjso?utm_source=share&utm_medium=member_desktop (accessed on 20 December 2022).
- Sharma, Aastha. 2022. Mental Health Awareness. Available online: <https://www.risely.me/how-to-manage-multiple-generations-in-the-workforce/> (accessed on 27 November 2022).
- Shiver, Matthew. 2022. Business Entrepreneur Investing. Available online: https://www.linkedin.com/posts/dr-matthew-shiver-business-entrepreneur-investing-activity-6958090396623134720-92GN?utm_source=share&utm_medium=member_desktop (accessed on 20 December 2022).
- Sienkiewicz, Matt. 2014. Start Making Sense: A Three-Tier Approach to Citizen Journalism. *Media, Culture & Society* 36: 691–701. [CrossRef]
- Sievert, Carson, and Kenneth E Shirley. 2014. *LDavis: A Method for Visualizing and Interpreting Topics*. Stroudsburg: Association for Computational Linguistics, pp. 63–70.
- spaCy. 2022. SpaCy—Natural Language Processing in Python. Available online: <https://spacy.io> (accessed on 20 December 2022).
- Sull, Donald, Charles Sull, and Ben Zweig. 2022. Toxic Culture Is Driving the Great Resignation. *MIT Sloan Management Review*. January. Available online: <https://sloanreview.mit.edu/article/toxic-culture-is-driving-the-great-resignation/> (accessed on 20 December 2022).
- Suma, Sugimiyanto, Rashid Mehmood, and Aiiad Albeshri. 2020. Automatic Detection and Validation of Smart City Events Using HPC and Apache Spark Platforms. In *Smart Infrastructure and Applications: Foundations for Smarter Cities and Societies*. Berlin/Heidelberg: Springer, pp. 55–78. [CrossRef]
- Thomas, McNeil. 2022. Health and Safe. Available online: <https://www.linkedin.com/feed/update/urn:li:activity:6955116185893924864?updateEntityUrn=urn%3Ali%3Afs%5Ctextunderscore%7B%7DfeedUpdate%3A%28V2%2Curn%3Ali%3Aactivity%3A6955116185893924864%29> (accessed on 20 December 2022).
- Tobi, Siti Noraini Mohd, Siti Noorsuriani Ma'on, and Norfazlina Ghazali. 2013. The Use of Online Social Networking and Quality of Life. Paper presented at 2013 International Conference on Technology, Informatics, Management, Engineering and Environment, TIME-E, Bandung, Indonesia, June 23–26; pp. 131–35. [CrossRef]
- Towbars, Allin. 2022. Family Business. Available online: https://www.linkedin.com/posts/allin-towbars_allin-towbars-towingaccessories-activity-6844446344803946496-tmgN?utm_source=share&utm_medium=member_desktop (accessed on 20 December 2022).
- U.S. Bureau of Labor Statistics. 2022. *Labor Statistics*. Available online: <https://www.bls.gov> (accessed on 20 December 2022).
- UN News. 2019. A Free Press Is 'Cornerstone' for Accountability and 'Speaking Truth to Power': Guterres. Available online: <https://news.un.org/en/story/2019/05/1037741> (accessed on 20 December 2022).
- UN News. 2022. Social Media Poses 'Existential Threat' to Traditional, Trustworthy News: UNESCO. Available online: <https://news.un.org/en/story/2022/03/1113702> (accessed on 20 December 2022).
- Wall, Melissa. 2015. Citizen Journalism. *Digital Journalism* 3: 797–813. [CrossRef]
- Wang, Yu, Eugene Agichtein, and Michele Benzi. 2012. TM-LDA: Efficient Online Modeling of Latent Topic Transitions in Social Media. Paper presented at ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Beijing, China, August 12–16; pp. 123–31. [CrossRef]
- Wilson, Raj. 2022. TikTok Classes Might Be the next Big Thing in Education. Available online: https://www.linkedin.com/posts/rajwilson2009_tiktok-classes-might-be-the-next-big-thing-activity-6938254168537071616-rC8r?utm_source=share&utm_medium=member_desktop (accessed on 20 December 2022).

- World Economic Forum. 2022. Great Resignation Not over: 20% of Workers Will Quit in 2022. Available online: https://www.weforum.org/agenda/2022/06/the-great-resignation-is-not-over/?utm_source=linkedin&utm_medium=social_video&utm_term=1_1&utm_content=26751_country_planning_quit&utm_campaign=social_video_2022 (accessed on 20 December 2022).
- WTS Energy. 2022. Training Young Generations in Renewable Energy. Available online: https://www.linkedin.com/posts/wts-energy-official_training-young-generations-in-renewable-energy-activity-6957649973614145536-bPAy/?utm_source=share&utm_medium=member_desktop (accessed on 20 December 2022).
- Zeng, Xin, Savyasaachi Jain, An Nguyen, and Stuart Allan. 2019. New Perspectives on Citizen Journalism. *Global Media and China* 4: 3–12. [CrossRef]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.

Article

Media Self-Regulation in the Use of AI: Limitation of Multimodal Generative Content and Ethical Commitments to Transparency and Verification

Pilar Sánchez-García ¹, Alba Diez-Gracia ¹, Ignacio Repilado Mayorga ¹ and Pedro Jerónimo ^{2,*}

¹ Department of Modern, Contemporary, American History and Journalism, University of Valladolid, 47011 Valladolid, Spain; pilar.sanchez@uva.es (P.S.-G.); alba.diez.gracia@uva.es (A.D.-G.); nachorepmay@pronton.me (I.R.M.)

² LabCom, Department of Communication, Philosophy and Politics, University of Beira Interior, 6201-001 Covilhã, Portugal

* Correspondence: pj@ubi.pt

Abstract: The expansion of the use of artificial intelligence (AI) across different stages of production and distribution in journalism is opening a debate on its applications within newsrooms and in business models. This research studies how different media outlets, media groups and institutions are beginning to create internal regulations for the use of AI, both from a technical and an ethical perspective. To do so, an international sample (N = 45) of editorial stylebooks and internal self-regulatory guidelines published between 2023 and early 2025 have been compiled—all links are openly available here—and put through a process of content analysis. The results indicate that the self-regulatory guidelines emerge from an individual initiative of the media themselves, with a focus on limiting the use of generative AI, particularly in text creation. The guidelines emphasize ethical commitments such as transparency, content verification, and respect for data and copyright while underlining the importance of human oversight. Key objectives include avoiding bias, ensuring information quality, and strengthening audience trust. Despite progress, regulation remains in its early stages and requires continuous adaptation to keep pace with technological advancements.

Keywords: AI; automated journalism; artificial intelligence; digital journalism; ethics; generative AI; self-regulation; style books; transparency; verification

1. Introduction

While there are studies exploring the adoption of AI in journalism, few address, in detail, how news organizations have developed internal guidelines for the self-regulation of AI use. This study seeks to fill this gap by investigating emerging self-regulatory practices with a focus on transparency, human oversight, and ethical management of AI. This gap is addressed through the analysis of 45 recently published guidelines and style manuals, allowing for a comprehensive understanding of current self-regulation practices.

After seven decades of development, artificial intelligence (AI) has recently entered the mainstream with accessible tools like Chat-GPT (Pavlik, 2023). AI's ability to process algorithms, learn from data, and perform tasks with or without human oversight (Rouhiainen, 2018) has given rise to two models: analytical and generative. Although the two are related, their differences lie in the capabilities and applications required of each. Generative AI is capable of creating multimodal content (Feuerriegel et al., 2023) and is especially used in the creation of text, images, videos, music, etc., whereas analytical

AI focuses on data analysis and decision making based on that data (Lim et al., 2023; Jiménez Martínez et al., 2025) and is used in the identification of patterns and prediction of results (Codina, 2024).

AI's applications span various sectors, including journalism, where it supports processes from data collection to automated content creation and personalized dissemination (Túñez-López et al., 2021; Sánchez-García et al., 2023). Described as 'automated journalism' or 'robojournalism' (Caswell & Dörr, 2018; Latar, 2018), AI addresses growing user demands (Canavilhas & Giacomelli, 2023).

In the professional field, the implementation of AI in newsrooms has barely been in development for a decade. It began in an experimental way with examples such as the use of Quakebot for *The Los Angeles Times* with an earthquake alert in 2014, and the automation of content with AI baptized as Heliograf in *The Washington Post* in 2016 (Flores-Vivar, 2020). Since then, different national and local media have been introducing experimentation in a progressive way, although with limitations and even some distrust in companies (Sánchez-García et al., 2023), especially because of the challenges that still represent the generation of automated content in terms of errors of the so-called 'hallucinations' of AI, copyright, the need for verification and issues of lack of transparency. However, despite the fact that some of its risks must be constantly assessed, the effectiveness of generative AI has already been demonstrated in newsrooms, such as in some documentation work; in the creation of economic content, sports content (Segarra-Saavedra et al., 2019), and electoral content, such as the case of RTVE in Spain; in the organization of data (Biswal & Gouda, 2020) or even in the creation of avatars and synthetic products. Its usefulness is being routinely demonstrated in specific automatable tasks such as audio-to-text transcription, summary generation, automatic translation, audiovisual editing, metadata or documentation (Lopezosa et al., 2024), besides audiovisual editing, social media management, trend analysis and content distribution, among other repetitive tasks that can leave more room for creativity to the journalist. It is confirmed that the use of AI in an integrated way throughout the journalistic process is possible (Sánchez-García et al., 2023).

From an academic research point of view, a debate has arisen, highlighting both the benefits of AI for journalism and its associated risks. Different academic studies highlight three main benefits of the use of AI in newsrooms: the ability to increase the accuracy and verification of content (Sandoval Martín et al., 2019), reduce work time and costs (Hansen et al., 2017; Hassan & Albayari, 2022) and give space to journalists to explore their creativity and grow in other areas (Ufarte Ruiz & Manfredi Sánchez, 2019). Hassan and Albayari (2022, p. 175) consider that the survival of the press "lies in its adoption of the concepts of flexibility, sustainability, coexistence with uncertain conditions, and the transition to the new normal (...) including the acceleration of the adoption of advanced technologies such as artificial intelligence".

From a more pessimistic view, different threats stand out, specifically ethical debates (Noain Sánchez, 2022) and the perceptions of journalists themselves about being able to retain their jobs in a debate that is divided between integration or replacement (Saad & Issa, 2020), resistance to change (Sánchez-García et al., 2023), lack of budget or technical abilities and the influence of the institutional landscape (de-Lima-Santos & Ceron, 2021).

Both perspectives highlight the need to deepen the debate and, especially, to analyze how the media propose to regulate or establish internal guidelines for the uses of AI by their journalists. This is not only because of how these technologies fit into the newsrooms but also because of journalistic work processes, which introduce new challenges to AI usage before—such as care in training AI with heterogeneous data and instructions to avoid bias—and after its application—such as verification and data processing (Rojas & Ramírez, 2023). The following is a set of "issues to regulate or legislate and assess from an

ethical-philosophical point of view” (Diego Olite et al., 2023, p. 4) that address transparency and accountability of journalists and media outlets: “To what extent can news media and journalism be held to account for the use of AI-driven tools? And to what extent can the implementation of AI tools in news media be effectively regulated?” (Porlezza, 2023, p. 372). These are questions that have not yet been investigated academically from a perspective that addresses the decisions made by media outlets on the internal use of AI, which this research attempts to address.

This study offers a unique contribution to the field, mapping the first concrete initiatives for AI self-regulation in journalism and highlighting critical areas for future academic reflections and journalistic practices.

Self-Regulation and Ethics of Artificial Intelligence Usage in the News Media

Researching the impacts of AI in society requires an understanding of its ethical implications. AI ethics, also known as “machine ethics”, appears as an emerging interdisciplinary field that studies theories, guidelines, policies, principles, rules, and regulations related to artificial intelligence, with the goal of programming it according to values and principles of right and wrong (Huang et al., 2022).

Given the risks and challenges posed by the advance of AI and the uncertainty of its future, ethical issues and limitations are among the priorities of supranational organizations. In the last five years, key recommendations have been issued in this regard. The report on the ethical use of AI agreed by UNESCO in 2021 focuses on preserving human rights and equality in the face of technological progress and establishes concrete recommendations on its use that can be summarized in three principles: transparency, responsibility and equity (UNESCO, 2021). Along the same lines, the OECD, in its first recommendations (2019, updated in 2024), prioritizes respect for human rights and democratic values, recommending an innovative and, at the same time, reliable use of AI-based concepts such as transparency, explainability and accountability (OECD, 2019–2024). From the professional field specializing in technology, the recommendations made by the Institute of Electrical and Electronics Engineers (IEEE), the main body that brings together the engineering sector, recommends safety, transparency and accountability in its development through specific principles (IEEE, 2019) that has been progressively updated through specific standards and frameworks are also worth noting.

Based on these non-binding ethical frameworks, more specific legislative frameworks have begun to develop. For the time being, the most successful approach has been the European Union’s AI Regulation, popularly known as the AI Act (European Parliament, 2024). This is the first international AI regulatory law that limits the uses of artificial intelligence by setting different levels of risk, and among its aims is the effort to protect human rights and to support a human-centric, ethical and responsible use of AI (Helberger & Diakopoulos, 2022; European Parliament, 2024). The AI Act project started in 2018 when the European Commission published a communication on AI governance, which was followed by the announcement of a European AI Strategy and the creation of a High-Level Group on Artificial Intelligence.

The AI Act, which will require subsequent development in each EU Member State, does not include regulation in specific sectors, which, as is the case for media, depend on their own internal criteria of use. According to Porlezza’s study (2023), existing regulations on AI in the European Union and the Council of Europe rarely refer to media or journalism. When the media is mentioned, it is generic, and the focus is on four main axes: risks posed by AI usage, literacy, social responsibility and press freedom and the need to include the media as part of the AI policy and governance debate. However, the guidelines and

recommendations on its use are generic, leaving ‘many open questions’ and ‘uncertainty’ about how to delimit it in the Communication sector (Porlezza, 2023).

Some researchers and scholars delimit journalistic ethics in the use of AI in specific aspects that are considered key to the sector. Reinecke et al. (2021) point out aspects to regulate, such as security, privacy and safety but also principles, standards, protocols and guidelines. The authors highlight, among other aspects, the importance of copyright regulations (Trapova & Mezei, 2022) for AI-generated content used by the media or the relevance of transparency ‘in order to nurture a trusting relationship between journalistic media and their audience and to provide the latter with an instrument they can use to report suspected error or unethical conduct in news coverage’ (Haapanen, 2022, p. 81). The need to address the identified gap in delimiting the use of AI is seen as global, affecting both countries in the developed North and the so-called Global South, where the expansion of the use of newsroom automation is confirmed, such as in sub-Saharan Africa (Gondwe, 2023), with codes of conduct and training (Radcliffe, 2025) that are becoming increasingly necessary in these geographic areas as well.

Like other types of journalistic guidelines, these regulations are developed and made explicit in two types of documents: style books and manuals and codes of ethics. The former refers to purely journalistic norms and criteria, including the correct and standardized use of language and linguistic formulas—abbreviations, acronyms, etc. (Font, 2008). The latter is a compilation of moral criteria and forms of conduct established and assumed by professionals in a given sector, such as journalists’ professional organizations and associations. These include, for example, ethical codes and recommendations on the coverage of sensitive issues, such as humanitarian catastrophes and tragedies, communication for development or violence against women, among other ethical aspects related to the corresponding editorial line. Thus, it is a matter of delimiting questions of journalistic quality and ethical limits that, in some way, commit them to their readers.

This type of manual and guideline constitutes a fundamental tool in the history of journalism, implying a public recognition of the ethical conscience of a given profession or activity (Aznar, 1997). In the media sector, these regulations and ‘self-regulation’ manuals have evolved depending on the social, cultural and technological context. Thus, the guidelines of traditional media have been adapted to the digital environment, regulating, for example, broadcasting in digital environments and the journalistic use of social networks as a source or as a distribution channel, among other aspects (Confino, 2010). And in this evolution, it is again necessary to adapt to the new context of the expansion of artificial intelligence as a statement of intent to the risks and ethical dilemmas that shape issues such as automated content creation, authorship rights, automated content, data protection or cyberattacks, among other risks (Rojas & Ramírez, 2023).

In this context of technological and journalistic change, it is pertinent to ask how the media and media organizations propose to regulate their use within their newsrooms and business models and whether they are already doing so. This research is relevant given the limited academic studies on the subject, limited to specific topics, such as the implications of copyright laws adapted to the use of AI in countries like China, Europe, and the United States (Kuai et al., 2022; Kuai, 2024); AI regulatory frameworks at institutional and European level (Helberger & Diakopoulos, 2022; Porlezza, 2023); and specific self-regulation in European media councils, the latter ‘waiting and watching’ (Haapanen, 2020, p. 5). It is, therefore, a matter of providing solutions to the knowledge gap on the ‘self-regulation’ of the media in the face of AI.

2. Objectives and Background Assumptions

The main objective of this research is to analyze self-regulation proposals on the usage of artificial intelligence tools in the news media, which have been published by companies, collectives and journalistic entities (O1). The study unfolds into three specific objectives:

- o1. Collect and review different editorial style manuals and/or internal guidelines that include recommendations and regulations for the use of AI in international media (local, regional and/or national) and gather their metadata in open access.
- o2. Analyze the permitted, limited and/or prohibited uses of AI in journalistic production, especially around the generation of multimodal content.
- o3. Identify the ethical stance and role of human oversight in the application of AI, transparency of usage and data verification.

The design of these research objectives is based on a starting assumption, based on an initial field observation, that the media are particularly concerned about the use of AI and have recently begun to publish recommendations in their newsrooms focused on delimiting the use of generative AI and establishing ethical commitments to transparency, also seeking audience trust.

3. Materials and Methods

This research uses a content analysis methodology, one of the most widespread methods in the Social Sciences, as it allows the researcher to systematically and objectively study the characteristics of messages, identify and quantify patterns and infer meanings in order to draw valid and replicable conclusions (Aigner, 1999) through the establishment of categories and variables (Cauas, 2015).

One of the difficulties posed by the object of study lies in the complexity of gathering a limited and systematic international sample of AI media self-regulation guidelines due to the dispersion of their open publications and the absence of previous work on the subject due to the recent nature of the topic. For this reason, different systems were used to locate the sample, starting with the 'snowball' sampling technique recognized in academic literature (Van Meter, 1990; Voicu & Babonea, 2011; Alloatti, 2014), typically recommended for experimental studies and especially advisable when the sample is small, limited and difficult to find.

Thus, the final refined sample (N = 45) was obtained with two collection patterns. On the one hand, non-systematized random searches were conducted across the academic and grey literature, among which the international lists provided by Liuzzi (2024), Mayoral Sánchez et al. (2023) and Repilado (2024) stand out. These contributions are complemented, on the other hand, by manual searches with the keywords 'artificial intelligence guidelines' or 'manual of style' combined with the names of relevant media outlets, international news agencies and media groups and other entities of various kinds. Both findings feed back into the aforementioned 'snowball' process, resulting in a final sample of N = 45, which includes 38 guidelines, 5 stylebooks, 1 standard and 1 usage policy published between 2023 and 2024 and beginning of 2025 across 26 media outlets and 18 international groups and entities.

The snowball sampling method was selected due to the limited availability of publicly accessible self-regulation guidelines on AI in journalism. As this field is nascent and evolving, relevant documents are often scattered, unpublished or inconsistently indexed. Snowball sampling effectively identified resources by leveraging connections between organizations and researchers, a technique suited for studies with small or hidden populations (Van Meter, 1990; Voicu & Babonea, 2011).

This method, however, carries limitations such as selection bias and the over-representation of proactive or interconnected entities. To address these issues, random

searches in the academic and grey literature, along with manual keyword-based queries, complemented the sampling process. Despite these efforts, the findings are exploratory and not generalizable, highlighting the need for future research with larger, systematically sourced datasets.

The limited sample size also reflects the scarcity of published guidelines during the 2023–2024 period. This exploratory study aims to provide an initial overview of practices rather than a comprehensive inventory. Nonetheless, the sample includes a diverse range of media outlets, organizations, and geographies, offering a representative cross-section of available resources and can serve as a reference for the media’s first steps in ‘self-regulating the use of AI’ and can serve as models for other similar entities.

Each unit of analysis is subjected to a coding sheet based on five categories (Table 1) that allow for the delimitation of the object of study—AI self-regulation in the media—and analysis across 13 variables.

Table 1. Coding sheet for the analysis of self-regulation and ethical dilemmas of AI in international media.

C1. Identification	-Media -URL -Date -Country	
C2. Type of AI and use	Generative AI	1. Prohibition 2. Limitation
	Analytic AI	3. Wide use 4. Not mentioned
C3. Multimodal use	Regulation on text generation	1. Yes a. No limits b. Limited
	Regulation of photo and/or video generation	2. Prohibited 3. Not mentioned
C4. Ethical regulation	Allusion to the importance of respecting copyright	
	Transparency measures	1. Yes
	Allusion to verification and ‘fact-checking’	2. Not mentioned
	Regulation of data processing and protection	
C5. Human supervision	Reminder of the importance of human supervision	1. Yes 2. Not mentioned

C1. Identification. This includes data such as the type of document (style guide or guidelines), the responsible medium, group or entity, the URL, the date of publication and the country of origin.

C2. Types of AI and their usage. This includes the tools and applications mentioned (generative or analytical) and whether the document prohibits, totally permits or does not mention their use.

C3. Multimodal use. This includes indications on the use of AI to generate text, photographs and/or videos and graphics and whether it is allowed (with or without limits), prohibited or not mentioned.

C4. Ethical regulation. Code whether the document includes references to ethical issues such as copyright, transparency, verification and fact-checking or the processing of personal data.

C5. Human oversight. This determines whether or not the documents include a reminder about the importance of human oversight in the AI journalistic process.

4. Results

The main results of the analysis of media self-regulation documents on the use and application of AI tools are presented below, following the order of the proposed study categories through a comparative analysis. Due to the size of the sample (N = 45), the data are given in nominal numbers.

Firstly, we present, as a main result of the study, the open compilation of the guidelines and stylebooks found in this experimental sample (Table 2) with access to their content and with the first metadata of their identification (C1): the responsible medium, agency, group or entity, the date of publication and the country to which it belongs as an expandable list. The titles of each of them are linked to the corresponding document analyzed, providing open access to the entire sample.

Table 2. Sample of editorial style books and guidelines by news media, groups and entities on AI use (2023–2024). Click on each medium to consult the original document ¹.

(A) News Media Outlets and Agencies			
Type of Document	Media/Agency	Date	Country
Guidelines	Aftonbladet	5 April 2023	Sweden
Editorial style book	Agencia EFE	30 January 2023	Spain
Guidelines	Al Jazeera	10 July 2023	Qatar
Guidelines	Algemeen Nederlands Persbureau (ANP)	April 2023	Netherlands
Guidelines	Associated Press	16 August 2023	USA
Guidelines	BBC	February 2024	United Kingdom
Guidelines	Business Insider	April 2023	USA
Guidelines	CBC	12 June 2023	Canada
Editorial style book	El País	19 January 2025	Spain
Guidelines	Expresso	14 June 2024	Portugal
Guidelines	Heidi News	11 April 2023	Switzerland
Editorial style book	Hong Kong Free Press (HKFP)	No date available	China
Guidelines	Jot Down	April 2024	Spain
Guidelines	Mensagem de Lisboa	10 May 2024	Portugal
Guidelines	New York Times	9 May 2024	USA
Guidelines	Norwegian Tabloid	12 April 2023	Norway
Guidelines	The Guardian	16 June 2023	United Kingdom
Guidelines	Thomson Reuters	No date available	Canada
Guidelines	Todo Jujuy	No date available	Argentina
Guidelines	Wired	No date available	USA
Guidelines	NPR	2024	USA
Guidelines	Núcleo	No date available	Brazil
Guidelines	The Globe and Mail	15 June 2023	Canada
Guidelines	USA Today	4 December 2023	USA
Guidelines	Verdens Gang (VG)	12 April 2023	Norway
Guidelines	Volkskrant	No date available	The Netherlands
(B) Groups and Media Organizations			
Type of Document	Group/Entity	Date	Country
Guidelines	Atresmedia	8 February 2024	Spain
Editorial style book	CDMSI	30 November 2023	European Union
Guidelines	DJV	No date available	Germany
Guidelines	DPA	3 April 2023	Germany
Usage policy	Estadão (Group Estado)	23 November 2023	Brazil
Guidelines	Flemish Organization for Journalism	No date available	Belgium
Guidelines	Groupe Les Echos Le Parisien	24 May 2023	France
Guidelines	Mediahuis	No date available	Belgium

Table 2. Cont.

(B) Groups and Media Organizations			
Type of Document	Group/Entity	Date	Country
Guidelines	News Media Alliance	24 April 2024	USA
Editorial style book	Nordic AI Journalism	2024	Sweden
Rules of use	Radiotelevisión española (RTVE)	5 September 2024	Spain
Guidelines	Ringier	30 May 2024	Switzerland
Guidelines	RSF	10 November 2023	France
Guidelines	RTDNA	No date available	USA
Guidelines	RVDJ	No date available	Belgium
Guidelines	Sanoma	16 February 2024	Finland
Guidelines	Sociedad Interamericana de Prensa	6 September 2023	Latin America
Guidelines	STT	No date available	Finland
Guidelines	TT Nyhetsbryan	No date available	Sweden

¹ Online access to the guides and manuals has been provided from April 2024 to January 2025.

4.1. Levels and Types of AI Regulation in International Media

The first category of analysis (C1) allows us to identify the general characteristics of the sample (N = 45). The documents on AI usage produced by media outlets and news agencies are grouped into two main types: guidelines or ‘guides’, in the form of a ‘declaration of principles’, to help guide journalists’ work (39), and so-called ‘style books’ (both in PDF and web format), which provide guidance on standards and recommendations to ensure consistency and quality in the writing and presentation of media content (5). All of them are published openly and are accessible to the general public on the organizations’ own websites, which indicates a first exercise in transparency on the part of the media outlets analyzed, both towards their employees and towards the audience. Exceptionally, the sample also includes the first internal regulation on the use of AI, approved by the public media group Radio Televisión Española (1), and a usage policy of the Brazilian Estado Group, found in the media Estadão (1).

The breakdown of the data makes it possible to distinguish regulations across several levels: on the one hand, self-regulation of the media as individual entities (26) and, on the other, recommendations established either by media groups, such as Atresmedia or RTVE; by media organizations and alliances, such as Nordic AI Journalism or the Inter-American Press Association or by state press associations and institutions operating at the EU level, such as the Council of Europe (specifically, the Steering Committee on Media and Information Society, CDMSI) (19). Regarding the dates of publication, it is worth noting that these have only recently been published, which confirms that the process is only beginning. Most of the documents included in the analysis were published between mid-2023 (20), 2024 (11), 2025 (1), and others are undated (13).

The coding of the country of origin allows us to determine that there are more regulations at a national level (20) than at the regional or community level (with only one document in the European Union and Latin America, respectively) or local level (with only one case found in the Portuguese Mensagem de Lisboa).

The United States leads the sample with 8 manuals, followed by Spain (5), and, with 3 manuals or guidelines each, Belgium, Sweden and Canada.

The geographic diversity of the materials found, as well as the variety in size of the media entities that have published it—local, regional, national—reflect that the drive for AI ‘self-regulation’ in the media is an international phenomenon that affects large and small entities in all countries of the world.

4.2. Types of AI and Regulation of Their Use (C2)

The analysis of the types of AI mentioned across media guidelines and editorial style manuals indicates a greater concern for the regulation of generative AI—AI that creates content—which is specified in 42 of the 45 manuals analyzed. Analytical AI—AI that reads datasets to identify patterns and make predictions—is mentioned in 15 manuals, with more generic references to data use and personalization.

The concerns around generative AI are expressed in the limitation of its use on the majority of the documents (39), as opposed to a broader or ambiguous permissiveness (3) that corresponds to organizations such as Nordic AI Journalism, the journalists' association RVDJ or the European Commission, which, operating outside of the media outlets themselves, seek to establish generic recommendations which will then be subjected to the final responsibility of editors and publishers.

The limitations include the use of generative AI only as an aid to the journalist, never as a substitute: 'We will never use AIs to generate the entire content of a publication, as an editor or final producer' (Núcleo); "AI will be at the service of professionals to improve the quality of journalistic work and not to replace it" (El País); 'We do not intend to publish editorial content generated in whole or even in part by an AI without editorial and human supervision' (Les Echos-Le Parisien). The documents also associate this limitation with their commitment to the supervision of the AI-generated content and its verification: 'There is no room for unreliability in our journalism, nor our marketing, creative and engineering work. At a simple level, this means that the use of genAI requires human oversight' (The Guardian) or 'It is essential to review, check and verify every input we take from AI tools' (EFE).

4.3. Internal Recommendations on the Multimodal Use of AI (C3)

The analysis of the mentions of multimodal use of AI in the media shows it is typically applied to three main types of content: text generation, photographs and/or videos and graphics (Figure 1). When the use of these resources appears in media guides and guidelines, it is with reservations, i.e., with limitations in scope of usage or limited to specific use cases. The only exception is the generation of graphics, which is allowed without limits in Norwegian Tabloid (Norway) and Núcleo (Brazil).

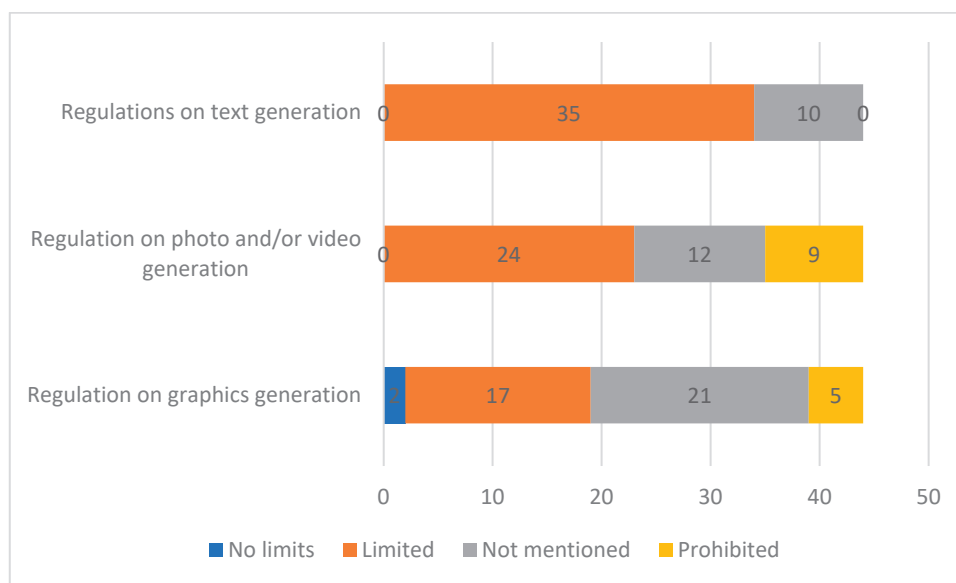


Figure 1. Self-regulation on the multimodal use of generative AI on news media, groups and entities.

The use of generative AI is clearly limited in text creation (32), which is not expressly prohibited in any of the analyzed documents but is also not allowed without limitations. Its application is limited to specific tasks, such as translation, proofreading, synonym search and headline writing.

The use of generative AI to create multimedia content such as photographs or videos reflects a greater disparity of criteria: nine media outlets, such as Hong Kong Free Press (China), Mensagem de Lisboa (Portugal) or Business Insider (USA), explicitly prohibit it. Some of them make very specific exceptions, such as when AI is the news itself (Associated Press, TT Nyhetsbryan) or when it is used to create illustrations (STT, Verdens Gang). Most of the books and guidelines analyzed, however, do allow a reserved use of this technology (24) for image editing, cropping or processing, although they are stricter regarding the creation of photorealistic content (banned in media outlets such as The Globe and Mail, Norweigan Tabloid, USA Today and Verdens Gang).

The generation of AI graphics is the least mentioned multimodal use. Even so, an explicit ban is included in media outlets' documentation (The Volkskrant, TT Nyhetsbryan, Mensagem de Lisboa, Estadão and STT), and limitations are found in 17 of them. The use cases for this type of content are less explicit, with general allusions such as 'requiring the consent of editors-in-chief' (ANP).

Each media outlet's self-regulatory guidelines reflect a spectrum of measures, from the strictest and most explicit to the laxest. *The Associated Press*, for example, stipulates that text generation will only be allowed internally and in experimentation, while the *CBC* allows it 'provided it is identified and approved'. This lack of specificity is also identified in media organizations and groups, such as the Flemish Organization for Journalism, which makes each media outlet responsible for the decision of whether to use these tools or not without providing specific guidelines or example cases.

On the other hand, RTVE's regulations stand out as some of the most specific in the prohibition of practices, listing four forbidden usage cases (deployment of subliminal techniques, exploitation of the vulnerabilities of a specific group of people, profiling of people according to their behavior, or facial recognition systems), although they do not mention any permitted uses of generative or analytical AI.

Table 3 shows the individually analyzed measures by the media and entities, after the application of the categories and variables of the study.

Table 3. Analysis of media style books and guidelines regulating the use of AI in journalistic work: multimodal use allowed (✓) or limited (x) in alphabetical order.

Multimodal Use (C3)		
	Text Generation	Multimedia Generation
Aftonbladet	✓ Suggest ideas or headlines	✓ No photo manipulation
Agencia EFE	✓	x Only specific cases
Al Jazeera	Not mentioned	Not mentioned
Algemeen Nederlands Persbureau (ANP)	✓	✓
Associated Press	x Only internal experimentation, not publishable	x Only if an AI-generated image is the subject of the news story
Atresmedia	Not mentioned	Not mentioned
BBC	x Not informative content	x Can be used in graphics and deepfakes for anonymity, no deception
Business Insider	✓	x Will check again in the future

Table 3. Cont.

	Multimodal Use (C3)	
	Text Generation	Multimedia Generation
CBC	✓ As long as it is identified and approved	✓ As long as it is identified and approved
CDMSI	✓ With supervision	✓ With supervision
DJV	✓ With participation of the journalist	Not mentioned
DPA	✓ Transcriptions, translations	Not mentioned
El País	✓ Limited use with oversight and transparency	✓ Do not create content that confuses with reality. No full illustrations
Estadão	✓ Transcriptions, translations, data analysis, text edition	x Generating photos, illustrations, videos or audio is prohibited
Expresso	✓ As a support tool	✓ As a support tool
Flemish Organization for Journalism	✓ Dependent on editorial decisions	✓ Dependent on editorial decisions
Groupe Les Echos Le Parisien	✓ With supervision	✓ With supervision
Heidi News	✓ Synonyms search and proofreading	✓ Certain cases and illustrative purposes
Hong Kong Free Press (HKFP)	x Except for summarizing or in-house tools	x
Jot Down	✓ With reservations	✓ With reservations
Mediahuis	Not mentioned	Not mentioned
Mensagem de Lisboa	x Only translations	x
New York Times	Not mentioned	Not mentioned
News Media Alliance	✓ As long as it is a transparent use and respects copyright	✓ As long as it is a transparent use and respects copyright
Nordic AI Journalism	✓ Text review, transcriptions	✓ Document states that any limitations do not fall within its purview
Norwegian Tabloid	Not mentioned	✓ Image processing and cropping ✓ Illustrations, graphics x Photorealistic images or editing
NPR	Not mentioned	Not mentioned
Núcleo	✓ To summarize, transcription improvements	✓ Only urgent cases
Radiotelevisión española (RTVE)	Not mentioned	Not mentioned
Ringier	Not mentioned	Not mentioned
RSF	✓ With reservations	✓ With reservations
RTDNA	Not mentioned	Not mentioned
RVDJ	✓ Dependent on editors criteria	✓ Dependent on editors criteria
Sanoma	Not mentioned	Not mentioned
Sociedad Interamericana de Prensa	Not mentioned	Not mentioned
STT	✓ Automated translation, suggestions of headlines x No content writing	x Only illustrations
The Globe and Mail	✓ Headline ideas x Not for summarizing or writing	x No photorealistic images, only basic editing
The Guardian	✓ Ideas, proofreading and suggestions	Not mentioned
Thomson Reuters	Not mentioned	Not mentioned
Todo Jujuy	✓ Summaries, improving or cutting out wording	✓ Illustrations in urgent and exceptional cases
TT Nyhetsbryan	✓ As long as it has been started and reviewed by a journalist	x Only when the multimedia content is the news itself
USA Today	✓	x No photorealistic images, always with supervision

Table 3. Cont.

Multimodal Use (C3)		
	Text Generation	Multimedia Generation
Verdens Gang (VG)	Not mentioned	x No photorealistic images or complex editing ✓ Illustrations and graphics
Volkskrant	x Only for transcriptions or text-audio translations	x Except to show how AI works
Wired	x Only exceptional, like text suggestions or cutting out wording	x Only in certain conditions and without replacing files

The analysis of the main results in Table 3 shows a majority of the recommendations made by the media on the use of AI for text creation. Thus, 30 of the guidelines make specific mention of its use in text format, and of these, 100% limit its use to specific tasks that are permitted, such as text translation, audio transcription, summaries, or the contribution of ideas, mainly under the supervision of the journalist. Some expressly prohibit the creation of news content with AI (BBC), and most express it in other ways, such as allowing its use only internally and not for publication. As for the multimodal use of images and other types of content, it is expressly delimited in just over half of the references (27), of which two cases prohibit its use and the rest limit its use with three main ideas: do not use it to create realistic images that confuse with the normative reality; use it limited to AI topics; it is allowed for infographics, with identification of the authorship of the AI.

4.4. Regulations and Ethical Considerations on AI Usage (C4)

Regulations on ethics and good practice are set out in detail in Table 4, which reflects how they are present in most of the guidelines and style guides under analysis (summarized in Figure 2). Most of the sample includes references to transparency measures (43), followed by references to the verification and fact-checking of AI-generated content (34), while references to copyright (29) and data processing regulations (28) come in third and fourth place.

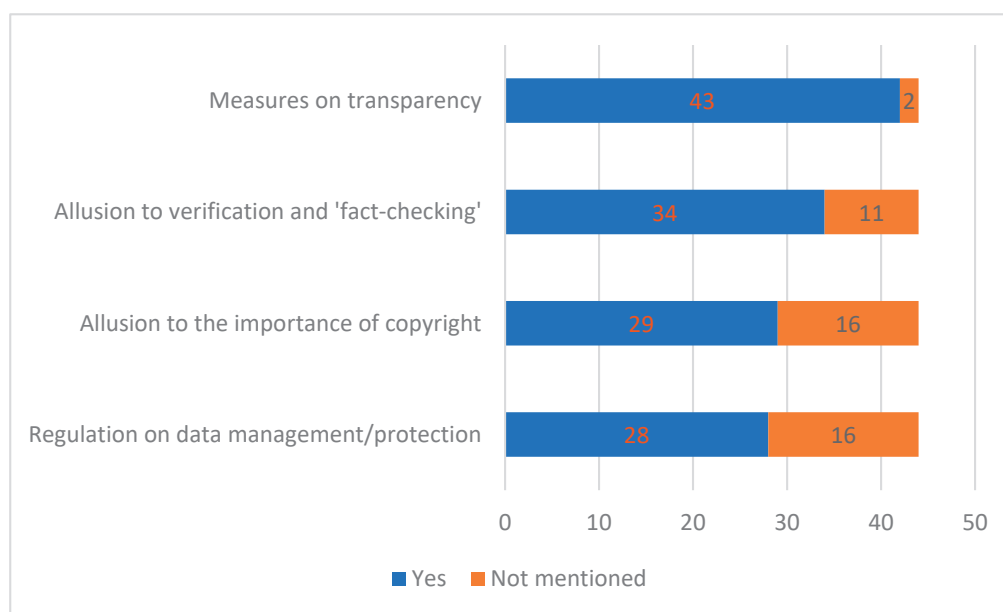


Figure 2. Ethical dilemmas that reference the media in the self-regulation of the use of AI: copyright, transparency and processing of personal data.

Table 4. Analysis of media style books and guidelines that regulate the use of AI in journalistic work: ethical dilemmas in copyright, transparency and data. (✓ means: concept mentioned).

Ethical Regulations (C4)				
	Respect for Copyright	Transparency for the Audience	Importance of Fact-Checking	Personal Data Protection
Aftonbladet	Not mentioned	✓ If the content has impact	Not mentioned	✓
Agencia EFE	Not mentioned	✓	✓	Not mentioned
Al Jazeera	Not mentioned	✓	✓	✓
Algemeen Nederlands Persbureau (ANP)	Not mentioned	✓	✓	Not mentioned
Associated Press	Not mentioned	✓	✓	✓
Atresmedia	✓	✓	✓	✓
BBC	✓	✓	✓	✓
Business Insider	✓	Not mentioned	✓	✓
CBC	✓	✓	✓	✓
CDMSI	✓	✓	✓	✓
DJV	✓	✓	✓	✓
DPA	Not mentioned	✓	✓	Not mentioned
El País	Not mentioned	✓	Not mentioned	Not mentioned
Estadão	✓	✓	✓	✓ Includes media business data protection/management
Expresso	✓	✓	✓	✓
Flemish Organization for Journalism	Not mentioned	✓	Not mentioned	
Groupe Les Echos Le Parisien	✓	✓	Not mentioned	Not mentioned
Heidi News	Not mentioned	✓	✓	Not mentioned
Hong Kong Free Press (HKFP)	✓	Not mentioned	✓	Not mentioned
Jot Down	✓	✓	✓	Not mentioned
Mediahuis	✓	✓	✓	✓
Mensagem de Lisboa	Not mentioned	✓	Not mentioned	✓
New York Times	Not mentioned	✓	✓	Not mentioned
News Media Alliance	✓	✓	Not mentioned	✓
Nordic AI Journalism	Not mentioned	✓ In what is published not mentioned Internal use tools	Not mentioned	Not mentioned
Norwegian Tabloid	✓	✓	Not mentioned	✓
NPR	✓	✓ When its use has a relevant role	✓	✓
Núcleo	✓	✓	✓	Not mentioned
Radiotelevisión española (RTVE)	✓	✓	✓	✓
Ringier	✓	✓	✓	✓
RSF	✓	✓	✓	✓
RTDNA	✓	✓	✓	✓
Sanoma	Not mentioned	✓	Not mentioned	✓
Sociedad Interamericana de Prensa	✓	✓	Not mentioned	✓

Table 4. Cont.

	Ethical Regulations (C4)			
	Respect for Copyright	Transparency for the Audience	Importance of Fact-Checking	Personal Data Protection
STT	Not mentioned	✓	✓	✓
The Globe and Mail	✓	✓	✓	✓
The Guardian	✓	✓	Not mentioned	Not mentioned
Thomson Reuters	Not mentioned	✓	✓	✓
Todo Jujuy	Not mentioned	✓	✓	Not mentioned
TT Nyhetsbryan	✓	✓	Not mentioned	✓
USA Today	✓	✓	✓	✓
Verdens Gang (VG)	Not mentioned	✓	✓	✓
Volkskrant	✓	✓	✓	Not mentioned
Wired	✓	✓	✓	Not mentioned

The transparency measures proposed by these institutions and organizations (43) focus on the general requirement to label and identify content generated by artificial intelligence with expressions similar to the following: ‘[Atresmedia] will be transparent in the use of AI tools and will inform its users of all the necessary aspects of their operation so that they have a sufficient understanding of their technological capabilities and expectations of their results’ (Atresmedia). Only media outlets such as NPR create further limitations in the name of transparency, limiting this labeling when the use of AI plays a ‘significant role’ in the creation of the journalistic piece. Nordic AI Journalism references the importance of warning readers about the use of AI in published content, although it does not note any need to inform the public about AI tools used internally. With the exception of this case, it should be noted that the importance that the media attach to transparency is consistent with the publication of the guidelines and measures in the form of press releases aimed at the audience, with the intention of ‘manifesting’ the principles and values regarding the use of AI that are self-imposed internally in the generation of content and the use of technological tools of this type in an exercise of explicit commitment, giving value to trust.

The justification for these transparency measures is often linked to respect for copyright (29) and original human content: ‘As with any editorial content, we want to protect ourselves against any risk of error, copyright infringement and also support the work of artists, photographers and illustrators’ (Les Echos-Le Parisien).

That same justification also highlights a commitment to content verification (34), focusing on internal reminders to journalists to constantly monitor and check AI-generated material, as it may be biased or contain ‘hallucinations’ (errors in which the AI produces incorrect or unfounded information); as well as security and privacy risks, alluding to special caution when dealing with sensitive or personal data (28) and including it in their prompts and AI queries.

4.5. Relevance of Human Supervision (C5)

The importance of human supervision in journalistic work with AI is reemphasized in 44 of the 45 manuals analyzed, except for News Media Alliance (USA) and RVDJ (Belgium), which make no references to the subject. The general discourse alludes to the use of AI as a complement to human work, never as a substitute or replacement: “The newsroom may use AI to facilitate or improve its work, but human intelligence remains at the core of all our editorial production. No content will be published without prior human oversight” (Heidi News); ‘If we wish to include significant elements generated by AI in a piece of work, we will only do so with clear evidence of a specific benefit, human oversight, and the explicit permission of a senior editor’ (The Guardian).

Professionals are seen as bringing critical judgment and cultural context that AI cannot replicate, ensuring journalistic quality and respect for ethics that technology alone would not be able to achieve: “Automation of routine tasks to AI means that journalists must monitor and intervene to ensure that stories are treated appropriately” (Al Jazeera).

Media outlets such as DJV connect human oversight and transparency in the use of AI to the quality of the final product, credibility and audience trust: “Credibility is and remains the most important prerequisite for journalism, and can only be maintained if people are responsible for selection and distribution” (DJV).

In this line, media outlets such as the Portuguese A Mensagem de Lisboa state their commitment “to identify and mitigate biases in all AI applications. Special attention will be given to ensuring that the voices of marginalized communities are not misrepresented or overlooked”. These values are also shared by the Spanish RTVE group, with its express commitment that “AI systems should be fairly designed, avoiding unfair and discretionary biases”, and they should be accessible and subjected to systems of accountability, governance and continuous evaluation to monitor compliance with the specified standards.

5. Discussion and Conclusions

This research on the regulation and self-regulation of AI across various international media organizations, groups and entities (O1) has compiled a first catalog of 45 guidelines, stylebooks and regulations in place in 18 countries and regions (o1). The analysis of this catalog confirms the starting assumption of this research about the existence of a recent and growing trend of media self-regulation in the use of AI. While awaiting more detailed regulation by the different governments, the journalistic sector itself or professional associations, it is the media that respond individually to the challenges of AI with an express commitment in line with their professional and ethical positioning. Their proposals, mainly based on verification, accountability and transparency, are aligned with the general recommendations of supranational organizations (Unesco, OECD and the Council of Europe). And, by publishing them in open digital formats, they reflect an intention to bring reliability to the audience in the ‘self-policing’ journalistic use of AI.

The study confirms the starting assumption that the media feel challenged about the ethical risks of AI and have recently begun to publish recommendations and codes that reflect two purposes: on the one hand, to establish internal indications to their editorial staff to delimit the use of generative AI to journalists; and, on the other hand, to publish these indications openly to express their ethical commitments to transparency, also seeking the trust of the audience.

This study on the internal allowances for AI usage and its limitations (o2) yields two main conclusions. Firstly, there is a greater concern on the part of the media about journalistic use of generative AI—that which creates ‘new’ textual and multimedia content (Feuerriegel et al., 2023)—than for analytical AI—that which analyses large amounts of data and detects patterns. This result can be explained as a possible reaction to the democratization of the use of this type of AI with the announcement of Chat-GPT, a generative AI tool made available to the general public (Pavlik, 2023) at the end of 2022, and subsequent similar technological developments.

Secondly, we are able to confirm that, although the generation of multimodal content is limited in most cases, this limitation is established differently across the self-regulatory documents analyzed, from specific guidelines and use cases—such as using AI to suggest headlines, but not to write information (The Globe and Mail)—to generic recommendations that allude to the supervision and prior approval of content (CBC, CDMSI, Groupe Les, El País, Echos Le Parisien). Only one internal regulation with a legal framework has been identified (RTVE), which serves to exemplify the primitive and still developing state of

media regulation in the face of AI in the context of rapid technological evolution and an accelerated need to respond with internal guidelines that require constant adaptations.

The analysis also allows us to detect the disparity in how media outlets and organizations express their ethical stances regarding transparency and the importance of human supervision in the application of AI (o3). There is consensus in the discourse: a majority notes that AI should not replace the journalist but act as an auxiliary tool (Canavilhas & Giacomelli, 2023) and as a support in specific tasks. In addition to their active participation in the process, the professional adds the supervision, verification and identification of the content that is generated, ensuring accuracy, reliability and mitigation of algorithmic biases. The ethical use of AI is linked to its relationship with the audience since most of the regulations declare the importance of publicly identifying any content generated with AI, linking this disclosure to upholding the quality of their information and the trust of their readers.

Overall, the reviewed guidelines reflect a concern on the part of the media with a technical perspective—by delimiting what content can be created—and an ethical one—by determining under what principles this content is created. However, the scarce mentions of analytical AI, the interest focused on resources such as the generation of text or images, and the uncertain generic recommendations found in some documents (Porlezza, 2023) indicate a still developing state for both the different uses of AI and the commitments to self-regulation. At the same time, it is opening a path of study and reflection for researchers and journalists in a continuous process of necessary internal updating. There is greater media concern about the internal limitation of the use of generative AI and a strong internal ethical positioning in favor of transparency, content verification and the correct treatment of data and copyright. Self-regulation in the use of AI is mostly directed towards a triple objective: avoiding bias, preserving informative quality and audience trust. These axes can serve as a reference for media and entities in future discussions about the development of specific regulations for the sector.

The geographic diversity of the materials and the variety in the size of media entities reflect that AI self-regulation in the media is an international phenomenon affecting both large and small entities worldwide.

This research has limitations that should not be overlooked: firstly, the difficulty of locating a suitable sample for the object of study, as it is dispersed, difficult to locate and cannot be considered representative in its entirety. The use of the snowball technique is the most appropriate for this type of exploratory study in order to overcome the absence of previous studies. However, at the same time, it implies a certain bias in the search, so it is recommended that future research be completed by expanding the sample, adding internal manuals that are not published openly and complementing with other techniques, such as interviews with media managers and editors regarding the self-regulation of the use of AI or establishing focus groups with experts to establish a guide that can be extrapolated to the sector as a whole.

This research serves as an approach to an issue that will continue to be subject to technological advances and ethical dilemmas and that, therefore, does not require that the media are “waiting and watching” (Haapanen, 2020, p. 5) but that it takes initiative toward the adoption of a framework for action that is applicable to all phases of the journalistic process in which AI already acts, as well as the implications that its use may have on business models, sustainability and the relationship with audiences.

Author Contributions: Conceptualization, P.S.-G.; Methodology, P.S.-G., A.D.-G. and I.R.M.; Validation, P.S.-G. and A.D.-G.; Formal analysis, P.S.-G., A.D.-G. and I.R.M.; Investigation, P.S.-G., A.D.-G. and I.R.M.; Resources, P.S.-G., and P.J.; Data curation, A.D.-G. and I.R.M.; Writing—original draft, P.S.-G. and I.R.M.; Writing—review & editing, P.S.-G., A.D.-G. and P.J.; Visualization, A.D.-G.; Super-

vision, P.S.-G. and P.J.; Project administration, P.S.-G. and P.J.; Funding acquisition, P.S.-G. and P.J. All authors have read and agreed to the published version of the manuscript.

Funding: With the support of the project: ‘Artificial Intelligence for the promotion of quality journalism and media literacy: Applied technological advances and challenges in the age of disinformation (IA-COM)’, funded by the Ministry of Science, Innovation and Universities (Spain) (1497590-B), and ‘MedaiTrust.Lab—Local Media Lab for Civic Trust and Literacy’, funded by the Fundação para a Ciência e a Tecnologia (Portugal) (PTDC/COM-JOR/3866/2020).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data are open documents available in the tables of the article as main results.

Conflicts of Interest: The authors declare no conflict of interest.

References

- Aigner, M. (1999). Análisis de contenido. Una introducción. *Metodología de la Investigación Social*, 3, 1–52. Available online: <https://revistas.udea.edu.co/index.php/ceo/article/view/1550> (accessed on 30 August 2024).
- Alloatti, N. (2014, August 27–29). *Una discusión sobre la técnica de bola de nieve a partir de la experiencia de investigación en migraciones internacionales*. IV Encuentro Latinoamericano de Metodología de las Ciencias Sociales, Heredia, Costa Rica. Available online: <https://www.memoria.fahce.unlp.edu.ar/library?a=d&c=eventos&d=Jev8286> (accessed on 30 August 2024).
- Aznar, H. (1997). El debate en torno a la utilidad de los códigos deontológicos del periodismo. *Anàlisi: Quaderns de Comunicació i Cultura*, 20, 125–144.
- Biswal, S. K., & Gouda, N. K. (2020). Artificial intelligence in journalism: A boon or bane? In A. Kulkarni, & S. C. Satapathy (Eds.), *Optimization in machine learning and applications* (pp. 155–167). Springer.
- Canavilhas, J., & Giacomelli, F. (2023). Artificial intelligence in sports journalism: A study in Brazil and Portugal. *Revista de Comunicación*, 22(1), 53–69. [CrossRef]
- Caswell, D., & Dörr, K. (2018). Automated journalism 2.0: Event-driven narratives. From simple descriptions to real stories. *Journalism Practice*, 12(4), 416–431. [CrossRef]
- Cauas, D. (2015). Definición de las variables, enfoque y tipo de investigación. *Bogotá, Biblioteca Electrónica de la Universidad Nacional de Colombia*, 2, 1–11.
- Codina, L. (2024). *IA en trabajos académicos: La publicación y las revistas científicas*. Available online: <https://www.lluiscodina.com/inteligencia-artificial-publicacion-revistas/> (accessed on 13 September 2024).
- Confino, J. (2010). *New social media guidelines for Guardian journalists*. The Guardian. Available online: <https://www.theguardian.com/sustainability/media-responsibility-social-media-csr> (accessed on 13 September 2024).
- de-Lima-Santos, M., & Ceron, W. (2021). Artificial intelligence in news media: Current perceptions and future outlook. *Media*, 3(1), 13–26. [CrossRef]
- Diego Olite, F. M., Morales Suárez, I. R., & Vidal Ledo, M. J. (2023). Chat GPT: Origin, evolution, challenges and impacts on education. *Educación Médica Superior*, 37(2), 1–23. Available online: <https://ems.sld.cu/index.php/ems/article/view/3876> (accessed on 13 September 2024).
- European Parliament. (2024). *Artificial intelligence act*. Available online: [https://www.europarl.europa.eu/thinktank/en/document/EPRS_BRI\(2021\)698792](https://www.europarl.europa.eu/thinktank/en/document/EPRS_BRI(2021)698792) (accessed on 23 October 2024).
- Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2023). Generative AI. *Business & Information Systems Engineering*, 66, 111–126.
- Flores-Vivar, J. M. (2020). Datos masivos, algoritmización y nuevos medios frente a desinformación y fake news. Bots para minimizar el impacto en las organizaciones. *Comunicación y Hombre*, 16, 101–114. [CrossRef]
- Font, A. G. (2008). *Los libros y manuales de estilo*. Cervantes Institute.
- Gondwe, G. (2023). ChatGPT and the Global South: How are journalists in sub-Saharan Africa engaging with generative AI? *Online Media and Global Communication*, 2(2), 228–249. [CrossRef]
- Haapanen, L. (2020). *Media councils and self-regulation in the emerging era of news automation* (pp. 1–20). Press Councils EU. Available online: <https://www.presscouncils.eu/wp-content/uploads/2023/02/Emerging-era-of-news-automation-Haapanen.pdf> (accessed on 30 August 2024).
- Haapanen, L. (2022). Adapting media self-regulation to the era of news automation. In V. J. E. Manninen, M. K. Niemi, & A. Ridge-Newman (Eds.), *Futures of journalism* (pp. 81–95). Palgrave MacMillan. Available online: <https://link.springer.com/book/10.1007/978-3-030-95073-6> (accessed on 30 January 2025).

- Hansen, M., Roca-Sales, M., Keegan, J., & King, G. (2017). *Artificial intelligence: Practice and implications for journalism*. Columbia University Libraries. Tow Center for Digital Journalism. [CrossRef]
- Hassan, A., & Albayari, A. (2022). The usage of artificial intelligence in journalism. In A. Hamdam, A. Harraf, P. Arora, B. Alareeni, & R. Khamis Hamdam (Eds.), *Future of organizations and work after the 4th industrial revolution* (pp. 175–197). Springer. [CrossRef]
- Helberger, N., & Diakopoulos, N. (2022). The European AI Act and how it matters for research into AI in media and journalism. *Digital Journalism*, 11(9), 1751–1760. [CrossRef]
- Huang, C., Zhang, Z., Mao, B., & Yao, X. (2022). An overview of artificial intelligence ethics. *Journals & Magazines*, 4(4), 799–819. [CrossRef]
- IEEE, Institute of Electrical and Electronics Engineers. (2019). *Ethically aligned design: A vision for prioritizing human well-being with autonomous and intelligent systems*. Available online: https://standards.ieee.org/wp-content/uploads/import/documents/other/ead_brochure_v2.pdf (accessed on 20 January 2025).
- Jiménez Martínez, K. A., Gamboa Rodríguez, P. G., Betanzos Valenzuela, O. H., & Jiménez Arteaga, G. (2025). Inteligencia artificial generativa desde la perspectiva de la educación superior: Estudio bibliométrico. *CIE Academic Journal*, 4(1), 32–38. [CrossRef]
- Kuai, J. (2024). Unravelling copyright dilemma of AI-generated news and its implications for the institution of journalism: The cases of US, EU, and China. *New Media & Society*, 26(9), 5150–5168. [CrossRef]
- Kuai, J., Ferrer-Conill, R., & Karlsson, M. (2022). AI ≥ Journalism: How the Chinese copyright law protects tech giants’ AI innovations and disrupts the journalistic institution. *Digital Journalism*, 10(10), 1893–1912. [CrossRef]
- Latar, N. L. (2018). *Robot journalism: Can human journalism survive?* World Scientific.
- Lim, W. M., Gunasekara, A., Pallant, J., & Pechenkina, E. (2023). Generative AI and the future of education: Ragnarök or reformation? A paradoxical perspective from management educators. *The International Journal of Management Education*, 21(2), 100790. [CrossRef]
- Liuzzi, Á. (2024). *La revolución de la IA en el periodismo*. Telecom. Available online: <https://institucional.telecom.com.ar/prensa/redacciones/periodismo-ia> (accessed on 20 July 2024).
- Lopezosa, C., Pérez-Montoro, M., & Rey Martín, C. (2024). El uso de la inteligencia artificial en las redacciones: Propuestas y limitaciones. *Revista de Comunicación*, 23(1), 279–293. [CrossRef]
- Mayoral Sánchez, J., Parratt Fernández, S., & Mera Fernández, M. (2023). Uso periodístico de la IA en medios de comunicación españoles: Mapa actual y perspectivas para un futuro inmediato. *Estudios Sobre el Mensaje Periodístico*, 29, 821–832. [CrossRef]
- Noain Sánchez, A. (2022). Addressing the impact of artificial intelligence on journalism: The perception of experts, journalists, and academics. *Communication & Society*, 35(3), 31–40.
- OECD, Organization for Economic Co-Operation and Development. (2019–2024). *AI principles*. Available online: <https://legalinstruments.oecd.org/en/instruments/OECD-LEGAL-0449> (accessed on 30 January 2025).
- Pavlik, J. (2023). Collaborating with ChatGPT: Considering the implications of generative artificial intelligence for journalism and media education. *Journalism & Mass Communicator Educator*, 78(1), 84–93. [CrossRef]
- Porlezza, C. (2023). Promoting responsible AI: A European perspective on the governance of artificial intelligence in media and journalism. *Communications*, 48(3), 370–394. [CrossRef]
- Radcliffe, D. (2025). *Many journalists in the Global South are already using AI and they want guidance on how to do this ethically*. Interview in Reuters Institute for the Study of Journalism. Available online: <https://reutersinstitute.politics.ox.ac.uk/news/many-journalists-global-south-are-already-using-ai-and-they-want-guidance-how-do-ethically> (accessed on 30 January 2025).
- Reinecke, P., Kokshagina, O., & Karanasios, S. (2021). Framing the regulation of artificial intelligence-based technologies. *AIS Electronic Library*, 35, 1–10.
- Repilado, I. (2024). *Tratamiento de las herramientas de inteligencia artificial generativa en los medios de comunicación: Análisis de libros de estilo y guidelines*. Unpublished Final Degree Project. University of Valladolid.
- Rojas, F. A. Z., & Ramírez, C. E. J. (2023). La función ética del periodismo en la era digital. *Prefacio*, 7(11), 35–43. [CrossRef]
- Rouhiainen, L. (2018). *Inteligencia artificial: 101 cosas que debes saber hoy sobre nuestro futuro*. Planeta.
- Saad, S., & Issa, T. (2020). Integration or replacement: Journalism in the era of artificial intelligence and robot journalism. *International Journal of Media, Journalism and Mass Communications*, 6(3), 1–13.
- Sandoval Martín, T., La Rosa Barrolleta, L., Erranz Fernández, F., & Franco Álvarez, G. (2019, May 30–31). *Estudio sobre la calidad de las noticias automatizadas en español* [Conference paper]. XXV Congreso Internacional SEP Oportunidades y Riesgos del Periodismo Interconectado, Bizkaia Aretoa, Bilbao.
- Sánchez-García, P., Merayo-Álvarez, N., Calvo-Barbero, C., & Diez-Gracia, A. (2023). Spanish technological development of artificial intelligence applied to journalism: Companies and tools for documentation, production, and distribution of information. *Profesional de la Información*, 32(2), 1–18. [CrossRef]
- Segarra-Saavedra, J., Cristòfol, F. J., & Martínez-Sala, A. (2019). Inteligencia artificial (IA) aplicada a la documentación informativa y redacción periodística deportiva: El caso de BeSoccer. *Doxa Comunicación*, 29, 275–286. [CrossRef]
- Trapova, A., & Mezei, P. (2022). Robojournalism—A copyright study on the use of artificial intelligence in the European news industry. *GRUR International*, 71(7), 589–602. [CrossRef]

- Túñez-López, J. M., Ceide Fieiras, C., & Vaz-Álvarez, M. (2021). Impact of artificial intelligence on journalism. *Communication & Society*, 34(1), 177–193. [CrossRef]
- Ufarte Ruiz, M. J., & Manfredi Sánchez, J. L. (2019). Algoritmos y bots aplicados al periodismo: El caso de narrativa inteligencia artificial: Estructura, producción y calidad informativa. *Doxa*, 29, 213–233. [CrossRef]
- UNESCO. (2021). *Recommendation on the ethics of artificial intelligence*. Available online: <https://udoc.unesco.org/ark:/48223/pf0000380455> (accessed on 30 January 2025).
- Van Meter, K. (1990). Methodological and design issues: Techniques for assessing the representativeness of snowball samples. In E. Lambert (Ed.), *Collection and interpretation of data from hidden populations* (pp. 31–43). NIDA Research Monograph.
- Voicu, M. C., & Babonea, A. M. (2011). Using the snowball method in marketing research on hidden populations. *Challenges of the Knowledge Society*, 1, 1341–1351.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.



Review

How Generative AI Is Transforming Journalism: Development, Application and Ethics

Yi Shi and Lin Sun *

School of Government and Public Affairs, Communication University of China, Beijing 100024, China;
2021100503z9001@cuc.edu.cn

* Correspondence: 2021100503z9003@cuc.edu.cn

Abstract: Generative artificial intelligence (GAI) is a technology based on algorithms, models, etc., that creates content such as text, audio, images, videos, and code. GAI is deeply integrated into journalism as tools, platforms and systems. However, GAI's role in journalism dilutes the power of media professionals, changes traditional news production and poses ethical questions. This study attempts to systematically answer these ethical questions in specific journalistic practices from the perspectives of journalistic professionalism and epistemology. Building on the review of GAI's development and application, this study identifies the responsibilities of news organizations, journalists and audiences, ensuring that they realize the potential of GAI while adhering to journalism professionalism and universal human values to avoid negative technological effects.

Keywords: generative artificial intelligence; news production; journalistic ethics; subjectivity; media accuracy

1. Introduction

Generative artificial intelligence (GAI) is a technology system based on algorithms, models, etc., designed to create text, audio, images, videos, and code. GAI includes various technologies and architectures to learn the underlying patterns and correlations in data, and subsequently generate content based on this acquired knowledge (Jovanovic and Campbell 2022). A research report published by Accenture in March 2023 shows that GAI ushers in a bold new future for science, business and society, with a profoundly positive impact on human creativity and productivity. Among business leaders, 98% of respondents agree AI foundation models will play an important role in their organization's strategies over the next three to five years. Furthermore, as much as 40% of all working hours will be supported or augmented by language-based AI, such as GPT-4 (Harper et al. 2023).

GAI is currently used to assist and accelerate particular procedural tasks, such as content creation, fact-checking, data processing, image generation, speech conversion and translation, reducing the burden on human and increasing efficiency (Caswell et al. 2021; Nishal and Diakopoulos 2024). With the widespread adoption of GAI in news production, academia has begun to scrutinize GAI news production from three perspectives. The first line of study is comparing GAI-assisted journalism and traditional journalism (Hong and Tewksbury 2024; Wang et al. 2023). The second is to examine how GAI is used in journalism of specific countries or regions. For example, Gondwe (2023) explored how journalists in sub-Saharan Africa use GAI, while Pinto (2024) investigated GAI in the Brazilian news industry. The third is reflecting on ethical challenges and calling for upholding journalistic professionalism and its core values. Some scholars argue that journalistic professionalism is compromised by GAI, championing "Without journalists, there is no journalism" (Fernández et al. 2023). Some scholars express concern that the growing integration of GAI into news production may have a profound impact on public opinion and even influence the future of democracy (Spennemann 2023; Arguedas and Simon 2023). These three lines of study, whether emphasizing operational aspects or ethical

concerns, isolate the examination of the ethical challenges posed by GAI in journalism and fail to contextualize these challenges within specific stages of news production for comprehensive investigation.

Therefore, this study attempts to discuss ethical challenges under the context of specific stages of news production. In addition to scrutinizing existing technological implementations, its goal is to offer theoretical perspectives that can guide researchers, professionals, and policymakers in leveraging the capabilities of GAI responsibly while upholding journalistic integrity and universal human values, thus mitigating adverse technological impacts.

2. Development of GAI in Journalism

AI has been used in the news industry for the past decade. The Associated Press (AP) was one of the earliest news media to integrate AI into news production (Radcliffe 2023). In 2014, the AP began using AI to process reports on corporate earnings. Before using AI, AP editors and journalists spent countless resources creating financial reports, which drew their focus away from news of greater significance. Despite considerable investment, the AP could only produce 300 financial reports per quarter, leaving thousands of potential corporate earnings reports unwritten. With the help of Wordsmith created by Automated Insights, now they are able to convert earnings data into publishable news stories within seconds; this is nearly 15 times more efficient than the traditional way (Miller 2015). Other media organizations including Bloomberg, Reuters, Forbes, The New York Times, The Washington Post, and the BBC also use AI for news production. The primary applications of AI in these large media organizations involve news gathering, production, and dissemination. In China, Tencent was the first to use AI for news writing. In September 2015, Tencent's financial channel used a news-writing robot known as "Dreamwriter" for a news report titled "August CPI rose 2.0% year-on-year, hitting a new high in 12 months". The content mainly consisted of data analysis and expert commentary on the data. Dreamwriter continued to release more reports, reaching 40,000 in the first three quarters of 2016 (Zhou 2015). On 18 November 2015, Xinhua News Agency unveiled a writing robot dubbed "Kuaibi Xiaoxin" or "Fast Pen Xiao Xin", designed to swiftly craft news reports by leveraging published information. This innovative tool operates through a systematic workflow involving real-time data collection, meticulous data cleaning, and standardization using cutting-edge big data technologies. It then tailors algorithmic models according to specific business requirements, conducting data analysis and calculation. Based on these analyses, the system identifies suitable templates and generates reports adhering to Chinese language standards and automatically places the reports in a queue for editor review and release (Zhong and Zhang 2019).

Since 2018, breakthroughs in natural language processing (NLP) and large pre-trained models have unraveled the intricacies of language, enabling machines to read, learn from text, infer intent, and autonomously generate content. Moreover, these models can be quickly fine-tuned for various tasks, driving the development of GAI (Lamri 2023). In November 2022, OpenAI unveiled ChatGPT, an AI-driven natural language processing tool powered by the neural network architecture of Generative Pre-trained Transformer 3.5. This innovative tool is engineered to process sequential data, allowing it to comprehend language and generate text. By being trained on extensive datasets of real-world conversations, ChatGPT boasts a wealth of knowledge and can engage in conversations that closely resemble human interaction. Besides its chatbot capabilities, ChatGPT excels in various tasks including email composition, video scripting, copywriting, translation, and coding. The launch of ChatGPT in November 2022, followed by the introduction of GPT-4 in March 2023, has prompted close scrutiny from the news industry, which is closely monitoring both the positive and negative impacts of these advancements. Nicholas Carlson, global editor-in-chief of *Business Insider*, encouraged journalists to explore ways to use GAI in newsrooms. "A tsunami is coming", he said in April 2023. "We can either ride it or get wiped out by it. But it's going to be really fun to ride it, and it's going to make us faster

and better (Korn 2023)”. In 2024, the Reuters Institute at the University of Oxford released a comprehensive report based on a year-long study involving extensive interviews with industry experts aimed at forecasting trends in journalism. According to the report, 56% of the respondents emphasized the significance of employing AI for various back-end news automation tasks, such as tagging, transcription, and copyediting. This was followed by 37% of respondents who highlighted the importance of AI in providing better content recommendations, while 28% focused on commercial uses. Moreover, the report predicts the appointment of more senior editorial figures to coordinate AI activities and strategy this year (Reuters Institute 2023).

There are three main types of application of GAI in news organizations:

2.1. GAI Tools

In this particular application scenario, GAI tools operate independently of news organizations. Journalists access GAI tools as individual users seeking assistance in news production. This approach necessitates journalists to register and create accounts in order to use AI tools effectively. Such a low-cost and convenient approach is widely prevalent. For instance, journalists may pose queries to ChatGPT to swiftly obtain information. Another example is one of the UK’s biggest newspaper groups, Reach. The publisher of the *Daily Mirror* and *Daily Express* newspapers is exploring whether ChatGPT could help journalists write short news stories, as media organizations look at ways of using AI. Reach chief executive Jim Mullen told local media that the company had set up a working group to examine how the tool might be used to assist human reporters compiling coverage of topics such as local weather and traffic (Alim 2023).

2.2. GAI Platforms

GAI platforms offer a range of APIs tailored for content production, encompassing services like content analysis, sentiment analysis, event extraction, summary generation, personalized recommendations, content editing, and visualization. In this model of human-machine collaboration, journalists primarily contribute textual data, while machines handle content generation and presentation tasks. Within the dynamic interaction involving machines, media entities, and end-users, the media serves as an intermediary between end-users and GAI. Specifically, GAI manages the technical implementation, and the media furnishes user interfaces. The end result is a GAI platform accessible to end-users. A prime illustration of this approach is The New York Times’ interactive product, A VALENTINE, FROM A.I. TO YOU, developed with assistance from ChatGPT (The New York Times 2023). GAI simplifies creative expression by only requiring media professionals to issue design instructions before producing interactive products.

2.3. GAI Systems

News organizations invest in the development of tailored GAI systems, a process that demands significant technical expertise and resources, including the creation of proprietary algorithms. This approach yields several advantages, primarily centered on embedding the core values of the media organization directly into the GAI system’s framework. By doing so, it ensures that the generated content adheres closely to the organization’s editorial style and principles. However, this approach typically entails substantial upfront costs, making it feasible primarily for larger media conglomerates with extensive financial resources. One notable example is Bloomberg’s BloombergGPT platform, which exemplifies this approach in action (Bloomberg 2023). The advancement of GAI systems facilitates the provision of personalized services across different phases of news production, tailored to the specific requirements of media organizations. For instance, within interactive platforms designed for financial media, when users input “Apple”, the system would primarily focus on information related to the American technology company rather than the fruit. Moreover, GAI systems offer the capability to establish direct links to exclusive databases, such as real-time trading data of publicly listed companies.

In general, three concurrent approaches are commonly observed. With the ongoing advancement of GAI, its integration with news organizations will further enhance. The third approach signifies a complete assimilation of GAI within the news organization, where it operates as a subsystem of the institution. Ultimately, as the integration of GAI with news organizations progresses, the thinking and expression of GAI will increasingly resemble those of human journalists, enabling it to better fulfill the demands of journalistic work. From the realm of AI to GAI, technological progressions have revolutionized traditional news production, rendering it more automated.

3. Applications of GAI in Journalism

Based on a literature review and online information, three main applications of GAI in journalism are summarized:

3.1. Information Gathering

Information gathering serves as the cornerstone of news production, where journalists assess the relevance and significance of various topics based on available information. With the integration of GAI, the landscape of information gathering has broadened, costs have decreased, and traditional methodologies have evolved. More specifically, GAI leverages sophisticated algorithms to sift through extensive datasets, discern pertinent data points, and deliver valuable insights. Through automated data processing, visualization tools, and interpretive capabilities, GAI unveils previously obscured layers of information, enhancing the efficiency and depth of information-gathering processes (Diakopoulos 2019; Gondwe 2023). Moreover, GAI can analyze past data, forecast trends for complex events and prepare journalists for unforeseen events. For example, Google's Bard, trained on a vast dataset of text and code spanning various topics such as history, science, technology, and current affairs, can use this information to forecast event trends (Patrick 2023).

Overall, in the information-gathering stage, the use of GAI involves three main aspects. First, GAI replaces journalists in completing repetitive and labor-intensive basic tasks, such as collecting background information. Reuters News Tracer is such an example. It runs machine-learning algorithms on a percentage of Twitter's 700 million daily tweets to find breaking news. These algorithms look for clusters of tweets that are talking about the same event, and the tool then generates a newsworthiness rating, questioning whether the event is worth reporting and verifying whether a piece of information is true. Reuters' journalists then independently verify the information through their own channels and reporting, before publishing (Reuters 2017).

Second, GAI serves to address the limitations of journalists in news reporting. Journalists often face constraints such as time and space, which may hinder their ability to promptly follow up on the latest developments. In such scenarios, GAI steps in to identify real-time information, continuously monitor unfolding events, and offer innovative perspectives for news coverage. This technological support enables journalists to stay updated with evolving stories and maintain relevance in their reporting despite constraints (Liu et al. 2017).

Third, journalists play a crucial role in training GAI systems to refine their capacity to evaluate newsworthiness, aiming for alignment with the editorial standards of the news organization. However, this process comes with a caveat. As GAI's ability to assess newsworthiness improves, its information gathering may become biased toward the values and priorities of the news organization. Consequently, there is a risk of overlooking marginal events and relying on a narrower set of sources. To mitigate this risk, ongoing collaboration among news organizations, journalists, and programmers is essential. This collaboration should focus on continuously enhancing GAI's cognitive and learning capabilities to adapt to emerging events and diverse news contexts (Simon 2022; Harcup 2023).

3.2. Content Production

The primary application of GAI in news production is to aid journalists in content creation. GAI systems can generate text tailored to the specific style and tone of news organizations, facilitating tasks such as transcription, translation, and daily news updates. This assistance not only enhances journalists' productivity but also improves the overall quality and readability of news reports. Additionally, GAI plays a crucial role in increasing the efficiency of news organizations in producing content in multiple languages, thereby expanding their reach and audience base. For example, the French newspaper *Le Monde* uses AI to assist in translating articles, enabling around 30 stories a day to appear in its English edition (Newman 2024).

News channels generated and driven solely by GAI without human journalists and editors have also emerged, with NewsGPT, an American news website launched on 1 March 2023, standing as the world's pioneering channel of its kind. NewsGPT's algorithms are able to analyze and interpret data from a wide range of sources, including social media, news websites, and government agencies. Then, it uses this data to create reports. The website even has its AI anchors (Ians 2023).

Specifically, GAI primarily assists content production in two main aspects. First is content creation, such as summaries and headlines. *Aftonbladet*, a Swedish newspaper found that news reports supplemented with bullet points generated by AI could increase overall engagement, especially among young readers (Newman 2024). Furthermore, GAI can assist in modality conversion between text and images, audio, and video. For instance, ReelFramer can convert traditional text formats to engaging video shorts that match the platform's style. GAI can provide suggestions on narratives, including characters, plots, backgrounds, and key information (Wang et al. 2023). The second is diversifying the writing. GAI can adapt news stories according to the style of news organizations, generating different writing styles, and even reframing stories semantically for different audiences. According to the research of Gina Chua (2023), the GAI tool Claude can narrate the same news content in different styles of *The New York Times*, *The New York Post*, *China Daily*, and *Fox News*. For news organizations, this feature may help attract audiences with different perspectives and values, thereby expanding their audience (Chua 2023).

3.3. Customization and Dissemination

Traditional news production typically follows a linear and unidirectional process, where professional journalists and editors progress through stages such as information gathering, writing, editing, and distribution of news to the audience. However, with the integration of GAI, this process undergoes enhancement through the introduction of algorithmic optimization and interactive dissemination. This transformation allows for seamless connectivity across different stages of news production, transitioning the linear process into a networked one. GAI systems have the capability to record and analyze the behavioral patterns of journalists and editors within newsrooms, thus enabling the creation of comprehensive databases. Leveraging this data, GAI can provide personalized recommendations for assigning journalists to specific news topics based on their expertise and past performance. By optimizing the allocation of human resources within a journalist team, GAI further enhances operational efficiency and overall productivity in news production workflows (Moravec et al. 2020; Zagorulko 2023; Cools et al. 2023). Furthermore, GAI involves the audience in new production through interactive dissemination, collecting the audience's information and personalizing their feeds. GAI can analyze the audience's data and content preferences and then customize summaries, headlines, and content for them (Marr 2024). For example, Forbes introduced Adelaide in the form of a search engine, where individuals can ask any question to the chatbot. Adelaide not only provides a concise answer but also recommends a series of news related to the question (David 2023). The news chatbot Charlie, launched by OneSub, assumes the role of a personal journalist for users. Charlie is dedicated to supporting users' emotional well-being by avoiding

sensational or negative content, alleviating users' stress and anxiety, and making obtaining information simpler and more interactive (Twipe 2023).

GAI has fundamentally transformed the conventional linear process of news production, shifting the focus of each stage towards facilitating information sharing and enhancing the accuracy and quality of tailored information dissemination. For instance, platforms like NewsCube enable users to explore complex news stories from diverse perspectives. Each face of the NewsCube contains content sourced from various media organizations or outlets, offering users a multifaceted view of the news landscape. This approach helps users navigate through the vast hypertext world of news content with greater direction and clarity. Furthermore, NewsCube collects data on user behaviors and preferences, which serve as valuable input for guiding future decision-making in news production and facilitating personalized content dissemination (Doherty and Stephen 2020). Audience involvement in news production not only encourages content diversity but also promotes a more vibrant public discourse. By incorporating viewpoints from various racial, religious, and cultural backgrounds, news outlets can enrich the reading experience for their audience. Furthermore, this engagement helps improve the accuracy of content by enabling feedback on the credibility of information. As audiences actively participate in verifying and fact-checking news stories, there is a gradual reduction in the dissemination of false or misleading information.

4. Ethical Reflections: Challenges of Journalistic Ethics in the Era of GAI

Though GAI has brought about some benefits to the news industry, its integration also necessitates reflection. Canadian scholar Geoffrey Winthrop Young once pondered how computers redefine the boundaries between humans and technology and how digital machines affect individual subjectivity and social structures. As GAI assumes a more prominent role in journalism, media professionals must navigate the dynamic landscape where AI shares the power of news production. This shift challenges traditional conceptions of journalistic practice and necessitates the development of new ethical standards. One significant risk is that the fundamental principles of journalistic ethics, including truth, accuracy, objectivity, and accountability, may face unprecedented challenges in this evolving paradigm (Ouchchy and Dubljević 2020). The term "journalistic ethics" refers to the set of values, professional standards, and behavioral guidelines that should be followed in the practice of news production and dissemination. Journalistic ethics not only dictate the values and ethical considerations of news reporting but also define the norms and boundaries of journalistic practices. This section identifies the ethical challenges in the three stages of information gathering, content production, and customization and dissemination.

4.1. Information Gathering: Human Subjectivity of Journalists

The enduring question of the relationship between humans and machines lies at the heart of the philosophy of human subjectivity, which fundamentally explores who holds control of this relationship. The ancient Greek philosopher Protagoras proposed that "Of all things the measure is Man", emphasizing that humans, due to their agency, are always the masters. In the traditional human-machine relationship, machines typically occupy a subordinate role to humans, with humans exerting control and direction over machine actions and functions (Mara and Hawk 2009). AI and automation represent two pivotal trends in contemporary technological advancement. AI encompasses machines' capacity to learn, reason, adapt, and make decisions akin to humans. Automation, on the other hand, involves machines or computers autonomously executing tasks with minimal human intervention. These trends signify a shift towards bidirectional interaction between humans and machines, wherein computers not only respond to human commands but also intelligently process and execute tasks based on human input and feedback. In the era of deep mediatization, characterized by equal interaction between humans and machines, the role of machines in this relationship has undergone transformation. Machines are no longer mere intermediaries but active participants in social processes, contributing

to the generation and dissemination of information. Furthermore, in human–machine communication, machines possess the capability to participate in meaning creation and context construction, further blurring the boundaries between human and machine agency.

In news production, GAI has become a quasi-subject with a certain degree of agency, reshaping the roles and responsibilities of journalists and other media professionals. For example, traditionally, the information gathered by journalists should possess societal significance and humanistic considerations, reflecting the intricate dynamics between individuals and society, while also adhering to principles of fairness, objectivity, and rationality. If journalists are entirely replaced by machines, and it is left to machines to decide what information to gather as news material, there is a risk that machines may indiscriminately collect personal information or user data without human constraints, thus infringing on individual privacy. As a result, news production may violate basic human rights as journalism forsakes its fundamental purpose of serving society and instead takes on the role of mass surveillance (Dilmaghani et al. 2019; Andrew and Huang 2023; Guembe et al. 2022). With intelligent systems in place, users' privacy is exposed, and the prerequisite for accessing intelligent services is the relinquishment of personal information.

Last year, June 29 witnessed sixteen individuals in the United States filing a lawsuit against ChatGPT. They accused the platform of collecting and revealing their personal information, such as account details, login credentials, emails, payment information, browsing history, social media interactions, chat logs, and other online activities, without adequately informing or obtaining consent from the users (Mauran 2023). Additionally, the restricted accuracy of GAI, particularly in comprehending intricate emotions, results in a growing prevalence of standardized news devoid of human touch in its delivery.

4.2. Content Production: Credibility

Credibility serves as not only a foundational principle in journalism but also a fundamental aspect of journalistic ethics. However, with the advent of the digital age, both scholars and professionals are reexamining the concept of “news credibility”. Alongside the digital transformation of the news industry, discussions surrounding the credibility of news have become increasingly prevalent. For instance, within the realm of digital news, discussions delve into nuanced concepts such as “experiential truth” within media technology, “perceived truth” within cognitive psychology, and “negotiated truth” concerning power dynamics. Despite the evolving definitions and discussions surrounding news credibility, its significance remains paramount in defining what qualifies as “news”.

In fact, truth is not absolute but falls within a measurable range. Thanks to technological advancements, journalism is now closer to truth than ever, sometimes even overly detailed and accurate, appearing clearer than reality itself. For example, the fact-checking ability of GAI is highly accurate—for example, ChatGPT achieves an accuracy rate of up to 68.79% (Hoes and Bermeo 2023). However, GAI's usefulness in making fabrications convincingly authentic is concealing its detrimental risks of blurring the boundaries of reality. GAI, characterized by technical rationale, stealthily integrates mechanistic cognition rooted in technical logic and preconceived judgments into news production. Extreme technology supporters become adherents of technological superstition (Shipley and Williams 2023). For example, GAI has caused deepfake challenges, where Generative Adversarial Networks (GANs) are used for face swapping, lip synchronization, facial re-enactment, motion transfer, and more. GAI's ability to generate fake content of individuals expressing opinions with specific emotions and even dancing has led to an upheaval in the news industry, making it more difficult for media professionals to ensure the authenticity of their content (Marconi and Daldrup 2018).

Moreover, the decreasing cost associated with producing deepfakes via GAI is exacerbated by the adoption of the Platform as a Service (PaaS) model in cloud services and cloud terminals. This trend intensifies the challenges posed by deepfake technology, amplifying its potential negative political ramifications. For example, a video features a two-minute-long conversation in which the leader of Progresívne Slovakia, Mr Michal

Simecka, appears to discuss buying votes from the Roma minority with a journalist. AFP fact-checkers consulted several experts who concluded that the audio was synthesized by an AI tool trained on real samples of the speakers' voices, and several copies are available on social media without a label marking them as misleading (Solon 2023). As Thomson et al. (2022) observe, "while the creation of synthetic media is not inherently problematic (for example, in the case of art, satire, or parody), issues emerge when those media are presented without transparency and masquerade as reality". Indeed, outlets like *The New York Times* have begun labeling AI-generated images as such to highlight their provenance.

4.3. Customization and Dissemination: Value Orientation

News values encompass the qualities that enhance the significance or appeal of a story to the public. Consistent factors of news values include credibility and timeliness, while variables are prominence, impact, proximity, and interest. The depth and diversity of values embedded within news facts directly correlate with the overall value of the news report. Traditional media pursue truth and fulfill social responsibilities. Their news values include timeliness, relevance, and prominence. Caring about what the audience want, they also produce interesting news or news that matter to a given audience. With the development of GAI, power replaces news values, which means that whoever possesses the technology and controls the resource decides what is newsworthy. Deploying GAI requires substantial resources such as digital infrastructure and training corpora that are controlled by countries and enterprises with the most resources and power, leading to their monopoly. Consequently, the AI models prioritize their worldviews and perspectives, while their technological regulations and standards establish global norms, and their value systems become universal, ultimately causing a shift in news values towards power (McIntosh 2018; Acemoglu 2021). New Zealand's data scientist David Rozado created a GAI model called RightWingGPT to express US right-wing political views. Research indicates that language models can subtly influence users' values, highlighting the potential serious consequences of political biases in GAI models (Knight 2023). Other researchers use DALL-E and Stable Diffusion to convert text into images, revealing that these models perpetuate common stereotypes. For instance, prompts related to cleaners consistently generate images depicting women (Bianchi et al. 2023).

The inherent flaws in large language models directly affect the output of GAI, which relies on machine learning to mimic human behavior and generate content. This situation leads to systemic biases, value conflicts, cultural hegemony, stereotypes, and misinformation (Zhou et al. 2024). In addition, GAI models lack common sense reasoning, making it difficult to comprehend complex issues and distinguish nuances in tone and subtle emotions. Issues like AI hallucinations emerge, where generated content may seem plausible but contradicts real-world knowledge or existing data (Salvagno et al. 2023; Alkaissi and McFarlane 2023). As a result, GAI values shape the customization and dissemination of news, hindering comprehension of events, narrowing perspectives, intensifying polarized discourse, and eroding public discourse.

To facilitate an understanding of the study, a figure is shown here to depict the application of GAI in news production and the associated ethical challenges (Figure 1).

Lastly, it is imperative to discuss the legal ramifications stemming from the integration of GAI in news production, particularly concerning potential violations of individual privacy rights and copyrights. On 15 February 2023, Francesco Marconi, a Wall Street Journal reporter, publicly accused OpenAI of unauthorized use of content from prominent foreign media outlets such as Reuters, The New York Times, The Guardian, and the BBC to train its ChatGPT model, without compensating the original sources. Presently, prevailing legal frameworks predominantly attribute responsibility to individuals, which may prove insufficient in addressing GAI as digital entities. Legal accountability demands the establishment of a direct causal link between the AI operator and any infringement, with penalties commensurate with the actual harm inflicted. However, existing legal standards lack the necessary mechanisms to precisely identify and attribute damages, as

well as engage in ongoing assessment and risk mitigation protocols to minimize adverse consequences. Moreover, the incorporation of GAI poses significant challenges to the protection of intellectual property. The question of whether AI-generated entities are entitled to intellectual property rights remains unresolved, although disputes over the rights of AI-generated entities have already arisen. Notably, in China, a defendant faced litigation for employing AI-generated images without the plaintiff's authorization as illustrations for articles. The Beijing Internet Court held that AI-generated images demonstrating human-like "originality" and intellectual input could be protected under copyright law as manifestations of creative intellectual endeavors.

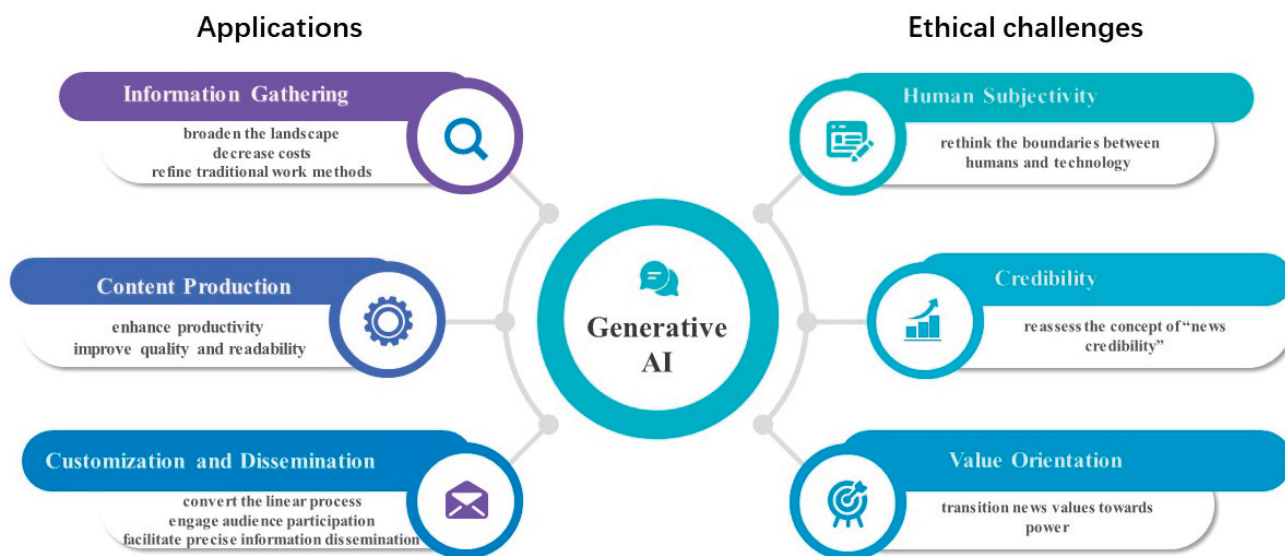


Figure 1. Application of GAI in news production and the associated ethical challenges.

5. Conclusions and Recommendations

This research extensively explores how GAI could potentially disrupt the conventional methods of news production. It delves deep into the integration of GAI within the news production workflow, thoroughly examining its current state and the ethical quandaries it introduces to the field of journalism. Through a meticulous examination of these ethical challenges, this study aims to offer invaluable insights into how GAI can play a constructive role in shaping the future of news production. Ultimately, its goal is to equip professionals and researchers with a comprehensive understanding to effectively navigate the continuous technological transformations occurring within the realm of journalism.

The advantages of GAI in news production are multifaceted. Firstly, GAI significantly enhances efficiency across various tasks such as collecting information, generating content, tailoring it to a specific audience, and disseminating it, thus optimizing the overall news production process. This relieves human reporters and editors of routine tasks, allowing them to focus on critical endeavors like fact-checking and closely monitoring unfolding news events. Moreover, GAI enriches the depth and breadth of news content, capturing the audience's attention and catering to their information and emotional needs. Lastly, GAI fosters interaction between the audience and media entities, empowering the audience and prompting news organizations to incorporate a spectrum of viewpoints into their reporting. By embracing diversity and minimizing biases, GAI contributes to nurturing a more robust and inclusive media landscape.

The ethical challenges presented by GAI in journalism are significant and cannot be overlooked. The integration and progression of GAI disrupt the traditional roles of human journalists and editors, offering convenience while also raising valid concerns about news credibility. Of particular concern is the subtle influence that GAI may have on audience values, which may be less overt compared to the cognitive effects of conventional news reporting. This subtle influence threatens to undermine the integrity and professionalism

of journalists, potentially resulting in a deterioration in the overall quality of media content. In response to these challenges, numerous media outlets have taken steps to develop guidelines for the responsible use of GAI, providing practical examples and guidance for newsrooms to effectively navigate these ethical dilemmas. For example, the Partnership on AI (PAI), a collaborative effort involving academic, civil society, industry, and media organizations, issued the *AI Procurement and Use Guidebook for Newsrooms* in August 2023. This guidebook aims to offer comprehensive measures for editorial departments to address the challenges posed by AI in a proactive and responsible manner (PAI Staff 2023).

To address these challenges, it is recommended that three key stakeholders—news organizations, journalists, and the audience—proactively embrace their roles in upholding journalistic ethics. For news organizations, responsible use of GAI is paramount. This involves ensuring that the benefits of GAI are harnessed for both the organization and the audience while mitigating the risks of amplifying biases and spreading misinformation with potential societal harm. Industry associations should establish guidelines or ethical standards for GAI application in journalism to facilitate this.

Journalists need to undergo a fundamental shift in their role, moving beyond simply producing information to serving as diligent fact-checkers. They must meticulously verify the credibility of news generated by GAI across a wide range of topics and domains, ensuring that only accurate information is disseminated to the public. Furthermore, journalists have a responsibility to actively inform the public of the truth and to critique any content that fails to meet the rigorous standards of journalism. In addition to these responsibilities, journalists should focus on enhancing their cross-disciplinary integration skills. This involves not only discovering news but also effectively integrating and organizing content from various sources and perspectives. Moreover, journalists must develop strong planning, organizing, and coordinating abilities through practical experience. By leveraging their innate human qualities such as intuition, adaptability, creativity, critical thinking, and a sense of humanistic care, journalists can maintain their agency and integrity in collaboration with GAI.

Audience members using news platforms driven by GAI should undergo thorough media literacy training to effectively navigate this evolving landscape. They must understand the nuances of GAI application to discern between true and false information generated by these systems. Additionally, it is vital to encourage users to minimize their reliance on GAI whenever possible, fostering critical thinking and independent judgment. Collaborative efforts from various stakeholders are essential to enhance audience media literacy. News organizations and journalists should seamlessly integrate media literacy education into their news practices, actively encouraging the audience to detect false information by facilitating the sharing of pertinent educational materials. Strengthening media literacy skills empowers the audience to adeptly identify misinformation and engage more meaningfully in the news ecosystem.

Author Contributions: Conceptualization, Y.S.; writing—original draft preparation, Y.S.; writing—review and editing, L.S.; supervision, Y.S.; project administration, L.S.; funding acquisition, L.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Tianjin Education Science Planning Project “Theoretical and Practical Research on Public Art Education as a Path for Building a Learning Society”, grant number EGE210268 and Special funding project for basic scientific research business expenses of Chinese central universities “Research on the Index System of the Influence of Chinese Civilization Communication Power”, grant number CUC230D046.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest.

References

- Acemoglu, Daron. 2021. *Harms of AI*. Working Paper No: 29247. Cambridge: National Bureau of Economic Research.
- Alim, Arjun Neil. 2023. Daily Mirror Publisher Explores Using ChatGPT to Help Write Local News. *Financial Times*. February 20. Available online: <https://www.ft.com/content/4fae2380-d7a7-410c-9eed-91fd1411f977> (accessed on 7 April 2024).
- Alkaissi, Hussam, and Samy I. McFarlane. 2023. Artificial hallucinations in ChatGPT: Implications in scientific writing. *Cureus* 15: e35179. [CrossRef] [PubMed]
- Andrew, Baker, and Casey Huang. 2023. Data breaches in the age of surveillance capitalism: Do disclosures have a new role to play? *Critical Perspectives on Accounting* 90: 102396. [CrossRef]
- Arguedas, Amy Ross, and Felix M. Simon. 2023. *Automating Democracy: Generative AI, Journalism, and the Future of Democracy*. Oxford: Balliol Interdisciplinary Institute, University of Oxford.
- Bianchi, Federico, Pratyusha Kalluri, Esin Durmus, Faisal Ladhak, Myra Cheng, Debora Nozza, Tatsunori Hashimoto, Dan Jurafsky, James Zou, and Aylin Caliskan. 2023. Easily accessible text-to-image generation amplifies demographic stereotypes at large scale. Paper presented at the 2023 ACM Conference on Fairness, Accountability, and Transparency, Chicago, IL, USA, June 12–15; pp. 1493–504.
- Bloomberg. 2023. Introducing BloombergGPT, Bloomberg’s 50-Billion Parameter Large Language Model, Purpose-Built from Scratch for Finance. March 23. Available online: <https://www.bloomberg.com/company/press/bloomberggpt-50-billion-parameter-llm-tuned-finance/> (accessed on 7 April 2024).
- Caswell, Gurevych, Fink, and Konstantin Dörr. 2021. Automated Journalism and Professional Identity: A Professional Community Analysis of News Writers and News Consumers. *Digital Journalism* 9: 850–69.
- Chua, Gina. 2023. Semfor. How Chatbots Can Change Journalism. Or Not. February 20. Available online: <https://www.semafor.com/article/02/17/2023/how-chatbots-can-change-journalism-or-not> (accessed on 11 March 2024).
- Cools, Hannes, Baldwin Van Gorp, and Michaël Opgenhaffen. 2023. The levels of automation and autonomy in the AI-augmented newsroom: Toward a multi-level typology of computational journalism. In *Research Handbook on Artificial Intelligence and Communication*. Cheltenham: Edward Elgar Publishing, pp. 284–99.
- David, Emilia. 2023. Forbes Now Has Its Own AI Search Engine. October 27. Available online: <https://www.theverge.com/2023/10/26/23933799/forbes-generative-ai-search-adelaide> (accessed on 26 March 2024).
- Diakopoulos, Nicholas. 2019. *Automating the News: How Algorithms Are Rewriting the Media*. Cambridge: Harvard University Press, p. 16.
- Dilmaghani, Saharnaz, Matthias R. Brust, Grégoire Danoy, Natalia Cassagnes, and Johnatan Pecero. 2019. Privacy and security of big data in AI systems: A research and standards perspective. Paper presented at 2019 IEEE International Conference on Big Data, Los Angeles, CA, USA, December 9–12; pp. 5737–43.
- Doherty, Skye, and Viller Stephen. 2020. Prototyping interaction: Designing technology for communication. In *Reimagining Communication: Experience*. Edited by Michael Filimowicz and Veronika Tzankova. New York: Routledge, pp. 80–96.
- Fernández, Peña, Simón Fernández, Koldobika Meso Ayerdi, Ainara Larrondo Ureta, and Javier Díaz Noci. 2023. Without journalists, there is no journalism: The social dimension of generative artificial intelligence in the media. *El Profesional de la Información* 32: 2. [CrossRef]
- Gondwe, Gregory. 2023. CHATGPT and the Global South: How are journalists in sub-Saharan Africa engaging with generative AI? *Online Media and Global Communication* 2: 228–49. [CrossRef]
- Guembe, Blessing, Ambrose Azeta, Sanjay Misra, Victor Chukwudi Osamor, Luis Fernandez-Sanz, and Vera Pospelova. 2022. The Emerging Threat of Ai-Driven Cyber Attacks: A Review. *Applied Artificial Intelligence* 36: 2037254. [CrossRef]
- Harcup, Tony. 2023. The Struggle for News Value in the Digital Era. *Journalism and Media* 4: 902–17. [CrossRef]
- Harper, Christian, Jenn Francis, and Julie Bennink. 2023. Accenture Technology Vision 2023: Generative AI to Usher in a Bold New Future for Business, Merging Physical and Digital Worlds. March 30. Available online: <https://newsroom.accenture.com/news/2023/accenture-technology-vision-2023-generative-ai-to-usher-in-a-bold-new-future-for-business-merging-physical-and-digital-worlds> (accessed on 7 April 2024).
- Hoes, Altay, and Juan Bermeo. 2023. Leveraging ChatGPT for Efficient Fact-Checking. *PsyArXiv* 3. Available online: <https://osf.io/qnjkf> (accessed on 7 April 2024).
- Hong, Chang, and David Tewksbury. 2024. Can AI Become Walter Cronkite? Testing the Machine Heuristic, the Hostile Media Effect, and Political News Written by Artificial Intelligence. *Digital Journalism* 12: 1–24. [CrossRef]
- Ians. 2023. Punjab News Express. World’s First AI-Generated News Channel Called NewsGPT Launched. March 16. Available online: <https://www.punjabnewsexpress.com/technology/news/worlds-first-ai-generated-news-channel-called-newsgpt-launched-203017> (accessed on 9 April 2024).
- Jovanovic, Mladan, and Mark Campbell. 2022. Generative artificial intelligence: Trends and prospects. *Computer* 55: 107–12. [CrossRef]
- Knight, Will. 2023. Meet ChatGPT’s Right-Wing Alter Ego. April 27. Available online: <https://www.wired.com/story/fast-forward-meet-chatgpts-right-wing-alter-ego/> (accessed on 11 April 2024).
- Korn, Jennifer. 2023. CNN Business, How Companies Are Embracing Generative AI for Employees. . . or Not. September 22. Available online: <https://edition.cnn.com/2023/09/22/tech/generative-ai-corporate-policy/index.html> (accessed on 15 March 2024).

- Lamri, Jeremy. 2023. How Do Generative Artificial Intelligences (GAI) Actually Work? *Medium*. January 21. Available online: <https://jeremy-lamri.medium.com/how-do-generative-artificial-intelligences-gai-actually-work-42670d1ca19> (accessed on 6 April 2024).
- Liu, Xiaomo, Armineh Nourbakhsh, Quanzhi Li, Sameena Shah, Robert Martin, and John Duprey. 2017. Reuters tracer: Toward automated news production using large scale social media data. Paper presented at 2017 IEEE International Conference on Big Data (Big Data), Boston, MA, USA, December 11–14; pp. 1483–93.
- Mara, Andrew, and Byron Hawk. 2009. Posthuman rhetorics and technical communication. *Technical Communication Quarterly* 19: 1–10. [CrossRef]
- Marconi, Francesco, and Till Daldrup. 2018. How the Wall Street Journal Is Preparing Its Journalists to Detect Deepfakes. November 15. Available online: <https://www.niemanlab.org/2018/11/how-the-wall-street-journal-is-preparing-its-journalists-to-detect-deepfakes/> (accessed on 11 April 2024).
- Marr, Bernard. 2024. How Generative AI Will Change the Jobs of Journalists. *Forbes*. March 22. Available online: <https://www.forbes.com/sites/bernardmarr/2024/03/22/how-generative-ai-will-change-the-jobs-of-journalists/?sh=64319f1c2847> (accessed on 4 April 2024).
- Mauran, Cecily. 2023. OpenAI Is Being Sued for Training ChatGPT with ‘Stolen’ Personal Data. *Mashable*. June 30. Available online: <https://sea.mashable.com/tech/24637/openai-is-being-sued-for-training-chatgpt-with-stolen-personal-data> (accessed on 7 April 2024).
- McIntosh, Daniel. 2018. We need to talk about data: How digital monopolies arise and why they have power and influence. *Journal of Technology Law & Policy* 23: 185–213.
- Miller, Ross. 2015. AP’s ‘Robot Journalists’ Are Writing Their Own Stories Now. January 30. Available online: <https://www.theverge.com/2015/1/29/7939067/ap-journalism-automation-robots-financial-reporting> (accessed on 9 March 2024).
- Moravec, Václav, Veronika Macková, Jakub Sido, and Kamil Ekštejn. 2020. The robotic reporter in the Czech news agency: Automated journalism and augmentation in the newsroom. *Communication Today* 11: 36.
- Newman, Nic. 2024. Journalism, Media, and Technology Trends and Predictions. Available online: <https://reutersinstitute.politics.ox.ac.uk/journalism-media-and-technology-trends-and-predictions-2024> (accessed on 7 April 2024).
- Nishal, Sachita, and Nicholas Diakopoulos. 2024. Envisioning the Applications and Implications of Generative AI for News Media. *arXiv*, arXiv:2402.18835.
- Ouchchy, Coin, and Veljko Dubljević. 2020. AI in the headlines: The portrayal of the ethical issues of artificial intelligence in the media. *AI & Society* 35: 927–36.
- PAI Staff. 2023. PAI Seeks Public Comment on the AI Procurement and Use Guidebook for Newsrooms. August 3. Available online: <https://partnershiponai.org/pai-seeks-public-comment-on-the-ai-procurement-guidebook-for-newsrooms/> (accessed on 7 April 2024).
- Patrick, Joseph. 2023. How Does the Conversation between a Journalist and Bard, the AI Chatbot at Google Occur? *Heart of Hollywood Magazine*. June 2. Available online: <https://www.heartofhollywoodmagazine.com/post/how-does-the-conversation-between-a-journalist-and-bard-the-ai-chatbot-at-google-occur> (accessed on 14 March 2024).
- Pinto, Barbosa. 2024. Artificial Intelligence (AI) in Brazilian Digital Journalism: Historical Context and Innovative Processes. *Journalism and Media* 5: 325–41. [CrossRef]
- Radcliffe, Damian. 2023. *Mediamakersmeet*. Unlocking the Power of AI: 6 Lessons from AP for Publishers. March 3. Available online: <https://mediamakersmeet.com/unlocking-the-power-of-ai-6-lessons-from-ap-for-publishers/> (accessed on 10 March 2024).
- Reuters. 2017. May 15. Available online: <https://www.reutersagency.com/en/reuters-community/reuters-news-tracer-filtering-through-the-noise-of-social-media/> (accessed on 15 March 2024).
- Reuters Institute. 2023. Trends and Predictions 2024. Available online: <https://reutersinstitute.politics.ox.ac.uk/journalism-media-and-technology-trends-and-predictions> (accessed on 18 March 2024).
- Salvagno, Michele, Fabio Silvio Taccone, and Alberto Giovanni Gerli. 2023. Artificial intelligence hallucinations. *Critical Care* 27: 180. [CrossRef] [PubMed]
- Shipley, Gerhard P., and Deborah H. Williams. 2023. Critical AI Theory: The Ontological Problem. *Open Journal of Social Sciences* 11: 618–35. [CrossRef]
- Simon, Felix M. 2022. Uneasy bedfellows: AI in the news, platform companies and the issue of journalistic autonomy. *Digital Journalism* 10: 1832–54. [CrossRef]
- Solon, Olivia. 2023. *Bloomberg Law*. Trolls in Slovakian Election Tap AI Deepfakes to Spread Disinfo. September 29. Available online: <https://news.bloomberglaw.com/artificial-intelligence/trolls-in-slovakian-election-tap-ai-deepfakes-to-spread-disinfo> (accessed on 7 April 2024).
- Spennemann, Dirk H. R. 2023. Will the Age of Generative Artificial Intelligence Become an Age of Public Ignorance? *Preprints* 2023091528.
- The New York Times. 2023. A Valentine, from A.I. to You. February 13. Available online: <https://www.nytimes.com/interactive/2023/02/13/opinion/valentines-day-chatgpt.html> (accessed on 4 April 2024).
- Thomson, T. J., Daniel Angus, Paula Dootson, Edward Hurcombe, and Adam Smith. 2022. Visual Mis/Disinformation in Journalism and Public Communications: Current Verification Practices, Challenges, and Future Opportunities. *Journalism Practice* 16: 938–62. [CrossRef]

- Twipe. 2023. The “Wild West” of Generative AI Experiments, for News Publishers. *Mediamakersmeet*. May 12. Available online: <https://mediamakersmeet.com/the-wild-west-of-generative-ai-experiments-for-news-publishers/> (accessed on 6 April 2024).
- Wang, Sitong, Samia Menon, Tao Long, Keren Henderson, Dingzeyu Li, Kevin Crowston, Mark Hansen, Jeffrey V. Nickerson, and Lydia B. Chilton. 2023. Reelf-ramer: Co-creating news reels on social media with generative AI. *arXiv*, arXiv:2304.09653.
- Zagorulko, Dmytro I. 2023. ChatGPT in newsrooms: Adherence of AI-generated content to journalism standards and prospects for its implementation in digital media. *Vcheni Zapysky TNU Imeni VI Vernadskoho* 34: 319–25. [CrossRef]
- Zhong, Y, and Han Zhang. 2019. “Kuaibi Xiaoxin”: Xinhua News Agency’s First Robot Reporter. *Xinwenzhanxian*. February 27. Available online: <http://media.people.com.cn/GB/n1/2019/0227/c425664-30905230.html> (accessed on 6 April 2024).
- Zhou, Tong. 2015. This Is a Manuscript Written by a Robot in One Second. September 11. Available online: <https://www.im2maker.com/news/20150911/475.html> (accessed on 9 March 2024).
- Zhou, Mi, Vibhanshu Abhishek, Timothy Derdenger, Jaymo Kim, and Kannan Srinivasan. 2024. Bias in Generative AI. *arXiv*, arXiv:2403.02726.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.



Article

The Effects of Assumed AI vs. Human Authorship on the Perception of a GPT-Generated Text

Angelica Lermann Henestroso ^{1,*} and Joachim Kimmerle ^{1,2}¹ Knowledge Construction Lab, Leibniz-Institut für Wissensmedien, 72076 Tübingen, Germany² Department of Psychology, Faculty of Science, Eberhard Karls University, 72076 Tübingen, Germany

* Correspondence: a.lermann-henestroso@iwm-tuebingen.de

Abstract: Artificial Intelligence (AI) has demonstrated its ability to undertake writing tasks, including automated journalism. Prior studies suggest no differences between human and AI authors regarding perceived message credibility. However, research on people's perceptions of AI authorship on complex topics is lacking. In a between-groups experiment ($N = 734$), we examined the effect of labeled authorship on credibility perceptions of a GPT-written science journalism article. The results of an equivalence test showed that labeling a text as AI-written vs. human-written reduced perceived message credibility ($d = 0.36$). Moreover, AI authorship decreased perceived source credibility ($d = 0.24$), anthropomorphism ($d = 0.67$), and intelligence ($d = 0.41$). The findings are discussed against the backdrop of a growing availability of AI-generated content and a greater awareness of AI authorship.

Keywords: automated journalism; automated text generation; science communication; credibility; GPT

1. Introduction

Automated text generation (ATG) has been garnering significant attention since it became freely available to everyone with internet access due to the release of ChatGPT (Chat-Generative pre-trained transformer). Although ATG has been used for over a decade in areas where structured and machine-readable data was available (e.g., automated journalism), it has long been a niche topic that has received less attention than other developments in artificial intelligence (AI). The availability of large datasets, the increased computational power, advancements in deep learning, and the introduction of the transformer architecture in 2017 (Vaswani et al. 2017), which is the backbone of various models (e.g., GPT from OpenAI or BERT from Google), led to a development boost in natural language generation (NLG) and large language models (LLM). Language, especially written language, is no longer the exclusive preserve of humans. On top of that, due to their training data, LLMs can now write on any topic imaginable. Whether they are also competent in terms of content is a different matter.

Before the emergence of LLMs, ATG had already been an established method in short news reporting, for example. By using structured, machine-readable data, AI-based algorithms can convert the raw data of weather parameters of a city into a consistent verbal weather report, for instance, no more distinguishable from a human-written text (Brown et al. 2020; Köbis and Mossink 2021). Since the release of ChatGPT in November 2022, the possibilities for text generation, even outside journalism, have become apparent. With today's LLMs, tools are at hand that can take away the effort of writing on any topic, only one prompt away. Besides their apparent pitfalls and limitations, they open new possibilities for knowledge access and science communication. For example, scientific information could be made more understandable and approachable by addressing specific target groups, explaining facts to the heart of the matter, summarizing, and breaking down complex information.

Due to the limited capacity of and the scarce attention to ATG before the release of ChatGPT, research is lagging regarding readers' perceptions of this specific form of AI and the perceptions of AI authorship as a novel source cue, especially regarding topics other than news reports. However, studies from the field of automated journalism suggest that at least these texts do not differ from human-written texts in their perceived credibility (Graefe and Bohlken 2020; Jang et al. 2021; Tandoc et al. 2020; Wölker and Powell 2021) or that machine authorship has only a small negative effect on credibility perceptions (Wang and Huang 2024). In a meta-analysis, Graefe and Bohlken (2020) found no difference in credibility perceptions between human and AI authorship across several number- and fact-based topics, such as sports reports or election polling. However, there might be meaningful differences between fully automated news generation, based on structured data, which Graefe and Bohlken took into account, and the support provided by generative AI tools, which has only recently emerged. Besides their finding that assuming an AI vs. a human as an author of a text decreased credibility perceptions in socio-political and environmental topics, Wang and Huang (2024) found no effect on news evaluations in their meta-analysis. However, their findings also revealed a moderating role of the actual source on news evaluation, which could have been due to the quality of the AI texts at the time and might be now less of a problem. On the other hand, Proksch et al. (2024), for example, investigated the effects of labeled authorship on moral topics and found lower author competence and content quality ratings for AI authorship. Also, Böhm et al. (2023) found lower competence ratings for AI-generated content regarding societal and personal challenges simply when the labeled source was AI. These findings indicate a role for the task context and the topic chosen.

While automated journalism research has focused on short news reporting, Lermann Henestrosa et al. (2023) extended this comparison to the topic of science communication. The authors found no differences in message credibility and trustworthiness between humans and AI authors. Still, participants in their study differentiated between the alleged authors regarding perceived anthropomorphism and intelligence, for which the human author was rated significantly higher than the AI author (Lermann Henestrosa et al. 2023). As former research often used only allegedly AI-written texts and was limited to the textual possibilities available at the time, research on actual AI-written content on broader topics is steadily gaining momentum. Moreover, due to small sample sizes in prior studies, small effects could hardly be found and might have led to inconsistent results or null effects.

Therefore, the present study aims to investigate the influence of labeled authorship on the perceived credibility of the message and the credibility of the source of an AI-written science journalistic article. More specifically, our research question was whether there is no difference in the perception of labeled AI authorship vs. human authorship on an actually AI-written scientific article as previous findings suggest (Graefe and Bohlken 2020; Lermann Henestrosa et al. 2023; Wang and Huang 2024). This extends previous research by using an actual AI-written text and expanding the topic to the actual possibilities of LLMs. Using equivalence testing, we responded to the small or non-significant effects of labeled authorship found in prior research. Therefore, we stated the following hypothesis preregistered on https://aspredicted.org/6BP_355 (accessed on 14 August 2024):

H1: *The mean difference in perceived message credibility scores in the two conditions (AI author vs. human author) will be equivalent: the article allegedly written by a human author will be perceived as statistically equally credible as the article allegedly written by an AI.*

Furthermore, previous findings by Lermann Henestroza et al. (2023) suggest significant differences in authorship perceptions—despite constant material—between alleged AI vs. human authorship, with the AI being perceived as less human-like and less intelligent than the human author. Therefore, we stated the following two hypotheses concerning the perceived anthropomorphism and intelligence of the respective authors:

H2: *There will be a main effect of the factor authorship on the perceived anthropomorphism of the author: the alleged human author will be perceived as more anthropomorphic than the alleged AI.*

H3: *There will be a main effect of the factor authorship on the perceived intelligence of the author: the alleged human author will be perceived as more intelligent than the alleged AI.*

In addition to previous studies, we included the perceived source credibility to directly query the credibility of the alleged author with the following open research question:

RQ1: Is there any effect of labeled authorship on participants' perceived source credibility?

To control for possible effects of attitude toward the text topic, we included the participants' prior attitudes exploratively as covariates.

2. Methods

The study was an online experiment with a one-factorial between-groups design (factor *labeled authorship*: AI author vs. human author). Participants were asked to read a science journalism article about biodiversity, specifically the spread of wolves in Germany, and to rate it on different scales. The exact same text was presented in both conditions, with the only difference being the labeled authorship that was introduced before. The article was created by using the autoregressive language model GPT-3 (OpenAI)—a predecessor model of the model underlying ChatGPT—according to the following procedure: We used the Davinci engine of the OpenAI playground and determined the following parameters: number of tokens = 100, temperature = 0.8, frequency = 0.0, and penalty = 0.0. As prompts, we used five content structuring sentences adapted from the material of Lermann Henestroza et al. (2023), which were first translated into English and then used to generate five trials per prompt (see Appendix G). From the generated output, a fitting GPT continuation of each of the five trials was selected to gain a complete paragraph, that is, the continuation that most closely matched the tone of a scientific article in terms of content. Thirty-three words had to be deleted because the autocompletion stopped at 100 tokens, resulting in incomplete sentences at the end of the paragraphs (e.g., “In Thuringia” was deleted from the selected autocompletion for the second paragraph). Afterward, the generated text was translated into German and consisted of 353 words. Besides adding three missing punctuation marks, the paragraphs were not edited.

2.1. Sample

A power analysis for a small effect size of $d = 0.21$, an alpha-error probability of 0.05, and a power of 0.80 revealed a total sample size of $N = 714$ participants needed for the intended equivalence test for H1. Data from a random and fully anonymized sample were collected via the recruiting platform Prolific. The only prerequisites were that participants had to speak German and be over 18 years old. Of 800 participants in the online experiment, 66 were excluded from the analysis due to preregistered exclusion criteria. The final sample consisted of $N = 734$ participants with a mean age of 29.04 years old ($SD = 9.65$). Participation took about 10 min., and participants were compensated with 1.25 GBP. Table 1 shows the absolute and relative distributions for gender and education. For the educational level classification according to school type, see Oehler et al. (2024).

Table 1. Absolute and relative (in percent) numbers of participants by gender and educational level.

	N	%
Gender		
Male	303	41.28
Female	420	57.22
Not specified	11	1.50
Educational level		
Low	4	0.54
Middle	114	15.53
High	616	83.92

2.2. Measures and Procedure

Participants were asked about their demographics (age, gender, educational level) after filling in the informed consent form in the online experiment. As they were told to read a science journalism article about a biodiversity topic, a short introduction to science communication followed, briefly explaining what it is and who practices it. Afterward, their prior *attitude toward wolves* was measured by five items based on a scale (Treves et al. 2013, 5-point Likert scale, e.g., “The spread of wolves in Germany is a positive trend”). Before reading an article, we randomly assigned participants to one of the two conditions, in which the text was either labeled as being written by a human author or by an AI. To make the manipulation clear and prevent participants from thinking that the AI would be taking its information uncontrollably from unclear sources, we briefly explained that the AI could analyze large amounts of data and produce text on this basis without human intervention.

Moreover, as the study was conducted before the launch of ChatGPT, we explained that the AI supposedly took the information for the article by using three reliable sources, which were listed (e.g., the Federal Statistical Office of Germany). The same information was provided for the alleged journalist who was also briefly introduced. The cover story claimed the article was published in 2020 in a German newspaper. For the authorship manipulation, see Sections A–D. For the original article, see Sections E and F. After reading the text, participants were asked how neutral they perceived the *tone* of the author to be (bipolar 5-point scale from “absolutely neutral” to “absolutely evaluative”) and answered two manipulation check items concerning the author and content of the article.

Dependent variables were the perceived *message credibility* of the text that was measured using the Message Credibility scale (Appelman and Sundar 2016; Sundar 1999) (19 items measured on a 5-point Likert scale). The sample items of this scale are “fair”, “accurate”, or “authentic”. Exploratively, we also measured *source credibility* on five bipolar items, such as “unbiased—biased” or “not trustworthy—trustworthy” (Flanagin and Metzger 2000) (6-point scale). Furthermore, we asked participants to rate the perceived *anthropomorphism* (e.g., “machine-like—human-like”) and perceived *intelligence* (e.g., “ignorant—knowledgeable”) of the author with five items each (Bartneck et al. 2009) (bipolar 5-point scale). Participants’ *attitude toward wolves* was then measured again. Finally, the *behavioral intention* to recommend the article to friends or family and to read such articles again was measured on two single items on a 5-point Likert scale. Before being debriefed, participants could indicate who they thought actually wrote the article by choosing between “I believe the text presented was actually written by an AI”, “I believe the text presented was actually written by a human”, or “I am not sure” (*true author*).

3. Results

3.1. Main Analyses

The means and standard deviations of all measures by labeled authorship can be seen in Table 2. The explorative analysis of the perceived *tone* of the author revealed no significant difference between the two conditions, Welch- $t(726.05) = 0.30$, $p = 0.762$. Participants perceived the author’s tone to be relatively neutral.

Table 2. Means and standard deviations of all measures by labeled authorship.

Variable	Human (<i>n</i> = 359)		AI (<i>n</i> = 375)	
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Author's tone	2.42	0.99	2.41	0.92
Message credibility	3.82	0.53	3.62	0.58
Anthropomorphism	3.80	0.77	3.24	0.88
Intelligence	4.09	0.68	3.80	0.73
Source credibility	4.54	0.96	4.31	1.03
Intention to recommend	3.09	1.16	2.86	1.18
Intention to read	3.75	1.09	3.54	1.12
Prior attitude	3.10	0.38	3.11	0.35
Posterior attitude	3.16	0.36	3.12	0.36

To examine H1, an equivalence test with equivalence bounds of $\pm$ the *smallest effect size of interest* (SESOI) of Cohen's $d = 0.21$ was conducted (1). For a detailed description of equivalence testing, see Lakens et al. (2018). The SESOI was determined based on the raw mean difference of 0.1 on a 5-point scale and the observed pooled variance of $s_p^2 = 0.23$ from a previous study.

$$d = \frac{\mu_1 - \mu_2}{\sqrt{s_p^2}} = \frac{0.1}{0.48} = 0.21 \quad (1)$$

The equivalence test (TOST [= two one-sided *t*-tests] procedure) concerning perceived *message credibility* was non-significant, $t(732) = 2.03$, $p = 0.978$, and the observed mean difference of 0.2 fell out of the predefined equivalence bounds. Instead, the null hypothesis significance test (NHST) revealed an effect of labeled authorship on message credibility, $t(732) = 4.87$, $p < 0.001$, $d = 0.36$. The text allegedly written by a human author was perceived as more credible than the same text allegedly written by an AI. The results of the TOST procedure are shown in Figure 1. Figure 2 illustrates the participants' distribution of responses regarding message credibility in each condition.

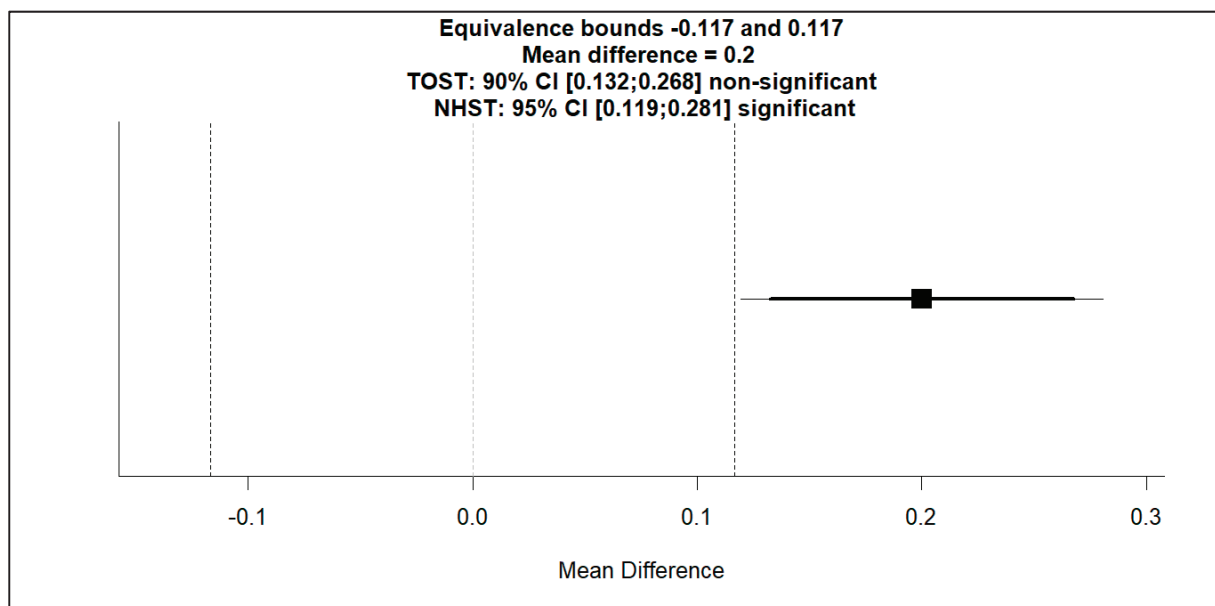


Figure 1. Results of the equivalence test on message credibility. The area between the vertical dashed lines represents the a–priori determined smallest effect size of interest (SESOI).

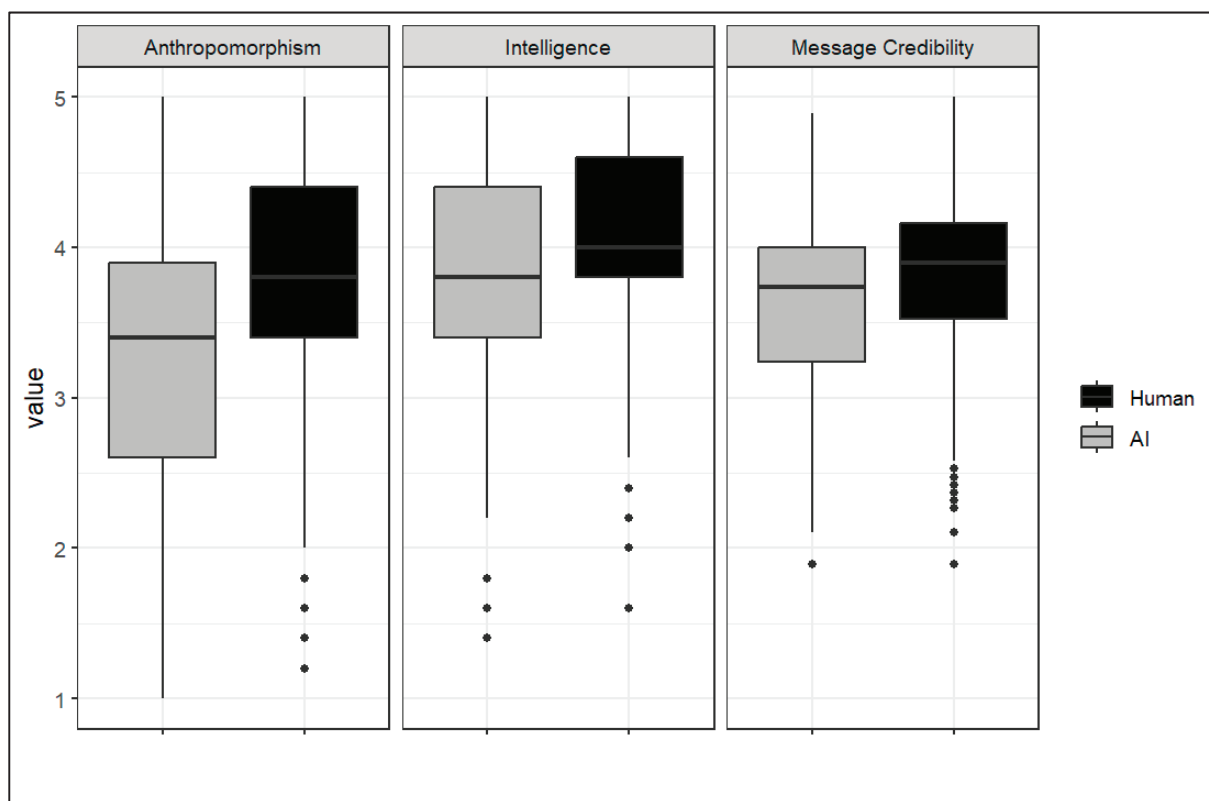


Figure 2. Boxplots of the dependent variables message anthropomorphism, intelligence, and message credibility by labeled authorship.

To examine H2 and H3, two Welch's t -tests were conducted due to missing homogeneity of variance. Concerning perceived anthropomorphism, the results revealed a significant difference between the conditions, $\text{Welch-}t(726.44) = 9.15, p < 0.001, d = 0.67$. As expected, and observed in previous studies, participants rated the human author as more anthropomorphic than the AI author. The same pattern resulted regarding perceived intelligence, $\text{Welch-}t(731.45) = 5.57, p < 0.001, d = 0.41$. The human author was perceived as more intelligent than the AI author (see Figure 2).

Regarding the open research question of whether the labeled authorship influenced perceived source credibility, we found a significant difference between the conditions, $\text{Welch-}t(731.39) = 3.25, p = 0.001, d = 0.24$. Participants rated the human author as more credible than the AI author. In addition, source and message credibility were highly correlated, with $r = 0.82$.

Participants also indicated they would recommend the text by the alleged human author more strongly than the one labeled to be written by an AI, $\text{Welch-}t(731.41) = 2.70, p = 0.007, d = 0.20$. Moreover, respondents' intention to read such an article again was higher in the human author condition than in the AI condition, $\text{Welch-}t(731.82) = 2.64, p = 0.009, d = 0.19$. These two items were also highly correlated, with $r = 0.73$.

Regarding the *true author* item, 52.65% of the participants in the human author condition believed that a human indeed wrote the text, 21.73% indicated an AI actually wrote it, and 25.63% were unsure. In the AI author condition, 39.47% were convinced that the AI was the actual author, 32.27% thought a human could be the real author, and 28.27% were not sure.

3.2. Further Analyses

Finally, we aimed to explore the prior attitudes toward wolves as a covariate in the analysis. However, we refrained from calculating an ANCOVA because the homogeneity of regression slope was violated concerning message credibility, as the interaction term

was significant, $F(1, 730) = 9.33, p < 0.001, \eta_p^2 = 0.01$. Figure 3 depicts the interaction effect between participants' prior attitudes toward wolves and labeled authorship, suggesting a positive relationship between participants' initial attitude and perceived message credibility in the human author condition but not in the AI author condition.

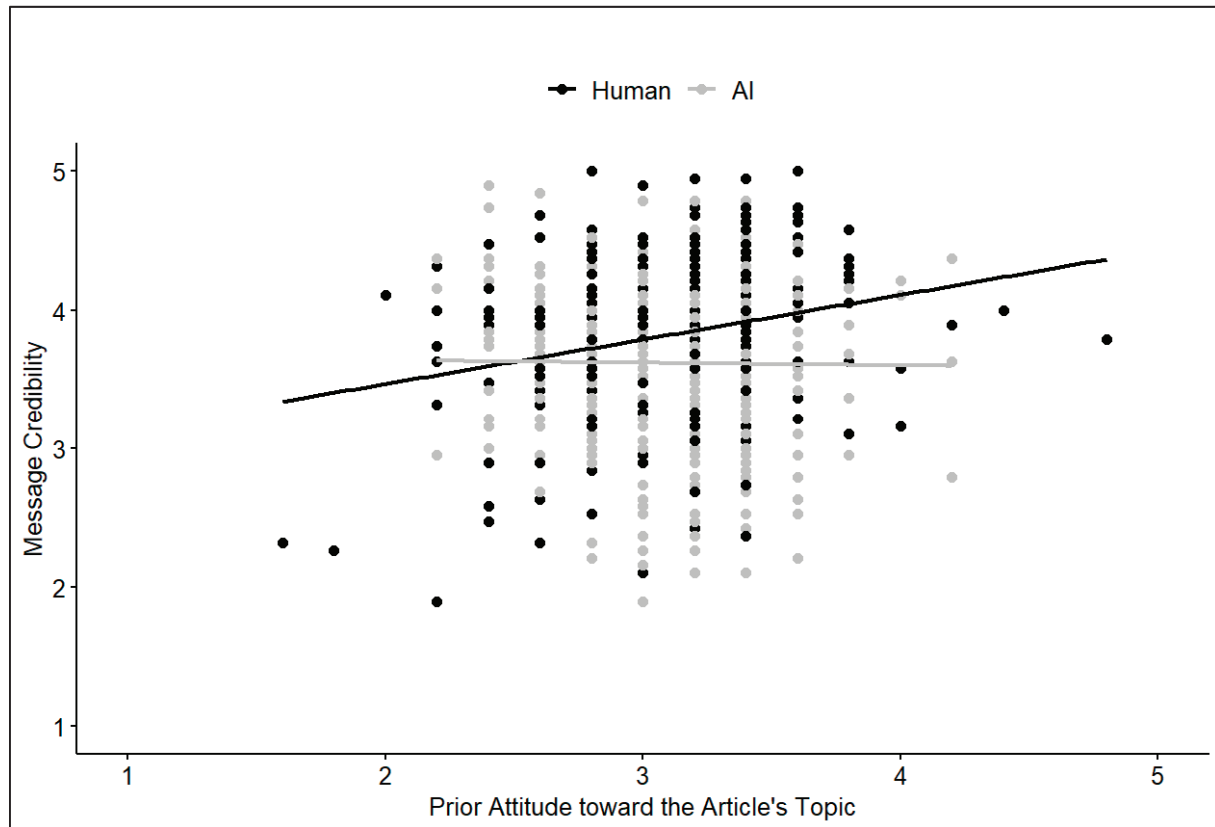


Figure 3. Regression lines depicting the relationship between prior attitude toward the article's topic and perceived message credibility by labeled authorship.

Moreover, an ANOVA with repeated measures regarding participants' attitudes revealed a main effect of treatment, $F(1, 732) = 10.99, p < 0.001, \eta_p^2 = 0.02$, and a significant interaction effect between treatment and labeled authorship, $F(1, 732) = 4.58, p = 0.033, \eta_p^2 = 0.01$. Participants' attitudes toward wolves turned out to be more positive after reading the article, especially when a human author had allegedly written the article.

4. Discussion

The study presented here aimed to extend the existing literature on automated journalism to more complex content about science communication. Specifically, we aimed at moving forward research on credibility perceptions of AI authorship on short news reports to a topic and a writing style that better reflects current AI capabilities. Moreover, as one of the first studies in this area, we tested the previously found null effects of human vs. AI authorship on credibility perceptions by using equivalence testing. We defined the smallest effect size of interest and collected a sufficiently large sample size to detect even small effects. Thus, the sufficiently large sample size and the custom-fit methodology to detect even minor differences revealed a small but substantial difference in both perceived message credibility and source credibility between an alleged human and an AI author. The findings show that introducing an AI as the author of a text led to less perceived credibility of the author and the article—even though it was the identical text in both conditions and actually written by an LLM.

In addition, the participants in this experiment were aware of the specific type of author they were dealing with. Besides the passed manipulation check regarding the authorship of all participants included in the analysis, the differences in perceived anthropomorphism and perceived intelligence of the respective authors speak to the differentiating perceptions of the readers: the AI author was rated as less realistic, human-like, intelligent, and competent than the human author. Furthermore, participants intended to recommend the provided article less, and they were less willing to reread such articles in the future when an AI allegedly wrote it. Investigating the factors that led to this evaluation and exploring whether credibility can be manipulated for both types of authors via perceived intelligence and perceived anthropomorphism is a task for future research.

This study is oriented toward current journalistic practice as the text was framed as a science journalism article published in a newspaper. Our experimental setting set a realistic and forward-looking scenario as ATG technology has already been used in journalism for several years and will indeed be deployed much more in the future. Current developments around generative AI, especially around ATG, point to a trend toward the increasing use of AI authorship and its participation in the journalistic process.

Moreover, the provision of scientific information by generative AI reflects actual potential uses of tools such as ChatGPT, also on the part of laypersons. With the increased use of generative AI, its use for information search and information gathering will likely increase. People might trust information provided by ChatGPT in a similar way as that obtained by Google or Wikipedia (Jung et al. 2024). In particular, the more subtle presentation of information in continuous text, when the primary aim may not have been to obtain facts, is still to be investigated and should be viewed critically.

Considering the relatively high credibility ratings for both authors in this experiment, the practical implications of an AI-authored article being perceived as slightly less credible than a human-authored one are unclear. Our study was conducted in January 2022, when peoples' experience with and attitude toward ATG and NLG might not have been highly developed due to missing labeling requirements. In addition, there is evidence that people had no clear concepts regarding ATG and that this has not changed considerably since the release of ChatGPT (Bodani et al. 2023; Lermann Henestroza and Kimmerle 2024). Given that it was a novel experience for participants to see an AI write about a scientific topic to this extent, the findings are intriguing and speak for a basic leap of faith.

Of course, this study provided very transparent conditions from the readers' perspective by declaring the authorship and the authors' alleged sources, which were reputable. It remains uncertain how transparently media organizations will handle AI in the text-production loop in the future. An extensive societal debate, reflecting the potential desire of readers for clear regulations, is needed to address this concern. For completeness, future studies should also ask for people's assessments of the sources, if provided, and consider today's LLMs' weaknesses in providing reliable sources. In addition, a distinction should be made between LLMs that cannot specify sources due to their basic structure and such models that can do so and would therefore be more appropriate for journalism. However, due to the lack of experience with automatically written journalism, the authorship introduction was necessary for our experiment to successfully manipulate the respective authorship and effectively compare human vs. AI journalism. Therefore, the results of the final question of who the participants ultimately thought was the real author should be interpreted with caution. While in the human condition, they bordered on guessing probability and the proportion of people who believed that an AI had written the text was relatively high given the lack of experience at this time. As technological development is progressing rapidly and debates about the strengths and limitations of ATG are constantly shaping public opinion, this picture might have already changed.

Our exploratory finding was that the credibility of the supposedly human-written article was positively associated with prior attitudes toward wolves, whereas this effect did not extend to the AI author. Additionally, the observation that attitudes toward the topic became more positive after reading the text—particularly with the human author—

suggests that not only could the credibility of human authors be perceived as higher, but their persuasiveness may also be greater. Future studies should further investigate the relationship between attitudes toward content and its perceived credibility, with a focus on how factors such as confirmation bias might influence these dynamics.

With the increased use of ATG technology in journalism, other textual content, and more transparent labeling, future readers will hopefully be much more aware of this novel authorship cue. Moreover, what might complicate or at least change the investigation of AI authorship in future research is the increasing co-authorship and, thus, the blurring of roles in the writing process (Cress and Kimmerle 2023; Luther et al. 2024). A fundamental investigation of the perception of AI authorship is, therefore, long overdue, especially since ChatGPT, but also everybody with the help of ChatGPT and other LLMs, can write about any topic regardless of the truthfulness of the information. Against this background, our results should be seen as a favorable vote of confidence in a technology that holds great potential. On the other hand, they are a warning signal in view of the obvious deficits of LLMs in consistently delivering reliable and robust scientific information.

5. Conclusions

This study contributes to exploring AI authorship on a scientific topic, considering today's LLMs' language and data access capabilities. Prior research suggested small or no differences in message credibility between human and AI authorship, which we tested by using equivalence testing and a sufficiently large sample size to detect even small effects. While the results revealed that the pure suggestion of AI authorship led to lower credibility ratings of the text and author evaluations, major negative effects on credibility were not observed, even on a topic more complex than a weather forecast. Our finding is particularly important in light of the increasing use of LLMs for information searches. Although work is constantly being invested to improve generative AI in terms of factual accuracy, its reliability should be critically scrutinized, especially where scientific information is concerned. More research and a broad public debate are needed to accompany the spread of this specific type of AI and investigate people's attitudes and acceptance of it. In particular, the role of further influencing factors, such as preconceptions and attitudes on generative AI, should be investigated. Since the awareness that an LLM's answers are based on the calculation of probabilities can significantly influence the assessment of the reliability of the information, credibility perceptions might vary with growing experience and attention on this AI area. Therefore, our approach is a step forward in exploring the perception and evaluation of AI authorship for complex topics, reflecting recent developments in NLG.

Author Contributions: Conceptualization, A.L.H. and J.K.; methodology, A.L.H. and J.K.; analysis, A.L.H.; resources, J.K.; data curation, A.L.H.; writing—original draft preparation, A.L.H.; writing—review and editing, A.L.H. and J.K.; visualization, A.L.H.; supervision, J.K.; project administration, J.K.; funding acquisition, J.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Leibniz-Institut für Wissensmedien (STB Data Science).

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Ethics Committee of the Leibniz-Institut für Wissensmedien (protocol code LEK 2020/053, approved on 12 November 2020).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The original data presented in the study are openly available in OSF at <https://osf.io/gpkc6/> (accessed on 14 August 2024).

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Authorship Manipulation—Factor Level “AI” (Original)

Im Folgenden werden Sie einen Text zum Thema Wölfe in Deutschland lesen. Dieser erschien im Frühjahr 2020 auf der Wissenschaftsseite der Süddeutschen Zeitung (SZ).

Er wurde vom Computeralgorithmus *AutomatedTXT* (Version 4.9) verfasst, der Methoden der künstlichen Intelligenz (KI) zur Analyse und Produktion natürlichsprachlicher Texte verwendet. Methoden der künstlichen Intelligenz zur Texterstellung finden bereits seit einigen Jahren Anwendung. *AutomatedTXT* ist so programmiert, dass er eine große Menge an Daten analysieren und die darin enthaltenen Informationen zu einem Text zusammenfügen kann. Eine Überprüfung durch einen Menschen ist dadurch nicht mehr notwendig.

Für den folgenden Text griff *AutomatedTXT* auf öffentlich zugängliche Informationen der Dokumentations- und Beratungsstelle des Bundes für den Wolf (DBBW), des Statistischen Bundesamtes sowie des Bundesministeriums für Umwelt, Naturschutz und nukleare Sicherheit (BMU) zurück.

Appendix B. Authorship Manipulation—Factor Level “AI” (English Translation)

Below, you will read a text on the topic of wolves in Germany. It appeared in spring 2020 on the science page of the Süddeutsche Zeitung (SZ).

It was written by the computer algorithm AutomatedTXT (version 4.9), which uses artificial intelligence (AI) methods to analyze and produce natural language texts. Artificial intelligence methods for text creation have been used for several years. AutomatedTXT is programmed to analyze a large amount of data and combine the information it contains into a text. This means that a human inspection is no longer necessary.

For the following text, AutomatedTXT used publicly available information from the Federal Documentation and Advisory Center for Wolves (DBBW), the Federal Statistical Office, and the Federal Ministry for the Environment, Nature Conservation, and Nuclear Safety (BMU).

Appendix C. Authorship Manipulation—Factor Level “Human” (Original)

Im Folgenden werden Sie einen Artikel zum Thema Wölfe in Deutschland lesen. Dieser erschien im Frühjahr 2020 auf der Wissenschaftsseite der Süddeutschen Zeitung (SZ).

Er wurde von Wissenschaftsjournalist Robert B. Meyer (Jahrgang 1971) verfasst. Seine journalistischen Schwerpunkte liegen in den Bereichen Biodiversität, Naturschutz und Meeresbiologie.

Für den folgenden Text griff der Journalist auf öffentlich zugängliche Informationen der Dokumentations- und Beratungsstelle des Bundes für den Wolf (DBBW), des Statistischen Bundesamtes sowie des Bundesministeriums für Umwelt, Naturschutz und nukleare Sicherheit (BMU) zurück.

Appendix D. Authorship Manipulation—Factor Level “Human” (English Translation)

Below, you will read an article on the topic of wolves in Germany. It appeared in spring 2020 on the science page of the Süddeutsche Zeitung (SZ).

It was written by science journalist Robert B. Meyer (born 1971). His journalistic focus is on the areas of biodiversity, nature conservation, and marine biology.

For the following text, the journalist used publicly available information from the Federal Documentation and Advisory Center for Wolves (DBBW), the Federal Statistical Office, and the Federal Ministry for the Environment, Nature Conservation, and Nuclear Safety (BMU).

Appendix E. Article (Original). Regarding the Authorship Manipulation, an Image of a White, Middle-Aged Man or a Symbol Image for an Algorithm (Program Code) Was Displayed; Not Shown for Copyright Reasons

27 February 2020, 17:08 Uhr
Wölfe in Deutschland

Der Wolf breitet sich in Deutschland wieder aus, eine Art, die vor einem Jahrhundert ein Symbol der Angst war und bis zur Ausrottung gejagt wurde. Die Jagd auf den grauen Wolf ist seit 1945 verboten. Heute leben in Deutschland etwa 150 Wölfe, 75 davon in einem Rudel. Die Art beginnt sich wieder vom Zentrum in die Randgebiete des Landes auszubreiten. In den letzten Jahren wurden Wölfe bis nach Hamburg und München gesichtet, was Naturschützer und Jäger gleichermaßen zur Wachsamkeit aufruft.

Die Zahl der Wölfe in Deutschland wird von der Dokumentations- und Beratungsstelle des Bundes für den Wolf (DBBW) überwacht. In einer am Dienstag veröffentlichten Erklärung teilte die DBBW mit, dass es derzeit zwischen 516 und 680 Wölfe in Deutschland gibt—ein leichter Anstieg gegenüber dem letzten Jahr. Das bedeutet, dass die Population nun den höchsten Stand seit dem 19. Jahrhundert erreicht hat.

Es besteht die Sorge, dass sich der Wolf in Deutschland unkontrolliert ausbreiten und Menschen angreifen könnte. Der erste Wolf in Deutschland kehrte 2012 aus Polen zurück und löste eine Kontroverse aus, nachdem er sechs Schafe im Land getötet hatte. Bayerische Schafhalter betonen, dass sie große Verluste erleiden würden, wenn sich solche Angriffe häufen würden. Wildtierschützer sagen, der Wolf habe ein Recht zu leben und sollte als gefährdete Art geschützt werden.

Die Landwirtschaft fordert Schutzmaßnahmen gegen den Wolf in Deutschland. Zumindest in Teilen Brandenburgs und Sachsens wird der Wolf als Bedrohung für Nutztiere angesehen. Diese Sichtweise erscheint Biologen übertrieben. Der Wolf hat in Deutschland noch nie große oder auch nur mittelgroße Schäden an Nutztieren verursacht, aber er wurde schon bejagt, wenn nur das Gerücht über solche Schäden aufkam.

Es gibt keine Gefahr durch den Wolf in Deutschland. "Wir brauchen keine Wolfsjagd", sagte ein Sprecher der deutschen Grünen, "die Landwirte können sich selbst schützen." Greenpeace ist der Meinung, dass die Wolfspopulation als wichtiges Element der Artenvielfalt weiterwachsen sollte, sagte Sprecherin Marie-Christine Keßler gegenüber Reuters. "Wir sind der Meinung, dass der Wolf als Art ein Recht auf Existenz hat", sagte sie. "Wenn die Behörden ihr Großwild schützen wollen, sollten sie das mit naturverträglichen Mitteln tun und nicht durch das Töten von Tieren."

Robert B. Meyer/AutomatedTXT

Appendix F. Article (English Translation). Regarding the Authorship Manipulation, an Image of a White, Middle-Aged Man or a Symbol Image for an Algorithm (Program Code) Was Displayed; Not Shown for Copyright Reasons

27 February 2020, 5:08 pm
Wolves in Germany

The wolf is spreading again in Germany, a species that was a symbol of fear a century ago and was hunted to extinction. Hunting the gray wolf has been banned since 1945. Today there are around 150 wolves living in Germany, 75 of them in a pack. The species is beginning to spread again from the center to the outskirts of the country. In recent years, wolves have been spotted as far away as Hamburg and Munich, calling for conservationists and hunters alike to be vigilant.

The number of wolves in Germany is monitored by the Federal Documentation and Advisory Center for Wolves (DBBW). In a statement released on Tuesday, the DBBW said there are currently between 516 and 680 wolves in Germany—a slight increase compared to last year. This means the population is now at its highest level since the 19th century.

There is concern that the wolf could spread uncontrollably in Germany and might attack humans. The first wolf in Germany returned from Poland in 2012 and sparked controversy after killing six sheep in the country. Bavarian sheep farmers emphasize that they would suffer major losses if such attacks became more frequent. Wildlife advocates say the wolf has a right to live and should be protected as an endangered species.

Agriculture calls for protective measures against the wolf in Germany. At least in parts of Brandenburg and Saxony, the wolf is seen as a threat to farm animals. This view seems exaggerated to biologists. The wolf has never caused large or even medium-sized damage to livestock in Germany, but it has been hunted whenever rumors of such damage arose.

There is no danger posed by the wolf in Germany. “We don’t need wolf hunting,” said a spokesman for the German Green Party, “farmers can protect themselves”. Greenpeace believes the wolf population should continue to grow as an important element of biodiversity, spokeswoman Marie-Christine Keßler told Reuters. “We believe that the wolf as a species has a right to exist,” she said. “If the authorities want to protect their big game, they should do so using nature-friendly means and not by killing animals.”

Robert B. Meyer/AutomatedTXT

Appendix G. Prompts Entered in GPT-3 Playground

1. The wolf is spreading again in Germany
2. The number of wolves in Germany is monitored by the Federal Documentation and Advisory Service for the Wolf (DBBW).
3. There is concern that the wolf could spread uncontrollably in Germany and might attack humans.
4. Agriculture calls for protection measures against the wolf in Germany.
5. There is no danger posed by the wolf in Germany

References

- Appelman, Alyssa, and Shyam S. Sundar. 2016. Measuring Message Credibility: Construction and Validation of an Exclusive Scale. *Journalism & Mass Communication Quarterly* 93: 59–79. [CrossRef]
- Bartneck, Christoph, Dana Kulić, Elizabeth Croft, and Susana Zoghbi. 2009. Measurement Instruments for the Anthropomorphism, Animacy, Likeability, Perceived Intelligence, and Perceived Safety of Robots. *International Journal of Social Robotics* 1: 71–81. [CrossRef]
- Bodani, Nikita, Abhishek Lal, Afsheen Maqsood, Sara Altamash, Naseer Ahmed, and Artak Heboyan. 2023. Knowledge, Attitude, and Practices of General Population Toward Utilizing ChatGPT: A Cross-Sectional Study. *SAGE Open* 13: 21582440231211079. [CrossRef]
- Böhm, Robert, Moritz Jörling, Leonhard Reiter, and Christoph Fuchs. 2023. People Devalue Generative AI’s Competence but Not Its Advice in Addressing Societal and Personal Challenges. *Communications Psychology* 1: 32. [CrossRef]
- Brown, Tom, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, and Amanda Askell. 2020. Language Models Are Few-Shot Learners. *arXiv* arXiv:2005.14165.
- Cress, Ulrike, and Joachim Kimmerle. 2023. Co-Constructing Knowledge with Generative AI Tools: Reflections from a CSCL Perspective. *International Journal of Computer-Supported Collaborative Learning* 18: 607–14. [CrossRef]
- Flanagin, J. Andrew, and J. Miriam Metzger. 2000. Perceptions of Internet Information Credibility. *Journalism & Mass Communication Quarterly* 77: 515–40. [CrossRef]
- Graefe, Andreas, and Nina Bohlken. 2020. Automated Journalism: A Meta-Analysis of Readers’ Perceptions of Human-Written in Comparison to Automated News. *Media and Communication* 8: 50–59. [CrossRef]

- Jang, Wonseok, Jung W. Chun, Soojin Kim, and Young W. Kang. 2021. The Effects of Anthropomorphism on How People Evaluate Algorithm-Written News. *Digital Journalism* 22: 103–24. [CrossRef]
- Jung, Yongnam, Cheng Chen, Eunhae Jang, and S. Shyam Sundar. 2024. Do We Trust ChatGPT as Much as Google Search and Wikipedia? In *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*. Honolulu: ACM, pp. 1–9. [CrossRef]
- Köbis, Nils, and Luca D. Mossink. 2021. Artificial Intelligence versus Maya Angelou: Experimental Evidence That People Cannot Differentiate AI-Generated from Human-Written Poetry. *Computers in Human Behavior* 114: 13. [CrossRef]
- Lakens, Daniël, Anne M. Scheel, and Peder M. Isager. 2018. Equivalence Testing for Psychological Research: A Tutorial. *Advances in Methods and Practices in Psychological Science* 1: 259–69. [CrossRef]
- Lermann Henestrosa, Angelica, and Joachim Kimmerle. 2024. Understanding and Perception of Automated Text Generation among the Public: Two Surveys with Representative Samples in Germany. *Behavioral Sciences* 14: 353. [CrossRef]
- Lermann Henestrosa, Angelica, Hannah Greving, and Joachim Kimmerle. 2023. Automated Journalism: The Effects of AI Authorship and Evaluative Information on the Perception of a Science Journalism Article. *Computers in Human Behavior* 138: 107445. [CrossRef]
- Luther, Teresa, Joachim Kimmerle, and Ulrike Cress. 2024. Teaming up with an AI: Exploring Human–AI Collaboration in a Writing Scenario with ChatGPT. *AI* 5: 1357–76. [CrossRef]
- Oehler, Felicitas, Sophia Kimmig, Robert Hagen, Joachim Kimmerle, Ulrike Cress, Klaus Hackländer, Janosch Arnold, Danny Flemming, and Miriam Brandt. 2024. The Role of Information Presentation for Wildlife Knowledge, Attitude, and Risk Perception. *Conservation Science and Practice* 6: e13089. [CrossRef]
- Proksch, Sebastian, Julia Schühle, Elisabeth Streeb, Finn Weymann, Teresa Luther, and Joachim Kimmerle. 2024. The Impact of Text Topic and Assumed Human vs. AI Authorship on Competence and Quality Assessment. *Frontiers in Artificial Intelligence* 7: 1412710. [CrossRef]
- Sundar, Shyam S. 1999. Exploring Receivers' Criteria for Perception of Print and Online News. *Journalism & Mass Communication Quarterly* 76: 373–86. [CrossRef]
- Tandoc, Edson C., Lim J. Yao, and Shangyuan Wu. 2020. Man vs. Machine? The Impact of Algorithm Authorship on News Credibility. *Digital Journalism* 8: 548–62. [CrossRef]
- Treves, Adrian, Lisa Naughton-Treves, and Victoria Shelley. 2013. Longitudinal Analysis of Attitudes Toward Wolves. *Conservation Biology* 27: 315–23. [CrossRef]
- Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention Is All You Need. *Advances in Neural Information Processing Systems* 30. Available online: <https://proceedings.neurips.cc/paper/2017/hash/3f5ee243547dee91fbd053c1c4a845aa-Abstract.html> (accessed on 14 August 2024).
- Wang, Sai, and Guanxiong Huang. 2024. The Impact of Machine Authorship on News Audience Perceptions: A Meta-Analysis of Experimental Studies. *Communication Research*, 00936502241229794. [CrossRef]
- Wölker, Anja, and Thomas E. Powell. 2021. Algorithms in the Newsroom? News Readers' Perceived Credibility and Selection of Automated Journalism. *Journalism* 22: 86–103. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.



Article

Consumer Trust in AI–Human News Collaborative Continuum: Preferences and Influencing Factors by News Production Phases

Steffen Heim ^{1,*} and Sylvia Chan-Olmsted ²¹ Institute of Marketing, Helmut-Schmidt-University, 22043 Hamburg, Germany² College of Journalism and Communications, University of Florida, Gainesville, FL 32611, USA; chanolmsted@jou.ufl.edu

* Correspondence: heims@hsu-hh.de

Abstract: AI has become increasingly relevant to the media sector, especially for news media companies considering the integration of this technology into their production processes. While the application of AI promises productivity gains, the impact on consumers' perceptions of the resulting news and the level of AI integration accepted by the market has not been well studied. Our research focused on the analysis of news consumers' preferred level of AI integration, AI news trust, and AI news usage intentions linked to the application of the technology in the discovery/information-gathering and writing/editing phases. By connecting a comprehensive set of factors influencing the perception of news and AI, we approached this gap through structural equation modeling, presenting an overview of consumers' responses to AI integration into news production processes. Our research showed that while participants generally prefer lower levels of AI integration into both phases of production, news trust and usage intention can even increase as AI enters the production process—as long as humans remain in the lead. These findings provide researchers and news media managers with a first overview of consumers' responses to news production augmentation and its implications for news perception in the market.

Keywords: media research; news trust; artificial intelligence; news production; AI trust; usage intention; structural equation modeling

1. Introduction

AI is becoming more and more relevant to (news) media companies (Broussard et al. 2019; Kim and Kim 2017). Based on its broad applicability and the possible productivity gains, it is now applied in all areas of (news) media, ranging from the aggregation of information (Benes 2018), the (pre-) production of content (Munoriyarwa et al. 2021), and the distribution of media (Lim and Zhang 2022) to the analysis of consumers' interactions and interests (Benes 2018). Recently, AI providers have even begun active talks with journalists and publishers about the integration of the technology into news production processes (Reuters 2023). Previous studies on the application of AI have already provided evidence for the actual integration of the technology into some parts of the media production process (de-Lima-Santos and Ceron 2021). While this integration of AI promises efficiency gains in productivity and relieves human employees and media companies of repetitive and mundane tasks (Kim and Kim 2017), consumers seem to have different perceptions and/or understandings of such applications (Samek and Müller 2019), or a fear and mistrust of AI in general (Andriole 2018).

Trust in the news, by nature, is of major relevance to news media companies, as trust is reflective of consumers' decisions for and against the consumption of certain media (Schranz et al. 2018). The impact of trust (and distrust) in news media goes even further because of its impact on political/social systems as a whole (Ariely 2015). The dual social–financial significance of trust is a critical factor in today's news media ventures

and operations, including the integration of AI as news organizations try to revamp their news processes and systems (Chakraborti et al. 2017). While research on the perception of AI as a part of media production processes has been conducted (e.g., Chan-Olmsted and Luo 2022; Kim and Kim 2020), there is limited literature addressing the topic of AI integration into different parts of news media production and consumers' trust in the resulting product. Accordingly, this study aimed to explore how consumers perceive and trust the integration of AI into traditionally human-centric news content production processes, especially from the more granular perspectives of different tasks/stages and degrees of AI-human collaboration. The study further investigated how various consumer factors such as AI-related perceptions and news use motivations affect consumers' trust and intention to use news content produced with AI in various contexts. The research contributes to the literature of technology applications in journalism and will provide news media organizations with insights into the integration of AI technologies into various phases of news production while keeping trust building in mind.

2. Conceptual Background and Research Questions

This study aimed to examine news perception and trust from a consumer-centric rather than news credibility perspective. Studies have shown the importance of investigating media "trust" beyond the traditional source-based, credibility-focused approach in today's media environment (Heim et al. 2022). There is extensive research on trust in brands/organizations in general (e.g., Delgado-Ballester and Luis Munuera-Alemán 2005; Kramer and Tyler 1996) and trust in AI in particular (Glikson and Woolley 2020). In recent years, combining research on trust in AI with trust in media companies using the technology in the production process has received increasing interest (e.g., Hofeditz et al. 2021; Kolo et al. 2022; Lee et al. 2020). Nevertheless, most studies have focused on the internal perception of AI integration into the production process (Kim and Kim 2020) or on consumers' ability to differentiate between content written by humans and AI (Kolo et al. 2022). Additional research has focused on the perception of brands using AI, not on the product specifically, leaving a research gap on the impact of including AI in various aspects of content production, especially those types of content that have significant social consequences, such as news.

To generate a more granular understanding of consumer perceptions and preferences in relation to AI integration into the production of news, this study teased out the content production process into different phases and considered various levels of AI integration into the process. Both conceptually and in practice, the news process can be divided into the four phases of (1) content development, (2) content selection, (3) content production, and (4) content distribution (Domingo et al. 2008; Marconi 2020). A broad range of additional definitions of the news production process can be found in the literature, ranging from three to five distinct stages and generally reflecting similar sequential activities to the above (e.g., Skovsgaard et al. 2012; Spyridou and Veglis 2016; Wu et al. 2018). Overall, both scholars and practitioners see the process of news content production as a series of steps from gathering input, to selecting content, to producing and disseminating the output. In the context of this study, we were most interested in two aggregated phases that offered contrasting skill sets and experiences: (1) discovery and information gathering, and (2) writing and editing (Shapiro 2010). In general, the first phase involves the activities of assigning and discovering newsworthy topics/issues, and the subsequent work of gathering relevant information about these topics/issues, while the latter phase involves the activities of selecting, writing, editing, and organizing the news content for the audience of the topics/issues from the previous phase. As AI can be integrated into each one of these phases (Chan-Olmsted 2019; Chen et al. 2021; Dong et al. 2011; Wang and Zhu 2021), responses from consumers related to the perceived levels of skills/competency they attribute to AI need to be differentiated between the different tasks at hand and compared/contrasted in terms of their perceived output.

While Kim and Kim (2020) have observed the influence of integrating AI into the news production process based on its implications for acceptance amongst individuals handling news production, this study dove deeper into the impact of AI on consumer perception of news products. By examining the application of AI technologies in the workflow of news production, we were able to generate better insights into the proper role of AI in a traditionally human-centric process. In addition, this study treated AI adoption in news as a continuum instead of a dichotomous application. As reported, AI technologies are transformational and unavoidable in almost all industries (Lee et al. 2020). Thus, AI adoption is a strategic choice of not only workflow/steps but also degree of integration.

Scholars have examined the scenarios of AI “augmentation” (i.e., the collaboration of humans with the technology to perform a task) and “automation” (i.e., machines fully taking over the human task) (Langer and Landers 2021; Raisch and Krakowski 2021). In the context of this study, we thus investigated the AI–human integration continuum at five different levels, ranging from human-only to AI-only adoption for each news production phase. As Owsley and Greenwood (2022) suggested, AI applications are likely to affect how consumers perceive the resulting news products. This study aimed to explore how consumers perceive and trust various levels of AI application in the different news production phases and the factors that play a role in this process. Specifically, aspects such as consumers’ AI performance expectations, which have been found to affect acceptance of AI integration into business processes (Gursoy et al. 2019; Xian 2021); usage motivations, which has been suggested to influence AI perceptions (Chan-Olmsted and Wang 2020; Lee 2013); and trust in the news based on experiences and perceptions of the news media (Mourão et al. 2018) were examined.

Accordingly, the first research question is posited below:

RQ1: What are the consumer perceptions of and preferences for AI applications during the main news production phases of discovery/information gathering and writing/editing, and what factors within the news production process play a role in shaping these perceptions and preferences?

As mentioned earlier, trust is essential to the integration of AI into a traditionally human-centric process, especially one with social and political significance. Kohring and Matthes (2007) argued that trust in news media is established through consumer perception of the selectivity of topics, the selectivity of facts, the accuracy of depictions, and the journalistic assessment. In line with our approach to the news production process, these dimensions can be attributed to either the discovery and information-gathering (i.e., selectivity of topics, selectivity of facts) or the writing/editing (i.e., accuracy of depictions, journalistic assessment) phases. Additional research has also highlighted the importance of credibility, reliability, transparency, and intentions/benevolence (Gurvies and Korchia 2003; Munuera-Aleman et al. 2003). Furthermore, studies have identified a strong connection between trust and respondents’ familiarity with AI (Gillath et al. 2021) and their general evaluation of the risks and benefits of the technology (Bao et al. 2022).

Our second research question thus focused on exploring the drivers of consumer trust in this context:

RQ2: What factors affect consumer trust in news when AI is used in the news production process?

While understanding the preferred level of AI integration into the news production process and its implications for consumer trust is beneficial, ultimately, the most relevant information for news media companies is the respective usage intentions of consumers. As presented by Lim et al. (2022), news organizations need to be aware of consumers’ general perceptions of the news and their attitude towards AI to be able to improve consumers’ usage intentions. This aspect can be separated into consumers’ positive (i.e., their perceptions of AI utility, societal and personal benefits, and, to some extent, emotional matters) and negative (i.e., dystopian views and especially negative emotions) attitudes towards the technology (Schepman and Rodway 2020). In line with this research, a wide

range of aspects is influential for the perception of news generated by or with AI and thus impacts the resulting usage intentions. Our third and final research question was therefore directed towards consumer intention to use AI news:

RQ3: Which factors influence consumer intention to use the news as AI is used in the various phases of the production process?

3. Materials and Methods

3.1. Data Collection

An online national survey in the United States was adopted for this study. Before the main test, a pre-test was carried out using Amazon's Mechanical Turk to check the reliability, readability, and possible questionnaire errors of the multi-item constructs applied in the survey. The study questionnaire was then adapted accordingly for the main test, which was conducted in the spring of 2023 using a Qualtrics general consumer panel. The sample quota was chosen to represent the national gender and age distribution of the population of the United States. This sample was chosen as our research focused on the broad perception of trust in news produced by or with AI amongst US citizens, demanding the analysis of the population as a whole. Responses were checked for quality via several measures (e.g., time constraints, straightlining, contradictions), resulting in a final dataset consisting of 702 responses. Quality checks were conducted in parallel to the sampling process, allowing for the recruitment of additional participants after the initial exclusion of responses and thus providing a nationally representative final dataset. The sample participants had a mean age of 46.1 (SD = 17.7). Of the sample participants, 49.1% of them were male, 49.7% were female, 0.7% self-identified as "other genders", and the rest preferred not to disclose their gender. To establish the final dataset used in the analysis, composite variables were generated for scale-item variables by adopting the z-value approach described by Song et al. (2013). Cronbach's alphas for all composites showed good reliability, with all measures >0.7 (Cortina 1993). As part of the reliability check, z-values were generated for relevant items and used to create the final composites for the targeted variables, along with other measures (see below).

3.2. Measures

3.2.1. Production Phase and Level of Integration

As indicated, the respondents were asked to consider their perceptions/preferences of AI integration in relation to two main phases of news production: "discovery/information gathering" and "writing/editing". All participants were provided with the same set of questions for both phases. Later analysis was then conducted on a split dataset consisting of only responses to each phase, respectively.

To understand consumers' perceptions of different levels of AI applications in the news production process, the survey incorporated five different scenarios on a continuum: (1) without AI, (2) with AI supporting humans, (3) with humans and AI working equally, (4) with humans supporting AI, and (5) with AI only. The range is indicative of the spectrum of all possible AI-human interaction/decision dynamics in a work environment. The participants were first asked which specific level of integration they preferred for each phase of the news process. Questions ranking the different levels of AI integration were ordered from 1 = "no AI" to 5 = "AI only". If perception-related questions were required for all different levels of AI integration (e.g., AI news performance), the same set of items was provided repeatedly.

3.2.2. AI Perception

Using a 5-point Likert scale with "1" meaning "strongly disagree" and "5" meaning "strongly agree", AI perception was assessed in terms of two aspects: positive and negative AI attitudes ($\alpha_{Pos} = 0.83$, $\alpha_{Neg} = 0.83$) (Schepman and Rodway 2020), and risk and benefit evaluations ($\alpha_{Risk} = 0.84$, $\alpha_{Benefit} = 0.87$) (Bao et al. 2022) (see Table A1 for specific measures).

These perception-related variables were also reviewed to establish the latent construct of AI perception.

3.2.3. AI Familiarity

AI familiarity was measured via a single-item question asking for the self-assessment of one's own familiarity with the technology. Responses were ranked from 1 = "not familiar at all" to 5 = "extremely familiar" (Chan-Olmsted and Luo 2022).

3.2.4. AI News Performance

Using the same 5-point scale, the expected performance of different levels of AI in the discovery/information-gathering and writing/editing phases of the news was measured using three items related to the level of errors, accuracy, and consistency of the production (Discovery: $\alpha_{\text{NoAI}} = 0.79$, $\alpha_{\text{AISup}} = 0.82$, $\alpha_{\text{Equal}} = 0.84$, $\alpha_{\text{HumanSup}} = 0.86$, $\alpha_{\text{AIOnly}} = 0.87$; Writing: $\alpha_{\text{NoAI}} = 0.83$, $\alpha_{\text{AISup}} = 0.84$, $\alpha_{\text{Equal}} = 0.86$, $\alpha_{\text{HumanSup}} = 0.86$, $\alpha_{\text{AIOnly}} = 0.87$) (Gursoy et al. 2019).

3.2.5. News Use Motives

Consumers' motives for news consumption were measured using established usage and gratification 5-point scale measures, separated by entertainment, information, opinion, and social needs related to news consumption ($\alpha_{\text{Ent}} = 0.83$, $\alpha_{\text{Inf}} = 0.87$, $\alpha_{\text{Opi}} = 0.78$, $\alpha_{\text{Soc}} = 0.77$) (Chan-Olmsted and Wang 2020; Lee 2013; Lin et al. 2004; Siakalli et al. 2015).

3.2.6. General News Trust

In this study, trust was measured in terms of two different aspects. First, measures of trust in the news in general were incorporated as a reduced form of the Trust in Mainstream News scale presented by Mourão et al. (2018). From this questionnaire, using the 5-point Likert scale, we extracted four items asking for participants' evaluations of the news and their perceptions of its reliability, truthfulness, and informativeness ($\alpha = 0.85$).

3.2.7. AI News Trust

Trust in news generated by or with AI was then measured via a specifically developed ranking of all levels of AI integration. Participants were asked to rank the different scenarios from highest to lowest trust in the resulting product (Chan-Olmsted 2019; Domingo et al. 2008; Marconi 2020).

3.2.8. Usage Intention

Consumers' intentions to use the news if produced by or with AI were measured using a slightly adapted version of the Technology Acceptance and Usage 5-point scale developed by Venkatesh et al. (2012). Since the usage intention was analyzed for all different levels of AI integration into the discovery/information-gathering and writing/editing phases, the data were separated into 10 different subsets comprising one respective combination each (Discovery: $\alpha_{\text{NoAI}} = 0.87$, $\alpha_{\text{AISup}} = 0.89$, $\alpha_{\text{Equal}} = 0.9$, $\alpha_{\text{HumanSup}} = 0.91$, $\alpha_{\text{AIOnly}} = 0.93$; Writing: $\alpha_{\text{NoAI}} = 0.89$, $\alpha_{\text{AISup}} = 0.9$, $\alpha_{\text{Equal}} = 0.9$, $\alpha_{\text{HumanSup}} = 0.92$, $\alpha_{\text{AIOnly}} = 0.93$).

3.3. Modeling Approach

In line with the three research questions, we established three structural equation models (SEMs) to analyze the respective factors. We decided during the development of the SEMs to allow for the integration of a wide range of composite and latent factors influencing our dependent variables into the analyses. By incorporating our research into such models, we were able to include individual composites well established in scales available in the literature (e.g., news usage intention, news performance, general news trust), individual items measurable through a single question (e.g., AI familiarity), and latent constructs focused on broader aspects and consisting of sets of multiple composite variables required to establish an adequate representation (e.g., AI perception, news use motives) in the same

model. Additionally, SEM allowed us to analyze the relationships between those elements to establish models providing a depiction of reality without significant measurement errors (Nachtigall et al. 2003).

Incorporating the area of interest of each research question, the three models used “AI level preference”, “AI news trust”, and “AI usage intention” as dependent variables, respectively. Items included in the survey were aggregated into composites as described above and included in the models separately or as latent constructs if conceptually sound. Depending on the RQ to be analyzed, a specific set of independent variables was selected to be incorporated into the model. For each research question, the models were calculated twice, analyzing the discovery/information-gathering and writing/editing phase responses separately. All findings were then generated from the respective model calculations for each research question and subsequently validated. Figure 1 displays the three models in an aggregated visualization with the connection to each relevant research question noted for each dependent variable (e.g., RQ1–3 for a dependent variable included in all three models). The SEM results and the corresponding insights from the data are presented next.

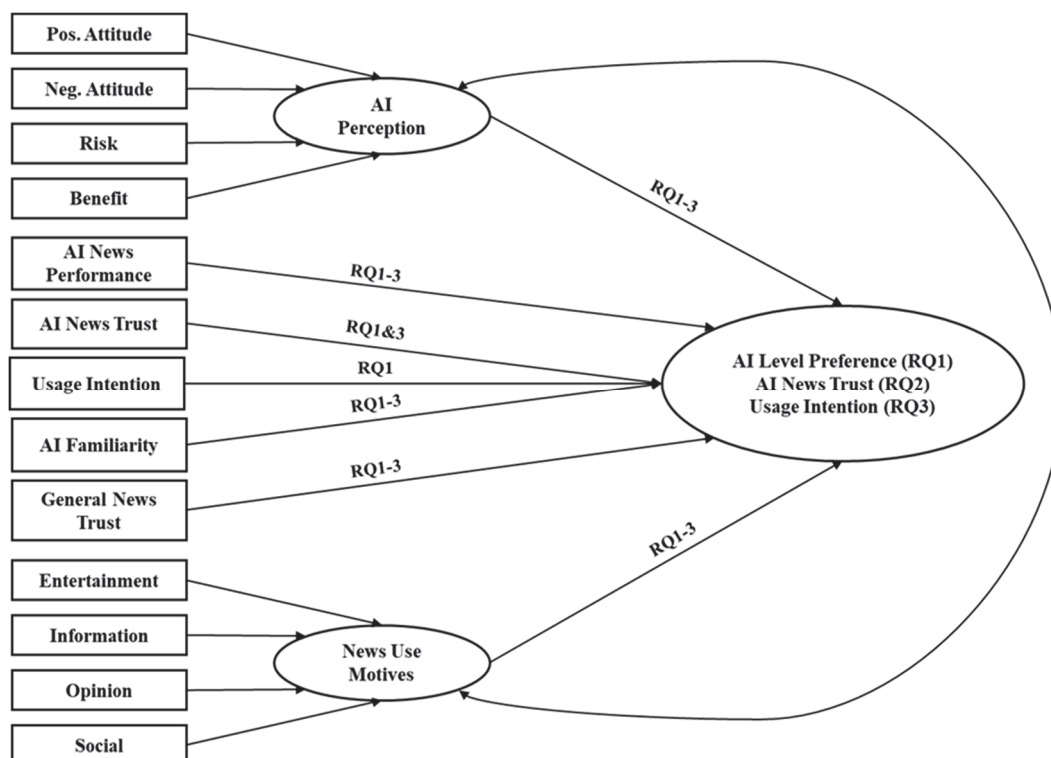


Figure 1. SEM—AI news trust analysis (RQ1–3).

4. Results

4.1. Consumers' Preferred Level of AI Integration

First, the survey showed that participants generally preferred lower levels of AI integration in both phases. Analyzing responses related to the preferred level of AI integration, we found that the majority of the respondents preferred “humans only” or “AI supporting humans” in the discovery/information-gathering and writing/editing phases (59% for both). However, participants did not reject the integration of AI into the production of news overall, resulting in “AI supporting humans” receiving the highest share (Discovery: 37%, Writing: 35%). Connecting this to the slightly higher preference for “Humans and AI working as equals” in the discovery/information-gathering phase (29% vs. 24%), we found that the general acceptance of AI augmentation appeared to be slightly higher in this initial phase of the news production. However, when it came to a stronger integration of AI and “Humans supporting AI”, the participants reported a slightly higher preference

in the writing/editing phase (11% vs. 7%). The lowest popularity of all provided options was found for “AI only” production, resulting in only 5% of all respondents choosing this option for both phases.

To dive deeper into how this perception of the general application of AI in the two distinct phases of the news production process emerged, we developed an SEM model connecting the comprehensive set of possible influences with consumers’ preference ratings. As described above, we gathered data on participants’ preferred levels of AI usage in each of the two phases by providing them with the five different levels (“No AI”, “AI supporting humans”, “AI and humans working as equals”, “Humans supporting AI”, “AI only”) and asking for their preferred mode of news production. This model consisted of the full set of available variables and was established to generate a global first understanding about the influences on consumers’ AI perceptions and connected preferences with regard to news production. Table 1 shows the results of the SEM analysis for all levels of AI integration into the two phases of news production. All models were analyzed and checked for model fit in the discovery/information-gathering and writing/editing phases, respectively (see Table A2 for details).

Table 1. SEM—Influences on AI level preference.

	No AI		AI Support		Equal		Human Support		AI Only	
Factor Loadings	Dis	Wri	Dis	Wri	Dis	Wri	Dis	Wri	Dis	Wri
PosAtt → AI Perception	0.649 ***	0.664	0.662 ***	0.672 ***	0.650 ***	0.669 ***	0.654 ***	0.661 ***	0.662 ***	0.668 ***
NegAtt → AI Perception	−0.291 ***	−0.295 ***	−0.294 ***	−0.296 ***	−0.292 ***	−0.296 ***	−0.292 ***	−0.294 ***	−0.293 ***	−0.294 ***
Risk → AI Perception	−0.213 ***	−0.219 ***	−0.220 ***	−0.223 ***	−0.214 ***	−0.222 ***	−0.216 ***	−0.218 ***	−0.218 ***	−0.221 ***
Benefit → AI Perception	0.928 ***	0.908 ***	0.910 ***	0.898 ***	0.927 ***	0.901 ***	0.921 ***	0.912 ***	0.912 ***	0.903 ***
Entertainment → News Use Motivation	0.654 ***	0.652 ***	0.653 ***	0.650 ***	0.653 ***	0.650 ***	0.653 ***	0.651 ***	0.652 ***	0.650 ***
Information → News Use Motivation	0.506 ***	0.509 ***	0.507 ***	0.512 ***	0.508 ***	0.513 ***	0.508 ***	0.513 ***	0.508 ***	0.512 ***
Opinion → News Use Motivation	0.801 ***	0.803 ***	0.801 ***	0.804 ***	0.802 ***	0.805 ***	0.802 ***	0.804 ***	0.802 ***	0.804 ***
Social → News Use Motivation	0.823 ***	0.821 ***	0.822 ***	0.820 ***	0.822 ***	0.819 ***	0.822 ***	0.819 ***	0.822 ***	0.820 ***
Path Coefficients										
AI Perception → AI Level Preference	0.257 ***	0.273 ***	0.293 ***	0.331 ***	0.294 ***	0.332 ***	0.235 ***	0.213 ***	0.210 ***	0.199 ***
AI Use Motivation → AI Level Preference	0.023	−0.046	0.000	−0.130 **	−0.025	−0.146 **	−0.021	−0.130 **	−0.012	−0.137 **
AI Performance → AI Level Preference	−0.013	−0.052	0.036	0.055	0.079 *	−0.011	0.066	0.095 *	0.080	0.119 **
AI News Trust → AI Level Preference	−0.190 ***	−0.060	−0.152 ***	−0.157 ***	0.025	−0.020	0.137 ***	0.109 **	0.140 ***	0.097 *
AI Familiarity → AI Level Preference	−0.099 **	0.164 ***	0.111 **	0.168 ***	0.134 ***	0.173 ***	0.105	0.152 ***	0.080	0.134 **
Usage Intention → AI Level Preference	−0.045	−0.166 ***	−0.039	−0.058	−0.005	0.041	0.080	0.117 **	0.123 **	0.133 **
General News Trust → AI Level Preference	0.009	0.002	−0.033	−0.076	−0.052	−0.109 **	−0.061	−0.107 **	−0.044	−0.099 **
Covariances										
AI Perception ↔ News Use Motives	0.482 ***	0.486 ***	0.486 ***	0.487 ***	0.482 ***	0.487 ***	0.483 ***	0.485 ***	0.486 ***	0.487 ***

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; standardized coefficients are reported.

Based on the latent construct of AI-perception-related variables, we found a significant and generally positive impact on the AI level preference, independent of the chosen level and phase of news production (Discovery/information gathering: $B = 0.210$ to 0.294 ; Writing/editing: $B = 0.199$ to 0.332). Observing the variables underlying AI perception overall showed that positive constructs (i.e., “Positive attitude towards AI” and “AI benefits”) improved AI preference in the discovery and writing/editing phases for all levels of AI integration ($\lambda_{\text{PosAtt}} = 0.649$ to 0.662 , $\lambda_{\text{Benefit}} = 0.91$ to 0.928), while negative variables (“Negative attitude towards AI” and “AI risk”) decreased this perception ($\lambda_{\text{NegAtt}} = -0.294$ to -0.292 , $\lambda_{\text{Risk}} = -0.22$ to -0.213). Diving deeper into the specific levels of AI usage, however, revealed varying levels of influence. While the impact of a positive perception was highest for “AI supporting humans” (Discovery: $B = 0.293$, Writing: $B = 0.331$) and “AI and humans working as equals” (Discovery: $B = 0.294$, Writing: $B = 0.332$) in both production phases, the net impact appeared to be stronger when little or no AI was applied in the writing/editing phase of news production. This stronger positive impact shifted from the writing/editing to the discovery/information-gathering phase as soon as AI had the upper hand on the production, and was stronger in the discovery/information-gathering phase for “Humans supporting AI” (Discovery: $B = 0.235$, Writing: $B = 0.213$) and “AI only” (Discovery: $B = 0.21$, Writing: $B = 0.199$).

Much stronger differences between the phases of the news production process were found regarding the impact of “news usage motivation” on the preferred level of AI integration. While there was hardly any impact for the discovery/information-gathering phase of the news ($B = -0.025$ to 0.023), which remained non-significant for all different levels of AI integration, we found a strong negative influence for the writing/editing phase ($B = -0.146$ to -0.046), which became significant as soon as AI was applied during production. Additionally, whereas the level was different for the discovery/information-gathering and writing/editing phases, the generally low to negative influence was similar for both models and was found for all four different news use motivations included in the latent construct (Discovery: $\lambda_{\text{Ent}} = 0.652$ to 0.654 , $\lambda_{\text{Inf}} = 0.506$ to 0.508 , $\lambda_{\text{Opi}} = 0.801$ to 0.802 , $\lambda_{\text{Soc}} = 0.822$ to 0.823 ; Writing: $\lambda_{\text{Ent}} = 0.65$ to 0.652 , $\lambda_{\text{Inf}} = 0.509$ to 0.513 , $\lambda_{\text{Opi}} = 0.803$ to 0.805 , $\lambda_{\text{Soc}} = 0.819$ to 0.821).

Analyzing the influence of “AI performance” generated from the ranking of the different levels of AI application in the two phases of news production, we found low but generally increasing loadings in the model (Discovery: $B = -0.013$ to 0.08 , Writing: $B = -0.052$ to 0.119). For both the discovery/information-gathering phase and the writing/editing phase, a positive perception of AI became increasingly important and affected the AI level preference positively with higher levels of integration. However, the loadings were only significant in the writing/editing phase and with higher levels of AI integration (“AI and humans working as equals” and higher).

Analyzing the results of “AI news trust” showed that the influence of this variable became increasingly positive with higher levels of AI integration for both phases of news production. While for lower levels of AI usage (i.e., “No AI” and “AI supporting humans”), the impact was negative (Discovery: $B = -0.19$ to -0.152 , Writing: $B = -0.152$ to -0.06), as soon as humans and AI worked as equals (Discovery/information gathering) or AI took the lead (Writing/editing), this effect changed (Discovery: $B = 0.025$ to 0.14 , Writing: $B = 0.97$ to 0.109). While these findings were significant for most scenarios analyzed in the SEM, the loadings were found to be insignificant for “Human only” production in the writing/editing phase and “AI and humans working as equals” in both phases.

When observing participants’ “AI familiarity”, we found the strongest positive impact on AI level preference for “AI and humans working as equals” for both phases of news production ($B_{\text{Dis}} = 0.134$, $B_{\text{Wri}} = 0.173$). While the impact increased for both phases from “No AI” to “AI and humans working as equals” (Discovery: $B = -0.099$ to 0.134 ; Writing: $B = 0.164$ to 0.173), this influence remained positive but decreased again as soon as AI took the lead (Discovery: $B = 0.08$ to 0.105 ; Writing: $B = 0.134$ to 0.152). “AI familiarity” loadings

were found to be significant for all levels of AI integration and both phases except for the “AI only” scenario in the writing phase.

Analyzing the reported “usage intention”, we found an increasingly positive impact on “AI level preference” for stronger applications of the technology. While the influence was negative for both the discovery/information-gathering and writing/editing phases with little or no AI integration (Discovery: $B = -0.045$ to -0.039 ; Writing: $B = -0.166$ to -0.058), the influence shifted to positive from “AI and humans working as equals” (Writing/editing) ($B = 0.041$ to 0.133) and “Humans supporting AI” (Discovery/information gathering) ($B = 0.08$ to 0.123). While these findings were significant in the writing/editing phase for all scenarios except “AI supporting humans” and “AI and humans working as equals”, loading in the discovery/information-gathering phase was only found to be significant in the SEM for “AI only” production.

Finally, “general news trust” had a decreasing influence on the “AI level preference” at higher levels of AI integration. While the impact in the “No AI” scenario was slightly positive for both the discovery/information-gathering ($B = 0.009$) and writing/editing ($B = 0.002$) phases, this impact remained negative for all different levels of AI integration into both phases of news production (Discovery: $B = -0.033$ to -0.061 ; Writing: $B = -0.076$ to -0.109). However, these findings were only significant for the “Humans and AI working as equals”, “Humans supporting AI”, and “AI only” scenarios for the writing/editing phase.

4.2. AI Integration Level Impact on Consumers’ Trust in the News

Analyzing participants’ responses related to their trust in news resulting from production by or with AI, we found the highest trust overall reported for the “AI supporting humans” scenario in both the discovery/information-gathering ($M_{AISup} = 3.51$) and writing/editing ($M_{AISup} = 3.45$) phases. Comparing reported trust in the different levels of AI integration into the news production process also showed that trust was higher when humans took the lead. This resulted in the mean level of trust for the “No AI” and “AI supporting humans” scenarios being higher (Discovery: 3.32; Writing: 3.35) than the average for the scenarios “Humans supporting AI” and “AI only”, which would leave the technology in control (Discovery: 2.41; Writing: 2.48). In terms of the general impact of AI integration into news production, however, we found that trust in news produced with some level of augmentation (i.e., “AI supporting humans” and “AI and humans working as equals”) was higher than trust in the “Human only” product (Discovery: $M_{NoAI} = 3.13$, $M_{AISup} = 3.51$, $M_{Equal} = 3.48$; Writing: $M_{NoAI} = 3.25$, $M_{AISup} = 3.45$, $M_{Equal} = 3.35$).

To establish a comprehensive analysis of these results in terms of RQ2, we developed a model to observe the influences on consumers’ level of trust in AI news. To establish this model, we connected the composite and latent constructs described above with the results from the trust ranking for both phases of news production. We thus generated SEM models analyzing the respective influences of all relevant aspects of consumers’ perceptions of and experience with AI for different levels of AI integration on the trust rankings of each participant. This model removed some of the elements included in the first SEM for conceptual reasons and retained the structure visualized in Figure 1. Table 2 shows the results of the trust in AI news SEM analysis for all levels of AI integration into the two phases of news production. As with the first models, all SEMs were checked for model fit in the discovery/information-gathering and writing/editing phases, respectively (see Table A3 for details).

In contrast to the first model, observing influences on AI news trust showed varying significant influences of AI perception. While lower levels of AI resulted in a negative impact for both the writing/editing and discovery/information-gathering phases, stronger AI integration resulted in a positive impact (Discovery: $B = -0.321$ to 0.148 , Writing: $B = -0.374$ to 0.185). Analyzing the components of AI perception showed that generally positive attributes such as “Positive attitude towards AI” and “AI benefits” increased AI perception ($\lambda_{PosAtt} = 0.595$ to 0.678 , $\lambda_{Benefit} = 0.886$ to 1.007), while negative traits (i.e.,

“Negative attitude towards AI” and “AI risks”) decreased the perception ($\lambda_{\text{NegAtt}} = -0.302$ to -0.275 , $\lambda_{\text{Risk}} = -0.236$ to -0.186) in both phases. Specifically looking into the respective influences of AI perception, however, showed that while an increased usage of AI improved AI news trust, the strongest positive impact was found for “AI and humans working as equals” in the discovery and writing of the news (Discovery: $B = 0.204$, Writing: $B = 0.185$).

Table 2. SEM—Influences on AI news trust.

	No AI		AI Support		Equal		Human Support		AI Only	
Factor Loadings	Dis	Wri	Dis	Wri	Dis	Wri	Dis	Wri	Dis	Wri
PosAtt → AI Perception	0.678 ***	0.651 ***	0.595 ***	0.633 ***	0.663 ***	0.661 ***	0.643 ***	0.645 ***	0.621 ***	0.623 ***
NegAtt → AI Perception	−0.302 ***	−0.299 ***	−0.275 ***	−0.288 ***	−0.295 ***	−0.293 ***	−0.290 ***	−0.291 ***	−0.285 ***	−0.285 ***
Risk → AI Perception	−0.236 ***	−0.219 ***	−0.186 ***	−0.205 ***	−0.221 ***	−0.217 ***	−0.210 ***	−0.212 ***	−0.200 ***	−0.201 ***
Benefit → AI Perception	0.886 ***	0.923 ***	10.007 ***	0.950 ***	0.909 ***	0.913 ***	0.937 ***	0.933 ***	0.967 ***	0.965 ***
Entertainment → News Use Motivation	0.652 ***	0.652 ***	0.654 ***	0.654 ***	0.652 ***	0.649 ***	0.653 ***	0.651 ***	0.648 ***	0.652 ***
Information → News Use Motivation	0.510 ***	0.508 ***	0.510 ***	0.507 ***	0.509 ***	0.511 ***	0.508 ***	0.511 ***	0.518 ***	0.512 ***
Opinion → News Use Motivation	0.804 ***	0.803 ***	0.802 ***	0.800 ***	0.802 ***	0.803 ***	0.801 ***	0.805 ***	0.806 ***	0.803 ***
Social → News Use Motivation	0.820 ***	0.821 ***	0.820 ***	0.823 ***	0.822 ***	0.822 ***	0.822 ***	0.819 ***	0.816 ***	0.819 ***
Path Coefficients										
AI Perception → AI News Trust	−0.321 ***	−0.374 ***	−0.277 ***	−0.109 *	0.204 ***	0.185 ***	0.109 *	0.133 **	0.148 ***	0.105 *
News Use Motivation → AI News Trust	0.112 *	0.084	0.077	−0.015	−0.004	0.088	−0.053	−0.148 **	−0.173 ***	−0.085
AI Performance → AI News Trust	0.155 ***	0.213 ***	0.109 **	0.162 ***	0.127 ***	0.067	0.122 ***	0.153 ***	0.170 ***	0.122 ***
AI Familiarity → AI News Trust	−0.106 **	−0.096 **	−0.083 *	−0.080 *	0.015	−0.095 *	0.079	0.092 *	0.142 ***	0.206 ***
General News Trust → AI News Trust	0.169 ***	0.085 *	0.057	0.036	−0.130 ***	−0.106 **	−0.057	−0.069	−0.119 ***	−0.069
Covariances										
AI Perception ↔ News Use Motives	0.489 ***	0.482 ***	0.453 ***	0.475 ***	0.486 ***	0.485 ***	0.479 ***	0.479 ***	0.467 ***	0.469 ***

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; standardized coefficients are reported.

The second latent construct, “news use motivation”, showed antithetical results. In contrast to the first latent construct, the results for the discovery/information-gathering and writing/editing phase varied and needed to be analyzed separately. In the discovery/information-gathering phase, a strong positive influence of news use motivation on trust in AI news steadily decreased with increasing levels of AI integration, resulting in negative influences as soon as humans and AI worked as equals ($B = -0.173$ to 0.112). However, the loadings were only found to be significant for the “No AI” and “AI only” scenarios. In the writing/editing phase, the overall direction was the same, while “AI and humans working as equals” was an outlier. In this phase, participants’ motivations to use the news positively influenced AI news trust in the “No AI” and “AI and humans working as equals” scenarios.

However, for all other levels of AI integration, we found a decreasing effect on trust in AI news ($B = -0.148$ to 0.088). In contrast to the discovery/information-gathering findings, the only significant loading in the writing/editing phase was measured for “Humans supporting AI”. While these differences were observed in terms of the impact of the latent construct “news usage motivation”, the composites underlying the construct showed similar coefficients in both phases, with information needs having the lowest and social need the highest relevance for consumers (Discovery: $\lambda_{Ent} = 0.648$ to 0.654 , $\lambda_{Inf} = 0.508$ to 0.518 , $\lambda_{Opi} = 0.801$ to 0.804 , $\lambda_{Soc} = 0.816$ to 0.820 ; Writing: $\lambda_{Ent} = 0.649$ to 0.654 , $\lambda_{Inf} = 0.507$ to 0.512 , $\lambda_{Opi} = 0.8$ to 0.805 , $\lambda_{Soc} = 0.819$ to 0.823).

The impact of “AI performance” on AI news trust was positive overall. However, significant differences were found regarding the level of impact between the two phases of news production. While the influence in the discovery/information-gathering phase was lowest for “AI supporting humans” and strongest for “AI only” ($B = 0.109$ to 0.170), in the writing/editing phase, the strongest positive impact was found for “No AI”, with the lowest influence measured for “AI and humans working as equals” ($B = 0.067$ to 0.213). However, of all SEM analyses, this lowest loading was the only measurement to be insignificant.

When examining the relevance of “AI familiarity” to AI news trust, similar results were found for the discovery/information-gathering and writing/editing phases. While the impact of familiarity with the technology on trust in AI news was negative for lower levels of AI integration, this impact became positive in line with the level of AI augmentation. In the discovery/information-gathering phase, the impact was positive as soon as AI and humans worked as equals. In contrast, AI needed to take the lead (i.e., “Humans supporting AI”) in the writing/editing phase to result in a positive impact (Discovery: $B = -0.106$ to 0.142 , Writing: -0.096 to 0.206). While most loadings were found to be significant, we found non-significant influences in the “AI and humans working as equals” and “Humans supporting AI” scenarios for the discovery/information-gathering phase.

Finally, the impact of “general news trust” showed similar results for both phases of news production. Overall, while loadings were measured to be significant in discovery/information gathering for the “No AI”, “AI and humans working as equals”, and “AI only” production scenarios, in the writing/editing phase, significant loadings were only found for the “No AI” and “Humans and AI working as equals” scenarios. While the impact on trust in AI news was positive for lower levels of AI integration, as soon as AI and humans worked as equals, this impact became negative. The strongest negative impact for both phases was found for the “Humans and AI working as equals” scenario (Discovery: $B = -0.13$, Writing: $B = -0.106$). However, the positive impact of a general trust in the news was strongest for the scenario of no AI applied in news production for both phases (Discovery: $B = 0.169$, Writing: $B = 0.085$).

4.3. AI Integration Level Impact on Consumers’ News Usage Intentions

Analyzing responses to the five items used to measure participants’ intentions to use news produced by or with AI showed a generally higher level of intention for lower AI integration. This was shown by the average rating of the intention items being similar for no and low AI integration (Discovery: $M_{NoAI} = 3.42$, $M_{AISup} = 3.41$, $M_{Equal} = 3.43$; Writing: $M_{NoAI} = 3.46$, $M_{AISup} = 3.45$, $M_{Equal} = 3.42$) and higher than the ratings for the “Humans supporting AI” and “AI only” scenarios (Discovery: $M_{HumanSup} = 3.12$, $M_{AIOnly} = 2.94$; Writing: $M_{HumanSup} = 3.16$, $M_{AIOnly} = 2.92$). These results indicate that while the intention to use news remained steady as long as humans retained input in both phases of news production, we observed a clear descent in usage intention as soon as AI took the lead.

To explore these findings in detail, our final model focused on the implications of consumers’ perceptions of and experience with AI on their actual usage intentions for news resulting from augmented or automated production processes. This model thus combined all relevant elements underlying participants’ evaluations of AI with the respective usage intentions for news discovered or written by or with AI. Table 3 shows the results of the

SEM analysis of usage intention at all levels of AI integration into the two phases of news production. In line with the first two analyses, the models were also checked for model fit in the discovery/information-gathering and writing/editing phases, respectively (see Table A4 for details).

Table 3. SEM—Influences on AI usage intention.

	No AI		AI Support		Equal		Human Support		AI Only	
Factor Loadings	Dis	Wri	Dis	Wri	Dis	Wri	Dis	Wri	Dis	Wri
PosAtt → AI Perception	0.653 ***	0.651 ***	0.635 ***	0.636 ***	0.641 ***	0.642 ***	0.617 ***	0.619 ***	0.614 ***	0.618 ***
NegAtt → AI Perception	−0.293 ***	−0.292 ***	−0.290 ***	−0.289 ***	−0.290 ***	−0.288 ***	−0.285 ***	−0.284 ***	−0.283 ***	−0.285 ***
Risk → AI Perception	−0.215 ***	−0.213 ***	−0.207 ***	−0.205 ***	−0.213 ***	−0.209 ***	−0.199 ***	−0.198 ***	−0.197 ***	−0.197 ***
Benefit → AI Perception	0.922 ***	0.926 ***	0.946 ***	0.947 ***	0.939 ***	0.939 ***	0.972 ***	0.971 ***	0.977 ***	0.972 ***
Entertainment → News Use Motivation	0.651 ***	0.654 ***	0.657 ***	0.653 ***	0.654 ***	0.658 ***	0.660 ***	0.658 ***	0.659 ***	0.660 ***
Information → News Use Motivation	0.527 ***	0.517 ***	0.517 ***	0.512 ***	0.515 ***	0.509 ***	0.499 ***	0.502 ***	0.499 ***	0.499 ***
Opinion → News Use Motivation	0.806 ***	0.806 ***	0.795 ***	0.801 ***	0.799 ***	0.796 ***	0.791 ***	0.794 ***	0.793 ***	0.791 ***
Social → News Use Motivation	0.810 ***	0.813 ***	0.821 ***	0.821 ***	0.820 ***	0.823 ***	0.830 ***	0.827 ***	0.829 ***	0.830 ***
Path Coefficients										
AI Perception → Usage Intention	−0.098 *	−0.076	0.218 ***	0.227 ***	0.347 ***	0.337 ***	0.379 ***	0.367 ***	0.344 ***	0.390 ***
News Use Motivation → Usage Intention	0.447 ***	0.417 ***	0.337 ***	0.301 ***	0.291 ***	0.196 ***	0.177 ***	0.166 ***	0.167 ***	0.200 ***
AI Performance → Usage Intention	0.153 ***	0.122 ***	0.141 ***	0.095 **	0.158 ***	0.180 ***	0.226 ***	0.211 ***	0.208 ***	0.175 ***
AI News Trust → Usage Intention	0.157 ***	0.151 ***	0.033	0.073 *	0.037	0.025	0.092 ***	0.097 **	0.218 ***	0.246 ***
AI Familiarity → Usage Intention	−0.016	−0.012	0.015	0.015	0.055	0.037	0.100 **	0.121 ***	0.171 ***	0.113 ***
General News Trust → Usage Intention	0.438 ***	0.422 ***	0.341 ***	0.351 ***	0.224 ***	0.291 ***	0.165 ***	0.155 ***	0.110 ***	0.074 *
Covariances										
AI Perception ↔ News Use Motives	0.482 ***	0.481 ***	0.478 ***	0.476 ***	0.479 ***	0.480 ***	0.470 ***	0.470 ***	0.468 ***	0.470 ***

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; standardized coefficients are reported.

When examining the usage intention for news discovered or written by AI, an increasing positive impact was found to be concomitant with increasing usage of the technology (Discovery: $B = -0.098$ to 0.379 ; Writing: $B = -0.076$ to 0.390). In line with the previous models, ratings of positive attributes of AI increased the perception of the technology ($\lambda_{\text{PosAtt}} = 0.614$ to 0.653 , $\lambda_{\text{Benefit}} = 0.922$ to 0.977), while negative attributes led to a decrease ($\lambda_{\text{NegAtt}} = -0.293$ to -0.283 , $\lambda_{\text{Risk}} = -0.215$ to -0.197) in both phases of news production. Comparing the discovery/information-gathering and writing/editing phases specifically showed that while the strongest positive impact on participants' usage intentions in the discovery/information-gathering phase was found for "Humans supporting

AI" ($B = 0.379$), the maximum impact for the writing/editing phase was measured for "AI only" production. Those loadings were all found to be significant except for the measured influence in the "No AI" scenario for the writing/editing phase.

Analyzing the motivation to use news produced by or with AI, we found a positive and significant impact for all levels of AI usage in both phases (Discovery: $B = 0.167$ to 0.447 ; Writing: 0.166 to 0.417). While the loading in the discovery/information-gathering phase steadily decreased with an increase of AI integration level, leading to the lowest positive impact in the "AI only" scenario ($B = 0.167$), the lowest impact in the writing/editing phase was found for "Humans supporting AI" ($B = 0.166$), with an increase measured towards "AI only" ($B = 0.2$). The composites underlying the latent construct "news usage motivation" all showed positive loadings for opinion and social needs, which had the strongest impact for both the discovery/information-gathering and writing/editing phases (Discovery: $\lambda_{Ent} = 0.651$ to 0.659 , $\lambda_{Inf} = 0.499$ to 0.527 , $\lambda_{Opi} = 0.791$ to 0.806 , $\lambda_{Soc} = 0.81$ to 0.83 ; Writing: $\lambda_{Ent} = 0.654$ to 0.66 , $\lambda_{Inf} = 0.499$ to 0.517 , $\lambda_{Opi} = 0.791$ to 0.806 , $\lambda_{Soc} = 0.813$ to 0.83). While the impact of entertainment and social needs showed a slight but steady increase with stronger integration of AI, the influence of information and opinion needs decreased accordingly.

Observing the influence of "AI performance" on consumers' news usage intentions showed positive and significant influences for all levels of AI usage (Discovery: $B = 0.141$ to 0.226 ; Writing: 0.095 to 0.211). For both phases, the strongest positive impact was found for the "Humans supporting AI" scenario, while the lowest impact was measured for "Humans and AI working as equals".

When analyzing consumers' trust in news created by or with AI, we found the strongest impact for the "No AI" and "AI only" scenarios for both phases. While the impact was low but positive for the different levels of AI augmentation (Discovery: $B = 0.033$ to 0.092 ; Writing: $B = 0.025$ to 0.097), loadings were stronger in the case of manual or automated production (Discovery: $B_{NoAI} = 0.157$, $B_{AIonly} = 0.218$; Writing: $B_{NoAI} = 0.151$, $B_{AIonly} = 0.246$). While these influences were found to be significant in most phases and scenarios, the loadings for "AI supporting humans" in the discovery/information-gathering phase and "AI and humans working as equals" in both phases remained non-significant.

"AI familiarity" was shown to have a negative influence on participants' news usage intentions when no AI was used in the process. However, with all different levels of AI integration into both phases of the production process, this influence became positive and showed an increasing impact with higher levels of AI usage (Discovery: $B = -0.016$ to 0.171 ; Writing: -0.012 to 0.122). In contrast to the other, mostly significant, independent variables in the model, the impact of "AI familiarity" was only found to be significant for both phases in the "Humans supporting AI" and "AI only" scenarios.

Finally, in line with the previous models, we found that the significant impact of "general news trust" decreased with higher levels of AI integration. While the influence stayed positive for all scenarios observed in the models, the strongest positive impact was found for "No AI" usage in production. The lowest impact was measured for the "AI only" scenario (Discovery: $B = 0.22$ to 0.438 ; Writing: $B = 0.074$ to 0.422).

5. Discussion and Conclusions

This study showed a wide range of influencing factors relevant to consumer perceptions/preferences regarding news organizations' AI applications in a traditionally human-centric production process. These granular insights regarding how consumers perceive/prefer and trust various approaches to AI-human collaboration in news production and their drivers will be beneficial for the news industry as it contemplates how best to incorporate AI technologies for a socially impactful consumer product. To increase the intelligibility of the conclusion, this paper aggregates all findings by the components included in the models to give an overview of the work and discuss its implications.

First, the results suggest the importance of existing, general AI perceptions in affecting consumers' preferences for the degree of AI-human collaboration in news production, as well as their AI news trust and usage intention. AI-perception-oriented variables were

found to be significant across the board. In particular, the results showed that positive perceptual attributes toward AI (i.e., “Positive attitude towards AI” and “Benefits of AI”) carried over to specific AI applications in news, and vice versa. This finding stands in line with previous publications on technology perception and its influences (e.g., Bao et al. 2022; Schepman and Rodway 2020). Nevertheless, there are some nuanced differences. While the impact of AI perception (RQ1) was positive for participants’ AI level preference at all levels of AI integration, we found an increasing positive impact on AI news trust (RQ2) and AI news usage intention (RQ3) with stronger integration of the technology. In the usage intention model, we found negative influences of AI perception only for the “No AI” scenario, showing that consumers perceiving AI to be performant wish for the technology to be applied. Regarding AI news trust, we found increasing influences of AI performance to be concomitant with increasing augmentation. This finding stands in line with the study presented by Bitkina et al. (2020), who also concluded that increasing trust in a new technology might be connected to increasing perception of its performance. Note that while there were some differences regarding application in the discovery/information-gathering and writing/editing processes, the respective variations were marginal.

Second, considering the role of news use motivation in the process, this study discovered some interesting dynamics depending on consumers’ specific news motives and involvement. In particular, while opinion and social news motives showed the strongest impact in all three models, entertainment and information news motives were less relevant. It seems that participants who were driven by more subjective and community-type content had stronger feelings and lower tolerance of AI integration. On the other hand, those who sought information/entertainment fulfillment from news were more open to the presence of AI in the news process. Additionally, addressing RQ1, we found that news consumers with high involvement (i.e., strong news usage motivations) tended to prefer the traditional, human-centric mode of news production, while consumers with less involvement (i.e., weak news usage motivations) were either more open to changes in or cared less about the integration of such technology into the news process. While we found non-significant loadings especially for lower levels of AI integration in the SEM focused on RQ2, which observed consumers’ preferences and trust in AI news, our findings were highly significant in the usage intention analysis (RQ3), indicating the major importance of consumers’ motivations in that regard.

Third, this study found the role of perceived “AI news performance” to differ significantly among the three models. In particular, there were variations by news production phase regarding this variable. While the results showed similar impacts of perceived AI news performance on participants’ AI news usage intentions (RQ3) and AI-human integration level preferences (RQ1) for both phases, its influence on AI news trust (RQ2) varied. Specifically, the performance variable showed a strong uplift of trust when automation (i.e., “AI only”) was used in the discovery/information-gathering phase only, while the writing/editing of news by humans only resulted in the strongest positive impact on AI news trust. The finding suggests that when it comes to the writing/editing of news, despite the general positive influence of a high AI performance perception, consumers still see humans as the best means of delivering trustworthy news content. However, AI is still capable of delivering consumer trust when it comes to discovering/gathering information to be used for the later stages of news production. While these influences on participants’ AI level preference were found to be non-significant for most observed scenarios, the impact was highly significant in almost all SEMs analyzing their impact on consumers’ AI news trust and usage intentions.

Fourth, regarding the role of AI familiarity, which has been well established in previous literature (e.g., Gillath et al. 2021), this study found some granular differences among the three models. While it had a positive impact on consumers’ preference for AI integration for almost all scenarios (RQ1), the influence was found to be increasingly positive concomitant with increasing AI integration in the AI news trust (RQ2) and use intention (RQ3) SEMs. While the impact was found to be significant in almost all models analyzing consumers’

AI level preferences and AI news trust, it remained non-significant for all scenarios with lower AI integration in the usage intention model. This could indicate that familiarity is highly relevant to consumers' perceptions of and trust in news produced by or with AI, while the impact on usage intention is only important if the production is dominated by AI (i.e., "Humans supporting AI" and "AI only" production). In addition, AI familiarity was increasingly essential in its contribution to the scenario of seeing AI as a viable option in the news writing/editing stage. In a sense, AI familiarity can be a positive or negative driver depending on the news production tasks and level of AI-human collaboration (e.g., negative influence on participants' news usage intentions when no AI was used in the process).

Fifth, regarding news trust, this study investigated this construct from both general and AI-specific perspectives and successfully highlighted the importance of general news trust in establishing AI news trust, especially in the scenarios of lower-level AI integration. While influences of AI news trust were found to be significant for AI level preference (RQ1) and AI news usage intention (RQ3), general news trust was mostly non-significant for AI level preference (RQ1) and AI news trust (RQ2) but showed significant influence on consumers' AI news usage intentions (RQ3). Analyzing these findings suggested that an increasing level of trust in AI news leads to a preference for the integration of the technology into the news production process. This confirms the results of previous studies such as the one presented by Bitkina et al. (2020), who showed that trust in a new technology is connected to the perception of specific attributes (such as the trustworthiness of news produced by or with AI as in this study) and connected this to trust in AI as the main motivator for consumers' positive responses to AI products. In contrast, general trust in the news decreased AI level perception and AI news trust with higher levels of AI integration. While general news trust remained positive in the SEM observing consumers' usage intentions, the impact nevertheless decreased with increasing AI integration. Analyzing this construct, the study found the strongest uplift for the "No AI" and "AI only" extreme scenarios. This suggests that trust in AI news is especially critical in the case of automation decisions involving AI.

Finally, regarding usage intention, in line with the AI news trust results, the study found an increasing and mostly significant impact of this variable on participants' preferences for increasing levels of AI integration (RQ1). It is logical that consumers with a high intention to use AI news created via lower levels of AI integration preferred a more human-centric product, and consumers who had a high intent to use augmented or automated production appreciated the application of AI technology.

6. Limitations and Future Outlook

This study has some limitations that need to be discussed. First, the data underlying our research were collected from a U.S.-only audience. Our results should therefore be expanded using additional surveys in other countries to make sure they hold under different circumstances and in different environments. Additionally, we developed all models from the same dataset and consequently had some overlaps of variables and analysis of mutual influences. Research should therefore consider additional surveys focused on one of the three aspects of consumers' perceptions only, ensuring our findings can be repeated when using such a specific approach.

Regarding the significance of findings, we clearly indicated that the influence of some variables remained non-significant for some scenarios and levels of AI integration. This is especially relevant for consumers' news use motivations and general news trust, which mostly showed significant influences in the usage intention SEM. While we still found and highlighted significant influences of these independent variables, future research could focus on the elements that showed significant impact throughout the analysis to gain more insights into these highly relevant aspects of consumers' AI news perceptions.

Addressing the scope of this research, our findings provide an initial and broad analysis of the perception of AI news and the impact of AI integration on consumers' trust

in and usage intentions for news resulting from such production processes. As this topic is focused on a current and fast-paced area, this top-level analysis is essential to build a foundation for more granular analysis in the future. For instance, additional studies may investigate specific media types or media formats and the impact of media usage habits or demographic information on consumers' AI news perceptions in such contexts.

Finally, our research was conducted under the premise of two general news production phases. More insights might be possible with specific steps included in the overall process.

Author Contributions: Conceptualization, S.H. and S.C.-O.; methodology, S.H. and S.C.-O.; software, S.H.; validation, S.H. and S.C.-O.; formal analysis, S.H.; investigation, S.H.; resources, S.H. and S.C.-O.; data curation, S.H.; writing—original draft preparation, S.H.; writing—review and editing, S.C.-O.; visualization, S.H.; supervision, S.C.-O.; project administration, S.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Institutional Review Board of the University of Florida (protocol code 17400, date of approval: 9 February 2023).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Data is unavailable due to privacy restrictions.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Survey item overview.

Item	Statement	Composite	Cronbach α	Construct	Sources
Familiarity	How familiar would you say you are with AI use in news?	Familiarity with AI			(Chan-Olmsted and Luo 2022)
Perception	In your opinion, when a news outlet creates news [...] it should: [1–5]	AI Usage Perception			
PosAtt1	AI is useful for people's daily lives				
PosAtt2	There are many beneficial applications of AI	Positive Attitude towards AI	$\alpha_{Pos} = 0.83$		
PosAtt3	AI is exciting				(Schepman and Rodway 2020)
NegAtt1	Organizations often use AI unethically	Negative Attitude towards AI	$\alpha_{neg} = 0.83$	AI Perception	
NegAtt2	AI is threatening				
NegAtt3	AI is dangerous				
Benefit1	AI will be beneficial for democratic society				
Benefit2	AI will be beneficial for me personally	AI Benefit	$\alpha_{Benefit} = 0.87$		
Benefit3	AI will be beneficial for most Americans				(Bao et al. 2022)
Risk1	AI will be risky for a democratic society				
Risk2	AI will be risky for me personally	AI Risk	$\alpha_{Risk} = 0.84$		
Risk3	AI will be risky for most Americans				

Table A1. Cont.

Item	Statement	Composite	Cronbach α	Construct	Sources
Entertainment1	I consume news because it's enjoyable	Entertainment Needs	$\alpha = 0.83$	News Use Motives	(Chan-Olmsted and Wang 2020; Lee 2013; Lin et al. 2004; Siakalli et al. 2015)
Entertainment2	I consume news because it's amusing				
Entertainment3	I consume news because it's entertaining				
Information1	I consume news to keep up with what's going on	Information Needs	$\alpha = 0.87$		
Information2	I consume news to learn about what's happening around me				
Information3	I consume news to get timely information				
Opinion1	I consume news to know about others' opinions	Opinion Needs	$\alpha = 0.78$		
Opinion2	I consume news to learn about other people's viewpoints				
Opinion3	I consume news to help form opinions on issues				
Social1	I consume news to learn about things to converse with others	Social Needs	$\alpha = 0.77$		
Social2	I consume news to appear informed to those around me				
Social3	I consume news to feel part of a community				
NewsTrust1	News aims to inform the public	General News Trust	$\alpha = 0.85$	General News Trust	(Mourão et al. 2018)
NewsTrust2	News is generally truthful				
NewsTrust3	News is a reliable source of information				
NewsTrust4	In general, news presents a true depiction of the world				
Performance1	In the scenario [1–5] what would you expect the news content to be?—Errors	AI News Performance	Discovery: $\alpha_{NoAI} = 0.79$ $\alpha_{AISup} = 0.82$ $\alpha_{Equal} = 0.84$ $\alpha_{HumanSup} = 0.86$ $\alpha_{AIOnly} = 0.87$ Writing: $\alpha_{NoAI} = 0.8$ $\alpha_{AISup} = 0.84$ $\alpha_{Equal} = 0.86$ $\alpha_{HumanSup} = 0.86$ $\alpha_{AIOnly} = 0.87$	AI News Performance	(Gursoy et al. 2019)
Performance2	In the scenario [1–5] what would you expect the news content to be?—Consistency				
Performance3	In the scenario [1–5] what would you expect the news content to be?—Accuracy				

Table A1. *Cont.*

Item	Statement	Composite	Cronbach α	Construct	Sources
Intention1	I would consume the news without hesitation	News Usage Intention	Discovery: $\alpha_{\text{NoAI}} = 0.87$ $\alpha_{\text{AISup}} = 0.89$ $\alpha_{\text{Equal}} = 0.9$ $\alpha_{\text{HumanSup}} = 0.91$ $\alpha_{\text{AIOnly}} = 0.93$ Writing: $\alpha_{\text{NoAI}} = 0.89$ $\alpha_{\text{AISup}} = 0.9$ $\alpha_{\text{Equal}} = 0.9$ $\alpha_{\text{HumanSup}} = 0.92$ $\alpha_{\text{AIOnly}} = 0.93$	News Usage Intention	(Venkatesh et al. 2012)
Intention2	I think consuming the news would lead to positive outcomes				
Intention3	I would feel comfortable relying on the news				
Intention4	I would plan to consume the news regularly				
Trust Ranking	Please rank-order the level of trust you would have on the news content in the following scenarios concerning the use of AI in the “discovery and information gathering” news phase.	AI News Trust		AI News Trust	(Chan-Olmsted 2019; Domingo et al. 2008; Marconi 2020)

Table A2. Model fit indices—consumers’ preferred level of AI integration.

		No AI		AI Support		Equal		Human Support		AI Only	
Factor Loadings		Dis	Wri	Dis	Wri	Dis	Wri	Dis	Wri	Dis	Wri
Model Fit Indices	χ^2	968.97	977.15	1027.92	983.76	1071.92	1029.64	1036.6	1039.62	1078.2	1129.58
	RMSEA	0.141	0.141	0.145	0.142	0.149	0.145	0.146	0.146	0.149	0.153
	CFI	0.602	0.601	0.58	0.598	0.57	0.587	0.59	0.595	0.583	0.578
	<i>p</i>	0	0	0	0	0	0	0	0	0	0

Table A3. Model fit indices—AI integration level impact on consumers’ trust in the news.

		No AI		AI Support		Equal		Human Support		AI Only	
Factor Loadings		Dis	Wri	Dis	Wri	Dis	Wri	Dis	Wri	Dis	Wri
Model Fit Indices	χ^2	755.76	790.26	827.91	834.28	841.64	849.99	840.13	861.8	886.46	905.75
	RMSEA	0.143	0.147	0.15	0.151	0.152	0.153	0.152	0.154	0.156	0.158
	CFI	0.636	0.634	0.61	0.606	0.607	0.601	0.607	0.604	0.595	0.592
	<i>p</i>	0	0	0	0	0	0	0	0	0	0

Table A4. Model fit indices—AI integration level impact on consumers’ news usage intention.

		No AI		AI Support		Equal		Human Support		AI Only	
Factor Loadings		Dis	Wri	Dis	Wri	Dis	Wri	Dis	Wri	Dis	Wri
Model Fit Indices	χ^2	835.2	858.08	887.04	853.14	889.15	896.53	882.05	897.86	945.19	957.32
	RMSEA	0.139	0.141	0.144	0.141	0.144	0.145	0.144	0.145	0.149	0.15
	CFI	0.681	0.674	0.66	0.67	0.663	0.661	0.668	0.662	0.654	0.655
	<i>p</i>	0	0	0	0	0	0	0	0	0	0

References

- Andriole, Steve. 2018. AI: The Good, the Disruptive, and the Scary. *Cutter Business Technology Journal* 31: 6–11.
- Ariely, Gal. 2015. Trusting the press and political trust: A conditional relationship. *Journal of Elections, Public Opinion and Parties* 25: 351–67. [CrossRef]
- Bao, Luye, Nicole M. Krause, Mikhaila N. Calice, Dietram A. Scheufele, Christopher D. Wirz, Dominique Brossard, Todd P. Newman, and Michael A. Xenos. 2022. Whose AI? How different publics think about AI and its social impacts. *Computers in Human Behavior* 130: 107182. [CrossRef]
- Benes, Ross. 2018. How Flipboard Sorts through Hundreds of Thousands of Articles Each Day. *Insider Intelligence*. March 22. Available online: <https://www.insiderintelligence.com/content/publishers-use-ai-for-content-recommendations-and-ad-targeting> (accessed on 24 November 2022).
- Bitkina, Olga V., Heejin Jeong, Byung Cheol Lee, Jangwoon Park, Jaehyun Park, and Hyun K. Kim. 2020. Perceived trust in artificial intelligence technologies: A preliminary study. *Human Factors and Ergonomics in Manufacturing & Service Industries* 30: 282–90. [CrossRef]
- Broussard, Meredith, Nicholas Diakopoulos, Andrea L. Guzman, Rediet Abebe, Michel Dupagne, and Ching-Hua Chuan. 2019. Artificial intelligence and journalism. *Journalism & Mass Communication Quarterly* 96: 673–95. [CrossRef]
- Chakraborti, Tathagata, Subbarao Kambhampati, Matthias Scheutz, and Yu Zhang. 2017. AI challenges in human-robot cognitive teaming. *arXiv arXiv:1707.04775*.
- Chan-Olmsted, Sylvia M. 2019. A review of artificial intelligence adoptions in the media industry. *International Journal on Media Management* 21: 193–215. [CrossRef]
- Chan-Olmsted, Sylvia M., and Anran Luo. 2022. Application of AI in Media Content Production: Perception, Decision, and Intention to Use. Paper presented at 2022 AEJMC, Detroit, MI, USA, August 3–6.
- Chan-Olmsted, Sylvia M., and Rang Wang. 2020. Understanding podcast users: Consumption motives and behaviors. *New Media & Society* 24: 684–704. [CrossRef]
- Chen, Keliang, Yunxiao Zu, and Danzhi Wang. 2021. Design and implementation of intelligent creation platform based on artificial intelligence technology. *Journal of Computational Methods in Sciences and Engineering* 20: 1109–26. [CrossRef]
- Cortina, Jose. M. 1993. What is coefficient alpha? An examination of theory and applications. *Journal of Applied Psychology* 78: 98–104. [CrossRef]
- Delgado-Ballester, Elena, and José Luis Munuera-Alemán. 2005. Does brand trust matter to brand equity? *Journal of Product & Brand Management* 14: 187–96. [CrossRef]
- de-Lima-Santos, Mathias-Felipe, and Wilson Ceron. 2021. Artificial intelligence in news media: Current perceptions and future outlook. *Journalism and Media* 3: 13–26. [CrossRef]
- Domingo, David, Thorsten Quandt, Ari Heinonen, Steve Paulussen, Jane B. Singer, and Marina Vujnovic. 2008. Participatory Journalism Practices in the Media and Beyond. *Journalism Practice* 2: 326–42. [CrossRef]
- Dong, Liang, Reid G. Smith, and Bruce G. Buchanan. 2011. Automating the selection of stories for AI in the news. In *Lecture Notes in Computer Science*. Berlin and Heidelberg: Springer, pp. 176–85. [CrossRef]
- Gillath, Omri, Ting Ai, Michael S. Branicky, Shawn Keshmiri, Robert B. Davison, and Ryan Spaulding. 2021. Attachment and trust in artificial intelligence. *Computers in Human Behavior* 115: 106607. [CrossRef]
- Glikson, Ella, and Anita Williams Woolley. 2020. Human Trust in Artificial Intelligence: Review of empirical research. *Academy of Management Annals* 14: 627–60. [CrossRef]
- Gursoy, Dogan, Oscar Hengxuan Chi, Lu Lu, and Robin Nunkoo. 2019. Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management* 49: 157–69. [CrossRef]
- Gurviez, Patricia, and Michaël Korchia. 2003. Proposal for a Multidimensional Brand Trust Scale. Paper presented at 32nd EMAC Conference Proceedings, Glasgow, UK, May 20–23.
- Heim, Steffen, Sylvia Chan-Olmsted, Claudia Fantapié Altobelli, Michael Fretschner, and Lisa-Charlotte Wolter. 2022. Exploring Trust in Media Brands today: Definition, Dimensions and cross-national Differences. *Discussion Paper of the Institute for Marketing at Helmut Schmidt University Hamburg* 11: 1–32.
- Hofeditz, Lennart, Milad Mirbabaie, Jasmin Holstein, and Stefan Stieglitz. 2021. Do you trust the AI-journalist? A credibility analysis of news content with AI-authorship. Paper presented at ECIS 2021 Proceedings, Marrakech, Morocco, June 14–16.
- Kim, Daewon, and Seongcheol Kim. 2017. Newspaper companies' determinants in adopting robot journalism. *Technological Forecasting and Social Change* 117: 184–95. [CrossRef]
- Kim, Soyoung, and Boyoung Kim. 2020. A decision-making model for adopting AI-generated news articles: Preliminary results. *Sustainability* 12: 7418. [CrossRef]
- Kohring, Matthias, and Jörg Matthes. 2007. Trust in news media. *Communication Research* 34: 231–52. [CrossRef]
- Kolo, Castulus, Joschka Mütterlein, and Sarah Anna Schmid. 2022. Believing journalists, AI, or fake news: The role of trust in media. Paper presented at the Annual Hawaii International Conference on System Sciences, Maui, HI, USA, January 4–7.
- Kramer, Roderick M., and Tom R. Tyler. 1996. *Trust in Organizations: Frontiers of Theory and Research*. Thousand Oaks: SAGE.
- Langer, Markus, and Richard N. Landers. 2021. The future of artificial intelligence at work: A review on effects of decision automation and augmentation on workers targeted by algorithms and third-party observers. *Computers in Human Behavior* 123: 106878. [CrossRef]

- Lee, Angela M. 2013. News audiences revisited: Theorizing the link between audience motivations and news consumption. *Journal of Broadcasting & Electronic Media* 57: 300–17. [CrossRef]
- Lee, Sangwon, Seungahn Nah, Deborah S. Chung, and Junghwan Kim. 2020. Predicting AI news credibility: Communicative or social capital or both? *Communication Studies* 71: 428–47. [CrossRef]
- Lim, Joon Soo, and Jun Zhang. 2022. Adoption of AI-driven personalization in digital news platforms: An integrative model of technology acceptance and perceived contingency. *Technology in Society* 69: 101965. [CrossRef]
- Lim, Joon Soo, Donghee Shin, Jun Zhang, Stephen Masiecat, Regina Luttrell, and Dennis Kinsey. 2022. News audiences in the age of artificial intelligence: Perceptions and behaviors of optimizers, mainstreamers, and skeptics. *Journal of Broadcasting & Electronic Media* 67: 353–75. [CrossRef]
- Lin, Carolyn, Michael B. Salwen, and Rasha A. Abdulla. 2004. Uses and gratifications of online and offline news: New wine in an old bottle? In *Online News and the Public*. London: Routledge, pp. 241–56. [CrossRef]
- Marconi, Francesco. 2020. *Newsmakers: Artificial Intelligence and the Future of Journalism*. New York: Columbia University Press.
- Mourão, Rachel R., Esther Thorson, Weiyue Chen, and Samuel M. Tham. 2018. Media repertoires and news trust during the early Trump administration. *Journalism Studies* 19: 1945–56. [CrossRef]
- Munoriyarwa, Allen, Sarah Chiumbu, and Gilbert Motsaathebe. 2021. Artificial intelligence practices in everyday news production: The case of South Africa's mainstream newsrooms. *Journalism Practice* 17: 1374–92. [CrossRef]
- Munuera-Aleman, Jose Luis, Elena Delgado-Ballester, and Maria Jesus Yague-Guillen. 2003. Development and validation of a brand trust scale. *International Journal of Market Research* 45: 35–54. [CrossRef]
- Nachtigall, Christoph, Ulf Kroehne, Friedrich Funke, and Rolf Steyer. 2003. (Why) Should We Use SEM? Pros and Cons of Structural Equation Modeling. *Methods of Psychological Research Online* 8: 1–22.
- Owsley, Chad S., and Keith Greenwood. 2022. Awareness and perception of artificial intelligence operationalized integration in news media industry and society. *AI & Society*, 1–15. [CrossRef]
- Raisch, Sebastian, and Sebastian Krakowski. 2021. Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review* 46: 192–210. [CrossRef]
- Reuters. 2023. Google Explores AI Tools for Journalists, in Talks with Publishers. *Reuters*. July 20. Available online: <https://www.reuters.com/technology/google-explores-ai-tools-journalists-talks-with-publishers-spokesperson-2023-07-20/> (accessed on 20 July 2023).
- Samek, Wojciech, and Klaus-Robert Müller. 2019. Towards explainable artificial intelligence. In *Explainable AI: Interpreting, Explaining and Visualizing Deep Learning*. Berlin and Heidelberg: Springer International Publishing, pp. 5–22. [CrossRef]
- Schepman, Astrid, and Paul Rodway. 2020. Initial validation of the general attitudes towards Artificial Intelligence Scale. *Computers in Human Behavior Reports* 1: 100014. [CrossRef] [PubMed]
- Schranz, Mario, Jörg Schneider, and Mark Eisenegger. 2018. Media trust and media use. In *Trust in Media and Journalism*. Wiesbaden: Springer Fachmedien Wiesbaden, pp. 73–91. [CrossRef]
- Shapiro, Ivor. 2010. Evaluating journalism. *Journalism Practice* 4: 143–62. [CrossRef]
- Siakalli, Michailina, Andreas Masouras, and Christos Papademetriou. 2015. Understanding online news: Uses and gratifications of mainstream news sites and social media. *International Journal of Strategic Innovative Marketing* 3. [CrossRef]
- Skovsgaard, Morten, Erik Albæk, Peter Bro, and Claes de Vreese. 2012. Media professionals or organizational marionettes? Professional values and constraints of Danish journalists. In *The Global Journalist in the 21st Century*. New York: Routledge.
- Song, Mi-Kyung, Feng-Chang Lin, Sandra E. Ward, and Jason P. Fine. 2013. Composite variables. *Nursing Research* 62: 45–49. [CrossRef]
- Spyridou, Lia-Paschalia, and Andreas Veglis. 2016. Convergence and the changing labor of journalism: Towards the 'super journalist' paradigm. In *Media Convergence Handbook*. Berlin and Heidelberg: Springer, vol. 1, pp. 99–116. [CrossRef]
- Venkatesh, Viswanath, James Y. L. Thong, and Xin Xu. 2012. Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly* 36: 157. [CrossRef]
- Wang, Xuya, and Feng Zhu. 2021. The application of artificial intelligence in AI news anchor. Paper presented at 2021 International Conference on Big Data Analytics for Cyber-Physical System in Smart City, Bangkok, Thailand, December 16–17; Singapore: Springer, pp. 1093–100. [CrossRef]
- Wu, Shangyuan, Edson C. Tandoc Jr., and Charles T. Salmon. 2018. Journalism reconfigured. *Journalism Studies* 20: 1440–57. [CrossRef]
- Xian, Xuelin. 2021. Psychological Factors in Consumer Acceptance of Artificial Intelligence in Leisure Economy: A Structural Equation Model. *Journal of Internet Technology* 22: 697–705.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.



Article

Rethinking the Relation between Media and Their Audience: The Discursive Construction of the Risk of Artificial Intelligence in the Press of Belgium, France, Portugal, and Spain

Cristian González-Arias ^{1,2,*} and Xosé López-García ^{1,*}

¹ Department of Communication Sciences, Faculty of Communication Science, University of Santiago de Compostela, 15782 Santiago de Compostela, Spain

² Instituto de Literatura y Ciencias del Lenguaje, Facultad de Filosofía y Educación, Pontificia Universidad Católica de Valparaíso, Viña del Mar 2530388, Chile

* Correspondence: cristian.gonzalez@pucv.cl (C.G.-A.); xose.lopez.garcia@usc.gal (X.L.-G.)

Abstract: It is believed that the way in which media speak about emerging technologies can influence the public perception of their benefits and risks. Risk statements highlight the possible negative effects, real or imaginary, that a particular event could have on audiences. Just as journalism varies over space and time, what is considered a risk is deeply rooted in specific social, economic, and technological contexts. This variability implies that journalistic practices are neither universal nor static; instead, they change and adapt according to circumstance. Moreover, technological advances have allowed the press to better understand their audiences and adhere to their demands. In this context, the discursive construction of the risk of artificial intelligence was studied in the press of four European countries: Belgium, Spain, France, and Portugal. In total, 290 texts published in January 2024 were examined. Mentions of “artificial intelligence” were found in the following newspapers: *Le Soir*, *El País*, *Le Figaro*, and *Público*. Fourteen risk categories and seven groups of voices responsible for their enunciation were identified, with significant variations between the studied newspapers. It was concluded that national contexts make it possible to differentiate the way in which the press communicates the risks associated with artificial intelligence. Although these results do not directly reflect public awareness of the risks in each of these countries, they open a line of research on the possible influences of the progressive monitoring and knowledge of audiences in the construction of the media agenda.

Keywords: risk; artificial intelligence; public debate; audience

1. Introduction

Research shows that the way the media reports on emerging technologies can shape perceptions of their possibilities, effects, benefits, harm, and risks to society (Vicente and Dias-Trindade 2021; Nguyen 2023; Sartori and Bocca 2023). For their part, Cave et al. (2020) argued that stories and myths about AI, from Homeric epics to contemporary science fiction, have shaped public expectations and fears regarding intelligent technologies. The role of technology in everyday life is a public concern as it affects broad societal dimensions, such as individual well-being, the labor market, economic growth, social stratification, culture, politics, and security (Nguyen 2023).

Paraphrasing Nguyen (2023), risks are sentences that emphasize the potentially negative and harmful impacts of AI development and its implementation, whether intended or unintended, recognized or minimized. In this sense, risks are not fixed; they are fluid. Risks emerge, evolve, and disappear over time. Factors such as changes in cultural norms, consumer trends, policies, and new forms of scientific knowledge shape risks and the assessment of their societal severity (Nguyen 2023). Furthermore, the sociocultural situation

of individuals and social groups influences the perception of trends, developments, and practices that are considered problematic (Luhmann 1991; Wynne 2002).

Few studies focus on and critically address the press discourse on artificial intelligence (von Pape et al. 2017; Paganoni 2019; Bunz and Braghieri 2022; Nguyen 2023; González-Arias and López-García 2023). Research regarding the representation of technology in the press and the debate about the risks associated with its implementation is linked to other complementary research areas, such as critical data literacy and data justice, which share the goal of increasing citizens' sensitivity to data risks and building resilience against data malpractice (Taylor 2017).

It is believed that media has the capacity to raise awareness among non-expert audiences regarding the benefits and risks of technology for different social groups (Paek and Hove 2017). In the "Global West", public discourses on digital transformation seem to be marked by contradictory tendencies between celebrating and criticizing the rise in data-driven technologies (Nguyen and Hekman 2022).

Sartori and Bocca (2023) point out how narratives about AI are filled with both utopian and dystopian exaggerations. These narratives shape both public perceptions and emotional responses toward technology. Examples of these narratives include themes of immortality versus dehumanization, freedom versus obsolescence, gratification versus alienation, and domination versus uprisings.

For their part, Cools et al. (2024) conclude that in the United States, media coverage of artificial intelligence and automation has been more positive than negative over time. However, there has recently been an increase in attention to dystopian frames. These dystopian frames include four main categories. First, the "Deficiency" frame refers to technologies requiring human assistance to function correctly. Second, the "Conflict" frame encompasses technologies causing struggle and resistance among different groups. Third, the "Kasparov Syndrome" describes technologies with the potential to surpass human capabilities in the future. Finally, the "Frankenstein's Monster" frame refers to technologies posing a crucial threat to humanity.

Sartori and Bocca (2023) argue that AI technology should not be viewed in isolation but as part of a socio-technical system where society and technology mutually influence each other. The socio-technical imaginaries and narratives surrounding AI play a crucial role in how society perceives and adopts these technologies.

In this landscape of technological development, the near real-time analysis that the media conducts on the interests of their audiences raises new questions about the effects of audience monitoring and adaptation practices on the construction of media discourses, specifically in the way content is presented, the approaches taken towards technological advancements, and the socio-technical imaginaries constructed around AI (Sartori and Bocca 2023). In this sense, it can be assumed that technology allows newspapers to tailor their content to the interests of their readers. Thus, it is not difficult to imagine that media offerings increasingly align more efficiently with audience preferences, creating a more direct relationship between audience interests and the products offered to them. However, this relationship between supply and demand occurs in specific, temporally, and spatially situated contexts. Therefore, the media's ability to cater to their audience's interests is also limited by available resources, the flexibility of their editorial project, and the relationship that the media establishes with other social actors, such as businesspeople and politicians.

In this context, we explore how newspapers handle content related to the risks of artificial intelligence over four newspapers from different national contexts. Specifically, we analyze the discursive construction of the risks associated with the implementation of artificial intelligence (AI) algorithms in the press of four European countries: Belgium, Spain, France, and Portugal.

Our research identified fourteen main risks and seven groups of voices; it also registered significant variations between newspapers in the countries studied. The main risk categories were described, and the results were linked to corresponding national contexts. The main takeaway from this is that national contexts allow us to differentiate the way in

which the press builds and communicates the risks related to artificial intelligence and the voices summoned to talk about it.

A careful reading of our results provides at least partial insight into how the media in different cultural and political contexts take globally circulating content and adapt it to their audiences. While it cannot be said that these results are an indicator of the public awareness of AI risks in each of the countries, due to advancements in technologies for monitoring media content consumption, a series of questions arise about the potential effects that the monitoring and understanding of audiences could have on the discursive practices of the media.

2. The Impact of AI on Journalism

The impact of AI started affecting journalism at the beginning of the 2020s, which is a moment when journalism reflected on its successes and failures after three decades of digitalization and the migration of its products to the web. Task automation, large-scale data analysis, and the increase in algorithms that allow audience tracking and content recommendation have been added to a long list of tools that demand critical reflection in order to face the challenges of the new wave of digitalization under the long-casting shadow of AI. Although no one doubts the contributions and facilities these new tools can offer journalism, it is necessary to contemplate the challenges faced when seeking to carry out journalism of social importance.

The increase in conferences, congresses, and forums in various countries, promoted by journalistic organizations and professional associations as well as communication researchers, reflects the importance of these issues.

The popular opinion is that AI will not be the elixir that solves the multiple problems of digital journalism (Simon 2024). There is a consensus on AI improving the capabilities of journalists, especially by saving time, which they can devote to added-value tasks (Canavilhas and Giacomelli 2023). In addition, AI can increase the industry's productive efficiency. However, it is also known that there are many open questions, and a change in mentality is required in the media and journalistic environment to address the many ethical issues AI raises, which implies the constant control and supervision of the processes carried out by artificial intelligence (Noain-Sánchez 2022).

To avoid diluting the roles and powers of journalism professionals and preventing vicious effects, the media must develop guidelines for the responsible use of AI. In addition, it is encouraged that the three key stakeholders—news organizations, journalists, and audience—proactively embrace their roles in upholding journalistic ethics (Shi and Sun 2024). This most certainly requires useful information on how journalistic practices are evolving.

3. A Communication Catalyst

Although research on AI has a long history and tradition in the scientific field, it has intensified particularly since 2015, when there was an observed increase in scientific articles dedicated to the subject, especially in the United States. Likewise, a diversification of perspectives can be observed in the field of communication, including the automatic generation of content, data journalism, big data, and its application to social media or information reviews (Calvo-Rubio and Ufarte-Ruiz 2021). Research on the use of these tools in newsrooms has revealed their progressive incorporation, which has become more intense in recent years, and their effectiveness in automating processes, rewriting texts, analyzing data, or serving as a generator of content ideas (Gutiérrez-Caneda et al. 2023).

Public interest in this technology and the tools that have become popular in recent years sparked at the beginning of the third decade of the current millennium. The public launch of ChatGPT in November 2022 was the event that caused a truly major upheaval in the communications sector, fueling social debate on the implications of artificial intelligence and intensifying academic research on this tool. AI technologies, which include automated learning, deep learning, natural language processing, and computer vision (Getchell et al.

2022), are present in all the processes of the networking society. For this reason, it is imperative to understand their capabilities and limitations when using them in the service of journalism.

Following the technological milestone of ChatGPT, the media discourse has highlighted the strengths of these technologies, the business potential they promise, the need for regulation, the ethical problems they bring to the table, and the limitations of the tool itself, such as the inability to distinguish between true or false information (González-Arias and López-García 2023). Simultaneously, research in the field of communication has provided evidence of the impact of AI on media and communication companies while uncovering the main areas of interest for researchers and experts where, among many others, ethical issues and transparency stand out (Codina et al. 2024).

Regarding the coverage of risks associated with technological development, the work of Nguyen (2023) is particularly noteworthy. Nguyen conducted a longitudinal study between 2010 and 2021 on the Anglo-Saxon press. This study identified what he calls “the risk of data”, including the development of AI. The study identifies the following risks: privacy invasion and surveillance, data bias and algorithmic discrimination, cybersecurity, and misinformation. It also reflects on how potential situations can be considered a risk or not and how this depends significantly on the perspectives and situations of the parties involved. Likewise, Nguyen suggests that for citizens to form an opinion and be able to participate in data risk discussions, they need to be aware of the potential threats, harms, and ethical challenges involved.

In this sense, as witnesses of technological developments, the media build their content by undertaking the role of informing and educating on aspects considered to be of public interest.

4. Materials and Methods

From the perspective of Discourse Analysis and Communication Studies, a qualitative and comparative study of the textual analysis of a corpus of journalistic articles of different genres from Romance language newspapers from different national contexts is proposed: *Le Soir* from Belgium, *El País* from Spain, *Le Figaro* from France and *Público* from Portugal. The selection of newspapers was guided by the criterion of the social relevance of each medium in the national media ecosystem¹ and the accessibility of the texts in databases available to the researchers. The texts were selected in their entirety through the Factiva tool, using the keywords “Inteligencia Artificial” or “AI” in the corresponding languages of French, Spanish, and Portuguese. A time criterion covering the whole month of January 2024 was established. The first month of the year was chosen because, traditionally, evaluations and projections are made on topics of social relevance in that period. A total of 290 texts were identified that referred at least once to artificial intelligence or its acronym AI. The details of the corpus can be seen in Table 1.

Table 1. Texts with mentions to AI during January 2024.

Country	Journal	Number of Texts
Portugal	<i>Público</i>	31
Spain	<i>El País</i>	86
France	<i>Le Figaro</i>	91
Belgium (fracophone)	<i>Le Soir</i>	82
Total		290

4.1. National Contexts and Journal Screening

Without intending to be exhaustive, this section briefly describes some aspects of the context in which the newspaper included in this study originated.

France has a proactive approach to AI regulation, driven by strong government initiatives and an interest in maintaining technological sovereignty. From France, we selected the newspaper *Le Figaro*, as it is one of the largest national circulating newspapers and is also available in the press database. *Le Figaro* is a generalist newspaper with a conservative line, identifying with the French center-right, with ample national circulation and a focus on political and economic news. The newspaper is owned by Serge Dassault and is part of the Dassault Group.

As the seat of the European Union, Belgium is heavily influenced by EU policies on AI and cybersecurity. Belgium has three linguistic communities, the most numerous being the Dutch and French-speaking ones. We selected the newspaper *Le Soir*, as it is the primary option in the French-speaking community and offers comprehensive coverage of national and international issues. The newspaper is identified with progressive ideas and is owned by the Rossel Group, which has a long tradition in the Belgian French-speaking press.

Portugal has shown a growing interest in technological innovation and has taken steps to attract technology companies. From Portugal, we selected *Público*, a newspaper founded in the 1990s that has achieved wide circulation. The newspaper is identified with progressive ideas in Portugal and is known for its in-depth coverage of current affairs. *Público* is owned by Sonae, a multinational business group.

Spain has expressed an interest in adopting emerging technologies and regulations to mitigate the risks associated with AI's impact. From this country, we selected the generalist newspaper *El País*, one of the traditional newspapers of reference in Spain. It is known for its extensive coverage of national and international current affairs. The newspaper is associated with the Spanish center-left and is owned by Grupo Prisa.

4.2. Analytical Procedures

The analysis was fundamentally interpretative. The labeling was carried out complementarily between the two researchers, and any doubts that arose during the process were collaboratively discussed and solved. The analysis involved the following steps:

- (a) Reading the texts to identify statements dedicated to risks to people derived from the development and implementation of AI.
- (b) Based on the identification of risk statements, the risk situation and the voices responsible for such mentions were coded. Risk situations were labeled according to the probable or potential harm involved in the broad spectrum of social activities of public interest. When coding voices, the author of the text himself or a source cited by the author of the text was labeled.
- (c) Once the mentions were identified through semantic similarity and abstraction, the risk situations and voices were grouped.

The interpretative analysis consisted of a global reading of the data and a comparison between the studied newspapers.

5. Results

Firstly, we present the general results, which display the risks built in each of the four newspapers studied. This was based on the count of the absolute frequencies of textual fragments dedicated to the presentation of risks associated with AI in the press. The risks are characterized by means of their percentage distribution and a descriptive characterization of the most prominent risk categories and the voices that appear responsible for these statements. Secondly, a comparison is made between the newspapers studied.

5.1. Risk Categories

Fourteen categories were established from 271 statements dedicated to the presentation of risks. Table 2 shows the percentage distribution of the categories. In the first place, with 25% of occurrences, *public opinion manipulation* stands out, followed by *general disarray and uncertainty*, and *content misappropriation*, with 13% of occurrences each. In fourth place, with 12%, is *job disruption*. These four risk categories account for 63% of the total risk occurrences.

Table 2. Risks of AI in journalism.

Risk Category	%
Public opinion manipulation	25
General disarray and uncertainty	13
Content misappropriation	13
Job disruption	12
Loss of privacy and security	8
Increased inequality	7
Manipulation of desires and feelings	6
Predominance of economic interests	5
Errors due to AI “hallucinations”	4
Increased mortality in armed conflicts	2
Bias and discrimination	2
Worsening of the environmental crisis	2
Loss of cognitive abilities	2
Loss of transparency and explainability	2

Next, as a way to illustrate the results, only the first four categories of artificial intelligence risks identified in the set of news outlets studied are described. It is worth noting that all the risks identified have a global scope and do not account for particular situations in individual countries. It is also worth mentioning that most of the risks identified directly and indirectly involve the press, with the most significant being the risks of public opinion manipulation and misappropriation of content.

5.1.1. Risk of Public Opinion Manipulation

Public opinion manipulation considers the risks of disinformation through the propagation of fake news and the ability to control the distribution of information by technology companies and governments, including the recommendation for algorithms and personalization that are being massively implemented on the Internet. This includes some of its most direct effects, such as the influence on electoral processes, polarization, and the proliferation of harmful content. Also included are the medium and long-term consequences of the manipulation of public opinion, such as the weakening of democracy and the loss of social cohesion.

Example 1

- “La inteligencia artificial generativa, en concreto, supone un doble riesgo: uno cuantitativo, pues ahora la producción de desinformación puede multiplicarse sin que tenga que haber un humano detrás de todo; y otro cualitativo, con el llamado deep fake, el falso profundo, con un altísimo nivel de credibilidad, una capacidad de persuasión extraordinaria y mayor dificultad para desmentir” (Rizzi 2024).
[“In particular, generative AI poses a double risk: On one hand, quantitative, because disinformation production can now multiply without the need for constant human input. On the other hand, it is qualitative, thanks to the so-called deep fake, AI technology with a very high level of credibility and an extraordinary capacity for persuasion, plus a greater difficulty to disprove”] [Author’s translation].

Example 2

- “Le boom de l’IA facilite la désinformation, pointée par un rapport récent du Forum économique mondial comme l’un des plus grands risques pour l’humanité alors que des milliards d’habitants de la planète sont appelés aux urnes cette année” (AFP 2024).

[“The AI boom facilitates misinformation. This was pointed out by a recent report from the World Economic Forum as one of the greatest risks for humanity as billions of the planet’s inhabitants are called to the polls this year”] [Author’s translation].

5.1.2. Risk of General Disarray and Uncertainty

Artificial intelligence generates significant stress due to its rapid and expansive nature, encompassing various societal sectors. Its disruptive capacity is comparable to the intrinsic risks of nuclear bombs. Not only does AI amplify existing dangers on the internet, but it also introduces uncertainties due to risks that are impossible to measure, posing a threat to human survival. The factors contributing to widespread risk are diverse: economic interests driving technological development or the competition between the United States and China, for example. Thus, humanity faces a significant challenge in that, without adequate regulation, AI represents a substantial danger. Although some see transhumanism as a favorable integration of AI, the uncertainty of our ability as humans to adapt to changes puts us at risk of being relegated to an insignificant role in the face of these powerful technologies.

Example 3

- “Jerry Brown, ex-governador da Califórnia e presidente executivo do Boletim, lamentou que os dirigentes mundiais estejam “a conduzir o mundo para uma catástrofe”, quase “como se estivessem no Titanic”, com “bombas nucleares, grandes emissões de carbono, agentes patogénicos perigosos e inteligência artificial” (Almeida Mendes 2024).
[“Jerry Brown, ex-governor of California and executive president of the Bulletin, lamented that world leaders are ‘driving the world towards catastrophe’, almost ‘as if they were on the Titanic’, with ‘nuclear bombs, large carbon emissions, dangerous pathogens, and artificial intelligence’”] [Author’s translation].

Example 4

- “En el caso de la IA, estamos ante una materia que tiene un riesgo intrínseco como no hemos conocido hasta este momento” (Ayuso 2024).
[“In the case of AI, we are dealing with a matter that has an intrinsic risk unlike anything we have known until now”] [Author’s translation].

5.1.3. Content Misappropriation

In the creative sector, there is growing concern about the use of artificial intelligence tools due to content misappropriation and copyright infringement. Large language models (LLMs) have faced criticism for breaching open-source licenses by appropriating vast amounts of data without proper recognition and compensation to their creators or owners. This issue directly implicates the press, as the American press led the first accusations of content misappropriation for training AI systems against OpenAI, the company that developed ChatGPT.

Example 5

- “Nous sommes les fournisseurs de matière première de cette nouvelle industrie de l’intelligence artificielle (IA) générative, et il est grand temps que nous soyons reconnus comme tel », martèle Emmanuel Parody, secrétaire général du Geste, la fédération des éditeurs français de presse en ligne” (Cohen 2024).
[“We are the raw material suppliers for this new industry of generative artificial intelligence (AI), and it is high time we were recognised as such”, asserts Emmanuel Parody, general secretary of Geste, the federation of French online press publishers.”] [Author’s translation].

Example 6

- “OpenAI a utilisé notre travail pour développer et commercialiser des produits d’intelligence artificielle (IA) générative sans avoir la permission du Times » affirme le quotidien” (Woitier 2024).

["OpenAI used our work to develop and market generative artificial intelligence (AI) products without the Times' permission", claims the newspaper] [Author's translation].

5.1.4. Job Disruption

Artificial intelligence raises serious concerns regarding job disruption through automation and the replacement of people with machines. AI is already reshaping organizational structures and significantly altering job roles, potentially leading to massive job losses and replacing humans in various work functions. It is estimated that 300 million jobs could disappear due to automation, affecting 60% of employment in advanced economies. This transformation threatens not only lower-skilled jobs but also extends its risks to higher-paying positions. The demand for young university graduates could decrease if their profiles become redundant, further deepening inequality.

Example 7

- "La question n'a pas été soulevée sur la place publique alors que, pour ne citer que cet exemple, l'impact de l'intelligence artificielle sur le marché du travail y est vivement débattu" (Smith 2024).
["The issue has not been raised in public, whereas, to cite just this example, the impact of artificial intelligence on the labour market is being hotly debated."] [Author's translation].

Example 8

- "L'IA aura également un impact sur le marché du travail et sur certains types d'emplois" (Duqué 2024).
["AI will also have an impact on the labour market and certain types of jobs."] [Author's translation].

5.2. Comparison between Newspapers

If we examine the data obtained separated by newspaper, significant differences can be observed. Table 3 presents the results in percentages relative to each newspaper, allowing for a comparison of each newspaper's orientations.

Table 3. Relative distribution of risks by newspaper.

Risks	<i>El País</i>	<i>Público</i>	<i>Le Soir</i>	<i>Le Figaro</i>
Public opinion manipulation	25	16	10	42
Content misappropriation	11	24	10	10
General disarray and uncertainty	22	12	8	2
Job disruption	16	4	10	10
Loss of privacy and security	4	12	10	10
Increased inequality	8	12	10	2
Manipulation of desires and feelings	1	0	13	10
Predominance of economic interests	1	8	13	2
Errors due to AI "hallucinations"	1	4	8	4
Increased mortality in armed conflicts	1	0	3	4
Bias and discrimination	3	4	3	0
Worsening of the environmental crisis	1	0	3	2
Loss of cognitive abilities	4	0	0	0
Loss of transparency and explainability	1	4	3	0

- *El País* (Spain) expresses concern about public opinion manipulation (25%) and the general disorder and uncertainty that AI can generate (22%). Together, these two issues account for nearly half of the risks raised in the newspaper. Additionally, it

also significantly addresses the risk of job disruption (16%). Other issues like loss of privacy and security (4%) and increased inequality (8%) are also mentioned, but with less prominence. The coverage reflects predominant concern about the potential destabilization of both the labor market and public perception by AI. *El País* also highlights a risk not addressed in any other newspaper, which is the risk of cognitive capacity loss (4%), highlighting the concern that relying on machines for tasks like writing or summarizing information might lead to a decline in our ability to perform these tasks ourselves.

- *Público* (Portugal) emphasizes content misappropriation (24%), indicating a strong concern over lawsuits filed by the North American press against OpenAI. Public opinion manipulation is at 16%, while concerns about general disorder and uncertainty, loss of privacy and security, and increased inequality each stand at 12%. These figures underscore *Público*'s critical stance on regulation and the impact of AI on rights and equity.
- *Le Soir* (French-speaking Belgium) presents a more varied coverage of associated risks. The two risks that appear most frequently are the risk of the manipulation of desires and feelings (13%) and the predominance of economic interests (13%). Both topics reflect concerns about the effects of personalization, persuasive technologies, and attention capture, which are significantly enhanced by AI tools. It also addresses, with 10% each, the manipulation of public opinion, the misappropriation of content, job destruction, loss of privacy and security, and an increase in inequality. Although less prominent, a general lack of control and uncertainty (8%) and AI 'hallucination' errors (8%) are also present.
- *Le Figaro* (France) stands out considerably for its high focus on public opinion manipulation (42%), reflecting a strong concern about the potential impact of AI on democracy and public perception. The other four risks it addresses each have a 10% occurrence: content misappropriation, job disruption, loss of privacy and security, and the manipulation of desires and feelings.

All four newspapers recognize the risk that AI poses for public opinion manipulation, with varying degrees of emphasis: *Le Figaro* reaches 42%, *El País* (25%), *Público* (16%), and *Le Soir* (10%). Regarding the risk of content misappropriation, *Público* stands out at 24%, *El País* reaches 11%, and *Le Soir* and *Le Figaro* remain at 10%. In the case of risks associated with general disorders and increased uncertainty, *El País* achieves the highest percentage at 25%, while both *Le Soir* and *Le Figaro* have significantly lower values, with *Le Figaro* notably achieving only 2%.

These differences reflect how newspapers prioritize different dimensions of AI risks in each country.

5.3. Voices Articulating the Risks

The voices responsible for the risk statements have been described through seven categories. The detailed percentage distribution can be seen in Table 4. The following provides a description of the identified voice categories:

- **Author of the Text:** This includes the individuals who write the articles, regardless of their profession or contractual relationship with the medium. This category also includes unsigned texts representing the newspaper. It broadly represents the voice of the newspaper through hired or invited individuals to write on its pages.
- **Researcher or Expert:** This category includes academics, scientists, or specialists in the field of AI or related disciplines. Specialists are consulted for various purposes: due to the highly specialized nature of the topics, to generate more credibility, or because experts seek to disseminate their research in the press.
- **Public Institution or International Organization:** This category includes governmental entities, non-governmental organizations (NGOs), or international bodies like the UN, the European Union, or the International Monetary Fund. These institutions present

- official positions and can access the media either due to media interest or as part of communication campaigns within the scope of their functions.
- **Politician:** Elected officials or delegates involved in public administration functions. These individuals participate in the discussion of topics of public interest at local, national, or international levels. Their statements reflect an interest in certain public policies or legislative orientations concerning AI.
 - **Tech Company Representative:** this includes leaders of local or international companies developing AI tools or providing services in the AI application area.
 - **Foreign Press and News Agencies:** this category includes citations from news-generating agencies or other national or international newspapers.
 - **Other Voices (Readers, Anonymous, and Religious Authorities):** this category includes mentions with low occurrence. Specifically, it includes readers, anonymous voices, and religious authorities such as the Pope.

Table 4. Voice groups.

	<i>El País</i>	<i>Público</i>	<i>Le Soir</i>	<i>Le Figaro</i>	Total
Author of the text	32	45	27	40	35
Researcher or expert	22	32	38	19	26
Public institution or international organization	18	5	24	9	15
Politician	12	9	0	17	10
Representative of a technological company	9	0	8	11	8
Other voices	4	5	0	2	3
Foreign press and news agencies	3	5	3	2	3

Certainly, the primary responsibility for the discourses circulating in the press lies with the journalistic enterprise, which has an editorial line built on an economic and political project that guides all the newspaper's activities. Within this framework, journalists, generically referred to here as the "Author of the Text", choose their sources to construct their texts. This decision is likely influenced by various factors: the editorial line, the degree of specialization of the topic, the journalist's training, material access to specialized sources, and the evaluation of the authority of a person to speak on a specific topic. Thus, the initial observation we need to make pertains to the "Author of the Text" category. In these cases, the article's author assumes the content's evaluation or assessment discursively. Considering the newspapers together, this category has the highest representation at 35%, which breaks down in descending order: *Público* with 45%, *Le Figaro* with 35%, *El País* with 32%, and *Le Soir* with 27%. These percentages show the extent to which the journalists and editors of these newspapers are involved in discussing and analyzing AI risks. It is noteworthy that *Le Soir* exhibits a different trend compared to the other newspapers, as it has the highest percentage in the "Researcher or Expert" category at 38%.

If we highlight the trends in the newspaper, it is noted that *El País* uses a variety of sources to address AI risks, while *Público* concentrates most of the voices on the authors of the text and researchers or experts. *Le Soir*, with the highest percentage of researchers or experts (38%), also stands out for citing public institutions or international organizations, indicating a preference for specialized and academic sources to discuss AI risks. Conversely, *Le Figaro* presents a lower percentage of researchers or experts (19%) and has the highest percentage in the political category (17%). Politicians are also an important source for *El País* (12%), while they do not appear in *Le Soir*.

The absence of representatives of tech companies in *Público* contrasts with the other newspapers, especially *Le Figaro* at 11% and *El País* at 9%.

The voices of other readers, anonymous sources, and religious authorities are minimal in all newspapers, with *Público* and *El País* recording the highest values (5% and 4%, respectively). Similarly, the presence of foreign press and news agencies is low and uniform in all newspapers, indicating a lower dependence on external sources to discuss AI risks.

6. Discussion

AI-based algorithms are ubiquitous and powerful tools that are transforming multiple sectors, from the economy to health, culture, education, and the arms industry. In this sense, it is a transversal and global issue. Consequently, at least in Europe, the impacts of AI will occur in all countries, most likely in the same sectors and the same manner. This circumstance arouses interest in exploring how different newspapers manage knowledge about the impact of AI on society, particularly the treatment of risks associated with AI developments.

From the perspective of Marres et al. (2024), who analyzed controversies about AI through the voices of experts, social media, and the press in England, it was concluded that contemporary AI is seen as a harmful technology for society. This perception differs from other controversial topics of the 20th century, such as nuclear energy and genetically modified foods, which were characterized by a denial of risks by companies. In the case of AI, it has been the scientists and developers of AI tools themselves who have raised the alarm about the risks of AI.

Similarly, in line with the observations of Marres et al. (2024), the risks of AI identified in our research not only address scientific issues but also articulate the structural problems of social justice, economy, politics, and ethics of diverse origins. In other words, each of the stated risks amplifies social problems that preexisted the technological developments of AI.

For his part, Ananny (2024) suggests that the public importance of generative artificial intelligence arises from its dual identity as both an ontological and epistemological concern. This duality manifests in the failures of AI, such as errors in facial recognition or biased chatbot responses, which illustrate, combine, and extend the ideals of the public.

This ontological concern addresses issues related to the nature and existence of AI, which implies reflecting on what AI is, how it exists, and how it affects our understanding of being and reality. On the other hand, the epistemological concern refers to issues related to the knowledge and truth of AI, reflecting on how we know and understand AI, how knowledge is constructed through it, and how it affects our perception of the truth. Ananny (2024) argues that this duality of generative AI manifests in its failures, as the limitations and technical problems of AI illustrate how these deep concerns interact and affect the public sphere, influencing our understanding and management of matters of common interest. From our perspective, the differentiated attention paid to the risks of AI in each of the national contexts studied also reflects, to some extent, a different configuration in the construction of the meaning of the public opinion.

Also concerning public interest, risk communication carries a social responsibility as it involves an interest in modifying the recipient's behaviors in the face of risk situations. In some cases, the aim is to mobilize the population to develop behaviors that minimize harm, and in others, it is to pressure the authorities to take measures to prevent negative effects on the population. However, in the specific context of the press, it could also be that the presentation of risks is aimed at capturing readers' attention with the simple interest of increasing the time spent on the reading page or having the news shared with other readers.

In any case, the media depend on the relationship they establish with their audiences, which they must nurture, maintain, and, as far as possible, increase. This involves a constant effort to bring the content closer to and adapt it to their audience. In this regard, Sun et al. (2020) argued that the impact of media coverage on emerging technology is deeper when that technology is linked to reality, stimulates plural interpretations, and sparks controversy.

Given that audience knowledge is always partial, the audience to which the media direct their messages is always imagined (Charaudeau 2003). In this context, it is relevant to

consider that, at present, it is the technological development itself that enables journalistic companies to continually improve their methods for monitoring and understanding audiences. Consequently, to varying degrees, journalistic companies progressively have more information with which to adapt their messages to the characteristics of their audience.

In this context, we can assume that the differences observed in how newspapers address risk reflect the image they construct of their audiences. However, what other factors could we associate with these differences? In light of these findings, it can be noted that the construction of AI risks could be influenced by at least three contextual elements: the socio-political and economic situation of each country, the presence and development of the local technology sector, and the editorial project of each newspaper.

Regarding the socio-political and economic context, for example, it can be seen that *Le Figaro*'s high concern about the manipulation of public opinion may reflect political tensions and polarization in France, while *Público*'s focus on copyright may be related to the specific cultural and creative policies of Portugal.

The presence and development of the local technology sector can influence how AI risks are addressed. Nguyen (2023) suggested that the sense of remoteness versus the immediacy of technology's effects could be a factor likely to shape perceptions of technology's relevance and impact. For example, if France has a more developed technology industry with greater investments in AI, this could explain *Le Figaro*'s concern about the risks of public opinion manipulation. On the other hand, in Portugal, with fewer companies developing AI technology but where the creative industry may have significant weight, *Público* focuses on copyright and content appropriation.

Lastly, the editorial project of each newspaper can also influence the selection and emphasis of topics. *Le Figaro*, with a more conservative editorial line, may focus on risks to democracy and public opinion, while *Público*, with a more progressive audience, may be more concerned with equity and creators' rights.

The variation in voices that convey concerns can be read as an achievement of greater or more limited pluralism in the construction of AI risk. This diversity of voices can allow for a more complex and rich perspective, while a concentration of few voices restricts an adequate understanding of the risks and their implications. However, the ability to bring diverse voices to the newspaper often depends more directly on material resources: having journalists specialize in technological topics and securing (whether through payment or not) authoritative voices to address specialized issues. Another relevant factor is the relationships that the media establish with political powers or business powers, which determine the ease with which these actors participate in the public debate generated in the media public space.

7. Conclusions

Studying the discursive construction of technological risks in the press from different national contexts provides valuable information on various aspects of journalistic practices and their production environments. These include the socio-economic and political contexts, the presence and development of the local technology sector, as well as editorial projects.

On the one hand, the identification of the fourteen categories of risk and their relative distribution offers a snapshot of the circulation of ideas in four countries of the European Union. It is noteworthy that no risks were identified that particularly affected any of the countries studied, as might occur with other types of risks, such as environmental or war-related risks. We have observed that in all cases, these are global risks that would potentially affect the entire population accessing AI technology in a similar manner.

The frequency of occurrence of risk statements in the press shows a significant predominance of fear in public opinion manipulation. While this is an issue that directly concerns the press due to its role in organizing public space, it is also true that it has been a widely disseminated concern by international non-governmental organizations, such as the World Economic Forum, which identifies misinformation as the most serious global risk alongside environmental collapse and war conflicts (World Economic Forum 2024).

Similarly, the second most widespread risk, the misappropriation of content, also directly involves the press, as American journalism companies have led the first wave of lawsuits for using their articles to train AI models, such as Microsoft, against OpenAI.

Because these are global risks, the differences found in the coverage of these risks by the media studied become even more interesting. If we consider the significant development of various techniques for monitoring and understanding audiences, we can imagine that the relationship between media offerings and audience demand is becoming closer. This suggests that audience knowledge may be increasingly considered in journalistic production.

In this sense, a greater understanding of the relationship between media and their audiences on these issues can help better appreciate and value the social role that media can play in the face of the rapid technological changes we are experiencing.

A hasty conclusion might lead us to consider that the uneven distribution of risks in the studied press reflects the interest and public awareness of these issues in respective national audiences. However, we cannot disregard the role that highly relevant aspects, such as national political contingencies, the presence of the technology sector, and the editorial line, may play, complementarily influencing the media agenda.

Following this line of thought, the main conclusion of this research is that national contexts significantly influence how the press constructs and communicates the risks associated with artificial intelligence, as well as the selection of voices summoned to discuss the issue. It is established as a working hypothesis for future research to confirm whether technological developments that enhance audience understanding lead to the increasing influence of audience interests in the construction of the media agenda and the configuration of their products. If this hypothesis is confirmed, it could be argued that media offerings and the treatment of critical issues, such as risk discourses, may reflect the degree of public awareness of these issues.

The interpretation of these results should consider the limitations of this work. Firstly, it would be advisable for future endeavors to expand the sample of newspapers per country to have a more ideologically representative sample, one that reflects the various linguistic communities of Belgium, for example. Undoubtedly, through a more extensive effort, the sample could be expanded to various countries inside and outside of the European Union.

Finally, it can be noted that in this tumultuous time of change that strains public communication, the press must find a sustainable business model and strive not to lose social relevance. For this reason, it is crucial to develop research that relates to journalistic practices, technological development, and audiences.

Author Contributions: Conceptualization, C.G.-A. and X.L.-G.; methodology, C.G.-A.; software, C.G.-A.; validation, C.G.-A. and X.L.-G.; formal analysis, C.G.-A. and X.L.-G.; investigation, C.G.-A. and X.L.-G.; resources, X.L.-G.; data curation, C.G.-A. and X.L.-G.; writing—original draft preparation, C.G.-A.; writing—review and editing, C.G.-A.; visualization, C.G.-A.; supervision, X.L.-G.; project administration, X.L.-G.; funding acquisition, X.L.-G. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by MICIU/AEI and FEDER/UE grant number PID2021-122534OB-C21.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: González Arias, Cristian, 2024, "The Discursive Construction of the Risk of Artificial in the Press of Belgium, France, Portugal, and Spain", <https://doi.org/10.7910/DVN/M1MLJV>, Harvard Dataverse, V1.

Conflicts of Interest: The authors declare no conflict of interest.

Notes

- ¹ In the case of France, the first choice was Le Monde, but it was not available in the database used. In the case of Belgium, which has three linguistic communities, we chose the French-speaking press because of limitations in our knowledge of Dutch and German.

References

- AFP. 2024. Forum économique mondial: Li Qiang et Volodymyr Zelensky ouvrent le bal à Davos. *Le Soir*, January 16. Available online: <https://www.lesoir.be/561587/article/2024-01-16/forum-economique-mondial-li-qiang-et-volodymyr-zelensky-ouvrent-le-bal-davos> (accessed on 15 February 2024).
- Almeida Mendes, Filipa. 2024. Relógio do Apocalipse continua a 90 segundos do fim, o mais perto que já esteve. *Público*, January 23. Available online: <https://www.publico.pt/2024/01/23/ciencia/noticia/relogio-apocalipse-continua-90-segundos-fim-perto-ja-2077831> (accessed on 15 February 2024).
- Ananny, Mike. 2024. Making Generative Artificial Intelligence a Public Problem. Seeing Publics and Sociotechnical Problem-Making in Three Scenes of AI Failure. *Javnost—The Public* 31: 89–105. [CrossRef]
- Ayuso, Silvia. 2024. Hemos dado un golpe encima de la mesa regulando la IA. *El País*, January 10. Available online: <https://elpais.com/tecnologia/2024-01-10/iban-garcia-del-blanco-negociador-de-la-ley-europea-de-inteligencia-artificial-hemos-dado-un-golpe-encima-de-la-mesa.html> (accessed on 30 January 2024).
- Bunz, Mercedes, and Marco Braghieri. 2022. The AI doctor will see you now: Assessing the framing of AI in news coverage. *AI & Society* 37: 9–22. [CrossRef]
- Calvo-Rubio, Luis Mauricio, and María-José Ufarte-Ruiz. 2021. Artificial intelligence and journalism: Systematic review of scientific production in Web of Science and Scopus (2008–2019). *Communication & Society* 34: 159–76. [CrossRef]
- Canavilhas, João, and Fábio Giacomelli. 2023. Inteligencia artificial en el periodismo deportivo: Estudio en Brasil y Portugal. *Revista De Comunicación* 22: 53–69. [CrossRef]
- Cave, Stephen, Kanta Dihal, and Sarah Dillon, eds. 2020. *AI Narratives: A History of Imaginative Thinking about Intelligent Machines*. Oxford: Oxford University Press.
- Charaudeau, Patrick. 2003. *El Discurso de la Información. La Construcción del Espejo Social*. Barcelona: Gedisa.
- Codina, Lluís, María-José Ufarte-Ruiz, and Sandra-L. Borden. 2024. Introducción. Avivar las llamas de la inteligencia artificial en los medios: Más allá de las ganancias de eficiencia y productividad. *Comunicación y Sociedad* 37: 221–25. [CrossRef]
- Cohen, Claudia. 2024. Intelligence artificielle: Les éditeurs français s’organisent pour faire reconnaître leurs droits. *Le Figaro*, January 9. Available online: <https://www.lefigaro.fr/medias/intelligence-artificielle-les-editeurs-francais-s-organisent-pour-faire-reconnaitre-leurs-droits-20240109> (accessed on 30 January 2024).
- Cools, Hannes, Baldwin Van Gorp, and Michael Opgenhaffen. 2024. Where exactly between utopia and dystopia? A framing analysis of AI and automation in US newspapers. *Journalism* 25: 3–21. [CrossRef]
- Duqué, Magali. 2024. Vers un marché du travail plus flexible? *Le Soir*, January 26. Available online: <https://www.lesoir.be/563997/article/2024-01-26/vers-un-marche-du-travail-plus-flexible> (accessed on 15 February 2024).
- Getchell, Kristen M., Stephen Carradini, Peter W. Cardon, Carolin Fleischmann, Haibing Ma, Jolanta Aritz, and James Stapp. 2022. Artificial Intelligence in Business Communication: The Changing Landscape of Research and Teaching. *Business and Professional Communication Quarterly* 85: 7–33. [CrossRef]
- González-Arias, Cristian, and Xosé López-García. 2023. ChatGPT: Stream of opinion in five newspapers in the first 100 days since its launch. *Profesional De La información* 32: e320524. [CrossRef]
- Gutiérrez-Caneda, Beatriz, Jorge Vázquez-Herrero, and Xosé López-García. 2023. AI application in journalism: ChatGPT and the uses and risks of an emergent technology. *Profesional de la Información* 32: e320514. [CrossRef]
- Luhmann, Niklas. 1991. *Risk: A Sociological Theory*. Berlin: Walter de Gruyter.
- Marres, Noortje, Michael Castelle, Beatrice Gobbo, Chiara Poletti, and James Tripp. 2024. AI as super-controversy: Eliciting AI and society controversies with an extended expert community in the UK. *Big Data & Society*, 11. [CrossRef]
- Nguyen, Dennis. 2023. How news media frame data risks in their coverage of big data and AI. *Internet Policy Review*, 12. [CrossRef]
- Nguyen, Dennis, and Erik Hekman. 2022. A ‘new arms race’? Framing China and the U.S.A. in A.I. news reporting: A comparative analysis of the Washington Post and South China Morning Post. *Global Media and China* 7: 58–77. [CrossRef]
- Noain-Sánchez, Amaya. 2022. Abordar el impacto de la inteligencia artificial en el periodismo: La percepción de expertos, periodistas y académicos. *Comunicación y Sociedad* 35: 105–21. [CrossRef]
- Paek, Hye-Jin, and Thomas Hove. 2017. Risk perceptions and risk characteristics. In *Oxford Research Encyclopedia of Communication*. Oxford: Oxford Research Encyclopedias, pp. 1–14. [CrossRef]
- Paganoni, Maria Cristina. 2019. *Framing Big Data. A Linguistic and Discursive Approach*. New York: Palgrave Pivot. [CrossRef]
- Rizzi, Andrea. 2024. La amenaza de la desinformación en el gran ciclo electoral de 2024 inquieta al foro de Davos. *El País*, January 16. Available online: <https://elpais.com/internacional/2024-01-16/la-amenaza-de-la-desinformacion-en-el-gran-ciclo-electoral-de-2024-inquieta-al-foro-de-davos.html> (accessed on 30 January 2024).
- Sartori, Laura, and Giulia Bocca. 2023. Minding the gap(s): Public perceptions of AI and socio-technical imaginaries. *AI & Society* 38: 443–58. [CrossRef]

- Shi, Yi, and Lin Sun. 2024. How Generative AI Is Transforming Journalism: Development, Application and Ethics. *Journalism and Media* 5: 582–94. [CrossRef]
- Simon, Felix M. 2024. *Artificial Intelligence in the News. How AI Retools, Rationalizes, and Reshapes Journalism and the Public Arena*. Columbia: Tow Center for Digital Journalism at Columbia University. Available online: https://towcenter.columbia.edu/sites/default/files/content/Tow%20Report_Felix-Simon-AI-in-the-News.pdf (accessed on 25 May 2024).
- Smith, Stephen. 2024. L'immigration pour compenser une faible fécondité: Une solution périlleuse. *Le Figaro*, January 17. Available online: <https://www.lefigaro.fr/vox/monde/stephen-smith-la-poursuite-de-l-immigration-massive-pour-compenser-une-faible-fecondite-est-une-solution-perilleuse-20240116> (accessed on 30 January 2024).
- Sun, Shaojing, Yujia Zhai, Bin Shen, and Yibei Chen. 2020. Newspaper coverage of artificial intelligence: A perspective of emerging technologies. *Telematics and Informatics* 53: 101433. [CrossRef]
- Taylor, Linnet. 2017. What is data justice? The case for connecting digital rights and freedoms globally. *Big Data & Society* 4: 1–14. [CrossRef]
- Vicente, Paulo Nuno, and Sara Dias-Trindade. 2021. Reframing sociotechnical imaginaries: The case of the Fourth Industrial Revolution. *Public Understanding of Science* 30: 708–23. [CrossRef]
- von Pape, Thilo, Sabine Trepte, and Cornelia Mothes. 2017. Privacy by disaster? Press coverage of privacy and digital technology. *European Journal of Communication* 32: 189–207. [CrossRef]
- Woitier, Chloé. 2024. IA: OpenAI négocie des accords de licence avec les médias américains. *Le Figaro*, January 6. Available online: <https://www.lefigaro.fr/medias/ia-openai-negocie-des-accords-de-licence-avec-les-medias-americains-20240105> (accessed on 15 February 2024).
- World Economic Forum. 2024. *The Global Risks Report 2024*, 19th ed. Geneva: World Economic Forum. Available online: https://www3.weforum.org/docs/WEF_The_Global_Risks_Report_2024.pdf (accessed on 25 May 2024).
- Wynne, Brian. 2002. Risk and environment as legitimacy discourses of technology: Reflexivity inside out? *Current Sociology* 50: 459–77. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.



Article

Artificial Intelligence in Journalism: A Ten-Year Retrospective of Scientific Articles (2014–2023)

Fabia Ioscote ^{1,*}, Adriana Gonçalves ² and Claudia Quadros ¹

¹ PPGCOM, Federal University of Paraná, Curitiba 80035-010, Brazil; clauquadros@gmail.com

² LabCom, University of Beira Interior, 6201-001 Covilhã, Portugal; adriana.goncalves@ubi.pt

* Correspondence: ioscore.fabia@gmail.com

Abstract: Academic interest in AI in journalism has been growing since 2018. Through a systematic review of the literature from 2014 to 2023, this study discusses the evolution of research in the field and how AI has changed journalism. The aim is to understand the impact of AI on journalism, based on a review of academic papers and a qualitative analysis of the most cited articles. This study combines: a systematic review of scientific articles extracted from Web of Science and Scopus (n = 699) and a qualitative approach with categorical content analysis of those with more than 50 citations (n = 59). The results (n = 699) highlight the prominence of authors from the Universities of Amsterdam and Santiago de Compostela. The United States has the largest number of authorships: 261 distributed across 99 institutions. The categorical content analysis (n = 59) shows a focus on issues like the work of the journalist, because AI is replacing journalists with repetitive and monotonous tasks, raising several questions about the role of the journalist. The findings show the rise of computational methods, highlighting the pervasiveness of AI in research, which has not been explored in previous work. Ethics, regulation, and journalism education remain under-discussed in research.

Keywords: artificial intelligence; automated journalism; news production; GenAI; NLP; systematic review

1. Introduction

The history of AI took its first steps in the 1950s, marked by pioneering scientists such as John McCarthy, who coined the term artificial intelligence (AI). However, it was not until the launch of ChatGPT in November 2022 that AI gained significant visibility, registering new developments in society. With financial investments exceeding USD 90 billion in 2021 and 2022 (Thormundsson 2023), AI has become ubiquitous in people's daily lives (Minh et al. 2022), especially in communication processes (Diakopoulos 2019; García-Orosa et al. 2023).

AI, virtual reality, augmented reality, big data, robotics, and Internet of Things (IoT) technologies are part of Industry 4.0, which is characterised by the constant exchange of information over networks (Shrivastava et al. 2023). The widespread use of these tools is contributing to a revolution in society, industry, and journalism, which has attracted academic interest. In 2021, there were 500,000 scientific articles registered on AI, a significant increase compared to the 200,000 papers published in 2010 (Maslej et al. 2023). These data show that AI is increasingly prominent in all areas of society, raising questions, issues, and transformations that have been discussed in scientific work.

Regarding AI in journalism, other systematic review studies, such as those by Calvo-Rubio and Ufarte-Ruiz (2021), Parratt-Fernández et al. (2021); Ioscote (2021), and García-Orosa et al. (2023), have shown the prospect of increasing publications in academia, especially since 2018. Other studies have also carried out similar systematic reviews in different time periods (Pinto and Barbosa 2024; Peña-Fernández et al. 2023). Between 2008 and 2019, Calvo-Rubio and Ufarte-Ruiz (2021) identified a variety of topics in information production, such as data journalism, information verification, social media applications,

and big data. Between 2015 and 2020, Parratt-Fernández et al. (2021) found that topics such as the reformulation of the role of the journalist, the personalisation of content, and the integration of AI in journalism education were missing from the bibliography studied. This suggests a gap in journalism studies, perhaps due to a reluctance to assume that this new tool is reshaping the journalism industry.

In a study covering the period from 2010 to 2020, both globally and in the Brazilian context, Ioscote (2021) found that articles in journals focus mainly on tools and applied research, with an emphasis on data and news, while conferences focus on discussing algorithms and their impact on journalism, including the replacement of the human journalist. García-Orosa et al. (2023), covering the period from 2017 to 2021, identified a predominance of issues related to the use of AI in journalism (production, profession, and audience), its impact on the public sphere, democracy and public communication, and the role of algorithms on digital platforms. In general, these systematic review articles demonstrate how AI studies in journalism have evolved and raised new questions. For instance, the questioning of the journalist's role, the future of work, and the influence of algorithms on the values and ethics of journalism are emerging themes, yet still relatively underexplored in the literature. These and other issues require more in-depth theoretical discussions that seek to understand how AI is challenging the traditional assumptions of journalism.

Based on the assumption that AI can be understood as a tool and ally in journalistic work (Beckett 2019; Marconi 2020), the questions that mobilises this study are: What are the main topics studied about AI in journalism in scientific articles between 2014 and 2023? How does AI impact journalism? Other aspects surrounding the research question have the following specific objectives: (a) to highlight the evolution of the publication of articles on AI in journalism over a ten-year period (2014–2023), emphasising authors, affiliations, and journals; and (b) to identify the main topics covered and the methods used by the authors. All these characteristics will allow us to identify more precisely the authors, universities, and journals that have dedicated themselves to the study of AI in journalism, in order to later understand the main concerns of these researchers in relation to the subject under study. Qualified production on AI in journalism must be mapped and subjected to critical analysis to advance studies. Our hypothesis is that artificial intelligence, a field of research in computer science that is pervasive in society, is depicted in journalism as a tool. A simplified view of AI as a mere tool can hinder understanding of implications such as bias, ethics, and transparency.

1.1. *The 4 Waves of AI*

A pertinent question for communication and journalism researchers is: What do we mean when we talk about artificial intelligence in this field of study? To be clear, AI is a field of research within computer science. From the research of the 1950s, initiated by the computer scientist John McCarthy, to the current stage of technological progress, there has been a remarkable acceleration with the Internet in the mid-1990s. The four waves of AI (Lee 2019) contribute to understanding the role of AI in the digital sphere. The AI waves are organised in chronological order: (1) internet AI, (2) business AI, (3) perception AI, and (4) autonomous AI.

The first wave, from 1998, applied deep learning to online content personalisation and recommendation systems. The second, starting in 2004, focused on improving business processes, such as credit scoring by banks and decision support. The third wave, under development since 2011, uses IoT (Internet of Things) sensors to understand the physical world. Examples include speech-to-text software, translators, facial recognition systems, and more natural and intuitive human–machine interaction. The fourth wave, which began in 2015, aims to create autonomous systems capable of making decisions without constant human intervention (Lee 2019). These waves represent the continuous evolution of AI, each bringing new applications and challenges. However, this is not a strict timeline, and sometimes the waves overlap. At the intersection of the timeline of digital journalism and the evolution of AI, the third wave, which began around 2011, stands out as the most

aligned with innovation in the newsroom. This phase saw the emergence of advances such as IoT sensors, voice assistants, automated translation, and transcription systems. Notable examples include the launch of Google Glass in 2013, Alexa in 2014, and the virtual and augmented reality game Pokémon Go in 2016, among other key milestones. The theoretical foundations for ChatGPT, and similar programs based on the Transformer architecture¹, trace back to a seminal paper titled Attention is All You Need, published by Vaswani et al. (2017), a team from Google Research.

Another important point to clarify is the difference between analytical AI and generative AI (GenAI). Analytical AI is more related to the first and second waves of AI, focused on business, able to classify and analyse data, make predictions, and support decision-making processes. Generative AI is the third wave, perceptive, creating new images, videos, and texts useful for the design and personalisation of content. GenAI gains prominence starting in 2022 with the launch of programs like ChatGPT, MidJourney, and Stable Diffusion, among others. Some of these tools were made available for free with limited-use functionalities. Therefore, there was no democratisation of GenAI usage. The intention was to create a necessity for their use, and users were indeed able to integrate them into daily tasks. Since the inception of GenAI, significant changes have been recorded in various fields, such as programming and journalism.

As has happened throughout the history of journalism, many emerging technologies have been integrated and adopted by journalists to facilitate their work. The same applies to analytical and generative AI, which are being applied at different levels in the field of journalism (Beckett 2019; Beckett and Yaseen 2023), as will be discussed further.

1.2. The Impact of AI on Journalism

AI has an impact throughout the news ecosystem, which can be understood in three stages: (1) newsgathering, which includes searching for topics, events, and obtaining information; (2) production, which includes creating texts, images, sounds, or videos; and (3) distribution, which includes news delivery processes, strategies for interacting with the public, personalising content, or techniques for attracting subscribers (Diakopoulos 2019; Beckett 2019; Marconi 2020). These systems have been incorporated into routine, monotonous, and error-prone tasks that do not generate financial value, such as translating content and transcribing interviews, but also in more relevant functions such as news writing or fact-checking (Beckett and Yaseen 2023; Newman et al. 2023; Cardoso et al. 2021; Lindén 2017). This is changing the way journalists work and raising various concerns, particularly about the possible replacement of journalists by machines (Gonçalves et al. 2024).

This expansion of the use of AI in journalism comes at a time when the news industry is going through a structural crisis. This crisis is the result of social, economic, political, and cultural factors. The acceleration of technological development and the ubiquity of smartphones and the Internet in people's lives are triggering new processes of information consumption and the failure of the traditional model of funding journalism, based on advertising revenue. The news industry has been profoundly affected by the logics of platformisation: business models, advances in computing infrastructures, and socio-technical and cultural issues (Poell et al. 2020). Thus, access to information has become predominantly mediated by smartphones, digital platforms, and algorithms. As a result, accessing news on a smartphone has become a recurrent practice, giving rise to mobile journalism and forcing the journalistic field to adapt (Westlund 2013; Nelson 2020; Canavilhas 2021). All these changes are being driven by three factors: the Fourth Industrial Revolution, the global economic recession, and the emergence of digital platforms as the preferred way to access and share information (Jukes 2013). Combined with this situation, significant progress in the research and application of AI in different sectors (Lee 2019), highlights a chapter of changes in everyday life, possibilities, and implications, such as time optimisation, innovation, reduction in production costs, and, on the other hand, the reduction of jobs and the ethical challenges related to the use of AI.

Survival in this capitalist era means the ability to innovate and reinvent, and AI strategy needs to be both “informed and imaginative—not just in terms of monetisation” (Deuze and Beckett 2022). Thus, news organisations have adopted smart technologies to be more productive, innovative, and competitive as a strategy to overcome the shortage of human resources and to maintain an economically sustainable activity (Simon 2024). The integration of high technologies in journalism has become increasingly important since 2014, the year in which an increase in experiences with chatbots, voice assistants, virtual reality, 360° videos, and AI systems was registered (Pérez-Seijo and Vicente 2022). As a result, new formats and different ways of doing journalism are emerging, causing concern and uncertainty for journalists.

In this sense, we believe that a news organisation that refuses to use AI will struggle to remain competitive. On the other hand, it is important to consider that the use of AI in journalism may not be useful where there is not an abundance of data—a vital condition for machine learning. Furthermore, the use of AI must be combined with the journalistic values of transparency, objectivity, and truthfulness. The media must therefore develop strategies to harness the potential of AI without compromising the role of journalism as a public service and to allow journalists to continue to do their job of gathering information, interpreting facts, and putting them into context—something machines cannot yet do because they do not have a “nose for news” (Thurman et al. 2017).

Different tensions in the field of journalism arise when AI is applied in all three stages of news production. The first one, newsgathering, selection, and filtering, has always been one of the most important functions of journalists, who follow the knowledge of their profession to choose the most relevant information to report. For decades, this process was based on news values and was the origin of the gatekeeping theory, dedicated to explaining the selection and control procedures of journalists over the topics reported. So how does AI recognise these values and norms in order to select a newsworthy issue? How can the machine have this human instinct in its code? If only machines decide which stories to cover, what will journalism look like?

However, with the ubiquity of social platforms, search engines, and websites in communicative processes, gatekeeping also began to be performed by algorithms whose performance criteria did not follow journalistic standards (Wallace 2018). Thus, many of the steps inherent to newsgathering began to be subjected to new filtering logics, guided by the acquisition of profits for technology companies such as Google, Meta, Microsoft, and Apple (Diakopoulos 2019; Simon 2022). Even at this stage of newsgathering, media organisations are using AI systems to filter large amounts of data, whether on social media or search engines. It is only with these technologies that it has become possible to access and analyse vast amounts of data on the internet, resulting in new journalistic stories (Diakopoulos 2019).

The second stage, news production, is the one that has been most affected by the arrival of generative AI, in 2022. This technology allows the creation of text, sound, audiovisual, graphic, and infographic content using deep learning techniques that emulate human learning (Franganillo 2023). These models process large amounts of complex and unstructured data and use it to produce new content in the same format (Franganillo 2023).

In this sense, generative AI differs from news automation, the latter described as automated journalism (Graefe 2016) or algorithmic journalism (Dörr 2016). The first experiences with the automation of journalistic writing (analytical AI) were registered in 2010, with a diversification of automated topics between 2014 and 2018, and a consolidation of the use of this technology between 2018 and 2022 (Canavilhas 2023). Automation works on predictable themes with low variability and a wealth of statistical data, such as the economy, sports, earthquake warnings, or weather forecasting (Sirén-Heikel et al. 2019). However, it was not until the end of 2022, with the launch of ChatGPT, that generative AI became a possibility in newsrooms, sparking new discussions and controversies (Pavlik 2023). While automation works with templates set by programmers and only with structured data, generative AI can create entirely new content by correlating the vast amounts of data it is given. Nevertheless, its use in the production of journalistic content opens space for

questioning the values of the profession, including public service, commitment to truth, strictness, and transparency. The quality and credibility of news are another area of tension with the use of AI, particularly in news writing. Journalists and researchers have been concerned about the loss of news quality and the risk that the public will see journalism as less credible because of the use of AI. However, on certain topics with a lot of statistical data, for example, sports, automated news has been well received by audiences, who even see it as more objective because it has a lot of numbers (Murcia Verdú et al. 2022). This does not mean that all news can be written by software, especially long stories, where creativity and human interpretation are essential.

In the distribution stage, AI systems have contributed to accelerating the diffusion of content to the public, which is increasingly fragmented and distributed across different online platforms. Through algorithmic operations, the distribution of news has become increasingly personalised and interactive, through sharing and commenting between users, alerts, and recommendations (Carlson 2018). AI is also used in content moderation on social media and newspaper websites to exclude explicitly violent, racist, extremist, hateful, or sexual content, which could lead to the rejection of offended users (Diakopoulos 2019). In addition, analytical AI is being applied to marketing and sales strategies, such as paywalls and analysis of audience metrics (Simon 2024).

As media organisations explore more applications of algorithmic systems and AI, it becomes urgent to discuss the ethical, economic, and professional challenges. At the newsgathering stage, the problems are more complex, as journalists need to have knowledge of computational methods for handling big data, from extraction to data cleaning. In the production stage, analytical AI and generative AI help journalists without the need for programming skills, as tools are available for text transcription, text correction, and summarisation. However, they raise many questions about the authorship of the work and the transparency of this process. In the final stage, analytical AI allows us to extract insights and create recommendation systems, but the biggest constraint is the filtering done by the platforms, which affects all stages. This raises several questions: What are the main changes in the work, skills, and authority of journalists (Carlson 2014; Hermida and Young 2017; Lewis et al. 2019)? How does the use of AI affect the credibility of news (Waddell 2018; Graefe et al. 2018; Wölker and Powell 2021)? What are the ethical risks associated with the use of these tools (Dörr and Holnbuchner 2017; Diakopoulos and Koliska 2017)? What are the main implications of AI for the public sphere and democracy (Powers 2017; Entman and Usher 2018; Helberger 2019; Nechushtai and Lewis 2019)? These questions have motivated several scientific articles in the social sciences, but also in the field of computer sciences.

2. Materials and Methods

The methodological procedure includes a systematic review ($n = 699$) and a qualitative approach with categorical content analysis ($n = 59$). It was structured based on a previously validated protocol and consisted of the following steps: (a) definition of the central research question; (b) search strategy; (c) selection of studies with eligibility criteria; (d) analysis of the results; and (e) discussion and presentation of the findings.

Based on the results of previous studies (Calvo-Rubio and Ufarte-Ruiz 2021; Ioscote 2021), this research started with these questions: RQ1: What are the main topics studied about AI in journalism in scientific articles between 2014 and 2023? RQ2: How does AI impact journalism? To answer this question, we turned to the Web of Science (WoS) and Scopus databases. These platforms stand out as the most widely used in academic research (Quevedo-Silva et al. 2016) and were also used in the studies by Calvo-Rubio and Ufarte-Ruiz (2021); Ioscote (2021), and García-Orosa et al. (2023), which allows comparisons to be made.

The search used the Boolean operators AND and OR to combine relevant keywords with the term “journalism” in the titles, abstracts, and/or keywords of the articles (Table 1). The keywords were chosen based on literature studies on this topic (Carlson 2014; Beckett 2019; Diakopoulos 2019; Thurman et al. 2019). Thus, the inclusion criteria for the articles in the sample were strictly based on the presence of the terms, requiring their occurrence

in at least one of the following places: title, abstract, and/or keywords. This resulted in 979 articles in Scopus and 908 in WoS. It should be noted that no filters were applied in terms of fields of knowledge. After cleaning² to remove coincidences and false hits in each database and cross-referencing between databases, the corpus of analysis resulted in 699 articles ($n = 699$) (Table 1).

Table 1. Search results.

Keywords	Number of Articles	
	Scopus	WoS
Journalism AND Artificial Intelligence	212	166
Journalism AND Algorithm OR Algorithmic	344	344
Journalism AND Automated OR Automation	348	325
Journalism AND Robot OR Robotic	75	73
Total on each base	979	908
Coincidences	396	652
Total number of coincidences in each base	583	256
Total articles	839	
Coincidences in each base	140	
Total	699	

In order to identify the evolution of the publication of articles on AI in journalism, the journals and authors with the most publications, simple statistical operations, such as average, sum, and counting of numerical values, were used in Microsoft Excel on the database ($n = 699$). In addition, the Python programming language was used, using the spaCy library for Natural Language Processing (NLP) and the support of Jupyter Notebook to create clouds of the most frequent terms in the keywords of the articles. The journals have also been classified according to the SCImago Journal and Country Rank (SJR) areas. We also used SPSS software to visualise the prominent areas of the journals. To analyse specific quantitative data where a cut-off was necessary for the presentation of the data, such as authors and journals with the highest number of publications, the statistical cut-off method was applied in a frequency distribution table (Battisti and Battisti 2008).

In a second stage, a qualitative approach with categorical content analysis was conducted for 59 articles, aligned with the proposal of Sampaio and Lycarião (2018). For scientific validation, content analysis must be based on three fundamental epistemological principles of scientific development: replicability, reliability, and validity. In this regard, an approach using tests to validate coding indices, as well as the use of a codebook, can reduce the subjectivity present in qualitative investigations. In this regard, an approach using tests to validate coding indices, as well as the use of a codebook, can reduce the subjectivity present in qualitative investigations. Therefore, a codebook was created to handle the reading of the 59 articles. According to Sampaio and Lycarião (2018, 2021), codes can derive from existing theories or practices, as well as from previous experiences and research.

The categorical content analysis was carried out on articles with at least 50 citations ($n = 59$), based on the abstracts, and if the abstract did not answer the questions, the article was read in full. Thus, the abstracts were read with the aim of categorising them based on the common elements identified. For this purpose, a codebook (Table 2) was created, inspired by previous results (García-Orosa et al. 2023) and adapted for the purposes of this research.

In the categorical content analysis, we looked at: (A) phase of the journalistic process; (B) the main themes of the articles; (C) focus, whether theoretical or empirical/experimental; (D) approach, whether quantitative, qualitative, or mixed; and (E) collection techniques. In item (E) collection techniques, we chose to distinguish between digital and computational methods, as we understand digital methods as part of a research design (Rogers 2017),

whereas computational methods require the use of machine learning techniques, natural language processing (NLP), a subfield of artificial intelligence, and even the development of algorithms in specific research cases.

Table 2. Variables and categories.

Variable	Category
(A) Phase of the journalistic process	1—Gathering 2—Production 3—Distribution ND (not defined/does not fit) ³
(B) Themes	1—Disinformation 2—Ethics and regulation 3—GenAI 4—Journalist’s work 5—Tools/framework 6—Public sphere, democracy and political communication 7—Business models, startups and organisation management 8—Fact-checking 9—Audience 10—Journalism research and education 11—Platforms 12—Others
(C) Focus	1—Theoretical 2—Empirical/experimental
(D) Approach	1—Quantitative 2—Qualitative 3—Mixed
(E) Collection techniques	1—Interview 2—Ethnographic method 3—Questionnaire 4—Digital methods 5—Focus group 6—Framing 7—Others 8—ND (not defined)

To guarantee the validity and replicability of the categorisation procedure adopted, 16% of the qualitative sample (n = 59) was subjected to a reliability test, assessed using Krippendorff’s alpha coefficient with SPSS software. In general, the results of the test achieved reliability indices above 0.779. Variables A and C reached an index of 1.00, while variables B, C, and E reached indices of 0.882, 0.795, and 0.779, respectively. According to Sampaio and Lycarião (2018), Krippendorff’s alpha coefficient values above 0.8 are considered sufficiently reliable, while values between 0.667 and 0.8 are considered sufficient for experimental variables (in improvement).

3. Results and Discussion

3.1. Journalism and AI Research in Numbers

The first variable examined was the number of articles published in each year of analysis. The results show growth, indicating a progressive increase in interest in the topic of AI and journalism. The annual graphic shows a consistent growth pattern, 2000% when comparing the period from 2014 to 2023, with a significant jump from 2018 (Figure 1).

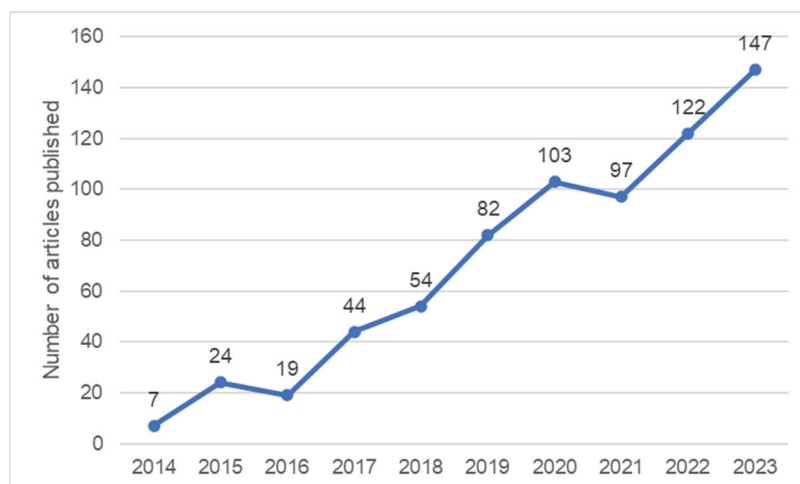


Figure 1. Annual growth in articles.

The observed growth can be understood as a reflection of the growing interest in academic studies in the face of the journalism industry's need to incorporate innovative technologies. This need stems largely from the current challenges posed by platformisation, covering aspects such as audience retention, the fight against disinformation, and the search for monetisation strategies, among others (Carlson 2018; Diakopoulos 2019; Marconi 2020). Above all, the period analysed coincides with significant advances in processing capacity, machine learning, and AI software (Lee 2019), providing a more robust technological base that can be implemented in journalism.

Two hundred and eighty-three journals were identified, of which the British journals *Digital Journalism* (103 articles), *Journalism Studies* (31 articles), *Journalism* (28 articles), and *Journalism Practice* (28 articles) stand out for their significant concentration of publications, together with the Spanish journal *Profesional de La Información*⁴ (24 articles), for a total of 214 articles, or 30.6% of the base ($n = 699$). In part, these results are similar to those described by Calvo-Rubio and Ufarte-Ruiz (2021); Ioscote (2021), and García-Orosa et al. (2023), who noted the predominance of these same journals. In addition, the Portuguese *Media and Communication* (20 articles) and the British *New Media and Society* (17 articles) should be mentioned. García-Orosa et al. (2023) found 12 and 18 articles, respectively, published in these two journals.

The results show the evolution of publications over the period considered, taking into account the five journals with the highest number of publications (Figure 2).

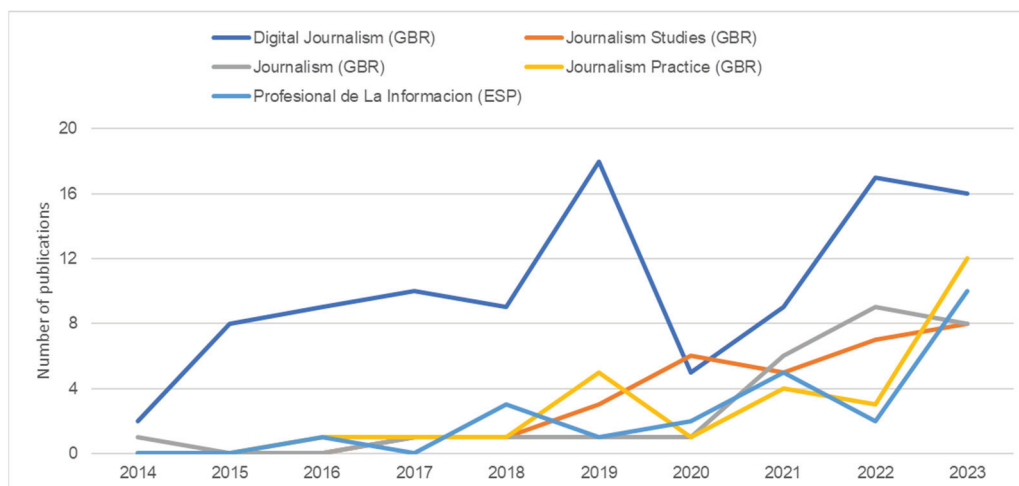


Figure 2. Annual growth of articles in the five journals with the highest number of publications.

The journals were distributed according to the parameters established by SCImago Journal and Country Rank (SJR) in relation to the different fields of knowledge. This distribution was used because no filters were applied to the fields at the time of collection. Of the 283 journals analysed, the field of social sciences predominates with 59.7% of the total. This is followed by computer sciences with 15.7% of the journals evaluated. It should be noted that some journals were classified in more than one field, reflecting the multidisciplinary and interrelated nature of the knowledge represented in the publications.

It is worth considering that seeking publication in computer sciences journals may reflect the need to link communication research to specific technological advances. These journals can attract a specific audience interested in technical developments and algorithms to improve efficiency, personalisation and automation, thus giving greater visibility to research on the integration of AI in journalism. In addition, computer science journals can provide a propitious environment for developing and sharing specific methodologies related to the implementation of AI in the journalism context. An example is the article *FactRank: Developing automated claim detection for Dutch-language fact-checkers* by Berendt et al. (2021), which addresses the importance of fact-checking in journalism and highlights the need to support human fact-checkers with semi-automated methods due to the increasing volume and speed of news, as well as the increase in disinformation. Another study, *An exploratory approach to the computational quantification of journalistic values*, authored by Choi (2019), explored how news algorithms shape the presentation of information and influence public discourse. The study sought to quantify journalistic values in an algorithmically readable way, combining natural language processing (NLP) with automated content analysis and a survey of journalism students.

Further detail of the database ($n = 699$) reveals the distribution of article authorship, reflecting the diversity of the scholarly collaboration mode. It can be observed that 31.9% of the articles have a single author, while 27.5% have two authors. Articles with three authors represent 23.2% of the sample, those with four authors 8.7%, and those with five or more authors 8.7%. In line with the findings of García-Orosa et al. (2023), the majority of articles in this sample (68.2%) are the result of research between two or more authors, as opposed to 31.9% with a single author, indicating a strong collaboration between researchers (Table 3).

Table 3. Distribution of article authorship.

Authorship	Number of Articles	Percentage (%)
1 (author)	223	31.9%
2 (authors)	192	27.5%
3 (authors)	162	23.2%
4 (authors)	61	8.7%
5 (authors or more)	61	8.7%
Total	699	100.0%

Among the most prominent researchers, a group of 29 authors stand out who have signed at least five articles (Table S1), either as main author or co-author. The author with the most articles is Nicholas Diakopoulos from Northwestern University (USA), with a total of 10 articles. His topics of research interest include: computational journalism, algorithmic accountability and transparency, automation, and algorithms in news production. We identified Seth C. Lewis from the University of Oregon (USA), Xosé Lopéz-García from the Complutense University of Madrid (ESP), and María José Ufarte-Ruiz from the University of Castilla-La Mancha (ESP) with nine articles each. Seth C. Lewis has dedicated his research to the social implications of emerging technologies, with an emphasis on the digital transformation of journalism. Xosé Lopéz-García's research focuses on the study of digital and printed media. He analyses the implications of technology for mediated communications, examining the performance and financing of the cultural industries and exploring the history of communication. María José Ufarte Ruiz investigates the influence of technology on journalistic genres and the relationship between genres on the border

between journalism and literature. Her research has also focused on how the precariousness of journalists' work affects the quality of news information.

These data do not establish the level of success of the researchers based on the number of articles; they simply show which authors have dedicated themselves to the study of this topic based on our selection. As the research is conducted in English, papers in other languages are not covered, which introduces a bias, so it is to be expected that researchers with papers in other languages are not included in the sample.

Regarding the affiliation⁵ of the authors, the analysis showed that some authors are signed by more than one institution, resulting in 1.705 authorships. According to the analysis, the University of Amsterdam stands out with 59 authorships, followed by the University of Santiago de Compostela (Table 4). These data help us better understand which centres and universities have been most active in publishing articles in English on AI in journalism, many of them in countries where the use of AI in newsrooms is more advanced, such as the Netherlands or Germany (Bäck et al. 2019).

Table 4. Distribution according to affiliation.

#	Affiliation	Country	Authorships	Authors	Articles
1	University of Amsterdam	NED	59	35	33
2	University of Santiago de Compostela	ESP	51	16	24
3	University of Zurich	SUI	40	20	18
4	Lomonosov Moscow State University	RUS	23	16	10
5	University of Vienna	AUT	22	17	11
6	University of Castilla-La Mancha	ESP	21	5	10
7	University of Ljubljana	SLO	21	8	11
8	Ludwig Maximilians University Munich	GER	20	11	14
9	Nanyang Technological University	SGP	20	10	9
10	University of Münster	GER	20	11	8
11	Others		1.408	1.149	551
Total		69	1.705	1.298	699

Examining the 1.705 authorships by country, the United States has the highest quantity. There are 261 authorships distributed across 99 institutions, with Northwestern University (18 authorships; 10 authors) and The University of Texas at Austin (15 authorships; 11 authors) standing out. A further analysis of the data shows that 671 (96.0%) of the articles were written by authors from universities, institutes, and academic research centres. On the other hand, 28 (4.0%) of these articles were written by authors from partnerships between universities, companies, non-governmental organisations, and government agencies. We recognise that collaboration between academia and industry is uncommon in scientific publications. Nevertheless, we argue that collaboration between researchers, technology companies, and the media can make better use of the knowledge of different professionals and provide contexts for experimentation and improvement of AI systems governed by journalistic criteria.

Regarding the keywords extracted from the database (n = 699), a word cloud was created highlighting the 50 most frequent terms (Figure 3). The first highlights the scenario of digital journalism, where terms such as "journalism", "news", "medium", "social", and "digital" indicate a concentration of efforts and discussions focused on journalistic issues, especially in the online environment. Furthermore, the presence of terms such as "artificial" and "intelligence" reflects the growing influence of AI in the field, suggesting the possible integration of advanced technologies into journalistic practices.

33.9% of articles did not clearly attribute their research to a specific phase or did not fit into any of the phases mentioned (ND), such as theoretical articles discussing epistemological issues (Parasie 2015; Primo and Zago 2015; Lewis and Westlund 2015). These articles are from before 2021, which may justify an inclination towards a more epistemological discussion about the consequences of platformisation for journalism or journalistic practices. In addition, it was noted that the term AI appears only once in the titles. This gives us clues to the idea that the use of analytical AI in the first and second waves attracted the attention of researchers for other terms such as big data, algorithms, machines, and automation.

Articles dedicated to the distribution phase (25.4%) explore the advantages and disadvantages of using AI at this moment. Moreover, it is important to mention that in this set of articles there was also a predominant discussion of the role of social media in the distribution of news, especially Twitter and Facebook. There was no discussion of how the implementation of AI could solve problems related to the filtering or hierarchy of content.

As advantages, the works highlight the reduction in costs and the amplification of news distribution (Blankespoor et al. 2018). As disadvantages, several problems with algorithmic filtering are recognised, such as the excessive personalisation of content (Bakir and McStay 2018), the hierarchy of news according to algorithmic criteria, and the risk of confusing the editorial, algorithmic, and social filters that coexist in the online environment (Boczkowski et al. 2018). These factors can reduce the diversity of content to which readers are exposed, creating filter bubbles that undermine democratic values and critical thinking. It is therefore necessary for researchers to assess the impact of these technologies on the quality, diversity, and plurality of ideas (Nechushtai and Lewis 2019).

Finally, the newsgathering represents only 6.8% of the sample, suggesting that the first stage of the news process has not received as much attention from academics. One possible reason for this is that some procedures in the newsgathering require more specific computer skills, such as data extraction and manipulation, depending on the type and size of the database. Another hypothesis could be related to the strong presence of traditional journalistic assumptions, where the journalist is the main gatekeeper of information, due to his knowledge of news values and newsworthiness criteria. In this sense, researchers may consider that AI does not have as much influence at this stage.

In the variable themes, the journalist's work (10 articles) and tools/framework (10) stood out (Table 4). These themes had already been identified by Ioscote (2021). However, the author considers that the articulation of the journalist's work in the face of algorithms was a first movement. The articles that discussed the work of journalists, especially those presented at conferences, considered the implications of the algorithm for the profession, which included risks such as the replacement of human journalists (Ioscote 2021). As shown in previous studies, such as Ioscote's (2021), the tools/frameworks try to show the possibilities of automation for journalism.

The articles in the journalist's work highlight the centrality of AI, automation, algorithms, and big data in journalism, and the ways in which these tools challenge the functions of the journalist. Automated journalism is seen by researchers as a disruptive practice that strains journalistic authority (Carlson 2014) and raises questions about algorithmic authorship and judgement (Montal and Reich 2017; Carlson 2018). In this sense, some articles discuss hybrid practices and the challenges of human-machine communication (Hermida and Young 2017; Lewis et al. 2019). This evolving scenario suggests a future in which the role of the journalist will not be diminished, but transformed, just as the incorporation of other technological innovations has done to journalism throughout history. The challenge lies in integrating these technologies in a way that increases the journalist's integrity and trust.

Regarding the theme of tools/framework, the findings point to the rise of computational methods as a methodological resource in social sciences studies, especially the use of topic modelling, application inventory, and natural language processing (NLP). Here, the use of such methods results in tools that support journalism in the data extraction and processing stages. Sometimes, depending on the type of data, whether structured or unstructured, it is

also necessary to test different algorithms to help deal with the data. In addition, computational methods are presented in different approaches, from dictionaries to machine learning techniques⁶, which can be useful in new tests. These data confirm the growing use of AI in newsrooms, with around 75% of media outlets surveyed using AI in at least one of the areas—newsgathering, production, or distribution (Beckett and Yaseen 2023). However, a pertinent question, which has not been addressed in this article, is whether the implementation of computational methods is the responsibility of journalists or computer specialists. This opens a gap to reflect on to what extent the values intrinsic to journalism are applied to the use of these experiments with algorithms and AI. This also makes us consider that transdisciplinary studies can be a useful strategy for integrating journalism and computer science and for developing AI systems adapted to the needs of journalism.

The third most relevant theme was audience (8 papers), which included research on the impact of AI and algorithms on information consumption and news quality (Table 4). Most studies investigated readers' perceptions when reading news written by machines compared to news written by human journalists (Wölker and Powell 2021; Graefe et al. 2018; Jung et al. 2017). Another systematic review identified 18 articles published in Scopus and WoS between 2014 and 2022 that analysed the quality of automated news (Sandoval-Martín and Barrolleta 2023). This is an important point because the quality of journalism is a characteristic that could be compromised by the automation of journalistic writing. The use of AI puts a strain on several points of journalistic quality and credibility, firstly by raising the question of how machines follow the news values and ethical principles to which journalists are committed.

Text quality and credibility were two of the characteristics measured in these articles. "In summary, the available evidence suggests that the quality of computer-written news is competitive with that of human journalists for routine tasks for which well-structured, machine-readable and reliable data exist" (Graefe et al. 2018, p. 605). Similarly, in terms of credibility indices, news stories written by software performed similarly to those written by humans and performed better in the case of sports articles (Wölker and Powell 2021). These studies show that automated writing is often imperceptible to readers, proving that this technology can be an asset in content production. On the other hand, incidental news consumption and news personalisation mechanisms have also been addressed as two consequences of the use of algorithms in journalism and digital platforms (Boczkowski et al. 2018; Powers 2017).

Other themes emerged from the sample, reflecting the diversity of approaches and challenges posed by AI in the information ecosystem. These papers discussed issues related to the use and functioning of digital platforms, generative AI, disinformation scenarios, consequences for the public sphere, democracy and political communication, and the need to promote ethical values by regulating the use of AI, among others (Table 5). It is important to mention that the sample (n = 699) included five articles on ChatGPT published in 2023. Only one article was included in the sample (n = 59) because it met the minimum criterion of at least 50 citations. In general, these articles discuss the possibilities and limitations of using ChatGPT in journalistic routines.

The variable article focus also showed that 69.5% of the articles had an empirical/experimental focus, while 30.5% of the articles had a theoretical focus. With regard to the variable approach, 78.0% of the articles followed a qualitative approach, 16.9% followed a mixed approach, and 5.1% followed a quantitative approach. These results show that the preference for qualitative methods is a constant in studies on AI and journalism (Parratt-Fernández et al. 2021).

Finally, in relation to the variable collection techniques, a predominance of digital methods (36.6%), interviews (24.4%), and questionnaires (17.1%) was observed. On this parameter, this study represents a novelty in relation to previous ones, as it shows the rise of digital and computational methods for the study of this topic. Of the 15 articles (36.6%), at least 5 used techniques of topic modelling, NLP, and supervised machine learning to extract data and perform automated text analysis. These five articles were published in

2016, which may indicate a movement of interest in using computational methods to solve journalistic problems, given the abundance of data in a digital environment.

Table 5. Results of variable B “Themes”.

Themes	Quantify	%
1—Disinformation	3	5.1%
2—Ethics and regulation	3	5.1%
3—GenAI	5	8.5%
4—Journalist’s work	10	16.9%
5—Tools/framework	10	16.9%
6—Public sphere, democracy and political communication	3	5.1%
7—Business models, startups and organisation management	2	3.4%
8—Fact-checking	2	3.4%
9—Audience	8	13.6%
10—Journalism research and education	1	1.7%
11—Platforms	5	8.5%
12—Others	7	11.9%
Total	59	100.0%

At this point, we see the possibility of applying AI to digital journalism with NLP, a sub-area of AI. It is worth mentioning that natural language processing is gaining more notoriety with advances in large language models (LLMs), which are available to the public in a more simplified way, like ChatGPT, since 2022. However, creating an LLM for journalistic purposes is a challenge for most of the world’s media sectors. Although initiatives such as Bloomberg’s already exist (Bloomberg 2023), there are financial and purpose challenges.

This also highlights the importance of integrating a transdisciplinary approach, where computational methods are applied to meet the needs of journalism. To implement such an approach, it is necessary to empower journalists to make use of these software tools and foster critical debate around ethics, authorship, and credibility.

4. Conclusions

The analysis of scientific articles published over a decade allowed us to take a broad and, at the same time, detailed look at the evolution of studies on AI and journalism. Firstly, the exponential increase in articles published in WoS and Scopus stands out (7 works in 2014 and 147 in 2023). The year in which the collection started, 2014, marks the beginning of the diversification of topics in the field of automated journalism (Canavilhas 2023). The period between 2018 and 2022 is seen as the consolidation of automated journalism (Canavilhas 2023), which coincides with the increase in the number of scientific articles, mainly published in British Q1 magazines. Among the five journals with the most articles on this topic, the only non-British one is the Spanish journal *Profesional de La Información* (Q1 in Scopus), which has a permanent open call on AI.

The growth in interest in the subject of AI in journalism addresses other questions: which AI is being studied by researchers? Although this investigation was limited to examining a decade of studies up to the year 2023, we identified five articles that explored the possibilities of using ChatGPT in journalistic routines. Consequently, with the growing trend of discussing tools based on large language models (LLMs), it is crucial to consider the intersection of this technology with journalistic values. This raises another question: Is AI in journalism studies synonymous with automation, algorithms, or tools? If there is evidence of a consolidation of automation in newsrooms, it is necessary to specify the uses, methods, and relevance of AI in journalism.

Given the importance of British journals, it might be expected that the most frequent affiliations would be to British institutions, but this hypothesis did not hold. The results showed that the three institutions with the highest number of affiliations were the Univer-

sity of Amsterdam (Netherlands), the University of Santiago de Compostela (Spain), and the University of Zurich (Switzerland). The presence of research centres dedicated to the intersection of AI and journalism, such as the AI, Media, and Democracy Lab (University of Amsterdam) and New Media (Trends, Cybermedia, and Printed Media) (University of Santiago de Compostela), can be seen as the driving force behind these universities. It is relevant to mention that the United States holds the highest quantity of authorships; however, they are distributed across different universities.

To answer the research question RQ1: “What are the main topics studied about AI in journalism in scientific articles between 2014 and 2023?” and RQ2: “How does AI impact journalism?”, the categorical content analysis ($n = 59$) showed that the most cited works problematise the work of the journalist, use AI as a tool or framework, and bring the audience’s perceptions about the use of AI in journalism. In relation to AI in journalists’ work, pertinent points such as authorship and human judgement are articulated in the sample ($n = 59$). However, we also noticed a dystopian view of AI in articles that, in a way, try to compare the human–machine relationship. We understand that this discussion is productive, but nevertheless, predicting when, how, and if a robot will take the place of a human journalist does not depend solely on technology.

The main novelty in relation to previous systematic reviews is the predominance of AI as a journalistic tool, as evidenced by studies that propose the use of digital and/or computational methods. We also argue that this is a new point in relation to previous systematic reviews, but that the need for digital and/or computer methods is yet another consequence of platformisation. Nevertheless, it is at this point that the use of AI becomes more relevant and journalistic values can be confronted.

On the other hand, issues related to ethics, regulation, and journalism education are poorly represented in the sample of most cited articles. This can be seen as a gap in academic work, which may also be related to the lack of clear strategies for using AI in newsrooms (Beckett and Yaseen 2023). However, a more targeted search using a string containing the terms “ethics”, “regulation”, or “education” may give different results.

It is also worth noting that the platformisation of information plays a significant role in the intersection of AI and journalism. However, this issue was underemphasised in the sample ($n = 59$). We observed this as well in the larger sample ($n = 699$) from the 50 most frequent terms in a word cloud, where platformisation does not appear. This leads us to consider that the advancement of AI might be interpreted by the researchers as a phenomenon dissociated from platformisation. We understand that AI represents a new chapter in the transformative landscape imposed by the logics of platformisation. Consequently, journalism jobs may be transformed, but they are also at risk of extinction. Above all, the dependence on digital platforms for the different stages of news production could also have an impact on the quality of information, especially due to advances in GenAI.

Research involves choices that allow us to achieve or not achieve our objectives. The methodological procedures used in this study allowed us to identify important trends and gaps in research on artificial intelligence in journalism. Nevertheless, we acknowledge that there are limitations related to the methodological procedures. For example, the choice of strings can be a limiting factor in the collection of articles. The selection was necessary. This does not prevent new research from being conducted with new selections and intentions. The experimental categories can also be a limitation, but they serve as a basis for future research. Additionally, researchers can review and improve the code used. There are also articles from the field of computer sciences among the investigated articles, which is why many computational methods are present in the topics. However, we decided to keep them because we understand that this is a transdisciplinary topic that benefits from various disciplines and different fields of knowledge. By selecting articles with more than 50 citations, we also considered that more recent articles would be excluded, especially those that include research on generative AI, a topic that becomes more prominent from

2022 with the launch of ChatGPT. On the other hand, the most cited articles help us understand the foundation for the discussion of AI in contemporary times.

For future research, a more in-depth analysis of the research centres and laboratories involved in studying the intersection between AI and journalism can provide a more complete understanding of the direction of scientific knowledge in this field. Understanding the dynamics of these centres and the collaborations between researchers can provide important insights into the trends and future directions of research in this constantly evolving field.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/journalmedia5030056/s1>, Table S1: Authors with at least five articles (author or co-author).

Author Contributions: Conceptualisation, F.I. and A.G.; methodology, F.I.; software, F.I.; validation, F.I. and A.G.; formal analysis, F.I. and A.G.; investigation, F.I. and A.G.; resources, F.I.; data curation, F.I.; writing—original draft preparation, F.I. and A.G.; writing—review and editing, F.I., A.G. and C.Q.; visualisation, F.I.; supervision, C.Q. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by *Coordenação de Aperfeiçoamento de Pessoal de Nível Superior—Brasil (CAPES)* through PhD scholarship—Finance Code 001: Fabia Ioscote (88881.934176/2024-01) and *Fundação para a Ciência e a Tecnologia (FCT)* through PhD scholarship: Adriana Gonçalves (UI/BD/152717/2022).

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Conflicts of Interest: The authors declare no conflicts of interest.

Notes

- ¹ The Transformer architecture is a type of machine learning model used for tasks involving natural language processing (NLP).
- ² Database cleansing is performed in Microsoft Excel using duplicate filter functions.
- ³ We created the ND (not defined) category for articles that do not mention the collection technique in the abstract and at the same time are not available in the full version for consultation.
- ⁴ From January 2024, *Profesional de La Información* is being published by Oxbridge, UK.
- ⁵ Affiliation includes universities, research institutes and centres, companies and non-governmental organisations.
- ⁶ Dictionaries provide static definitions of terms. Machine learning is a dynamic technique that allows computers to learn from data and make predictions or decisions without being explicitly programmed.

References

- Bakir, Vian, and Andrew McStay. 2018. Fake news and the economy of emotions: Problems, causes, solutions. *Digital Journalism* 6: 154–75. [CrossRef]
- Battisti, Iara, and Gerson Battisti. 2008. *Métodos estatísticos*. Rio Grande do Sul: Unijuí.
- Bäck, Asta, Nicholas Diakopoulos, Mark Granroth-Wilding, Lauri Haapanen, Leo Leppänen, Magnus Melin, Tom Moring, Myriam Munezero, Stefanie Sirén-Heikel, Caj Södergård, and et al. 2019. *News Automation: The Rewards, Risks and Realities of 'Machine Journalism'*. WAN-IFRA Report. Edited by Carl-Gustav Lindén and Hanna Tuulonen. Amsterdam: Elsevier B.V.
- Beckett, Charles. 2019. New Powers, New Responsibilities: A Global Survey of Journalism and Artificial Intelligence. The London School of Economics and Political Science, Polis Journalism and Society, & Google News Initiative. Available online: <https://bit.ly/3P4tf4G/> (accessed on 2 February 2024).
- Beckett, Charles, and Mira Yaseen. 2023. Generating Change: A global survey of what news organizations are doing with AI. *JournalismAI, Polis, Department of Media and Communications, The London School of Economics and Political Science*. Available online: <https://www.journalismai.info/research/2023-generating-change> (accessed on 2 February 2024).
- Berendt, Bettina, Peter Burger, Rafael Hautekiet, Jan Jagers, Alexander Pleijter, and Peter Van Aelst. 2021. FactRank: Developing automated claim detection for Dutch-language fact-checkers. *Online Social Networks and Media* 22: 100–13. [CrossRef]
- Blankespoor, Elizabeth, Ed deHaan, and Christina Zhu. 2018. Capital market effects of media synthesis and dissemination: Evidence from robo-journalism. *Review of Accounting Studies* 23: 1–36. [CrossRef]
- Bloomberg. 2023. Introducing BloombergGPT, Bloomberg's 50-Billion Parameter Large Language Model, Purpose-Built from Scratch for Finance. Available online: <https://www.bloomberg.com/company/press/bloomberggpt-50-billion-parameter-llm-tuned-finance/> (accessed on 5 February 2024).

- Boczkowski, Pablo, Eugenia Mitchelstein, and Mora Matassi. 2018. "News comes across when I'm in a moment of leisure": Understanding the practices of incidental news consumption on social media. *New Media & Society* 20: 3523–39. [CrossRef]
- Calvo-Rubio, Luis-Mauricio, and María-José Ufarte-Ruiz. 2021. Artificial intelligence and journalism: Systematic review of scientific production in Web of Science and Scopus (2008–2019). *Communication & Society* 34: 159–76. [CrossRef]
- Canavilhas, João. 2021. Epistemology of mobile journalism. A review. *Profesional de la información* 30: 1–20. [CrossRef]
- Canavilhas, João. 2023. Produção automática de texto jornalístico com IA: Contributo para uma história. *Textual & Visual Media* 17: 22–40. [CrossRef]
- Cardoso, Gustavo, Vania Baldi, Paulo Couraceiro, and Miguel Paisana. 2021. Algoritmos e notícias: A oportunidade da inteligência artificial no jornalismo. Available online: <https://ciencia.iscte-iul.pt/publications/algoritmos-e-noticias--a-oportunidade-da-inteligencia-artificial-no-jornalismo/83821> (accessed on 16 January 2024).
- Carlson, Matt. 2014. The Robotic Reporter. Automated journalism and the redefinition of labor, compositional forms, and journalistic authority. *Digital Journalism* 3: 416–31. [CrossRef]
- Carlson, Matt. 2018. Automating judgment? Algorithmic judgment, news knowledge, and journalistic professionalism. *New Media & Society* 20: 1755–72. [CrossRef]
- Caswell, David, and Konstantin Dörr. 2017. Automated Journalism 2.0: Event-driven narratives: From simple descriptions to real stories. *Journalism Practice* 12: 477–96. [CrossRef]
- Choi, Sujin. 2019. An exploratory approach to the computational quantification of journalistic values. *Online Information Review* 43: 133–48. [CrossRef]
- Deuze, Mark, and Charlie Beckett. 2022. Imagination, Algorithms and News: Developing AI Literacy for Journalism. *Digital Journalism* 10: 1913–18. [CrossRef]
- Diakopoulos, Nicholas. 2019. *Automating the News: How Algorithms Are Rewriting the Media*. Cambridge: Harvard University Press.
- Diakopoulos, Nicholas, and Michael Koliska. 2017. Algorithmic transparency in the news media. *Digital Journalism* 5: 809–28. [CrossRef]
- Dörr, Konstantin. 2016. Mapping the field of algorithmic journalism. *Digital Journalism* 4: 700–22. [CrossRef]
- Dörr, Konstantin, and Katharina Hollnbuchner. 2017. Ethical challenges of algorithmic journalism. *Digital Journalism* 5: 404–19. [CrossRef]
- Entman, Robert, and Nikki Usher. 2018. Framing in a fractured democracy: Impacts of digital technology on ideology, power and cascading network activation. *Journal of Communication* 68: 298–308. [CrossRef]
- Franganillo, Jorge. 2023. La inteligencia artificial generativa y su impacto en la creación de contenidos mediáticos. *Methaodos.Revista de Ciencias Sociales* 11: 15. [CrossRef]
- García-Orosa, Berta, João Canavilhas, and Jorge Herrero. 2023. Algoritmos y comunicación: Revisión sistematizada de la literatura. *Comunicar: Revista Científica Iberoamericana de Comunicación y Educación* 74: 9–21. [CrossRef]
- Gonçalves, Adriana, Luísa Torre, and Paulo Victor Melo. 2024. *Inteligência Artificial e Algoritmos: Desafios e Oportunidades para os media*. Covilhã: LabCom.
- Graefe, Andreas. 2016. *Guide to Automated Journalism*. New York: Columbia University. [CrossRef]
- Graefe, Andreas, Mario Haim, Bastian Haarmann, and Hans-Bernd Brosius. 2018. Readers' perception of computer-generated news: Credibility, expertise, and readability. *Journalism* 19: 595–610. [CrossRef]
- Helberger, Natali. 2019. On the democratic role of news recommenders. In *Algorithms, Automation, and News*. London: Routledge, pp. 14–33. Available online: <https://www.taylorfrancis.com/chapters/oa-edit/10.4324/9781003099260-2/democratic-role-news-recommenders-natali-helberger> (accessed on 17 January 2024).
- Hermida, Alfred, and Mary Lynn Young. 2017. Finding the data unicorn: A hierarchy of hybridity in data and computational journalism. *Digital Journalism* 5: 159–76. [CrossRef]
- Ioscote. 2021. Jornalismo e inteligência artificial: Tendências nas pesquisas brasileiras entre 2010 e 2020. Available online: <https://www.revistas.usp.br/novosolhares/article/view/188912> (accessed on 25 June 2024).
- Jukes, Stephen. 2013. A perfect storm. In *Journalism: New Challenges*. pp. 1–18. Available online: https://eprints.bournemouth.ac.uk/20937/1/2013-Journalism-New_Challenges-Fowler-Watt_and_Allan-v1-02.pdf (accessed on 25 June 2024).
- Jung, Jaemin, Haeyeop Song, Youngju Kim, Hyunsuk Im, and Sewook Oh. 2017. Intrusion of software robots into journalism: The public's and journalists' perceptions of news written by algorithms and human journalists. *Computers in Human Behavior* 71: 291–98. [CrossRef] [PubMed]
- Lee, Kai-Fu. 2019. *Inteligência artificial: Como os robôs estão mudando o mundo, a forma como amamos, nos relacionados, trabalhamos e vivemos*. Tradução: Marcelo Barbão—1ª ed. Rio de Janeiro: Globo Livros.
- Lewis, Seth C., and Oscar Westlund. 2015. Big data and journalism: Epistemology, expertise, economics, and ethics. *Digital Journalism* 3: 447–66. [CrossRef]
- Lewis, Seth C., Andrea L. Guzman, and Thomas R. Schmidt. 2019. Automation, journalism, and human-machine communication: Rethinking roles and relationships of humans and machines in news. *Digital Journalism* 7: 409–27. [CrossRef]
- Lindén, Carl-Gustav. 2017. Algorithms for journalism: The future of news work. *The Journal of Media Innovations* 4: 60–76. [CrossRef]
- Marconi, Francesco. 2020. *Newsmakers: Artificial Intelligence and the Future of Journalism*. New York: Columbia University Press.
- Maslej, Nestor, Loredana Fattorini, Erik Brynjolfsson, John Etchemendy, Katrina Ligett, Terah Lyons, James Manyika, Helen Ngo, Juan Carlos Niebles, Vanessa Parli, and et al. 2023. *Artificial Intelligence Index Report 2023*. New York: Cornell University. [CrossRef]

- Milosavljević, Marko, and Igor Vobič. 2019. 'Our task is to demystify fears': Analysing newsroom management of automation in journalism. *Journalism: Theory, Practice & Criticism* 22: 2203–21. [CrossRef]
- Minh, Dang, H. Xiang Wang, Y. Fen Li, and Tan N. Nguyen. 2022. Explainable artificial intelligence: A comprehensive review. *Artificial Intelligence Review* 55: 3503–68. [CrossRef]
- Montal, Tal, and Zvi Reich. 2017. I, robot. You, journalist. Who is the author? Authorship, bylines and full disclosure in automated journalism. *Digital Journalism* 5: 829–49. [CrossRef]
- Murcia Verdú, Francisco José, Rubén Ramos Antón, and Luis Mauricio Calvo Rubio. 2022. Análisis comparado de la calidad de crónicas deportivas elaboradas por inteligencia artificial y periodistas. *Revista Latina de Comunicación Social* 80: 91–111. [CrossRef]
- Nechushtai, Efrat, and Seth C. Lewis. 2019. What kind of news gatekeepers do we want machines to be? Filter bubbles, fragmentation, and the normative dimensions of algorithmic recommendations. *Computers in Human Behavior* 90: 298–307. [CrossRef]
- Nelson, Jacob. 2020. The Persistence of the Popular in Mobile News Consumption. *Digital Journalism* 8: 87–102. [CrossRef]
- Newman, Nic, Richard Fletcher, Kirsten Eddy, Craig T. Robertson, and Rasmus Kleis Nielsen. 2023. Digital News Report 2023. Available online: https://policycommons.net/artifacts/4164711/digital_news_report_2023/4973510/ (accessed on 15 January 2024).
- Parasie, Sylvain. 2015. Data-driven revelation? Epistemological tensions in investigative journalism in the age of "big data". *Digital Journalism* 3: 364–80. [CrossRef]
- Parratt-Fernández, Sonia, Javier Mayoral-Sánchez, and Monste Mera-Fernández. 2021. The application of artificial intelligence to journalism: An analysis of academic production. *Profesional de la Información* 30: e300317. [CrossRef]
- Pavlik, John. 2023. Collaborating with ChatGPT: Considering the implications of generative artificial intelligence for journalism and media education. *Journalism & Mass Communication Educator* 78: 84–93. [CrossRef]
- Peña-Fernández, Simón, Koldobika Meso-Ayerdi, Ainara Larrondo-Ureta, and Javier Díaz-Noci. 2023. Without journalists, there is no journalism: The social dimension of generative artificial intelligence in the media. *Profesional de la información* 32: e320227. [CrossRef]
- Pérez-Seijo, Sara, and Paulo Nuno Vicente. 2022. After the hype: How hi-tech is reshaping journalism. In *Total Journalism: Models, Techniques and Challenges*. Cham: Springer International Publishing, pp. 41–52.
- Pinto, Moisés Costa, and Suzana Oliveira Barbosa. 2024. Artificial Intelligence (AI) in Brazilian Digital Journalism: Historical Context and Innovative Processes. *Journalism and Media* 5: 325–41. [CrossRef]
- Poell, Thomas, David Nieborg, and José van Dijck. 2020. Plataformização. *Fronteiras* 22: 2–10. [CrossRef]
- Powers, Elia. 2017. My news feed is filtered? Awareness of news personalization among college students. *Digital Journalism* 5: 1315–35. [CrossRef]
- Primo, Alex, and Gabriela Zago. 2015. Who and what do journalism? An actor-network perspective. *Digital Journalism* 3: 38–52. [CrossRef]
- Quevedo-Silva, Filipe, Eduardo Biagi de Almeida Santos, Marcelo Moll Brandão, and Leonardo Vils. 2016. Estudo bibliométrico: Orientações sobre sua aplicação. *Revista Brasileira de Marketing* 15: 246–62. [CrossRef]
- Rogers, Richard. 2017. Foundations of digital methods. Query Design. In *The Datafied Society: Studying Culture through Data*. Edited by Mirko Schaefer and Karin van Es. Amsterdam: Amsterdam University Press, pp. 77–94.
- Sampaio, Rafael, and Diógenes Lycarião. 2018. Eu quero acreditar! Da importância, formas de uso e limites dos testes de confiabilidade na Análise de Conteúdo. *Revista De Sociologia E Política* 26: 31–47. [CrossRef]
- Sampaio, Rafael, and Diógenes Lycarião. 2021. *Análise de conteúdo categorial: Manual de aplicação*. Brasília: Enap.
- Sandoval-Martin, Teresa, and Leonardo La-Rosa Barrolleta. 2023. Research on the quality of automated news in international scientific production: Methodologies and results. *Cuadernos.Info* 55: 114–36. [CrossRef]
- Shrivastava, Anurag, K. Murali Krishna, Moti Lal Rinawa, Mukesh Soni, Gowtham Ramkumar, and Sushma Jaiswal. 2023. Inclusion of IoT, ML, and Blockchain Technologies in Next Generation Industry 4.0 Environment. *Materials Today: Proceedings* 80: 3471–75. [CrossRef]
- Simon, Felix. 2022. Uneasy bedfellows: AI in the news, platform companies and the issue of journalistic autonomy. *Digital Journalism* 10: 1832–54. [CrossRef]
- Simon, Felix. 2024. Artificial Intelligence in the News How AI Retools, Rationalizes, and Reshapes Journalism and the Public Arena. Available online: https://www.cjr.org/tow_center_reports/artificial-intelligence-in-the-news.php (accessed on 14 March 2024).
- Sirén-Heikel, Stefanie, Leo Leppänen, Carl-Gustav Lindén, and Asta Bäck. 2019. Unboxing news automation. *Nordic Journal of Media Studies* 1: 47–66. [CrossRef]
- Stavelin, Eirik. 2013. Computational Journalism: When Journalism Meets Programming. Doctoral thesis, (PHD Philosophiae)—Department of Information Science and Media Studies, University of Bergen, Bergen, Norway. Available online: https://stavelin.com/uib/ComputationalJournalism_EirikStavelin.pdf (accessed on 18 January 2024).
- Thormundsson, Bergur. 2023. Change in Artificial Intelligence (AI) Investments Worldwide in the Fiscal Year 2023. Statista. Available online: <https://www.statista.com/statistics/1368382/expected-ai-investment-in-the-next-fiscal-year/> (accessed on 18 January 2024).
- Thurman, Neil, Konstantin Dörr, and Jessica Kunert. 2017. When reporters get hands-on with robo-writing: Professionals consider automated journalism's capabilities and consequences. *Digital Journalism* 5: 1240–59. [CrossRef]
- Thurman, Neil, Seth C. Lewis, and Jessica Kunert. 2019. Algorithms, automation, and news. *Digital Journalism* 7: 980–92. [CrossRef]

- Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. Paper presented at the Conference on Neural Information Processing Systems, Long Beach, CA, USA, December 4–9, vol. 31, pp. 1–11. Available online: <https://bit.ly/483iwy7> (accessed on 16 January 2024).
- Waddell, T. Franklin. 2018. A robot wrote this? How perceived machine authorship affects news credibility. *Digital Journalism* 6: 236–55. [CrossRef]
- Wallace, Julian. 2018. Modelling contemporary gatekeeping: The rise of individuals, algorithms and platforms in digital news dissemination. *Digital Journalism* 6: 274–93. [CrossRef]
- Westlund, Oscar. 2013. Mobile news: A review and model of journalism in an age of mobile media. *Digital journalism* 1: 6–26. [CrossRef]
- Wölker, Anja, and Thomas E. Powell. 2021. Algorithms in the newsroom? News readers' perceived credibility and selection of automated journalism. *Journalism* 22: 86–103. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.



Article

Bibliometric and Content Analysis of the Scientific Work on Artificial Intelligence in Journalism

Alem Febri Sonni ^{1,*}, Vinanda Cinta Cendekia Putri ¹ and Irwanto Irwanto ²

¹ Communication Studies, Faculty of Social and Political Sciences, Hasanuddin University, Makassar 90245, Indonesia; vinanda.cinta@gmail.com

² Film Departement, School of Design, Bina Nusantara University, Jakarta 15143, Indonesia; irwanto001@binus.ac.id

* Correspondence: alemfebris@unhas.ac.id

Abstract: This paper presents a comprehensive bibliometric review of the development of artificial intelligence (AI) in journalism based on the analysis of 331 articles indexed in the Scopus database between 2019 and 2023. This research combines bibliometric approaches and quantitative content analysis to provide an in-depth conceptual and structural overview of the field. In addition to descriptive measures, co-citation and co-word analyses are also presented to reveal patterns and trends in AI- and journalism-related research. The results show a significant increase in the number of articles published each year, with the largest contributions coming from the United States, Spain, and the United Kingdom, serving as the most productive countries. Terms such as “fake news”, “algorithms”, and “automated journalism” frequently appear in the reviewed articles, reflecting the main topics of concern in this field. Furthermore, ethical aspects of journalism were highlighted in every discussion, indicating a new paradigm that needs to be considered for the future development of journalism studies and professionalism.

Keywords: artificial intelligence; journalism; bibliometric; news; Scopus

1. Introduction

The role of quality journalism in providing accurate and reliable information to the public cannot be underestimated. Journalism plays an important role in democracy by acting as a watchdog and holding those in power accountable. By reporting on important issues, exposing corruption or wrongdoing, and providing analysis and context, journalists help citizens make informed decisions about their communities and the wider world. Journalists have a responsibility to report news that is based on verified facts and presents a balanced view of events (Cobley and Schulz 2013; Martínez García and Capoano 2023; Karlsson and Clerwall 2019; McQuail 2010).

Journalists must strive for accuracy, objectivity, and clarity in their reporting. This is important to maintain media credibility and build trust with the audience. In a world where misinformation and fake news spread easily through social media and other online means, quality journalism is becoming increasingly important (Martínez García and Capoano 2023; Kovach and Rosenstiel 2021; Putri and Sonni 2023). Misinformation is generally unintentional, arising from inaccuracies or mistakes, while disinformation involves the deliberate intention to deceive by spreading false information (Di Domenico et al. 2021; Ireton and Posetti 2018). The difference between the two lies in the intention of the creator, with misinformation stemming from honest mistakes and disinformation being information that is strategically manipulated and spread to cause harm or deceive (Das and Ahmed 2022).

Responsible media organisations must ensure that their news is accurate, reliable, and unbiased (Trattner et al. 2022). To achieve this, responsible media entities can utilise advanced media technologies in a responsible manner. By leveraging these technologies, media organisations can personalise content to meet the specific needs and preferences of

their audience while minimising negative effects. This approach can help traditional media organisations maintain their competitive advantage and strengthen their reputations as reliable sources of information.

Artificial intelligence is becoming an increasingly important tool in various industries, including the field of journalism. In recent years, the news media has been greatly disrupted by the potential of technology-based approaches to the creation, production, and distribution of news products and services. In a study conducted by de-Lima-Santos and Ceron, it was found that artificial intelligence has emerged as a very effective tool that can assist society in overcoming the challenges faced by the news industry (de-Lima-Santos and Ceron 2022).

Can a computer programme write compelling news? According to Reuters' latest Technology Trends and Predictions report, 78% of 200 digital leaders, editors, and CEOs surveyed said that investing in artificial intelligence technology would help secure the future of journalism (Newman 2019). The survey results highlighted provide insight into the growing public awareness and adoption of AI-powered chatbots like ChatGPT in the context of journalism and publishing. The finding that 65% of UK adults have heard of at least one major chatbot points to the increasing mainstream visibility of these tools. ChatGPT's recognition figure stands at 59%, suggesting it has emerged as the current leading platform in this space (Newman 2024). Artificial intelligence is becoming an increasingly important tool in various industries, including the field of journalism. Recent studies on artificial intelligence in journalism have highlighted its significant impact on the creation, production, and distribution of news products and services. As the world of journalism continues to evolve, technological advances have played an important role in shaping its landscape (Horska 2020).

The media industry has undergone major changes due to technological advancements. The shift from analogue to digital media has changed the way media content is created, disseminated, and used. Digital platforms make it easier to produce, store, and share content (Küng 2024).

Likewise, the widespread use of the internet and mobile devices has changed the way people access and enjoy media. Streaming services, social media, and mobile apps are becoming popular channels for content distribution and consumption (Doyle 2013). Moreover, technology also allows media companies to collect data on user preferences and behaviour so as to provide personalized content recommendations and targeted advertising (Napoli 2011).

The increasing use of algorithms and artificial intelligence in news production and distribution has raised concerns about the potential for bias and a lack of human oversight (Diakopoulos 2019). The spread of misinformation and fake news on digital platforms has also posed a significant challenge regarding the credibility of and trust in journalism (Lazer et al. 2018).

Despite these challenges, technological disruption has also created new opportunities for journalism, such as the ability to reach global audiences, engage with readers in real-time, and experiment with innovative forms of storytelling (Witschge et al. 2016). As the journalism industry continues to evolve in response to technological change, it will be crucial for news organizations to adapt and innovate.

The adoption of AI in journalism still faces challenges such as competition for talent and ethical issues around automated storytelling. Moreover, the integration of artificial intelligence in journalism raises important ethical issues regarding accuracy, fairness, and transparency in reporting (Grzybowski et al. 2024; Kieslich et al. 2022). Today, digital media has intensified news dissemination in manifold ways. The influx of digital media has revolutionised news dissemination (Holt et al. 2019), with artificial intelligence playing an important role in this transformation. While AI has shown significant potential in experimental studies, especially in scientific and technological fields, its application in journalism is not without its challenges. Competition for talent and ethical issues surrounding automated news generation are some of the hurdles AI faces in journalism.

As the use of AI in news media becomes more prevalent, fostering digital literacy and algorithmic awareness among journalists and audiences is crucial. News organisations should prioritise educating staff and the public about the capabilities and limitations of AI technologies, empowering them to critically assess AI-generated content and understand the implications of algorithmic decision-making (Ozmen Garibay et al. 2023). By promoting algorithmic literacy, news organisations can facilitate informed and intelligent interactions with AI-driven news products and services.

In facing the ethical challenges of AI integration, news organisations have a responsibility to uphold the principles of journalistic integrity, transparency, and accountability. By integrating human judgement, addressing biases in AI algorithms, prioritising data privacy, and promoting algorithmic literacy, the journalism industry can harness the potential of AI in a rigorous and ethical manner (Silberg and Manyika 2019). This approach ensures that AI serves as a tool for advancing the quality and depth of news reporting while preserving the fundamental values of journalism in the digital age.

The integration of artificial intelligence (AI) in journalism has emerged as a significant area of research, with many studies exploring its impact on the creation, production, and distribution of news products and services. Bibliometric analysis, a quantitative approach to assessing research trends and impacts, offers valuable insights into the current state of AI research in journalism and identifies opportunities for further exploration. By uncovering salient research trends, mapping the intellectual structure of the field, evaluating the impact of specific contributions, identifying knowledge gaps, and facilitating evidence-based decision-making, bibliometric analysis plays an important role in shaping the future of news media in the digital age. As the journalism industry navigates the challenges and opportunities presented by AI technologies, insights gained from bibliometric analysis will guide resource allocation, strategic planning, and policy development, ensuring that AI investments are aligned with the needs and priorities of the journalism industry.

2. Materials and Methods

In this research, we use bibliometric methods to analyse the development of scholarly works on artificial intelligence in journalism. The corresponding methodology involved the categorisation and classification of articles based on various criteria, such as year of publication, journal source, and author affiliations. This classification process facilitates a comprehensive understanding of the temporal and institutional distribution of scholarly work on artificial intelligence in journalism.

Overall, the applied methodology includes a systematic and rigorous approach to analysing and evaluating the development of scholarly works on artificial intelligence in journalism, providing a foundation for the findings and subsequent discussions in this research study.

The cited researcher used bibliometric analysis to examine relevant articles on artificial intelligence in journalism (Moed 2009). This study collected data from the Scopus database, specifically selecting articles published between 2019 and 2023. The Scopus database was chosen as the data source for this study because it is considered one of the most complete and up-to-date databases used in scientific research.

A complete and rigorous search was performed using the keywords “Artificial Intelligence”, “AI”, “Artificial Intelligence (AI)”, “Journalism”, “News”, and “Media”, as well as Boolean operators, i.e., logical operators that connect words to expand or narrow search results, such as “and”. Articles that met the inclusion criteria set for this study were selected, including research articles published in social sciences journals. The aim was to provide an evolutionary overview of the subject.

Bibliometric analysis is a method used to measure and analyse the trends, patterns, and impact of research in a particular field through scientific publications. In the context of this research, bibliometric analysis was conducted on journal articles published and indexed in the Scopus database with the keywords “artificial intelligence”, “ai”, “Artificial Intelligence (AI)”, “journalism”, “news”, and “mass media”. Restrictions were made, with

only English-language articles, content from social science fields, and research published within the 2019–2023 timeframe being selected.

Data were extracted according to the possibilities in Scopus, and descriptive data on the articles were recorded, such as title, authorship, journal, year of publication, keywords, abstract, abstracts, citations received, academic affiliation and research funding, etc. With the data extracted from Scopus, two databases were created: one in Excel format for quantitative content analysis and another in CSV format (a file that divides values by commas) to perform bibliometric analysis with VOSviewer Version 1.6.20.

After collecting and combining the relevant articles, the next step was data analysis using bibliometric analysis software, specifically the VOSviewer application. VOSviewer is a commonly used tool for visualising and analysing bibliometric networks (Mejia et al. 2021). This software allows researchers to perform co-citation analysis, co-authorship analysis, and keyword co-occurrence analysis to identify the most influential articles, authors, and keywords in the field of artificial intelligence in journalism.

This research study, involving a bibliometric analysis of the development of scholarly works on artificial intelligence in journalism, uses a systematic methodology. The findings from the bibliometric analysis shed light on significant trends and patterns in scholarly works relating to artificial intelligence in journalism. This detailed analysis provides valuable insights into the evolving landscape of artificial intelligence in journalism and the key contributors to its development (Wang 2021).

3. Results

Based on data obtained from the Scopus Document Search, 331 articles were found. Each year shows a significant upward trend (Figure 1). In 2019, there were 41 articles published, while in 2023, the number of articles increased dramatically to 122 articles. This increase indicates that interest and research related to the application of Artificial Intelligence (AI) in the fields of journalism, news, and media are increasing every year.

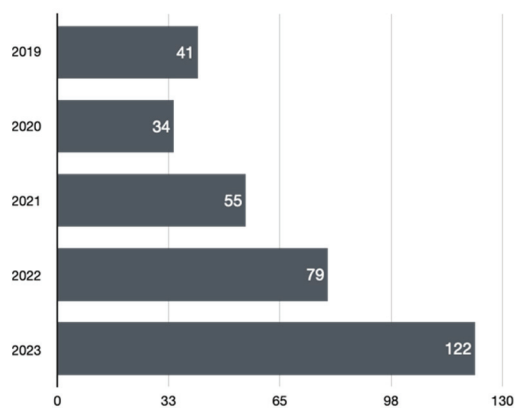


Figure 1. Article distribution for the 2019–2023 period.

The United States has the highest number of documents (82) and citations (1729) in the dataset, indicating a strong presence in AI journalism research. Other countries with significant numbers of documents and citations include the United Kingdom (33 documents, 881 citations), Spain (46 documents, 534 citations), and China (21 documents, 160 citations).

Countries such as the Netherlands (19 documents, 454 citations), Canada (14 documents, 278 citations), and Brazil (13 documents, 118 citations) also have prominent research results in this area. Interestingly, the United Arab Emirates has a relatively high number of citations (691) compared to its number of documents (10), indicating the high impact of AI journalism research. Some countries, such as Russia (six documents, 4 citations) and Portugal (six documents, 26 citations), have a lower research output in this area based on the available data (Table 1). Publishers who publish articles are quite diverse, there are 12 publishers, the majority of which are reputable publishers (Table 2).

Table 1. Country-based distribution of articles' authors and citations (>5).

Country	Documents	Citations
United States	82	1729
Spain	46	534
United Kingdom	33	881
India	22	84
China	21	160
Netherlands	19	454
Canada	14	278
Brazil	13	118
Germany	13	119
South Korea	11	85
Australia	10	213
Switzerland	10	80
United Arab Emirates	10	691
Italy	9	33
Norway	9	30
Taiwan	9	181
Saudi Arabia	8	56
Singapore	7	169
Austria	6	27
Portugal	6	26
Russian federation	6	4

Table 2. Number of published articles from publishers (>5).

Publisher	Articles
Routledge	58
SAGE Publications Inc.	37
Elsevier	21
Springer	18
Multidisciplinary Digital Publishing Institute (MDPI)	17
Emerald Publishing	11
Taylor and Francis	11
Institute of Electrical and Electronics Engineers Inc.	9
Association for Computing Machinery	6
CEU Ediciones	6
El Profesional de la Informacion	6
Oxford University Press	6

3.1. Citation Analysis

Of the 331 articles on Artificial Intelligence in journalism, there were 10 articles that were the most cited. This indicates that these articles have significant impact and influence in the related research field. Only 1 of the 10 articles, "On the Democratic Role of News Recommenders" (Helberger 2019), is linked to or cited by other articles in this study (Table 3). Meanwhile, the other 8 of the 10 most cited articles do not have links or are not cited by other articles in this study.

- Other heavily cited articles may have links or citations from articles outside the scope of this study.
- There may be limitations in the data collection process or methodology used, so links or citations between articles may not be identified.
- The articles may be pioneering or discourse-opening writings in the field of AI and journalism, so they are widely cited as primary references but have not been developed or cited in other articles studied.

Table 3. The 10 most cited articles.

Document	Citations	Links
The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI (Shin 2021)	398	0
Fake news detection: A hybrid CNN-RNN based deep learning approach (Nasir et al. 2021)	310	0
Deepfakes and Disinformation: Exploring the Impact of Synthetic Political Video on Deception, Uncertainty, and Trust in News (Vaccari and Chadwick 2020)	259	0
Ethical Implications and Accountability of Algorithms (Martin 2019)	242	0
Collaborating with ChatGPT: Considering the Implications of Generative Artificial Intelligence for Journalism and Media Education (Pavlik 2023)	226	1
On the Democratic Role of News Recommenders (Helberger 2019)	172	10
War of the chatbots: Bard, Bing Chat, ChatGPT, Ernie and beyond.	159	0
The new AI gold rush and its impact on higher education (Rudolph et al. 2023)	127	0
An incentive-aware blockchain-based solution for internet of fake media things (Chen et al. 2020)	122	0
Strategizing in a digital world: Overcoming cognitive barriers, reconfiguring routines and introducing new organizational forms (Volberda et al. 2021)	119	0
Automation, Journalism, and Human–Machine Communication: Rethinking Roles and Relationships of Humans and Machines in News (Lewis et al. 2019)		

To understand this situation more deeply, further analysis of the content of the articles, the research methodology used, and the context of publication and research developments in the field of AI and journalism is required.

3.2. Keyword Analysis

Identifying the most frequently used keywords in the articles can give an idea of the specific topics that are widely researched. From the 331 articles processed using the vosviewer application with a minimum occurrence rate of 5 (Table 4), 43 keywords were obtained that were interconnected and formed a network. The network was formed from four clusters: cluster 1 has 13 keywords, with the most occurrences of artificial intelligence, amounting to 181; cluster 2 has 12 keywords, with the most occurrences of fake news, amounting to 47; cluster 3 has 11 keywords, with the most occurrences of automated journalism, amounting to 17; and cluster 4 has 7 keywords, with the most occurrences of journalism, amounting to 38 keywords.

Table 4. Keyword clusters and frequency of occurrence (>5).

Cluster 1		Cluster 2		Cluster 3		Cluster 4	
Keyword	N *	Keyword	N *	Keyword	N *	Keyword	N *
artificial intelligence	181	fake news	47	automated journalism	17	journalism	38
algorithms	23	social media	23	ChatGPT	8	media	11
automation	16	disinformation	20	ethics	8	technology	11
big data	10	machine learning	20	robot journalism	8	data journalism	10
bots	7	misinformation	20	chatbots	7	fact-checking	9
news production	7	natural language processing	11	computational journalism	7	news	8
communication	6	deep learning	10	trust	6	innovation	7
content analysis	6	COVID-19	9	algorithmic journalism	5		

Table 4. Cont.

Cluster 1		Cluster 2		Cluster 3		Cluster 4	
Keyword	N *	Keyword	N *	Keyword	N *	Keyword	N *
news media	6	deepfake	8	education	5		
newsrooms	6	Twitter	7	higher education	5		
democracy	5	social networking (online)	6	human-machine communication	5		
public opinion	5	feature extraction	5				
robotics	5						

* Occurrence.

4. Discussion

Basically, the development of journalism always goes hand in hand with the development of information technology. This can be seen from the evolution of print media into online media as well as the use of social media as a means of disseminating news. Information technology has enabled journalists to search, collect, and present information more quickly and efficiently.

One of the main impacts of the development of information technology in journalism is the creation of a faster, wider, and more open information environment. This provides opportunities for the public to obtain news in real time and enables active participation in the journalism process.

However, this development also brings new challenges to the journalism industry, such as the spread of fake news or hoaxes, as well as changes in the media business model (Pavlik 2023). Therefore, it is important for journalists and media stakeholders to continuously adapt to the ever-changing developments in information technology. The development of information technology also allows for the diversification of news presentation, featuring multimedia formats such as video, audio, and infographics. This not only enriches the reader's experience but also provides freedom of expression for journalists in delivering information (Deuze 2004).

In addition, information technology also plays an important role in increasing accessibility to information. Thanks to the internet, one can access news from various sources and viewpoints, allowing for a more comprehensive understanding of an issue.

However, journalists also need to improve their understanding of ethics in regard to the use of information technology, especially in relation to data privacy and security. The skills to sort and verify information are also becoming more important in an era where information can be easily processed and edited (Díaz-Campo and Segado-Boj 2015).

In the study of journalism today, we see significant developments as information technology advances. Artificial Intelligence (AI) is one of the factors that greatly influences the way information is produced; the accuracy, trustworthiness, and understanding of journalism has changed drastically.

Based on bibliometric analysis, it can be seen that studies on journalism and information technology still do not have a wide distribution. Developed countries with a high level of information technology development are the dominant topics in studies in this field (Figure 2). The use of keywords in this study indicates the existence of several new paradigms in journalism studies that are strongly influenced by technology (Figure 3). Some of the new paradigms that have emerged are shown below.

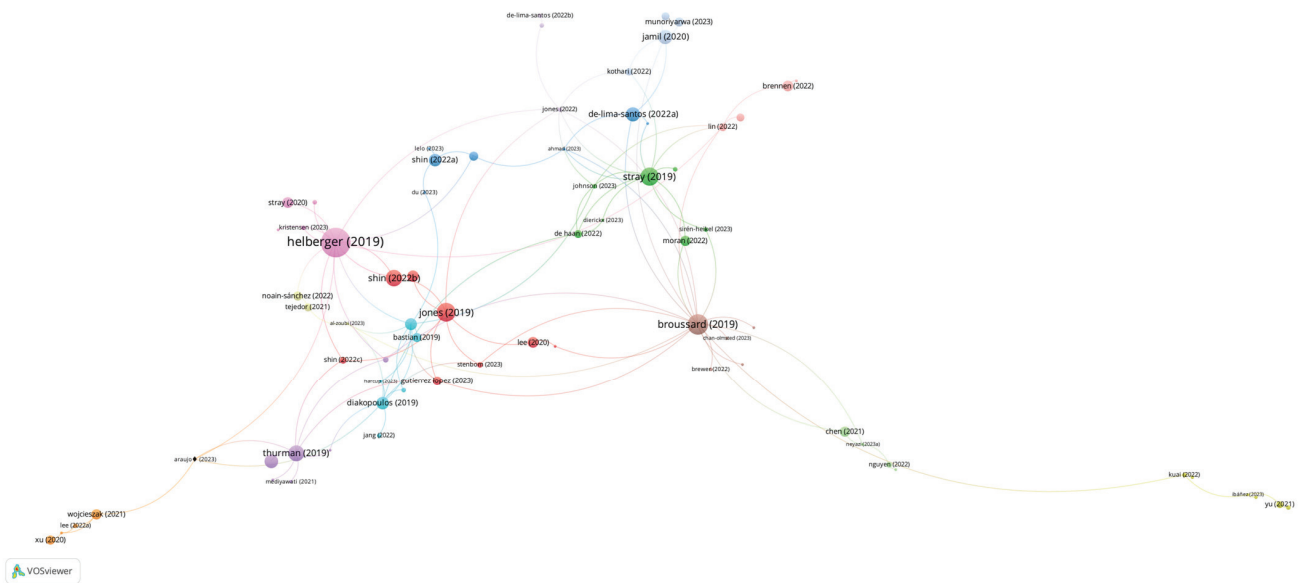


Figure 2. Visual citation analysis.

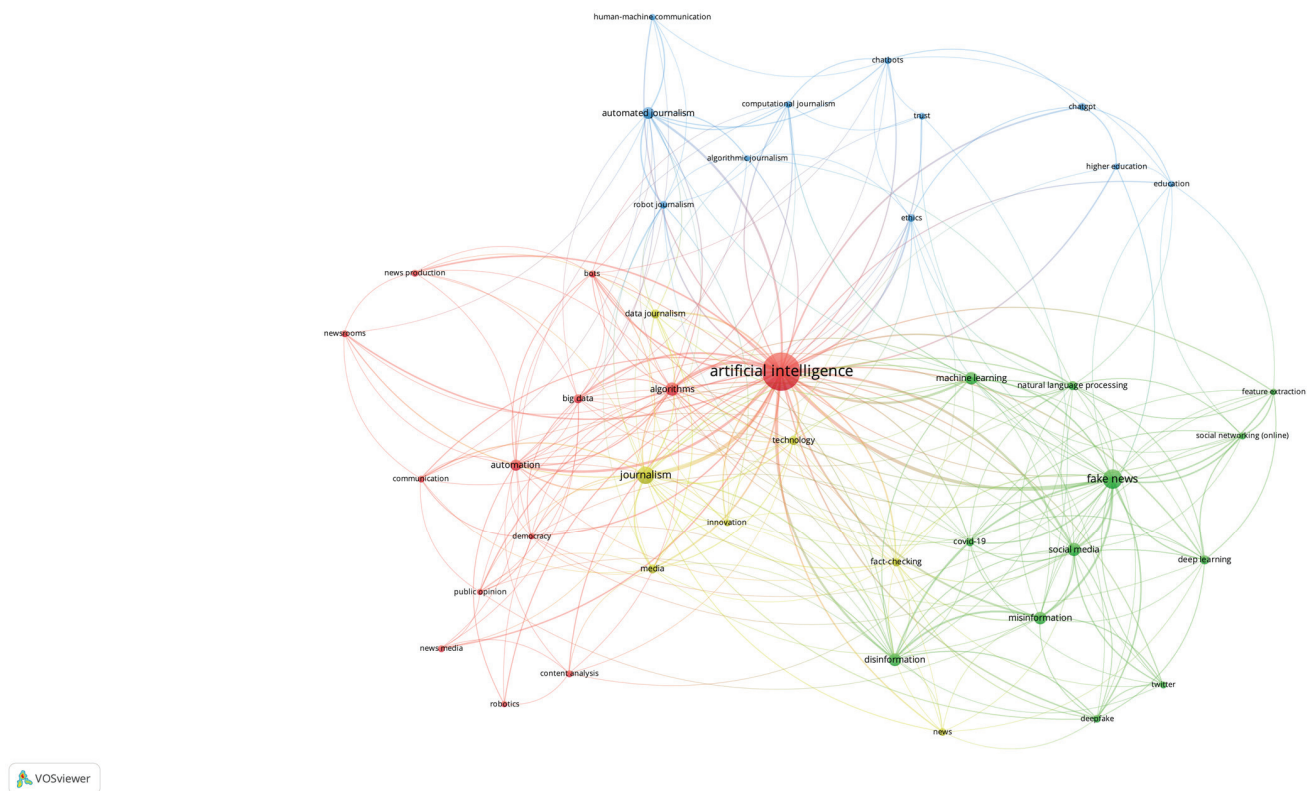


Figure 3. Visual occurrence analysis.

4.1. Fake News

The term fake news is used to describe false or misleading information presented as news. Fake news can take the form of fabricated stories, manipulated images or videos, or deliberately misleading headlines. The spread of fake news has become a major concern in today's digital age, as it can have serious impacts on public opinion and decision-making. It is important for individuals to critically evaluate the source and validity of the news they encounter and rely on trusted and reputable news sources for information. Efforts are being made by various organisations and platforms to combat the spread of fake news and educate the public about media literacy. Fake news is intentionally false or misleading

information presented as news. Fake news is designed to deceive readers and manipulate public opinion (Weikmann and Lecheler 2023).

Fake news has become a rampant issue in today's media landscape, posing a significant threat to the integrity of journalism. The spread of misinformation and disinformation has the potential to erode public trust in the media and undermine the important role of journalism in a democratic society.

One of the main challenges in combating fake news is the ease and speed at which it spreads through digital platforms and social media. Without robust fact-checking and verification processes, false information can quickly spread and influence public opinion. In addition, the monetisation of clickbait and sensational content creates perverse incentives to create and amplify fake news.

Journalism, as a profession dedicated to reporting the truth, faces the daunting task of regaining public trust and combating the spread of fake news. This requires a multi-faceted approach that involves promoting media literacy, strengthening editorial standards, and holding the spreaders of fake news accountable.

To address these issues, journalists and media organisations must prioritise transparency, accuracy, and ethical reporting practices. By upholding these principles, journalism can serve as a bulwark against the spread of fake news and continue to fulfil its important role in informing the public and fostering an informed society (Kovach and Rosenstiel 2021).

4.2. Algorithms

Algorithms have undeniably revolutionised journalism in the age of Artificial Intelligence. With the ability to parse large amounts of data at an incredible speed, algorithms have become an essential tool for journalists in gathering and analysing information. These technological advancements have enabled news organisations to deliver more personalised content to their audiences and conduct in-depth investigative reporting. However, as algorithms play a greater role in determining the content that will be shown to audiences, concerns about algorithmic bias and potential misinformation have also surfaced (de-Lima-Santos and Ceron 2022).

In addition to aiding news gathering, AI-powered algorithms have also facilitated automated content creation, natural language processing for real-time language translation, and the identification of patterns and trends in data sets. As AI evolves, it is imperative for journalists to critically assess the impact of this technology on the integrity and quality of journalism and utilise its potential to enhance storytelling and audience engagement (Kotenidis and Veglis 2021).

Algorithms not only automate news production but also make it faster and cheaper, and they potentially make fewer errors than human journalists (Graefe 2016). This raises concerns about the future of work in the newsroom.

4.3. Automated Journalism

In recent years, the increasing role of AI in news media has sparked heated debates. Some argue that AI technology can improve the efficiency and productivity of journalism, while others express concern about the potential impact on news quality and authenticity (Wang et al. 2021). One of the key areas where AI is making an impact is in automated news generation. By utilising natural language generation algorithms, AI systems can now generate simple news articles, earnings reports, and sports summaries.

The application of AI in newsrooms has also raised questions about potential job losses for human journalists. While AI can handle routine reporting and data analysis, human journalists are essential for complex investigative reporting, critical analysis, and ethical decision-making (de-Lima-Santos and Ceron 2022). Therefore, the future of journalism may depend on a harmonious balance between AI automation and human expertise.

As AI evolves, news media organisations must adapt and evolve their practices to harness the benefits of AI while upholding journalistic integrity and accuracy. In addition, ethical considerations related to the use of AI in news reporting, including with respect to

issues of bias and transparency, need to be carefully addressed to maintain audience trust (Dörr and Hollnbuchner 2017).

5. Conclusions

The application of bibliometric analysis in the study of artificial intelligence in journalism provides valuable insights into the evolution of the dynamic intersection between technology and media. Through the analysis of citation patterns, collaboration networks, and keyword trends, researchers can gain a comprehensive understanding of the growth of research, key contributors, and the most influential publications in the field. This method not only identifies emerging trends and areas to be explored in the future but also informs academic research, publication strategies, industry practices, and policy decisions. By keeping up with the latest developments and incorporating insights from bibliometric analyses into broader discussions, stakeholders can ensure that technological advancements are in line with the broader interests of journalism and media. Overall, bibliometric analyses play an important role in advancing the understanding of artificial intelligence in journalism and driving innovation in this field.

While this bibliometric analysis provides valuable insights into the current state of research on artificial intelligence in journalism, there are several promising avenues for future research that could further contribute to our understanding of this rapidly evolving field. Another promising area for future research is the impact of AI on the changing roles and skills of journalists. As AI takes on more tasks traditionally performed by human journalists, such as data analysis, content generation, and fact-checking, the nature of journalistic work is likely to evolve. Researchers could study how journalists' roles and required skills are changing in response to AI and propose new models for journalism education and professional development that prepare journalists to work effectively alongside AI technologies.

Additionally, future research could explore the potential of AI to enhance and transform journalistic practices in new and innovative ways. Researchers could also study how AI could be leveraged to promote greater diversity and inclusion in news coverage by identifying and mitigating biases in AI algorithms and enabling the surfacing of underrepresented perspectives.

Finally, future research could contribute to the development of new tools and platforms for AI-powered journalism. Researchers could work with industry partners to design and test new AI technologies specifically tailored to the needs of journalists and news organizations, such as tools for automated fact-checking, content moderation, and audience engagement.

The application of bibliometric analysis in the study of artificial intelligence in journalism provides valuable insights into the evolution of the dynamic intersection between technology and media. Through the analysis of citation patterns, collaboration networks, and keyword trends, researchers can gain a comprehensive understanding of the growth of research, key contributors, and the most influential publications in this field.

By keeping up with the latest developments and incorporating insights from bibliometric analyses into broader discussions, stakeholders can ensure that technological advancements are in line with the broader interests of journalism and media. Furthermore, by pursuing promising avenues for future research, such as developing ethical frameworks, studying the changing roles of journalists, exploring innovative applications of AI, and contributing to the development of new AI-powered tools and platforms, scholars can continue to make valuable contributions to this important and rapidly evolving field.

Author Contributions: Conceptualization, A.F.S. and V.C.C.P.; methodology, A.F.S.; software, I.I.; validation, A.F.S., V.C.C.P. and I.I.; formal analysis, A.F.S.; investigation, I.I.; resources, I.I.; data curation, V.C.C.P.; writing—original draft preparation, V.C.C.P.; writing—review and editing, A.F.S.; visualization, I.I. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available upon request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

References

- Chen, Qian, Reza M. Parizi, Gautam Srivastava, Moayad Aloqaily, and Ismaeel Al Ridhawi. 2020. An incentive-aware blockchain-based solution for internet of fake media things. *Information Processing and Management* 57: 102370. [CrossRef]
- Cobley, Paul, and Peter J. Schulz. 2013. *Theories and Models of Communication*. Berlin and Boston: De Gruyter Mouton. [CrossRef]
- Das, Ronnie, and Wasim Ahmed. 2022. Rethinking Fake News: Disinformation and Ideology during the time of COVID-19 Global Pandemic. *IIM Kozhikode Society and Management Review* 11: 146–59. [CrossRef]
- de-Lima-Santos, Mathias-Felipe, and Wilson Ceron. 2022. Artificial Intelligence in News Media: Current Perceptions and Future Outlook. *Journalism and Media* 3: 13–26. [CrossRef]
- Deuze, Mark. 2004. What is multimedia journalism1? *Journalism Studies* 5: 139–52. [CrossRef]
- Di Domenico, Giandomenico, Jason Sit, Alessio Ishizaka, and Daniel Nunan. 2021. Fake news, social media and marketing: A systematic review. *Journal of Business Research* 124: 329–41. [CrossRef]
- Diakopoulos, Nicholas. 2019. Towards a Design Orientation on Algorithms and Automation in News Production. *Digital Journalism* 7: 1180–84. [CrossRef]
- Díaz-Campo, Jesús, and Francisco Segado-Boj. 2015. Journalism ethics in a digital environment: How journalistic codes of ethics have been adapted to the Internet and ICTs in countries around the world. *Telematics and Informatics* 32: 735–44. [CrossRef]
- Doyle, Gillian. 2013. *Understanding Media Economics*. London: SAGE Publications Ltd. [CrossRef]
- Dörr, Konstantin Nicholas, and Katharina Hollnbuchner. 2017. Ethical Challenges of Algorithmic Journalism. *Digital Journalism* 5: 404–19. [CrossRef]
- Graefe, Andreas. 2016. *Guide to Automated Journalism*. New York: Tow Center for Digital Journalism, Columbia University. [CrossRef]
- Grzybowski, Andrzej, Katarzyna Pawlikowska-Łagód, and W. Clark Lambert. 2024. A History of Artificial Intelligence. *Clinics in Dermatology* 42: 221–29. [CrossRef]
- Helberger, Natali. 2019. On the Democratic Role of News Recommenders. *Digital Journalism* 7: 993–1012. [CrossRef]
- Holt, Kristoffer, Tine Ustad Figenschou, and Lena Frischlich. 2019. Key Dimensions of Alternative News Media. *Digital Journalism* 7: 860–69. [CrossRef]
- Horska, Kateryna. 2020. A New Test of Artificial Intelligence: Should the Media Industry Be Afraid? *Science and Education a New Dimension* VIII: 26–29. [CrossRef]
- Ireton, Cherilyn, and Julie Posetti, eds. 2018. *Journalism, "Fake News" and Disinformation: Handbook for Journalism Education and Training*. Paris: United Nations Educational, Science, and Cultural Organization.
- Karlsson, Michael, and Christer Clerwall. 2019. Cornerstones in Journalism: According to citizens. *Journalism Studies* 20: 1184–99. [CrossRef]
- Kieslich, Kimon, Birte Keller, and Christopher Starke. 2022. Artificial intelligence ethics by design. Evaluating public perception on the importance of ethical design principles of artificial intelligence. *Big Data and Society* 9: 20539517221092956. [CrossRef]
- Kotenidis, Efthimis, and Andreas Veglis. 2021. Algorithmic Journalism—Current Applications and Future Perspectives. *Journalism and Media* 2: 244–57. [CrossRef]
- Kovach, Bill, and Tom Rosenstiel. 2021. *The Elements of Journalism*, 4th ed. New York: Crown.
- Küng, Lucy. 2024. *Strategic Management in the Media: From Theory to Practice*. London: SAGE Publications Ltd. [CrossRef]
- Lazer, David M. J., Matthew A. Baum, Yochai Benkler, Adam J. Berinsky, Kelly M. Greenhill, Filippo Menczer, Miriam J. Metzger, Brendan Nyhan, Gordon Pennycook, David Rothschild, and et al. 2018. The science of fake news. *Science* 359: 1094–96. [CrossRef]
- Lewis, Seth C., Andrea L. Guzman, and Thomas R. Schmidt. 2019. Automation, Journalism, and Human–Machine Communication: Rethinking Roles and Relationships of Humans and Machines in News. *Digital Journalism* 7: 409–27. [CrossRef]
- Martin, Kirsten. 2019. Ethical Implications and Accountability of Algorithms. *Journal of Business Ethics* 160: 835–50. [CrossRef]
- Martínez García, Luisa del Carmen, and Edson Capoano. 2023. Bibliometric Study on Quality Journalism in the Scopus Database: Evolution of the Topic and Characteristics. *Comunicacao e Sociedade* 44: 1–18. [CrossRef]
- McQuail, Denis. 2010. *Mass Communication Theory*. London: SAGE.
- Mejia, Cristian, Mengjia Wu, Yi Zhang, and Yuya Kajikawa. 2021. Exploring Topics in Bibliometric Research Through Citation Networks and Semantic Analysis. *Frontiers in Research Metrics and Analytics* 6: 742311. [CrossRef]
- Moed, Henk F. 2009. New developments in the use of citation analysis in research evaluation. *Archivum Immunologiae et Therapiae Experimentalis* 57: 13–18. [CrossRef] [PubMed]
- Napoli, Philip M. 2011. *Audience Evolution: New Technologies and the Transformation of Media Audiences*. Colombia: Columbia University Press.

- Nasir, Jamal Abdul, Osama Subhani Khan, and Iraklis Varlamis. 2021. Fake news detection: A hybrid CNN-RNN based deep learning approach. *International Journal of Information Management Data Insights* 1: 100007. [CrossRef]
- Newman, Nic. 2019. *Journalism, Media, and Technology Trends and Predictions 2019*. Oxford: Reuters Institute for the Study of Journalism.
- Newman, Nic. 2024. *Journalism, Media, and Technology Trends and Predictions 2024*. Oxford: Reuters Institute for the Study of Journalism.
- Ozmen Garibay, Ozlem, Brent Winslow, Salvatore Andolina, Margherita Antona, Anja Bodenschatz, Constantinos Coursaris, Gregory Falco Stephen M. Fiore, Ivan Garibay, Keri Grieman, John C. Havens, and et al. 2023. Six Human-Centered Artificial Intelligence Grand Challenges. *International Journal of Human-Computer Interaction* 39: 391–437. [CrossRef]
- Pavlik, John V. 2023. Collaborating with ChatGPT: Considering the Implications of Generative Artificial Intelligence for Journalism and Media Education. *Journalism and Mass Communication Educator* 78: 84–93. [CrossRef]
- Putri, Vinanda Cinta Cendekia, and Alem Febri Sonni. 2023. *Ketika Cadar Jadi Alat Persuasi: Strategi Beauty Influencer di era Digital*. Kota Makassar: Unhas Press.
- Rudolph, Jürgen, Shannon Tan, and Samson Tan. 2023. War of the chatbots: Bard, Bing Chat, ChatGPT, Ernie and beyond. The new AI gold rush and its impact on higher education. *Journal of Applied Learning and Teaching* 6: 364–89. [CrossRef]
- Shin, Donghee. 2021. The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. *International Journal of Human Computer Studies* 146: 102551. [CrossRef]
- Silberg, Jake, and James Manyika. 2019. *Notes from the AI Frontier: Tackling Bias in AI (and in Humans)*. New York: McKinsey Global Institute.
- Trattner, Christoph, Dietmar Jannach, Enrico Motta, Irene Costera Meijer, Nicholas Diakopoulos, Mehdi Elahi, Andreas L. Opdahl, Bjørnar Tessem, Njål Borch, Morten Fjeld, and et al. 2022. Responsible media technology and AI: Challenges and research directions. *AI and Ethics* 2: 585–94. [CrossRef]
- Vaccari, Cristian, and Andrew Chadwick. 2020. Deepfakes and Disinformation: Exploring the Impact of Synthetic Political Video on Deception, Uncertainty, and Trust in News. *Social Media and Society* 6: 2056305120903408. [CrossRef]
- Volberda, Henk W., Saeed Khanagha, Charles Baden-Fuller, Oli R. Mihalache, and Julian Birkinshaw. 2021. Strategizing in a digital world: Overcoming cognitive barriers, reconfiguring routines and introducing new organizational forms. *Long Range Planning* 54: 102110. [CrossRef]
- Wang, Xiaocui, Chuanlin Liu, and Yue Qi. 2021. Research on New Media Content Production Based on Artificial Intelligence Technology. *Journal of Physics: Conference Series* 1757: 012062. [CrossRef]
- Wang, Yongming. 2021. Overview of Development and Recent Trends in Bibliometrics and Research Evaluation. *International Journal of Librarianship* 6: 105–8. [CrossRef]
- Weikmann, Teresa, and Sophie Lecheler. 2023. Cutting through the Hype: Understanding the Implications of Deepfakes for the Fact-Checking Actor-Network. *Digital Journalism* 11: 1–18. [CrossRef]
- Witschge, Tamara, Chris W. Anderson, David Domingo, and Alfred Hermida. 2016. *The SAGE Handbook of Digital Journalism*. London: SAGE Publications.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.



Recommender Systems and Over-the-Top Services: A Systematic Review Study (2010–2022)

Paulo Nuno Vicente ^{1,*} and Catarina Duff Burnay ²

¹ ICNOVA, Universidade Nova de Lisboa, 1069-061 Lisboa, Portugal

² CECC, Universidade Católica Portuguesa, 1649-023 Lisboa, Portugal; cburnay@ucp.pt

* Correspondence: pnvicente@fcsh.unl.pt

Abstract: Artificial intelligence (AI) technologies have been increasingly developed and applied in the audiovisual sector. Over-the-top (OTT) services, directly distributed to viewers via the Internet, are associated with a shift towards automation through algorithmic mediation in audiovisual content led by digital platforms. However, scientific knowledge regarding algorithmic recommender systems and automation in OTT services is not yet systemized; researchers, practitioners, and the public thus lack full awareness about the still largely opaque phenomena. To address this gap, we conduct a systematic literature review in the communication domain (2010–2022) and answer four key research questions: What research objectives have been pursued? What concepts have been developed and/or applied? What methodologies have been privileged? Which OTT platforms have received the most research attention? Challenges and opportunities are highlighted, and an agenda for future research is advanced.

Keywords: recommender systems; over-the-top (OTT) services; algorithms; artificial intelligence (AI); Amazon Prime; Disney+; HBO; Hulu; Netflix

1. Introduction

Owing to the profound social and cultural transformations underway in the contemporary world, particularly those directly related to digital technologies, the notions of ‘automation’ and ‘algorithm’ have been acquiring the sense of a convenient shortcut. In public discourse, these terms often designate the whole by the part, shortening by metonymy the distance to the broader territory of artificial intelligence (AI). AI refers to the development of computer systems capable of performing tasks that typically require human intelligence, such as learning, reasoning, problem-solving, and decision-making (AI HLEG 2019). The emerging relevance of machine-learning algorithms—computational systems that recognize patterns and generate predictions from large-scale datasets—has not gone unnoticed among social scientists. Due to their socio-technical opacity, these systems have been compared with black boxes (Pasquale 2015) and are responsible for one of the great challenges arising from the application of automation techniques: the explainability problem, which is the struggle of computer scientists to clearly understand and specifically explain how these systems produce their results.

As defined by Robert Kowalski (1979) in now classical terms, an algorithm has two layers: (1) logic, which specifies what there is to accomplish, and (2) control, which determines how to achieve it. As such, algorithm = logic + control. When logically structured, an algorithm is less like a ‘list of instructions’ and more like a conditional formulation: if this = true, then that. It is not a simple list of steps as in a cooking recipe; it corresponds to a finite set of actions, with a single beginning and a single end, based on the recognition of each of the entities that will be used as the raw material for the calculation and on the establishment of commands that must be followed so that the operation can proceed.

Unlike traditional, manually pre-programmed algorithms, machine-learning algorithms are potentially prone to unpredictable ‘behaviors’. In domains such as medical

and pharmaceutical research, this unpredictability can lead to a ‘Eureka!’ moment of scientific discovery, whereas, in the social and cultural sphere, it has generated problematic effects (e.g., Cowgill and Tucker 2020; Gupta et al. 2021; Modgil et al. 2021). Moreover, a contemporary algorithm is, in a strict sense, a multiple of itself: because programmers promote constant efficiency tweaks, the same algorithm has different versions over time and is thus a persistently ephemeral socio-technical entity (Gomez-Urbe and Hunt 2016).

Distinctive contributions have been made to the critical study of algorithms (e.g., Gillespie and Seaver 2016; Kitchin 2017; Bucher 2018), the rationality they internalize (Lowrie 2017), the cultural and social power they embody (Striphas 2015; Dourish 2016; Beer 2017), and the normativities (Lee and Björklund Larsen 2019) and automation anxieties (Goffey 2019) they instate. These endeavors articulate crucial contemporary phenomena such as the politics of digital platforms (Gillespie 2010), the datafication of social life (Van Dijck 2014; Couldry 2020; Møller Hartley et al. 2021), algorithmic governance (Ananny 2016; Ziewitz 2016), the quasi-communication between humans and ‘intelligent’ systems (Guzman and Lewis 2020; Hepp 2020), how news media shape our ideas about these emerging technologies (Nah et al. 2020), and, more recently, the growing concerns around algorithm literacy (Dogruel et al. 2021; Shin et al. 2021).

This article addresses the absence of a meta-synthesis of scientific knowledge on the automation processes inherent to over-the-top (OTT) services’ recommender systems in the field of communication. Overall, this study provides the research community with an analytical summary of what research questions have been proposed and how scholars are investigating about the deep integration of automation mechanisms on digital platforms, such as Amazon Prime Video, Disney+, HBO Max, Hulu, and Netflix, as well as its influence on the contemporary production and reception of audiovisual content. To this end, we conducted a systematic literature review with a longitudinal view (2010–2022). The overarching research question guiding the systematic review is as follows: What concepts, methodological approaches, and perspectives are used in the scientific literature on OTT services and recommender systems in the communication domain? We adopt a quantitative approach (meta-analysis), along with a qualitative approach (research synthesis).

2. Background

OTT services acquired relevance in 2010 when the then video rental company Netflix evolved into a digital-streaming-based business. High-speed Internet allowed access to an online platform comprising a catalogue of premium content from multiple devices directly connected to the network, without relying on television stations or telecommunications companies. This technological shift has promoted profound transformations in the audiovisual sector, with the Internet reinforcing its status as a medium—and no longer a complementary extension—simultaneously merging and directly competing with television (Johnson 2019).

Since its emergence and establishment as a medium in the 1950s, television has been challenged by the evolution of its fundamental basis, with changes in business architectures, in content grammars, and, consequently, in the ways viewers decode the meaning of television. The remote control, the video cassette recorder, and the multichannel era are just a few examples of how technological evolution has imprinted adjustments in market dynamics and created new social experiences, triggering, time after time, questions about what television is. Amanda Lotz (2007, 2018, 2022) and Lotz et al. (2018) mapped and analyzed these evolving contexts, referring to the need to not just understand the announced death of television in the face of the new and disruptive, but rather (re)think and (re)conceptualize the medium and realize how evolution gives way to revolution, in response to the convergence of technology with industrial and social practices.

Although offering different characteristics and experiences of usage and viewing than linear television, streaming services retain many of the practices and strategies of linear television to attract and maintain audience loyalty (Wolff 2015), revealing not only the porosity between different media but also the persistent idea of technological determinism that overshadows different contexts of use and domestication as well as socio-cultural rhythms (Frey 2021) and the short and medium term effects on business operations (Lobato 2019). Among the recent audiovisual phenomena is the strategic offering of weekly episodes/chapters rather than all content at once. *Bingewatching* or *epic viewing* as a practice (Baker 2017) maintains social stigma (Steiner 2017), and its normative use can diminish the life of certain content, contributing to a very time-centric buzz in media coverage and interactivity facilitated by digital social media, and potentially to disinterest in the platform by some subscribers.

Although the audience has been understood as a social and discursive production of media industries, brands and advertisers, and measurement companies (Napoli 2011), its evolution as a concept closely depends on the evolution of the technological field and digital uses, as well as on the environmental characteristics that shape societies and organizations. The ways of measuring and characterizing audiences have also evolved from the classical auditory technique to the widespread television audience measurement system, especially since the deregulation of the audiovisual sector (Bourdon and Méadel 2014) and the adoption of data-driven analytics (Behrens et al. 2021; Wayne 2021; Michalis 2022).

Regardless of the measurement technique used, content producers continue to desperately seek the audience (Ang [1991] 2006) and compete for its attention. However, today, they must deal with two key phenomena for an updated reading of this reality—fragmentation and autonomy (Napoli 2003, 2011)—which challenge established concepts such as mass media, mass audience, and audience work (Napoli 2010).

This platformization of taste shows the importance of knowing and understanding the audience and its agency as well as the strategies to capture and create engagement and its effects; however, many questions remain unanswered in audience research (Morley 2006): Is it enough today that production platforms, such as streaming platforms, provide a continuous and targeted flow of content as opposed to the programmed flow of television to attract and retain audiences (Williams [1974] 2003)? What are the audience analysis and measurement techniques currently used and what do they represent in the agency of individuals and the dynamics of markets?

This new audiovisual ecosystem paradigm affects market dynamics and social practices, showing the growing relevance of the phenomenon. Lobato (2019) defined Netflix as a shapeshifter: it mixes elements of various media and technologies and presents itself in different forms—digital media service, television, cinema, Pay-TV, and new media—depending on the area focused on and the context in which it is inserted. According to the author, television studies are familiar with hybridization and are sufficiently flexible and open to adopting new positions, and OTT services are a pertinent pretext to rethink what is known about television and reconstitute new knowledge. By stating ‘what is more important than what we call Netflix is how we think about it’, Lobato (2019, p. 44) launched the idea of the importance of looking at OTT services as frontier phenomena and adopting theoretical and empirical approaches that bridge screen and digital media studies.

3. Methods

To organize the currently available academic knowledge on automation as implemented in contemporary OTT services’ recommender systems, this study conducts a systematic literature review, understood as a rigorous method of collecting and synthesizing evidence from multiple studies to produce a whole greater than the sum of distinct research pieces (Purssell and McCrae 2020). In general, two main approaches coexist in the current practice of conducting a systematic literature review: (1) the quantitative, meta-analysis-oriented approach that often seeks to assess the effect of different types of interventions and involves the statistical handling of findings reported across a number

of primary research pieces (e.g., Skoric et al. 2016; Chen et al. 2017; Suri 2017; Spicer et al. 2021) and (2) the qualitative, narrative-oriented approach that focuses on attempting to link together many studies on different topics, either for the purposes of reinterpretation or interconnection. As such, narrative literature reviewing is a valuable theory-building technique, and it may also serve hypothesis-generating functions (Baumeister and Leary 1997, p. 312). In the domain of new media studies, exemplary in the latter approach are, among others, the works of Caers et al. (2013), Zhang and Leung (2015), Williams (2019), and Pérez-Escolar and Canet (2022).

Our approach seeks to reconcile these two epistemological perspectives by bringing the descriptive statistical treatment of the sampled literature, aimed at identifying key scientific trends (frequency of publication, significant journals, patterns of methodological approaches, and most analyzed digital platforms), together with content analysis, codification (thematic categories), and research synthesis (objectives, questions, concepts, theoretical frameworks, results, and future research recommendations) to enable the identification of the nuclei of meaning that reveal new clues about the field of studies.

As such, our systematic literature review addressed original research articles published between January 2010—Netflix’s year of business reconversion—and December 2022, allowing for an updated longitudinal view (12 years) of communication studies examining algorithmic recommender systems providing OTT services, and was restricted to English peer-reviewed manuscripts. The sample consisted of articles indexed by the Web of Science Core Collection (category Communication), as well as articles published in Q1 scientific journals in the communication category ($n = 92$) based on the Scimago Journal Rankings; only the scientific journals also indexed by Web of Science Core Collection were considered. This methodological approach seeks to reconcile the consideration of well-established academic journals (high impact factor) with emerging scientific publications. The feasibility of using Scopus and Web of Science databases for systematic reviews and meta-analyses has recently been demonstrated (Gusenbauer and Haddaway 2020). Nevertheless, we are aware that, by limiting the sampling to indexed journals, we may unintentionally be limiting the scope or foci of the sampled articles.

3.1. Data Collection

The identification and adoption of relevant search terms was based on the deductive articulation of three analytical levels: (1) technology (‘algorithmic recommender systems’, ‘recommendation agent’, and ‘recommendation system’), (2) digital platform (‘algorithmic platforms’, ‘over the top service’, ‘OTT’, ‘streaming television’, ‘SVoD’, ‘Amazon Prime Video’, ‘Apple TV’, ‘Disney+’, ‘HBO Max’, ‘Hulu’, ‘Netflix’, and ‘WeTV’), and (3) phenomena (‘algorithmic curation’ and ‘search experience’). Each of the online databases (Web of Science Core Collection, and Scimago Journal Rankings) were queried for original scientific research publications mentioning the above-stated keywords on the fields ‘Title’, ‘Abstract’, and ‘Author-specified keywords’.

A total of 665 records were initially identified. During the screening stage, both authors reviewed all records to confirm whether each met the inclusion and exclusion criteria: 580 records did not address the specific thematic scope of the review and/or its research questions and were therefore excluded. The remaining 85 records were assessed for eligibility: 41 records did not address the specific relationship between algorithmic recommender systems and OTT services, and 11 articles were duplicated and were excluded as such; and 33 original research articles remained. Figure 1 presents a flow chart of the articles included in the study.

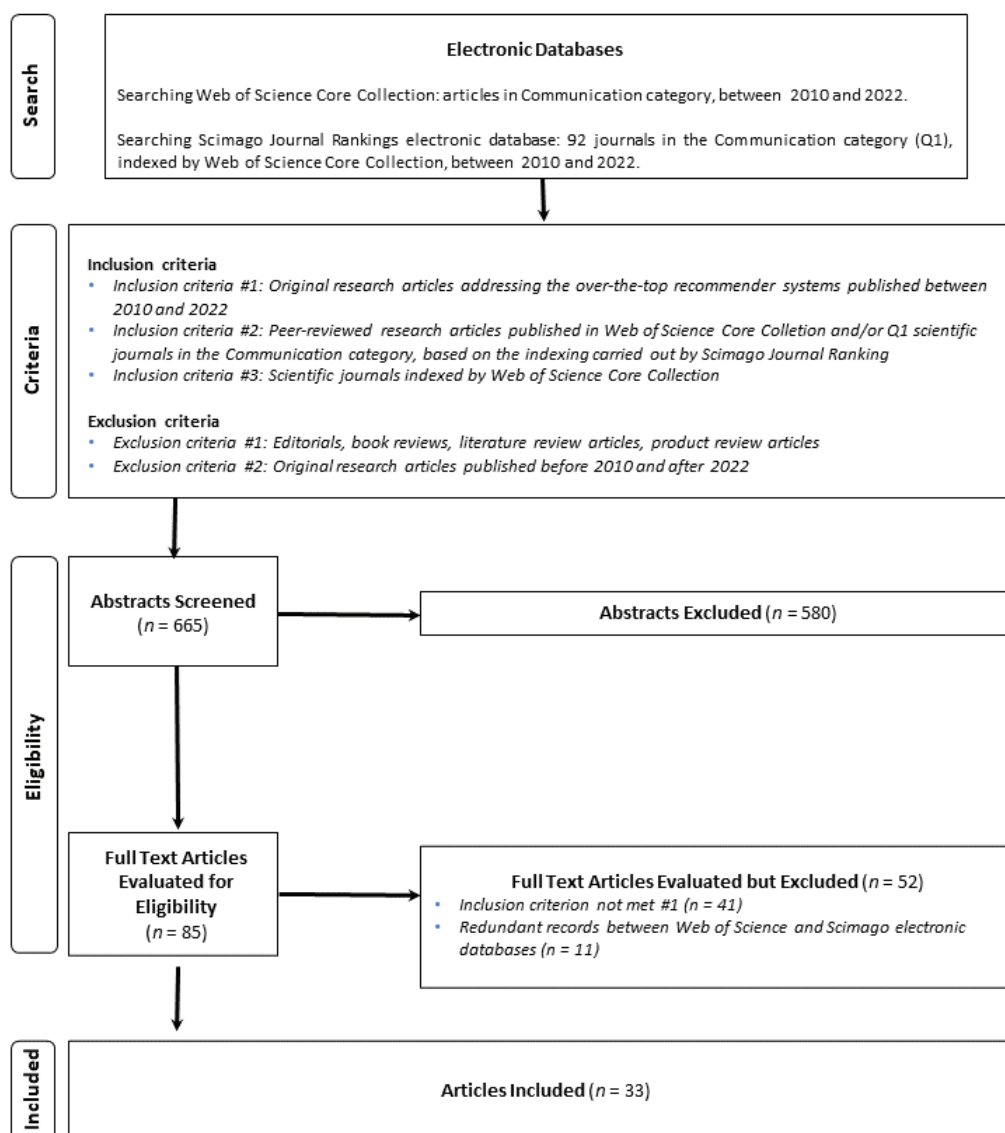


Figure 1. Systematic literature review flow chart.

3.2. Protocol and Coding

To determine the key characteristics of each of the included studies ($n = 33$), a data collection form was developed by following the procedure recommended by Petticrew and Roberts (2008). Fourteen levels of detail were included: article title, digital object identifier (DOI), journal, keywords, year of publication, research objective(s), research question(s), concept(s), theoretical framework(s), method(s), participant(s), OTT platform(s), results, and recommendation(s) for future research. The form was jointly developed by both authors of this study and piloted with test content: using a shared research protocol, each author independently completed the form. Following Higgins et al. (2019), the content separately extracted by each author was compared and gaps were identified. This procedure aimed to ascertain the adequacy of the synthesis instrument and identify biases on the part of the authors. The form was then established as the basis of the construction of thematic categories during the analysis and coding stage.

To develop the coding scheme, we adopted an inductive approach grounded on the analysis of the examined corpus at the levels of the articles' keywords, research objective(s), research question(s), concepts(s), and theoretical framework(s). This analysis allowed the constitution of five thematic categories: (1) data management as a strategic practice in the media industry, (2) the impact of recommender systems on viewers' experience, (3) the

impact of recommender systems on culture and cultural production, (4) algorithmic bias, inclusion, diversity, and digital divides, and (5) globalization, power, and the political economy of OTT services. Inter-rater reliability was statistically determined using the intraclass correlation coefficient (ICC) in SPSS to verify whether the ratings by the two different coders reflected the dimensions they were purported to reflect. Coder A and Coder B independently coded the full sample of scientific articles ($n = 33$). The inter-rater reliability test was performed by comparing the coding results of coders A and B. The ICC was 0.857 (in a 95% confidence interval, with a lower bound of 0.786 and an upper bound of 0.929), which means that the agreement between the two coders was very significant. Because the agreement rate was not absolute, the differences in coding were identified by the research team; the two coders returned to the original articles and the research synthesis form, and compared the previously assigned codes with the specific descriptions articulated in the coding scheme. This procedure allowed for collegial consensus-building. Table 1 summarizes data for each of the 33 articles included and the thematic categories in which they were coded.

Table 1. Research synthesis: distribution of articles per thematic category, key concept, research method, participants, and OTT services.

Thematic Category	Study	Year	Key Concept	Method	Participants	OTT Service
<i>Data management as a strategic practice in the media industry</i>	Fernández-Manzano et al. (2016)	2016	Business intelligence	Cross-sectional (bibliographic reviews, analysis of the data published by the firm itself, information provided by its staff in discussion forums, and analysis of data provided by specialized press)	N/A	Netflix
	Kelly (2019)	2019	Data divide; big data	General literature review	N/A	Netflix
	Burroughs (2019)	2019	Streaming lore	Cross-sectional (general literature review and media content analysis)	N/A	Netflix
	Fernández-Manzano and González-Vasco (2018)	2018	Privacy; security risks	General literature review	N/A	Netflix; Movistar+; HBO; Amazon Prime; Sky; Hulu; Disney; ESPN; Apple TV
	Shapiro (2020)	2020	Data behavioralism; streaming prestige television; datalogic turn; algorithmic television; Netflixism; algorithmic turn	General literature review	N/A	Netflix
	Fleischer (2020)	2020	Spotification	Media content analysis	N/A	N/A
	Zhao (2021)	2021	Data-driven fandom	General literature review	N/A	iQiyi

Table 1. Cont.

Thematic Category	Study	Year	Key Concept	Method	Participants	OTT Service
	Heredia-Ruiz et al. (2021)	2021	Flow TV	Content analysis	N/A	Netflix
	McKenzie et al. (2022)	2022	Viewing metrics	Descriptive analysis of the three distinct datasets released by Netflix	N/A	Netflix
	Klatt (2022)	2022	Conglomeration, flywheel economics, disruption	Case study	N/A	Amazon Prime Video
	van Es (2022)	2022	The myth of big data; data-driven organization; data-driven mindset; data–human divide	Discourse analysis	N/A	Netflix
	Siles et al. (2019)	2019	Mutual domestication	Interviews; inductive analysis of practices and profiles on the platform	25 interviewees	Netflix
<i>The impact of recommender systems on viewers' experience</i>	Pilipets (2019)	2019	Binge-watching; attachment	General literature review; network analysis	N/A	Netflix
	Kwon et al. (2020)	2020	Perceived diagnosticity; perceived serendipity	Online survey	212 survey respondents	Netflix
	Zarouali et al. (2021)	2021	Algorithmic awareness	Scale development and validation	5 experts; 26 respondents	YouTube; Netflix
	Benavides Almarza and García-Béjar (2021)	2021	Engagement	Survey	574 respondents	Netflix
	Shin et al. (2021)	2021	Algorithmic literacy; algorithmic divide	Online survey	775 survey respondents	Amazon; Netflix
	Eklund (2022)	2022	Personalization tactics, thumbnails as paratext	Pilot survey	6 participants	Netflix
	Ortega (2022)	2022	Planned differentiation	General literature review	N/A	Netflix
	Hallinan and Striphas (Hallinan and Striphas [2014] 2016)	2014	Algorithmic culture	General literature review	N/A	Netflix
<i>The impact of recommender systems in culture and cultural production</i>	McKelvey and Hunt (2019)	2019	Discoverability	General literature review	N/A	Netflix; YouTube; HBO; Amazon Prime

Table 1. Cont.

Thematic Category	Study	Year	Key Concept	Method	Participants	OTT Service
<i>The impact of recommender systems in culture and cultural production</i>	Navar-Gill (2020)	2020	Platformization of creativity	Cross-sectional (fieldwork, interviews, and discourse analysis)	13 TV screenwriters	Netflix; Amazon Prime; Hulu
	Borrajó et al. (2020)	2020	Taste communities; global niches	Case study	N/A	Netflix
	Pajkovic (2022)	2022	Taste-making	Reverse engineering (taste personas)	N/A	Netflix
	Gaw (2022)	2022	Algorithmic logics	Cross-sectional (reverse engineering: analysis of 60 documents and 100 media reports; and phenomenological approach: coding of 990 tweets)	N/A	Netflix
<i>Algorithmic bias, inclusion, diversity, and digital divides</i>	Kim (2022)	2022	Global SVoD players	Cross-sectional (semi-structured, in-depth interviews)	15 bureaucrats, 10 industry insiders	Netflix
	Meyerend (2023)	2023	Algorithmic representations of race	General literature review	N/A	Netflix
	Kennedy and Holcombe-James (2022)	2022	Digital divide; digital inclusion; digital exclusion	Cross-sectional (survey, and semi-structured interviews)	46 households (evaluation). 3 households as examples in the paper	Netflix, Disney Plus
<i>Globalization, power, and the political economy of OTT services</i>	Hildén (2021)	2021	Exposure diversity; personalization; selective exposure; nudging	Thematic semi-structured interviews	10 interviewees	Public service media in Europe
	Khoo (2022)	2022	Inclusion strategy; algorithmic cultures	Case study	N/A	Netflix
	Elkins (2019)	2019	Globalization; cosmopolitanism	Discourse analysis	N/A	Netflix
	Colbjørnsen (2021)	2020	Streaming network	General literature review; financial and other available information regarding four streaming services	N/A	Spotify; Apple Music; Netflix; Kindle
	Bonini and Mazzoli (2022)	2022	Agonistic pluralism; conviviality	General literature review	N/A	N/A

4. Results

Descriptive statistical treatment of the sampled literature was used to identify the main scientific trends, in particular, the frequency of publication in the observed time

interval (2010–2022), the most significant scientific journals, the patterns of methodological approaches, and the digital platforms that were most analyzed. Significantly, over the last decade, OTT recommender systems have received increasing research attention in the field of communication; this trend is particularly accentuated from 2019 onwards (Figure 2).

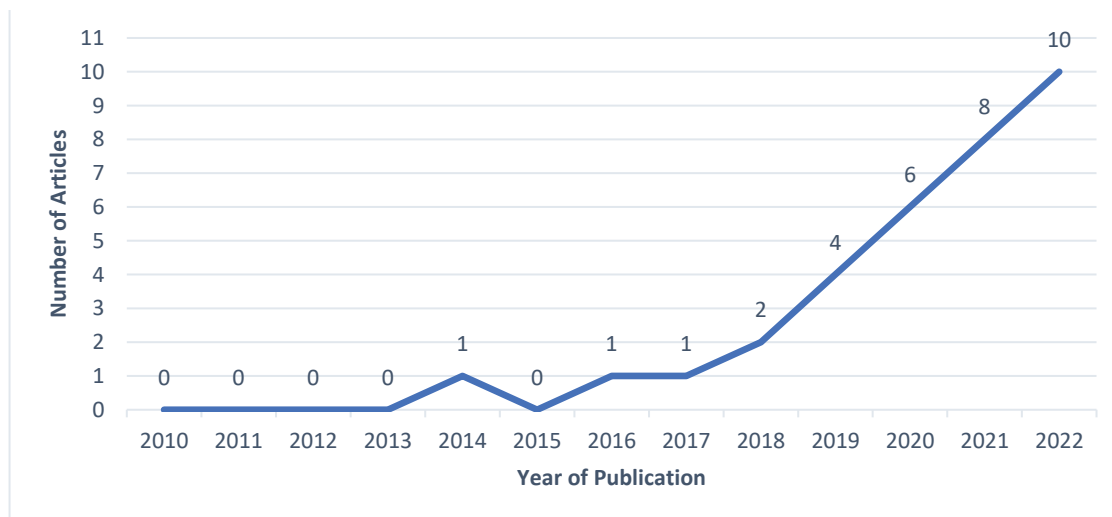


Figure 2. Frequency of articles by year (2010–2022).

Figure 3 summarizes the most significant scientific journals in the study interval. In the communication domain, research on recommender systems and OTT has been concentrated in sixteen academic publications.

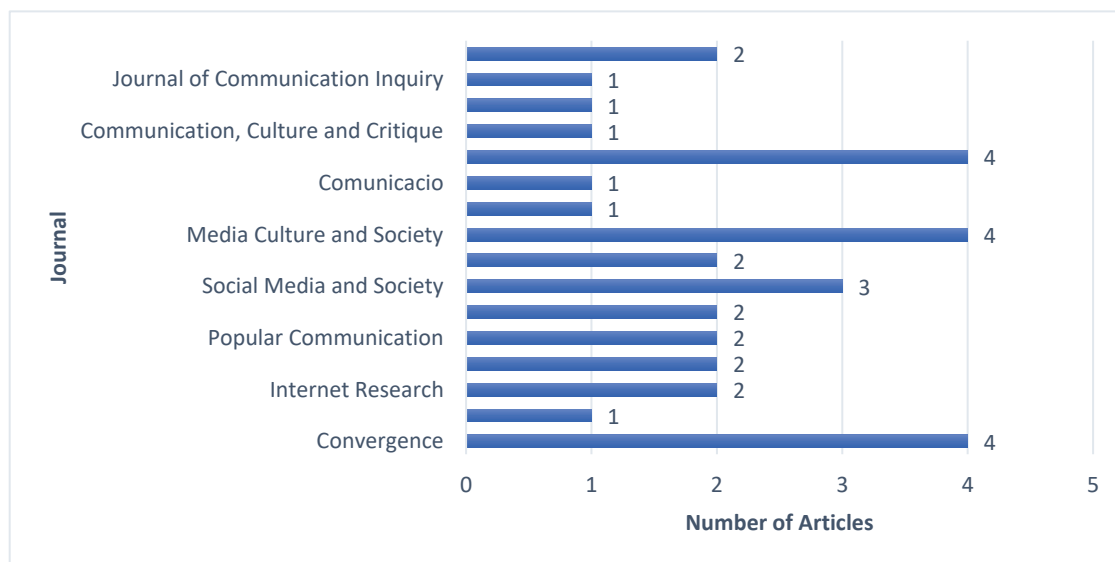


Figure 3. Frequency of publication of scientific articles by journal (2010–2022).

4.1. What Research Objectives Have Been Pursued?

Based on the review of the studies, we identified five major thematic categories: (1) Data management as a strategic practice in the media industry, aggregating articles focused on data-driven decision-making, platform politics, business intelligence, and their risks; (2) The impact of recommender systems on viewers' experience, focused on the reception of algorithm-mediated audiovisual content; (3) The impact of recommender systems on culture and cultural production, dedicated to specific emerging phenomena that are transforming the traditional notion of culture and how it is currently prone to

datafication and automation through algorithmic action; (4) Algorithmic bias, inclusion, diversity, and digital divides, aggregating articles focused on the analysis of algorithmic representation of race and emerging social issues related to pluralism and equity of access and uses; and, finally, (5) Globalization, power, and the political economy of OTT services, which includes articles dedicated to analyzing the intricate economic, commercial, and technological networks associated with the platformization of online distribution of audiovisual content.

4.1.1. Data Management as a Strategic Practice in the Media Industry

The cross-cutting objective of the articles coded under this thematic category is to analyze the logics of streaming as an instance of disruption or reformulation of previous audiovisual transmission logics. Of note are the economic and institutional dimensions of this shift—the ‘datalogic turn’ (Shapiro 2020)—as well as the discursive formulations through which they materialize.

With the aim of resituating the idea of ‘disruption’ caused by streaming services within the history of the moving image, Klatt (2022) develops a media industries analysis of the Amazon Prime Video phenomenon. According to the author, ‘disruption’ cannot be seen only as a buzzword of the moment, as it is necessary to consider the shared evolutionary history of the moving image, cinema, and television markets in the face of transformation. The entry of Big Tech companies in the film and television industries brought new strategies such as the use of artificial intelligence and big data and changes in business practices. In the case of Amazon, the tactics used are not all new and many are based on the synergies of their own technologies and infrastructures, materializing an internal capitalization of assets in a flywheel effect logic.

From a media business management perspective, the operational concept of big data integrates a strategic axis for the on-demand audiovisual content distribution industry. This line of work is particularly represented by Fernández-Manzano et al. (2016), who focus on the extractive nature of data mining, analysis, and data-driven decision-making as a competitive business advantage, as well as by Heredia-Ruiz et al. (2021), with an analysis of Netflix’s strategies around the notion of flow TV. This competitive advantage centers around user preferences, where the offering follows the segmentation into personalized content and the adoption of corporate strategies tailored to regional consumption patterns (e.g., Netflix Originals). The adoption of these datafied practices has stirred concern among researchers about the growing risks around security and the violation of privacy, conceptualized under the notion of ‘analytical surveillance’ (Fernández-Manzano and González-Vasco 2018).

Along with data management, the articles in this thematic category also focus on the discursive power of streaming corporations (van Es 2022). In this regard, the work of Burroughs (2019) is illustrative, calling attention to the recovery of industry lore—reformulated in terms of a *streaming lore*—and how it is intentionally used to constrain the markets and reinvent audience-viewing practices. Furthermore, Fleischer (2020) suggested that jargon is an active part of OTT services’ business model and advanced ‘spotification’ as a business metaphor for the normalization of subscription-based models as well as for curation through algorithmic recommender systems.

Owing to the centrality of digital data in OTT services, a subset of studies is dedicated to examining the emergence of a new paradigm of audience measurements that directly rely on social media platforms and real-time analysis. The investment in ‘live’ or event-dependent audiovisual content, as well as the new generation of digital divides—*data divide*—characterized by access asymmetries between the companies, which collect and use data as raw material for their business, and the individual viewers, are attributable to the adoption of social metrics (Kelly 2019). This push towards social data analysis is inseparable from the configuration of a turn to data-driven fandom, based on the measurability of the value of fans and their commodification (Zhao 2021). McKenzie et al. (2022) explore the importance of data presentation by streaming platforms for a better

understanding of the SVoD market in its relationship with audiences and media dynamics, particularly by researchers, through the direct analysis of three datasets released by Netflix in November 2021.

4.1.2. The Impact of Recommender Systems on Viewers' Experience

The second thematic category focuses on the interactive dimension between OTT recommendation agents and human users, in a process described as a 'mutual domestication' (Siles et al. 2019). An emerging concern is to understand how the values encoded in these automation systems and 'networked experiential environments' (Pilipets 2019) influence engagement (Benavides Almarza and García-Béjar 2021) and the search experience, particularly, *perceived diagnosticity* and *perceived serendipity*, which, in turn, affects decision satisfaction and continuance intention (Kwon et al. 2020). In this line of thought, Eklund (2022) explores the paratexts of SVoD platforms, such as Netflix's personalized thumbnails, to discuss the segmentation and customization strategies proposed by the algorithmic culture. These processes of personalizing the experience correspond to a 'planned differentiation' (Ortega 2022), responsible for the characteristics of deceptive limitlessness, customization, and the automation of content flow and ubiquity, currently recognized in streaming platforms' service/spectator relationship.

Owing to the importance of exploring whether people are mindful of algorithmic content recommendations, Zarouali et al. (2021) developed and validated the algorithmic media content awareness scale, which was tested for three different media platforms (Netflix, Facebook, and YouTube) and is aimed at making available a standardized instrument to assess users' awareness of content filtering, automated decision-making, human–algorithm interplay, and ethical considerations. In this line of work, the notion of *algorithmic literacy*, defined as the critical understanding of algorithm-based processes in terms of fairness, accountability, transparency, and explainability, begins to consolidate and is emphasized by Shin et al. (2021) through an analysis of how users engage with OTT services and how algorithmic literacy influences the sense of trust in automatic recommender systems.

4.1.3. The Impact of Recommender Systems on Culture and Cultural Production

A third thematic category of studies is structured around the concept of algorithmic culture and how information processing and automation systems are now not only technological artefacts but also emerging forms of cultural decision-making. Central to a culturological research route is the seminal article of Hallinan and Striphos ([2014] 2016) that focuses on how technology design and development competitions (e.g., The Netflix Prize) function as instances of service optimization and serve as examples for the progressive legitimization of knowledge engineering via opaque mathematical formulae and complex socio-technical systems.

This seminal perspective informs a set of later studies aimed at examining how algorithms affect the processes of taste-making in the film and television industry (Borrajó et al. 2020) and how mathematical abstraction infiltrates the cultural sphere today. To that extent, the works of Gaw (2022) and Pajkovic (2022) share a common focus and methodological approach (reverse engineering; i.e., the process of dissecting and analyzing a system to understand its design, functionality, and components) to the inner workings of the Netflix recommender system, which is a socio-technical assemblage of algorithmic logics at work as contemporary intermediaries. This dimension constitutes one of the vertices of McKelvey and Hunt (2019, p. 1) around the concept of *discoverability*, interpreted as 'a kind of media power constituted by content discovery platforms that coordinate users, content creators, and software to make content more or less engaging'. Navar-Gill (2020) examined the evolving paradoxes between being creatively free and being data-driven in the culture of professional Hollywood television screenwriters and how these integrate (or not) datafication into their creative work, stimulating tensions between the control of user data by companies and the possibilities of the narrativization of content by creators.

Kim (2022), in turn, puts into perspective the relationship between global streaming platforms and local cultural producers, through the study of the entrance of Netflix in Korea and the consequent constraints and opportunities for domestic media industries. Although co-production strategies are appealing to enable local projects with a higher quality and projection, the author identifies the risk of Korean producers becoming subcontractors of the SVoD global giants, suggesting the need to critically analyze the impacts of these power relations on cultural production and local cultural producers.

4.1.4. Algorithmic Bias, Inclusion, Diversity, and Digital Divides

A fourth thematic category consists of a subset of more recently published research articles that contribute to the field of communication studies with the introduction of a strongly sociological and critical focus. Kennedy and Holcombe-James (2022) investigate how ‘smart’ and automated technologies are being experienced in low-income households. This line of research makes it possible to frame automated technologies, especially services based on recommender systems, through the intersection of social and economic infrastructures. The study exposes how the recent policies of streaming platforms to restrict the possibilities of sharing usage accounts neglect the dynamics of low-income households and the costs associated with digital inclusion.

On the other hand, Meyerend’s article (2023) places centrality on how algorithmic technologies mediate identity, power, and the politics of racial identities. Through the analysis of Netflix’s recommendation system, the author concretizes the analysis of algorithmic cultures and representations of race, examining the identity of users and how their agency is delimited within algorithmic systems. One of the most recent lines of study of recommendation systems is related to the questioning around the policies of safeguarding exposure to the diversity of audiovisual content (Hildén 2021), potentially contrary to the personalization logics of the platforms’ algorithms, as well as, in the case of public media services in the European context, to the dynamics of the mercantile supply of the private actors of the sector (Khoo 2022).

4.1.5. Globalization, Power, and the Political Economy of OTT Services

Finally, and although still residual in communication studies dedicated to analyzing the relationship between OTT services and recommender systems, questioning is beginning to emerge around the role of streaming platforms as agents of globalization, particularly the discursive, technological, and business practices that propitiate their legitimization (Elkins 2019). Colbjørnsen’s work (2020) proposes that OTT services are embedded in a broader ‘streaming network’ deeply characterized by the circulation of flows not only of audiovisual content, but of data, money, and power, and the asymmetries arising from this. In this sense, Bonini and Mazzoli (2022) recognize that public service media risk losing their distinctive character, by not having yet developed an alternative model to envision, develop, and govern their online services and their data-driven systems.

4.2. What Concepts Have Been Developed and/or Applied?

Figure 4 represents the chronological evolution of the thematic categories and the emergence of the main concepts operationalized in the research. It is evident that the theme of *data management as a strategic practice in the media industry*, present since 2016, is the one that remains the most consistent over time (with the exception of 2019) and is accompanied by substantial conceptual development. In the opposite direction, it becomes equally evident that the thematic category encompassing *algorithmic bias, inclusion, diversity, and digital divides* has only very recently (2022) begun to emerge on the communication research agenda, following the most recent discussion about the need to regulate AI applications, considering their social impacts.

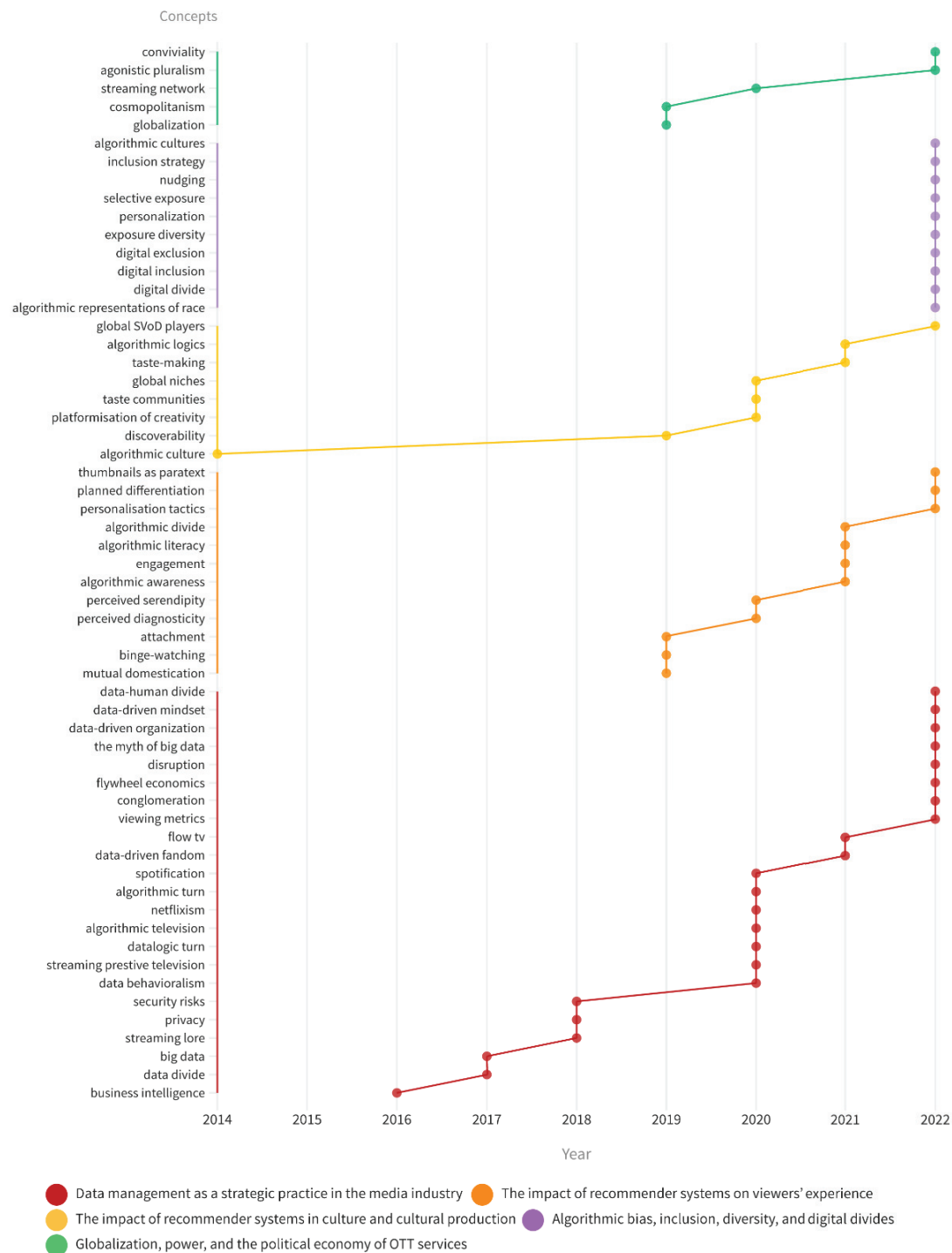


Figure 4. Frequency of the thematic categories and key concepts (2010–2022).

Although an article had been identified already in 2014, whose slant early on shows a culturological concern, it is only later (2019) that the need to better understand how recommendation systems shape the practices and tastes of receivers (e.g., engagement and binge watching) begins to be consolidated. In this sequence, the issues associated with literacy have aroused the interest of the scientific community from 2021.

4.3. What Methodologies Have Been Privileged?

The nature of the sampled articles is primarily speculative and/or theoretical/conceptual: twelve studies are based on a *general literature review* (non-systematic) (Hallinan and Striphas [2014] 2016; Kelly 2019; Fernández-Manzano and González-Vasco 2018; Burroughs 2019; McKelvey and Hunt 2019; Pilipets 2019; Shapiro 2020; Colbjørnsen 2021; Zhao 2021; Bonini and Mazzoli 2022; Meyerend 2023; Ortega 2022), seven resort to *content/discourse analysis* (Burroughs 2019; Elkins 2019; Fleischer 2020; Navar-Gill 2020; Heredia-Ruiz et al. 2021; Meyerend 2023; van Es 2022), five use *surveys* (Kwon et al. 2020; Benavides Almarza and García-Béjar 2021; Shin et al. 2021; Eklund 2022; Kennedy and Holcombe-James 2022), four analyze *case studies* (Fernández-Manzano and González-Vasco 2018; Borrajo et al. 2020; Klatt 2022; Khoo 2022), four implement original *interviews* (Siles et al. 2019; Navar-Gill 2020; Hildén 2021; Kim 2022), two employ *reverse engineering* (Gaw 2022; Pajkovic 2022), one uses *scale development and validation* (Zarouali et al. 2021), and, finally, one proceeds to use *dataset analysis* (McKenzie et al. 2022).

Facing a complex socio-technical object, characterized by access shielding (*blackboxing*), there is a predominance of long-established research methods in the domain of the social sciences and humanities to the detriment of innovative methodological and epistemological approaches that integrate the digital materiality of the medium and its articulation with the field of human-machine communication, and establish its connection to new research questions.

4.4. Which OTT Platforms Have Received the Most Research Attention?

In the analyzed sample, the most studied OTT service is Netflix; of the 33 studies, 27 (81.8%) analyze this streaming platform, and, in 21 cases (63.6%), Netflix is the sole focus of the article. This finding is suggestive of a research ‘hot zone’ with the flip side of leaving in the shade other digital realities demanding further academic attention; in our sample, this is represented by the study of the Chinese context by focusing on the iQiyi platform (Zhao 2021).

5. Future Directions

Of the 33 articles analyzed, 21 leave recommendations for future research based on circumstantial limitations or new questions that emerged in the course of the work. Most articles focus on the relationship between recommender systems and action on human and cultural contexts (Fernández-Manzano et al. 2016; Hallinan and Striphas [2014] 2016; Kwon et al. 2020; McKelvey and Hunt 2019; Borrajo et al. 2020; Shin et al. 2021; Pajkovic 2022; Zarouali et al. 2021; Zhao 2021; Benavides Almarza and García-Béjar 2021; Hildén 2021; Eklund 2022; Khoo 2022), whereas others present a market perspective, highlighting the business implications of using big data, platform strategies, and the development of streaming as an industry in a global environment (Kelly 2019; Burroughs 2019; Colbjørnsen 2021; Heredia-Ruiz et al. 2021; Klatt 2022; McKenzie et al. 2022; Kim 2022; van Es 2022).

Hallinan and Striphas ([2014] 2016), when discussing the implications of the Netflix Prize in constructing the meaning of the idea of culture and cultural practice, showed concern about the optimization of technological resources to operate as arbiters and decision-makers of taste and consumption. In the same vein, Zhao (2021) aimed to understand the new forms of audience measurement in the context of platformization and metricization, leaving as a future research avenue the necessary understanding of the sustainability of datafication, both for the industry and for the consumers, as well as of the cultural consequences of platformization logics. McKenzie et al. (2022) make a descriptive analysis of the three datasets released by Netflix in November 2021—a novelty in the market, since platforms do not make this kind of information public—and leave several clues for future research, namely, trying to understand if the demand for content on SVoD platforms differs from the demand for films and TV shows released in a traditional way or trying to understand if criticism and user reviews have lost importance in the era of algorithmic recommendation; “What is the influence of cultural affinity in the choice of content?”, or,

even, “What is the prevalence of non-English-speaking content in international catalogues?” are other future research proposal examples.

As McKelvey and Hunt (2019) advanced by studying the concept of ‘discoverability’ as media power, platforms have an increasing influence on global cultural flows through the coordination of users, creators, and software in the pursuit of engagement. This process of engagement through recommender systems was explored by Kwon et al. (2020) to understand, in a specific cultural context, the values of recommendation agents that influence ongoing subscription behaviors. However, as noted by the authors, the study and findings cannot be blindly replicated in other markets owing to cultural differences; it would, therefore, be interesting to develop localized studies as well as the use of other analysis variables, such as content characteristics or reviews left by other users, to better understand the subscriber loyalty process.

Fernández-Manzano et al. (2016) observed the use of data mining by Netflix to build user clusters with the exact aim of reducing the number of cancellations, proposing to conduct studies that explore the use of big data in other audiovisual platforms and understanding the relationship between new technologies, users, and content producers. Zarouali et al. (2021) and Shin et al. (2021) adopted a broad perspective in their approaches to recommender systems in relation to their users and their cultural contexts, drawing attention to the need to study subscribers’ levels of knowledge of recommender systems, digital literacy, and algorithmic literacy. Zarouali et al. (2021) developed the algorithmic media content awareness scale (AMCA), and Shin et al. (2021) applied the fairness, accountability, transparency, and explainability guidelines (FATE). They proposed the application of these mechanisms across different geographical and cultural contexts as well as the fine-tuning of the measurement processes with the main goal of contributing to the increase in users’ literacy levels, circumventing the effects of a divided society ill-prepared to use AI. It is in this line that Khoo (2022), when exploring the relationship of algorithmic recommendation systems with diversity and inclusion issues, makes clear the need to conduct audience research, allowing for a better understanding of whether the technology is perpetuating a similar product consumption, causing the illusion of diversity or whether, in fact, it is transforming consumption habits. Moving away from the Netflix–consumer axis, and still within this line of concern, Hildén (2021) observes the work of public service media (PSM) in the use of news’ recommendation systems and leaves as a proposal the importance of understanding how personalization may conflict with the basic objectives of a public service such as universality and diversity.

Benavides Almarza and García-Béjar (2021), working on the engagement of Mexican millennials with Netflix content, show the importance of better understanding the beliefs, thoughts, and ideas that emerge from this engagement to recognize people’s ties to the platforms and the content. In their view, these studies would be strengthened if qualitative analyses were developed involving not only consumers, but also producers and creatives, as well as content analysis, to promote a greater awareness of the establishment of social links with the platforms. Burroughs (2019) discussed the emergence of a streaming industry having its own rules and characteristics and proposed to develop holistic works on the changes and not the prevailing economic and institutional approaches. It is also in this sense that Colbjørnsen (2021) seeks to understand the power relations between the constituent parts of a streaming network, not settling on just one view and proposing that further studies show the relevance of the approach beyond the four platforms analyzed.

Through a case study about the Korean market, Kim (2022) emphasizes the need for works that critically analyze the influence of international platforms in local markets, aiming at finding a balance between the advantages of collaborating and making contents travel, and the danger of the local market becoming extinct. Heredia-Ruiz et al. (2021), in an analysis of the concept of television flow on Netflix (strategies and origin of content), shows how there is a constructed flow, supported by recommendation systems, and how there is a predominance of US titles. Through a study situated in time (2019), the author attests that there is still a way to go in the studies on the catalogues from the perspective of

cultural diversity in terms of imperialism, on the one hand, and, on the other hand, from the perspective of Netflix's business model to enter certain territories. In a connection with these ideas, we find Borrajo et al. (2020): at the intersection of market imperatives and content, the author proposes to conduct studies on Netflix's business model, such as the creation of hubs in European cities, to understand the possible impacts on the homogenization of products, challenging concepts such as creativity and originality. Moreover, Klatt (2022), through a case study on Amazon Prime Video, shows the relevance of watching other platforms beyond Netflix and tries to build knowledge and tools that can help us understand not only the strategies of large conglomerates in the streaming industry, but the individual performance of certain platforms in certain geographical and cultural contexts.

In the line of studies on audience behavior, Kelly (2019), who examined audience measurement from the perspective of television operators in the era of big data, and Pajkovic (2022), who analyzed reception, explore the use of recommender systems in the construction of taste and the definition of television culture. Kelly (2019), thus, suggests, as a challenge for other researchers, the analysis of the ethical issues of information use, particularly in view of the General Data Protection Regulation (GDPR) approval by the European Union, as well as the impacts on the democratic potential of large-scale information use. Pajkovic (2022) underscored the importance of understanding the ways in which commercial and corporate interests have taken as their own the effects of algorithm use on cultural contexts rather than understanding the inner working of algorithms themselves. It is also in this scope that Eklund (2022), by studying Netflix's personalization processes, identifies the need for further studies on the platform, as well as the examination of different SVoD platforms.

van Es (2022), through a study on Netflix as a technological company, but also as an entertainment company, explores the context of big data use and its relationship with human action. In his view, it is crucial to open the discussion to the when, how, and why of the use of information and algorithms, questioning the socio-technical systems, and stop working with concepts in the abstract.

6. Final Remarks

Our review aimed at the systematization of scientific knowledge regarding algorithmic recommender systems and automation in OTT services within the domain of communication. We intended to present a synthesis and balance instrument that would allow the research community to concretize new starting points based on the research contributions made over the last decade. One limitation of this study is the exclusion of potentially relevant sources due to the predefined search criteria, which might have led to the omission of pertinent literature (e.g., books, thesis, and dissertations). Despite this, the study provides a comprehensive foundation for future research, highlighting key trends and gaps that can guide subsequent investigations in the field of algorithmic recommender systems and digital platforms.

When synthesizing the proposals for future research suggested in previous studies, we identified three major lines of need. The first, well-expressed by the predominance of observations dedicated to the Netflix phenomenon, is constituted by the necessity to diversify the digital platforms under study and the respective algorithmic recommender systems. This inquiry path may certainly contribute to the ascertainment of socio-technical mimicry phenomena, by identifying and understanding how social behaviors and interactions are replicated or influenced by technological systems and algorithms; it also allows an investigation on the local, regional, and national micro spheres, avoiding the aprioristic assumption of a global 'Netflixization'. From here derives a concern to also 'de-westernize' the study of OTT services: from a cross-cultural and comparative perspectives, a much-needed inquiry path is that on the situated contexts of data and algorithms' use, the differences and similarities in automation systems' adoption, their influence on viewing decisions, the impacts on the construction of cultural tastes, and the consequences (direct and indirect) across distinct audiovisual sectors.

The second line we identified is related to the relevance of an empirical turn: over the last twelve years, most of the inspected studies have focused on the construction of critical analyses, which still lack solid empirical ‘fieldwork’. Faced with a phenomenon tending towards the rarefaction of methodological approaches owing to various technological and corporate shields, researchers experience the pressing need to develop creative approaches aimed at knowledge production. To date, only few studies have directly dealt with users to better understand their behaviors in the use of recommender systems. Frey (2021) recently discussed this issue when studying how the personal choice of movies and series has, in many cases, other sources of influence than the automation systems. Accordingly, it will be pertinent to develop geographically localized analyses that consider their own idiosyncrasies (economic, social, cultural, and political) and allow the understanding of the forms of use and the influence of recommender systems in the choice of content as well as in the levels of engagement and loyalty (to content and platforms).

Legal and regulatory issues related to recommendation platforms and systems also require further research, particularly as, for example in the European context, new regulatory initiatives are underway with a potential impact on the sector. Accordingly, we propose three complementary lines of action: (1) the study of trends in recommender systems’ regulation; (2) the study of content production by artificial intelligence services and copyright frameworks, and, (3) in association, we identified a near absence of discussions around literacy as a parallel path, showing itself to be a key area of work in articulation with regulatory issues.

Over the past decade, recommender systems have emerged in the digital ecosystem as key players in new mediated communication processes. As such, they need to be properly incorporated by research, academic and professional training agendas, desirably through increased collaboration between computer science, media, and communication studies. As our study signals a noticeable growth in the number of published articles addressing this topic in the last year observed (2022)—suggesting that the coming years will see an increase in knowledge production in this domain—continuous observation and analysis aimed at consolidating the production of sustained knowledge, enabling the advancement of science, industries, and markets, becomes central.

Author Contributions: Conceptualization, P.N.V. and C.D.B.; methodology, P.N.V. and C.D.B.; software, P.N.V.; validation, P.N.V. and C.D.B.; formal analysis, P.N.V. and C.D.B.; investigation, P.N.V. and C.D.B.; resources, P.N.V. and C.D.B.; data curation, P.N.V.; writing—original draft preparation, P.N.V. and C.D.B.; writing—review and editing, P.N.V. and C.D.B.; visualization, P.N.V. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Fundação para a Ciência e Tecnologia, grant numbers UIDB/05021/2020 and UIDB/00126/2020. The APC was funded by Fundação para a Ciência e Tecnologia.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest: The authors declare no conflict of interest.

References

- AI HLEG. 2019. High-level expert group on artificial intelligence. In *Ethics Guidelines for Trustworthy AI*; Brussels: European Commission, 6p.
- Ananny, Mike. 2016. Toward an Ethics of Algorithms: Convening, Observation, Probability, and Timeliness. *Science, Technology, & Human Values* 41: 93–117. [CrossRef]
- Ang, Ien. 2006. *Desperately Seeking the Audience*. London: Routledge. First published 1991.
- Baker, Djoymi. 2017. *Terms of Excess: Binge-Viewing, Epic-Viewing, and the Netflix Effect. The Age of Netflix: Critical Essays on Streaming Media, Digital Delivery and Instant Access*. Jefferson: McFarland and Company, pp. 31–54.
- Baumeister, Roy F., and Mark R. Leary. 1997. Writing Narrative Literature Reviews. *Review of General Psychology* 1: 311–20. [CrossRef]
- Beer, David. 2017. The Social Power of Algorithms. *Information, Communication & Society* 20: 1–13. [CrossRef]

- Behrens, Ronny, Natasha Zhang Foutz, Michael Franklin, Jannis Funk, Fernanda Gutierrez-Navratil, Julian Hofmann, and Ulrike Leibfried. 2021. Leveraging Analytics to Produce Compelling and Profitable Film Content. *Journal of Cultural Economics* 45: 171–211. [CrossRef]
- Benavides Almarza, Cristóbal Fernando, and Ligia García-Béjar. 2021. ¿ Por qué ven Netflix quienes ven Netflix?: Experiencias de engagement de jóvenes mexicanos frente a quien revolucionó el consumo audiovisual. *Revista de Comunicación* 20: 29–47. [CrossRef]
- Bonini, Tiziano, and Eleonora Maria Mazzoli. 2022. A convivial-agonistic framework to theorise public service media platforms and their governing systems. *New Media & Society* 24: 922–941.
- Borrajó, E. N., J. Clares-Gavilán, and J. Sánchez-Navarro. 2020. Impacto de los servicios over-the-top en la generación de comunidades de gustos y nichos globales: Netflix como estudio de caso. *Comunicació: Revista de Recerca i d'Anàlisi [Societat Catalana de Comunicació]* 37: 93–11.
- Bourdon, Jérôme, and Cécile Méadel. 2014. Television Audiences across the World: Deconstructing the Ratings Machine. London: Palgrave Macmillan.
- Bucher, Taina. 2018. *If... Then: Algorithmic Power and Politics*. Oxford: Oxford University Press.
- Burroughs, Benjamin. 2019. House of Netflix: Streaming media and digital lore. *Popular Communication* 17: 1–17. [CrossRef]
- Caers, Ralf, Tim De Feyter, Marijke De Couck, Talia Stough, Claudia Vigna, and Cind Du Bois. 2013. Facebook: A Literature Review. *New Media & Society* 15: 982–1002. [CrossRef]
- Chen, Liang, Shirley S. Ho, and May O. Lwin. 2017. A Meta-Analysis of Factors Predicting Cyberbullying Perpetration and Victimization: From the Social Cognitive and Media Effects Approach. *New Media & Society* 19: 1194–213. [CrossRef]
- Colbjørnsen, Terje. 2021. The streaming network: Conceptualizing distribution economy, technology, and power in streaming media services. *Convergence* 27: 1264–87. [CrossRef]
- Couldry, Nick. 2020. Recovering Critique in an Age of Datafication. *New Media & Society* 22: 1135–51. [CrossRef]
- Cowgill, Bo, and Catherine E. Tucker. 2020. Algorithmic Fairness and Economics. In *Columbia Business School Research Paper*. Available online: <https://ssrn.com/abstract=3361280> (accessed on 12 July 2024). [CrossRef]
- Dogruel, Leyla, Philipp Masur, and Sven Joeckel. 2021. Development and Validation of an Algorithm Literacy Scale for Internet Users. *Communication Methods and Measures* 16: 115–33. [CrossRef]
- Dourish, Paul. 2016. Algorithms and Their Others: Algorithmic Culture in Context. *Big Data & Society* 3: 2053951716665128. [CrossRef]
- Eklund, Oliver. 2022. Custom Thumbnails: The Changing Face of Personalisation Strategies on Netflix. *Convergence* 28: 737–60. [CrossRef]
- Elkins, Evan. 2019. Algorithmic cosmopolitanism: On the global claims of digital entertainment platforms. *Critical Studies in Media Communication*, 36. [CrossRef]
- Fernández-Manzano, Eva-Patricia, and María-Isabel González-Vasco. 2018. Analytic Surveillance: Big Data Business Models in the Time of Privacy Awareness. *El Profesional de La Información (EPI)* 27: 402–9. [CrossRef]
- Fernández-Manzano, Eva-Patricia, Elena Neira, and Judith Clares-Gavilán. 2016. Data management in audiovisual business: Netflix as a case study. *Profesional de la Información* 25: 568–77. [CrossRef]
- Fleischer, Rasmus. 2020. Universal Spotification? The Shifting Meanings of ‘Spotify’ as a Model for the Media Industries. *Popular Communication* 19: 14–25. [CrossRef]
- Frey, Mattias. 2021. *Netflix Recommends: Algorithms, Film Choice, and the History of Taste*. Berkeley: University California Press.
- Gaw, Fatima. 2022. Algorithmic Logics and the Construction of Cultural Taste of the Netflix Recommender System. *Media, Culture & Society* 44: 706–25.
- Gillespie, Tarleton. 2010. The Politics of ‘Platforms’. *New Media & Society* 12: 347–64. [CrossRef]
- Gillespie, Tarleton, and Nick Seaver. 2016. Critical Algorithm Studies: A Reading List. *Social Media Collective*, 15. Available online: <https://socialmediacollective.org/reading-lists/critical-algorithm-studies/> (accessed on 1 September 2017).
- Goffey, Andrew. 2019. Automation Anxieties and Infrastructural Technologies. *New Formations* 98: 29–47. [CrossRef]
- Gomez-Urbe, Carlos A., and Neil Hunt. 2016. The Netflix Recommender System: Algorithms, Business Value, and Innovation. *ACM Transactions on Management Information Systems (TMIS)* 6: 1–19. [CrossRef]
- Gupta, Manjul, Carlos M. Parra, and Denis Dennehy. 2021. Questioning Racial and Gender Bias in AI-Based Recommendations: Do Espoused National Cultural Values Matter? *Information Systems Frontiers* 24: 1465–81. [CrossRef] [PubMed]
- Gusenbauer, Michael, and Neal R. Haddaway. 2020. Which Academic Search Systems Are Suitable for Systematic Reviews or Meta-Analyses? Evaluating Retrieval Qualities of Google Scholar, PubMed, and 26 Other Resources. *Research Synthesis Methods* 11: 181–217. [CrossRef] [PubMed]
- Guzman, Andrea L., and Seth C. Lewis. 2020. Artificial Intelligence and Communication: A Human–Machine Communication Research Agenda. *New Media & Society* 22: 70–86. [CrossRef]
- Hallinan, Blake, and Ted Striphas. 2016. Recommended for you: The Netflix Prize and the production of algorithmic culture. *New Media & Society* 18: 117–37. First published 2014. [CrossRef]
- Hepp, Andreas. 2020. Artificial Companions, Social Bots and Work Bots: Communicative Robots as Research Objects of Media and Communication Studies. *Media, Culture & Society* 42: 1410–26. [CrossRef]
- Heredia-Ruiz, Verónica, Ana Catalina Quirós-Ramírez, and Beatriz Eugenia Quiceno-Castañeda. 2021. Netflix: Catálogo de contenido y flujo televisivo en tiempos de big data. *Revista de Comunicación* 20: 117–36. [CrossRef]

- Higgins, Julian P. T., James Thomas, Jacqueline Chandler, Miranda Cumpston, Tianjing Li, Matthew J. Page, and Vivian A. Welch. 2019. *Cochrane Handbook for Systematic Reviews of Interventions*. Hoboken: John Wiley & Sons.
- Hildén, Jockum. 2021. The Public Service Approach to Recommender Systems: Filtering to Cultivate. *Television & New Media* 23: 777–96. [CrossRef]
- Johnson, Catherine. 2019. *Online TV Data and Algorithm*. London: Routledge.
- Kelly, John-Paul. 2019. Television by the Numbers: The Challenges of Audience Measurement in the Age of Big Data. *Convergence* 25: 113–32. [CrossRef]
- Kennedy, Jenny, and Indigo Holcombe-James. 2022. ‘It’s Almost Impossible to Buy a Dumb TV’ Experiences of Automated Decision-Making and Smart Technologies in Low-Income Homes. *Telematics and Informatics* 68: 101767. [CrossRef]
- Khoo, Olivia. 2022. Picturing Diversity: Netflix’s Inclusion Strategy and the Netflix Recommender Algorithm (NRA). *Television & New Media* 24: 281–97. [CrossRef]
- Kim, Taeyoung. 2022. Critical Interpretations of Global-Local Co-Productions in Subscription Video-on-Demand Platforms: A Case Study of Netflix’s YG Future Strategy Office. *Television & New Media* 23: 405–21.
- Kitchin, Rob. 2017. Thinking Critically about and Researching Algorithms. *Information, Communication & Society* 20: 14–29. [CrossRef]
- Klatt, Tyler. 2022. The Streaming Industry and the Great Disruption: How Winning a Golden Globe Helps Amazon Sell More Shoes. *Media, Culture & Society* 44: 1541–58.
- Kowalski, Robert. 1979. Algorithm = logic + control. *Communications of the ACM* 22: 424–36. [CrossRef]
- Kwon, Yeeun, Jaecheol Park, and Jai-Yeol Son. 2020. Accurately or Accidentally? Recommendation Agent and Search Experience in over-the-Top (OTT) Services. *Internet Research* 31: 562–86. [CrossRef]
- Lee, Francis, and Lotta Björklund Larsen. 2019. How Should We Theorize Algorithms? Five Ideal Types in Analyzing Algorithmic Normativities. *Big Data & Society* 6: 2053951719867349. [CrossRef]
- Lobato, Ramon. 2019. *Netflix Nations: The Geography of Digital Distribution*. New York: New York University Press.
- Lotz, Amanda D. 2007. *The Television Will Be Revolutionized*. New York and London: New York University Press.
- Lotz, Amanda D. 2018. *We Now Disrupt this Broadcast. How Cable Transformed Television and the Internet Revolutionized It All*. Cambridge: The MIT Press.
- Lotz, Amanda D. 2022. *Netflix and Streaming Video: The Business of Subscriber-Funded Video on Demand*. Cambridge: Polity Press.
- Lotz, Amanda D., Ramon Lobato, and Julian Thomas. 2018. Internet-distributed television research: A provocation. *Media Industries* 5: 35–47. [CrossRef]
- Lowrie, Ian. 2017. Algorithmic Rationality: Epistemology and Efficiency in the Data Sciences. *Big Data & Society* 4: 2053951717700925. [CrossRef]
- McKelvey, Fenwick, and Robert Hunt. 2019. Discoverability: Toward a Definition of Content Discovery through Platforms. *Social Media+ Society* 5: 2056305118819188. [CrossRef]
- McKenzie, Jordi, Paul Crosby, and Sunny Y. Shin. 2022. Netflix Chills and Revamps Its Viewing Metrics: Preliminary Analysis and Opportunities for Research. *Poetics* 96: 101738. [CrossRef]
- Meyerend, Daniel. 2023. The Algorithm Knows I’m Black: From Users to Subjects. *Media, Culture & Society* 45: 629–45.
- Michalis, Maria. 2022. Trends and Perspectives on Digital Platforms and Digital Television in Europe | Public Service Broadcasting in the Online Television Environment: The Case for PSB VoD Players and the Role of Policy Focusing on the BBC IPlayer. *International Journal of Communication* 16: 20.
- Modgil, Sachin, Rohit Kumar Singh, Shivam Gupta, and Denis Dennehy. 2021. A Confirmation Bias View on Social Media Induced Polarisation During COVID-19. *Information Systems Frontiers* 26: 417–41. [CrossRef]
- Morley, David. 2006. Unanswered questions in audience research. *The Communication Review* 9: 101–21. [CrossRef]
- Møller Hartley, Jannie, Mette Bengtsson, Anna Schjøtt Hansen, and Morten Fischer Sivertsen. 2021. Researching Publics in Datafied Societies: Insights from Four Approaches to the Concept of ‘Publics’ and a (Hybrid) Research Agenda. *New Media & Society* 25: 1668–86. [CrossRef]
- Nah, Seungahn, Jasmine McNealy, Jang Hyun Kim, and Jungseock Joo. 2020. Communicating Artificial Intelligence (AI): Theory, Research, and Practice. *Communication Studies* 71: 369–72. [CrossRef]
- Napoli, Philip M. 2003. *Audience Economics: Media Institutions and the Audience Marketplace*. New York: Columbia University Press.
- Napoli, Philip M. 2010. Revisiting ‘mass communication’ and the ‘work’ of the audience in the new media environment. *Media, Culture & Society* 32: 505–16. [CrossRef]
- Napoli, Philip M. 2011. *Audience Evolution. New Technologies and the Transformation of Media Audiences*. New York: Columbia University Press.
- Navar-Gill, Annemarie. 2020. The Golden Ratio of Algorithms to Artists? Streaming Services and the Platformization of Creativity in American Television Production. *Social Media+ Society* 6: 2056305120940701. [CrossRef]
- Ortega, Vicente Rodríguez. 2022. ‘We Pay to Buy Ourselves’: Netflix, Spectators & Streaming. *Journal of Communication Inquiry* 47: 126–44. [CrossRef]
- Pajkovic, Niko. 2022. Algorithms and Taste-Making: Exposing the Netflix Recommender System’s Operational Logics. *Convergence* 28: 214–35. [CrossRef]
- Pasquale, Frank. 2015. *Black Box Society: The Secret Algorithms That Control Money and Information*. Cambridge: Harvard University Press.
- Petticrew, Mark, and Helen Roberts. 2008. *Systematic Reviews in the Social Sciences: A Practical Guide*. Hoboken: John Wiley & Sons.

- Pérez-Escolar, Marta, and Fernando Canet. 2022. Research on Vulnerable People and Digital Inclusion: Toward a Consolidated Taxonomical Framework. *Universal Access in the Information Society* 22: 1059–72. [CrossRef] [PubMed]
- Pilipets, Elena. 2019. From Netflix Streaming to Netflix and Chill: The (Dis)Connected Body of Serial Binge-Viewer. *Social Media + Society* 5: 1–13. [CrossRef]
- Purssell, Edward, and Niall McCrae. 2020. *How to Perform a Systematic Literature Review: A Guide for Healthcare Researchers, Practitioners and Students*. Berlin/Heidelberg: Springer.
- Shapiro, Stephen. 2020. Algorithmic Television in the Age of Large-scale Customization. *Television & New Media* 21: 658–63. [CrossRef]
- Shin, Donghee, Azmat Rasul, and Anestis Fotiadis. 2021. Why Am I Seeing This? Deconstructing Algorithm Literacy through the Lens of Users. *Internet Research* 32: 1214–34. [CrossRef]
- Siles, Ignacio, Johan Espinoza-Rojas, Adrián Naranjo, and María Fernanda Tristán. 2019. The Mutual Domestication of Users and Algorithmic Recommendations on Netflix. *Communication, Culture & Critique* 12: 499–518. [CrossRef]
- Skoric, Marko M., Qinfeng Zhu, Debbie Goh, and Natalie Pang. 2016. Social Media and Citizen Engagement: A Meta-Analytic Review. *New Media & Society* 18: 1817–39. [CrossRef]
- Spicer, Stuart Gordon, Laura Louise Nicklin, Maria Uther, Joanne Lloyd, Helen Lloyd, and James Close. 2021. Loot Boxes, Problem Gambling and Problem Video Gaming: A Systematic Review and Meta-Synthesis. *New Media & Society* 24: 1001–22. [CrossRef]
- Steiner, Emil. 2017. Binge-watching in practice. The ritual, motives and feelings of streaming video viewers. In *The Age of Netflix*. Edited by Cory Barker and Myc Wiatrowski. Jefferson: McFarland & Company, Inc., pp. 141–61.
- Striphas, Ted. 2015. Algorithmic Culture. *European Journal of Cultural Studies* 18: 395–412. [CrossRef]
- Suri, Harsh. 2017. Meta-Analysis, Systematic Reviews and Research Syntheses. In *Research Methods in Education*. London: Routledge, pp. 427–39.
- Van Dijck, José. 2014. Datafication, Dataism and Dataveillance: Big Data between Scientific Paradigm and Ideology. *Surveillance & Society* 12: 197–208.
- van Es, Karin. 2022. Netflix & Big Data: The Strategic Ambivalence of an Entertainment Company. *Television & New Media* 24: 656–72. [CrossRef]
- Wayne, Michael L. 2021. Netflix Audience Data, Streaming Industry Discourse, and the Emerging Realities of ‘Popular’ Television. *Media, Culture & Society* 44: 193–209. [CrossRef]
- Williams, Joshua R. 2019. The Use of Online Social Networking Sites to Nurture and Cultivate Bonding Social Capital: A Systematic Review of the Literature from 1997 to 2018. *New Media & Society* 21: 2710–29. [CrossRef]
- Williams, Raymond. 2003. *Television: Technology and Cultural Form*. London: Routledge. First published 1974.
- Wolff, Michael. 2015. *Television Is the New Television. The Unexpected Triumph of Old Media in the Digital Age*. New York: Portfolio/Penguin.
- Zarouali, Brahim, Sophie C. Boerman, and Claes H. de Vreese. 2021. Is This Recommended by an Algorithm? The Development and Validation of the Algorithmic Media Content Awareness Scale (AMCA-Scale). *Telematics and Informatics* 62: 101607. [CrossRef]
- Zhang, Yin, and Louis Leung. 2015. A Review of Social Networking Service (SNS) Research in Communication Journals from 2006 to 2011. *New Media & Society* 17: 1007–24. [CrossRef]
- Zhao, Elaine Jing. 2021. Reconfiguring audience measurement in platform ecologies of video streaming: iQiyi’s pivot toward data-driven fandom and algorithmic metrics. *International Journal of Communication* 15: 21.
- Ziewitz, Malte. 2016. Governing Algorithms: Myth, Mess, and Methods. *Science, Technology, & Human Values* 41: 3–16. [CrossRef]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.

MDPI AG
Grosspeteranlage 5
4052 Basel
Switzerland
Tel.: +41 61 683 77 34

Journalism and Media Editorial Office
E-mail: journalmedia@mdpi.com
www.mdpi.com/journal/journalmedia



Disclaimer/Publisher's Note: The title and front matter of this reprint are at the discretion of the Guest Editors. The publisher is not responsible for their content or any associated concerns. The statements, opinions and data contained in all individual articles are solely those of the individual Editors and contributors and not of MDPI. MDPI disclaims responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.



Academic Open
Access Publishing

mdpi.com

ISBN 978-3-7258-4844-7