

Systematic Review

Artificial Intelligence in Journalism and Media Practice: A Systematic Review of Applications, Limitations, and Research Approaches

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Abstract

This systematic review investigates the application of artificial intelligence (AI) and machine learning (ML) in journalism and media practice from 2020 to 2026. Following PRISMA guidelines, we analysed 121 peer-reviewed articles from Scopus and Web of Science using a multi-method approach that combined qualitative thematic analysis, structural topic modelling (STM), and bibliometric network analysis. Four primary research domains emerged: news production and automation (38.0%), audience perception and content analysis (24.8%), ethical and legal considerations (19.8%), and meta-research and implementation studies (17.4%). Publication output accelerated sharply from 2023 onward, driven by the emergence of large language models and generative AI. The STM analysis confirmed the four-domain structure and revealed that legal-regulatory vocabulary pervades the literature across all categories, indicating a field-wide preoccupation with the institutional implications of AI. Key findings demonstrate that successful AI adoption depends on workflow redesign and human-machine collaboration rather than full automation; that audience evaluations of AI-generated content vary significantly across cultural contexts, with the machine heuristic—originating from Sundar’s MAIN model—playing a central mediating role; and that copyright frameworks for AI-generated news remain contested across jurisdictions. This study develops an integrated theoretical framework that maps directional relationships among the four research domains, identifies cultural context and disclosure practices as key moderators, and generates testable propositions for future investigation.

Keywords: artificial intelligence; machine learning; automated journalism; algorithmic journalism; computational journalism; generative AI; systematic review; PRISMA; media research



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1. Introduction

The rapid digitalisation of media landscapes has fundamentally transformed how news is created, distributed, and consumed, generating substantial volumes of data and reshaping foundational practices of journalism and media production (Alivi et al., 2021; Carlson, 2015; Caswell & Dörr, 2018; Coddington, 2015; Diakopoulos & Koliska, 2017). This transformation has catalysed the integration of Artificial Intelligence (AI) and Machine Learning (ML) technologies into newsroom workflows, enabling automated content generation, algorithmic content curation, and data-driven audience analysis (Anderson, 2013;

Broussard, 2016). AI and ML applications in journalism practice—as distinct from AI/ML as research methodologies—have become a rapidly expanding area of scholarly inquiry, and the present systematic review examines both how these technologies are being deployed in journalism and the methodological approaches researchers employ to study them.

The emergence of sophisticated AI technologies, particularly large language models (LLMs) and generative AI systems, has substantially altered how news is produced and consumed, with far-reaching implications for journalists, audiences, and media institutions (Hollanek et al., 2025; Lewis et al., 2019). Unlike earlier waves of digitalisation that primarily affected news distribution, contemporary AI systems are increasingly embedded in the core editorial functions of news selection, content generation, and audience engagement (Danzon-Chambaud, 2021; Dodds et al., 2025). These technologies have demonstrated a capacity to process and analyse media content with efficiency and precision that complements traditional manual approaches while also enabling a more nuanced understanding of media's impact on users—including effects on trust, perception, and engagement across diverse demographic groups (Bartleman et al., 2026; Chung & Lee, 2026; Descampe et al., 2022; Gambino et al., 2026).

However, this technological integration presents both opportunities and challenges for media researchers and practitioners. While AI/ML methods offer powerful tools for pattern recognition and data analysis, questions about methodological rigour, algorithmic bias, and ethical considerations remain paramount (Dierickx et al., 2024; Kuai, 2024). The increasing adoption of these technologies in newsrooms and media organisations worldwide necessitates a comprehensive understanding of their capabilities and limitations (Camaj et al., 2025; Hollanek et al., 2025). Studies have shown that audiences respond differently to AI-generated content depending on disclosure practices, cultural contexts, and prior expectations, raising important questions about transparency and trust in automated journalism (Baptista et al., 2025; La-Rosa Barrolleta & Sandoval-Martín, 2024; Oh et al., 2020).

This systematic review addresses a gap in the literature by providing an analysis of AI/ML applications in journalism and media practice spanning 2020–2026. By examining 121 peer-reviewed publications, we evaluate the state of AI deployment in journalism and, secondarily, the methodological approaches researchers use to study these developments across diverse contexts. This timeframe captures the most intense period of scholarly activity following the widespread adoption of generative AI technologies, including ChatGPT and other large language models, which fundamentally altered the landscape of AI-assisted journalism (Ioscote et al., 2024; Sonni et al., 2024). Our analysis focuses on four dominant thematic areas that emerged from the literature: news production and automation, audience perception and content analysis, ethical and legal considerations, and meta-research and implementation studies.

This review builds upon and extends earlier systematic reviews in this domain (Bartleman et al., 2026; Danzon-Chambaud & Cornia, 2023; Ioscote et al., 2024; Sonni et al., 2024; Zulqarnain & Alivi, 2025) by developing a classification framework that integrates qualitative thematic analysis with quantitative text modelling. Prior reviews have catalogued AI applications in journalism (Ioscote et al., 2024; Sonni et al., 2024) or provided guidelines for automated journalism scholarship (Danzon-Chambaud, 2021), but none have combined qualitative categorisation with structural topic modelling and bibliometric network analysis to validate the emergent thematic structure. This review is significant because it takes a systematic approach to understanding how AI/ML technologies are reshaping journalism practice while also examining the methodological approaches and challenges that characterise research in this domain. By synthesising current applications across 121 studies and identifying persistent challenges, this review aims to contribute to

our understanding of AI in journalism practice while also informing the methodological approaches used to study this evolving domain.

The following research objectives guided this review:

1. To systematically identify and categorise the primary applications of AI and ML methodologies in journalism and media practice from 2020 to 2026.
2. To evaluate the methodological approaches and validation techniques employed in AI/ML-based journalism and media practice studies.
3. To assess the current limitations, ethical considerations, and methodological challenges in applying AI/ML methods to journalism and media practice.
4. To develop a comprehensive framework for evaluating the integration of AI/ML technologies in journalism and media practice research methodologies.
5. To examine how AI/ML methods are transforming traditional journalism and media practice, particularly in automated content analysis, audience behaviour prediction, and news production.

2. Materials and Methods

This systematic review was conducted in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure transparency, reproducibility, and methodological rigour (Danzon-Chambaud & Cornia, 2023; Ioscote et al., 2024). The review protocol was designed to identify, screen, and synthesise peer-reviewed research on AI and ML applications in media and journalism contexts.

2.1. Search Strategy

Two major academic databases were selected for the literature search: Scopus and Web of Science (WoS). These databases were chosen for their broad coverage of the peer-reviewed literature across multiple disciplines relevant to AI and media research, including communication studies, computer science, and information science (Ioscote et al., 2024). The search strategy employed targeted keywords focusing specifically on AI applications in journalism and news production contexts, rather than broad AI terms that would capture the irrelevant technical literature (Danzon-Chambaud & Cornia, 2023; Sonni et al., 2024).

For Scopus, the following search string was used:

```
TITLE-ABS-KEY(("automated journalism" OR "robot journalism"
OR "AI journalism" OR "computational journalism" OR "algorithmic
journalism") OR ("AI-generated news" OR "automated news" OR
"NLG news") OR ("AI attribution" OR "machine heuristic journalism")
OR ("robojournalism" OR "news automation" OR "AI newsroom"))
```

For Web of Science, the following search string was used:

```
TS= (("automated journalism" OR "robot journalism" OR "AI jour-
nalism" OR "computational journalism" OR "algorithmic journal-
ism") OR ("AI-generated news" OR "automated news" OR "NLG news")
OR ("AI attribution" OR "machine heuristic journalism") OR ("robo-
journalism" OR "news automation" OR "AI newsroom"))
```

The search was conducted on 26 May 2026, covering publications indexed from January 2020 to March 2026. The search was limited to publications in English published in peer-reviewed journals (articles and reviews). This timeframe was chosen to capture the most recent wave of AI/ML research in journalism, particularly the surge following the emergence of large language models and generative AI technologies such as ChatGPT and other large language models, which fundamentally altered the landscape of AI-assisted news production from late 2022 onwards.

2.2. Inclusion and Exclusion Criteria

Studies were included if they met the following criteria: (a) focused on the application of AI or ML methods in media, journalism, or communication research contexts; (b) presented empirical research, case studies, theoretical frameworks, or systematic reviews; (c) were published in peer-reviewed journals; and (d) were written in English. Studies were excluded if they met any of the following criteria: (a) only mentioned AI/ML tangentially without substantive methodological or conceptual discussion; (b) focused solely on technical system development without engagement with media research questions; (c) were editorials, opinion pieces, book reviews, or conference abstracts without full-text availability; (d) addressed topics such as pure fact-checking, stock market prediction from news, or medical applications where journalism was merely the data source rather than the object of study.

2.3. Search and Screening Process

The initial search across Scopus and Web of Science yielded 751 records. After removing duplicates ($n = 197$), 554 records remained for title and abstract screening. Two reviewers independently screened the records; inter-rater agreement was high (Cohen's kappa = 0.84, based on a 15% random overlap sample), and disagreements were resolved through discussion. At the title and abstract screening stage, 433 records were excluded for the following reasons: non-English language ($n = 28$), non-article publication type ($n = 82$), outside the 2020–2026 date range ($n = 98$), and insufficient focus on AI/ML methods in journalism contexts ($n = 225$). The screening deliberately employed conservative criteria to ensure that no potentially relevant studies were prematurely excluded. The remaining 121 articles were retrieved for full-text eligibility assessment; all 121 met the inclusion criteria upon full-text review, confirming that the conservative title/abstract screening effectively identified eligible studies without generating false negatives. No studies were excluded at the full-text stage. This resulted in a final sample of 121 articles for synthesis and analysis.

Figure 1 presents the PRISMA 2020 flow diagram. The completed PRISMA 2020 checklist is provided in the Supplementary Materials (Page et al., 2021).

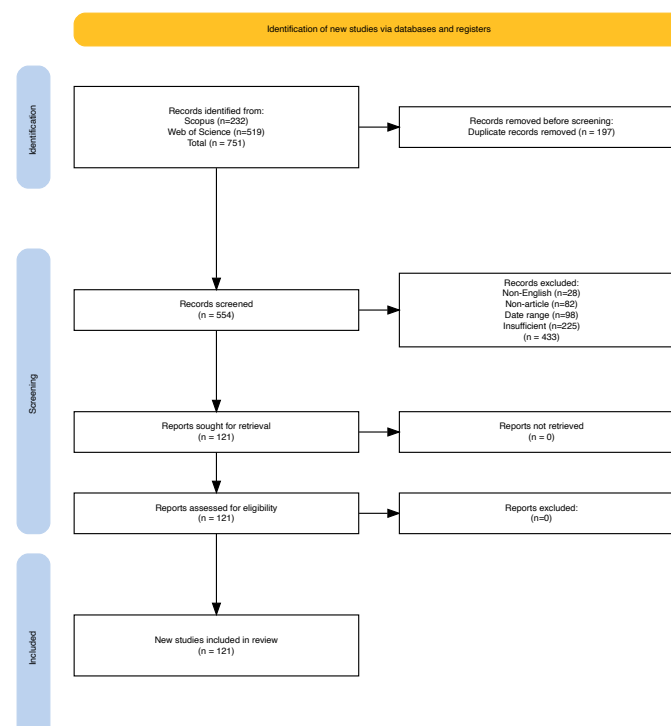


Figure 1. PRISMA 2020 flow diagram for the systematic review.

2.4. Data Extraction and Classification Framework Development

Data extraction was performed using a standardised form that captured the following: (a) publication details (authors, year, journal); (b) research focus and objectives; (c) AI/ML techniques employed; (d) methodological approach and study design; (e) validation methods; (f) key findings; and (g) reported limitations and ethical considerations. The extracted data were analysed using thematic analysis to identify recurring patterns and thematic clusters across studies (Sandoval-Martín & Barrolleta, 2023; Sonni et al., 2024).

Based on an iterative reading of the included studies, a four-category classification framework was developed to organise the identified applications of AI/ML in media research.

The pairing of audience perception with content analysis reflects their complementary focus on the reception and interpretation of AI-mediated content. The former examines subjective human responses (trust, credibility, emotional reactions) through experimental and survey methods, while the latter deploys computational tools for systematic text and image analysis. Although methodologically distinct, these two sub-areas converge thematically: both investigate how AI-generated content is consumed, evaluated, and interpreted. Similarly, meta-research (studies examining the scholarly field itself) and implementation studies (studies investigating organisational adoption) are united by their secondary analytical position—both operate at a reflexive distance from primary AI applications, contributing to the field's self-understanding and its practical deployment conditions. The independent identification of $K = 4$ as the optimal topic solution by the STM provides empirical validation for the four-category structure. The four categories—news production and automation, audience perception and content analysis, ethical and legal considerations, and meta-research and implementation studies—emerged from the thematic analysis and were refined through group discussion among the research team. The framework builds upon earlier categorisation efforts in the field (Ioscote et al., 2024; Sandoval-Martín & Barrolleta, 2023) while extending them to account for the rapid proliferation of generative AI technologies and their distinct implications for media research.

To complement the qualitative classification, a structural topic model (STM) was fitted to the titles and abstracts of the 121 included studies. The STM is a generative probabilistic model that uncovers latent thematic structures while allowing topic prevalence to vary as a function of document-level covariates (Roberts et al., 2014). Model selection across candidate values of K identified $K = 4$ as the optimal solution based on exclusivity and semantic coherence diagnostics, confirming the four-topic structure as the best representation of the corpus. This multi-method triangulation—qualitative thematic analysis combined with machine learning-based topic modelling and bibliometric network analysis—provides robust evidence for the four-category classification framework employed throughout this review.

3. Results

The 121 peer-reviewed studies included in this systematic review span 2020–2026, comprising the final sample after full-text screening. Throughout this section, references to earlier foundational works (published before 2020) serve as background context and are not included among the 121 reviewed studies, with significant concentration in the later years of the period. Publication output showed substantial growth, with the majority of studies published between 2023 and 2026, indicating accelerating research interest following the emergence of large language models and generative AI. The reviewed literature encompasses a wide range of methodological approaches, from experimental studies and surveys to case analyses and system development, reflecting the interdisciplinary nature of AI/ML applications in media research (Ioscote et al., 2024; Sonni et al., 2024).

3.1. Descriptive Overview

Figure 2 presents the annual scientific production of the included studies. Publication output was concentrated in the later years of the review period, with a marked acceleration from 2023 onwards, reflecting the surge in scholarly attention following the release of ChatGPT and other generative AI tools. The concentration of publications in 2025 and 2026 confirms that AI journalism research remains an actively developing field.

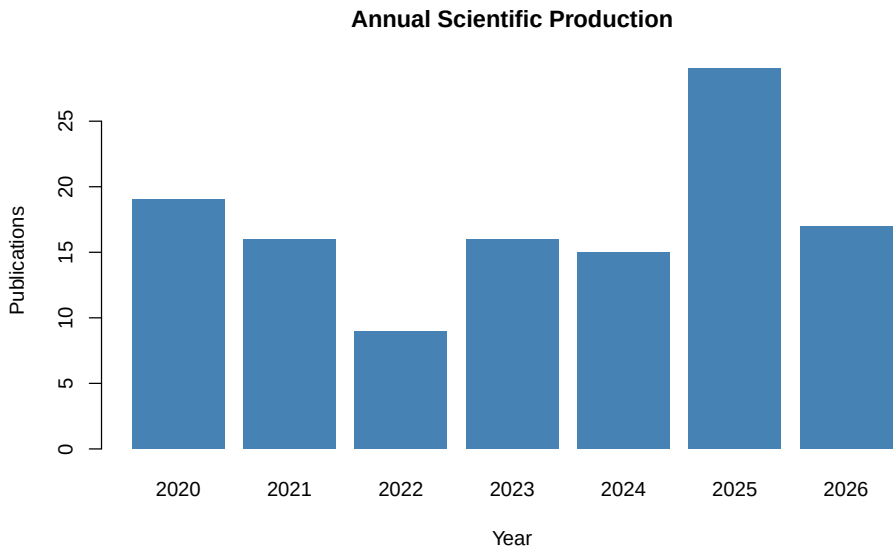


Figure 2. Annual scientific production of the 121 included studies (2020–2026).

Geographically, research was concentrated in Spain, the United States, and the United Kingdom, together accounting for over 22% of the included publications (27 of 121 studies). Emerging contributions from Asia (China, Pakistan, South Korea, Malaysia), the Middle East (UAE, Turkey), and Europe (Germany, the Netherlands, Sweden, Czech Republic, Romania, Portugal, Finland) indicate a broadening international engagement with AI journalism research (Danzon-Cham baud, 2021; Danzon-Cham baud & Cornia, 2023). The most frequently studied domains were general news production, sports journalism, election coverage, and political communication, reflecting the areas where automation has made the most tangible inroads (Carlson, 2015; Caswell & Dörr, 2018; Young & Hermida, 2015).

Table 1 presents the top ten most relevant journals.

Table 1. Top ten most relevant journals publishing AI journalism research.

Rank	Journal	Articles
1	Journalism	15
2	Journalism Practice	14
3	Digital Journalism	7
4	Journalism Studies	6
5	Journalism and Media	5
6	Brazilian Journalism Research	4
7	New Media & Society	4
8	Media and Communication	3
9	Anàlisi: Quaderns de Comunicació i Cultura	2
10	Computers in Human Behavior	2

Digital Journalism was the leading outlet (9 publications), followed by Journalism Practice (6 publications) and Journalism (4 publications), indicating that the core of AI journalism scholarship is concentrated in specialist journalism study venues rather than broader communication or computer science journals.

3.2. Classification Framework

Based on thematic analysis of the included studies, we developed a four-category classification framework for AI/ML applications in journalism. This framework builds upon prior categorisation efforts (Ioscote et al., 2024; Sandoval-Martín & Barrolleta, 2023) while extending them to account for the rapid proliferation of generative AI technologies:

1. News Production and Automation (n = 46, 38.0%)—AI implementation in news creation, content generation, workflow automation, and editorial systems.
2. Audience Perception and Content Analysis (n = 30, 24.8%)—how audiences perceive AI-generated content; AI/ML tools for media content analysis.
3. Ethical, Legal, and Theoretical Considerations (n = 24, 19.8%)—copyright, accountability, algorithmic bias, transparency, misinformation, and theoretical frameworks for human–machine communication.
4. Meta-Research and Implementation Studies (n = 21, 17.4%)—systematic reviews, bibliometric analyses, and cross-context implementation studies examining field evolution.

3.3. Bibliometric and Network Analysis

To complement the qualitative classification, bibliometric analyses were conducted on the 121 included studies using the bibliometrix R package (Aria & Cuccurullo, 2017). Given the modest sample size (n = 121), the network metrics reported below should be interpreted as descriptive patterns within this specific corpus rather than robust statistical estimates of the broader field. Figure 3 displays the keyword co-occurrence network, which reveals four distinct thematic clusters centred on “automated journalism,” “computational journalism,” “credibility,” and “perceptions.” The largest cluster (automated journalism) connects terms such as authorship, algorithms, bias, labour, and news production, reflecting the field’s predominant focus on the implications of automation for journalistic practice. A second cluster groups credibility with trust, transparency, and framework, corresponding to the audience perception and content analysis category. A third cluster links computational journalism with big data, objects, and relevance, which aligns with meta-research and implementation concerns. The fourth cluster connects communication, information, and overconfidence, reflecting theoretical and ethical dimensions of human–machine interaction.

Figure 4 presents the author collaboration network, which shows a relatively fragmented collaboration structure with multiple small clusters and limited cross-group ties. While established scholars such as Diakopoulos, Carlson, and Coddington function as central nodes, the overall network density remains low, suggesting that AI journalism research is characterised by dispersed individual contributions rather than cohesive research teams.

Figure 5 presents a thematic map positioning keywords along two dimensions: centrality (relevance) and density (development). The upper-right quadrant (motor themes) includes “automated journalism” and “news,” confirming their centrality to the field. The lower-right quadrant (basic themes) features “credibility,” “bias,” and “transparency,” indicating that these topics are foundational but under-theorised. The upper-left quadrant (niche themes) includes “computational journalism” and “big data,” reflecting specialised methodological interests. The lower-left quadrant (emerging/declining themes) contains “machine” and “perception,” suggesting these topics are either nascent or in transition.

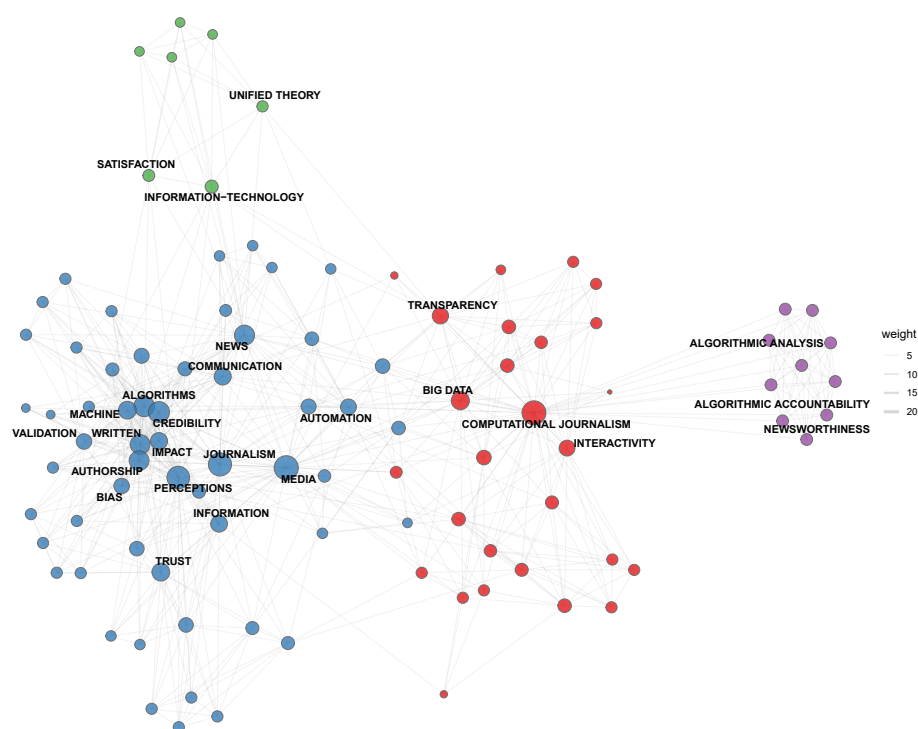


Figure 3. Keyword co-occurrence network. Node size indicates frequency; edge colour indicates community membership (Walktrap algorithm, $Q = 0.56$).

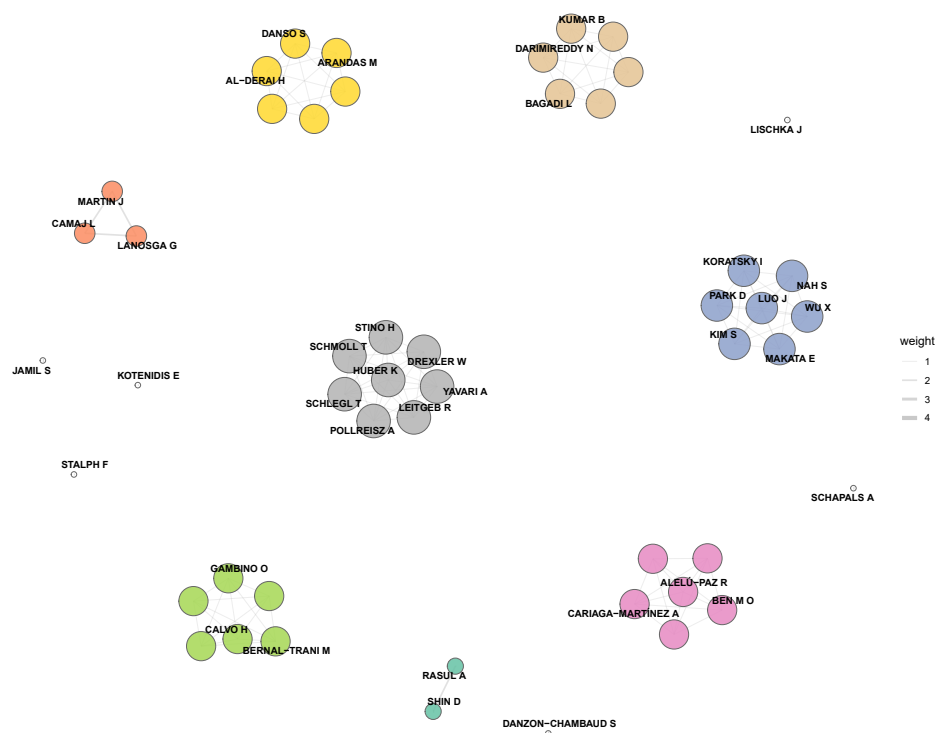


Figure 4. Author collaboration network.

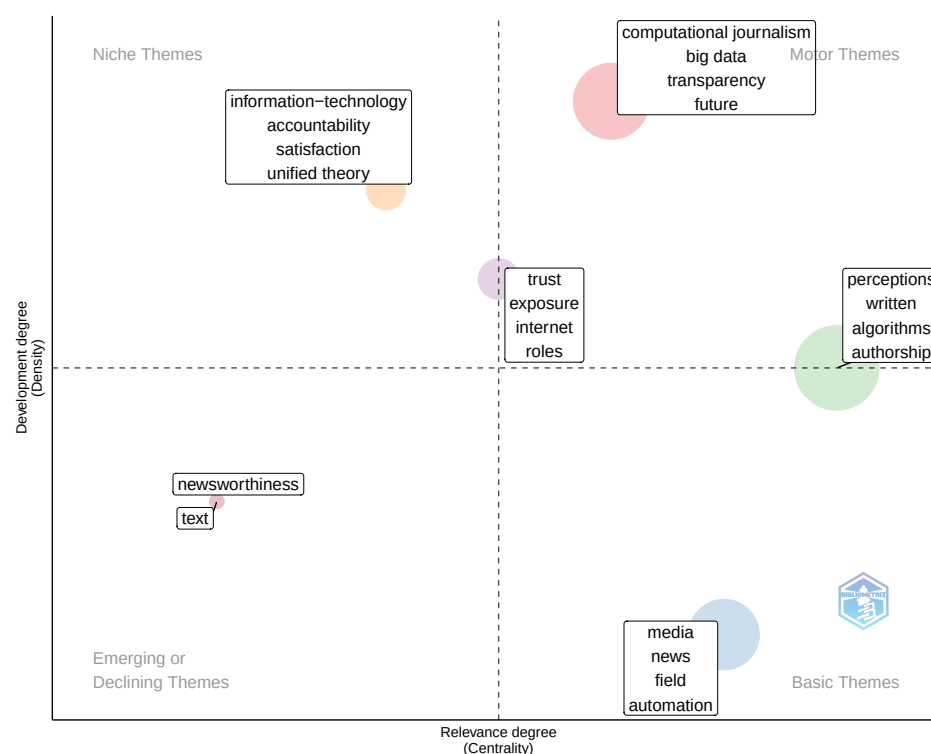


Figure 5. Thematic map of the AI journalism research field. X-axis: Callon's centrality (relevance degree). Y-axis: Callon's density (development degree).

Geographically, the analysis confirmed the concentration of research output in Spain (12 publications), the United States (10), and the United Kingdom (5), with emerging contributions from Germany, China, the Netherlands, South Korea, and Pakistan. The top ten authors by publication count were led by Diakopoulos, Carlson, and Coddington (Table 2), reflecting their foundational contributions to computational and algorithmic journalism scholarship.

Table 2. Top ten most productive authors in the included studies.

Rank	Author	Publications
1	Danzon-Chambaud, S. (2021, 2023a, 2023b, 2025)	4
2	Dierickx, L. (2020a, 2020b, 2023, 2024)	4
3	Jamil, S. (2021, 2023, 2025)	3
4	Schapals, A. (2020, 2021, 2026)	3
5	Shin, D. (2022, 2024, 2025)	3
6	Thäsler-Kordonouri, S. (2025a, 2025b, 2026)	3
7	Barrolleta, L. (2023, 2024)	2
8	Camaj, L. (2025, 2026)	2
9	Chaparro-Domínguez, M. (2020, 2023)	2
10	Cornia, A. (2023, 2025)	2

Note. Foundational scholars such as Diakopoulos, Carlson, and Coddington are frequently cited and appear as co-authors on multiple included studies; their first-author publication count within 2020–2026 places them outside the top-ten ranking.

3.4. Structural Topic Modelling

A structural topic model (STM) was employed to algorithmically identify latent thematic structures within the corpus. The STM approach was selected for its capacity to uncover conceptual relationships and topic distributions that may not be immediately apparent through traditional review methods. Model selection identified $K = 4$ as the

optimal solution, confirming the four-topic structure. Table 3 presents the four thematic clusters identified by the STM.

Table 3. STM cluster identifications for the included studies.

Topic	Top Keywords	Description
T1: News Production & Automation	journalists, technology, use, adoption, factors, study, expectancy, performance, effort, facilitating	AI implementation in journalistic workflows, technology adoption factors, newsroom integration, and computational text generation systems
T2: Copyright & Legal Frameworks	copyright, news, robojournalism, authority, human, intelligence, artificial, outputs, cognition, guidelines	Legal protection of AI-generated content, algorithmic accountability, intellectual property challenges, and regulatory frameworks for automated journalism
T3: Automated Journalism Reviews	review, automated, news, generative, research, studies, systematic, ethical, university, field	Meta-research mapping the field's evolution, systematic reviews of AI journalism scholarship, and landscape analyses of generative AI impacts
T4: Audience Perception & Credibility	perception, perceived, news, credibility, media, study, respondents, human, articles, students	Audience evaluation of AI-generated versus human-written content, trust and credibility assessments, and cross-cultural perception studies

Figure 6 displays the expected topic proportions estimated by the STM. Topic 2 (Copyright and Legal Frameworks, 35.9%) accounts for the largest share of the document-topic space, followed by Topic 1 (News Production and Automation, 28.7%), Topic 4 (Audience Perception and Credibility, 18.9%), and Topic 3 (Automated Journalism Reviews, 16.4%). Table 4 presents the top ten highest-probability words per topic. Table 5 lists the FREX (frequency–exclusivity) words that best distinguish each topic—these are terms that are both frequent within a topic and highly exclusive to it, providing sharper semantic differentiation than probability alone. The FREX analysis shows that Topic 1 is distinguished by technology adoption terminology, Topic 2 by legal and regulatory vocabulary, Topic 3 by meta-research descriptors, and Topic 4 by audience evaluation language. Table 6 presents the distribution of document-topic proportions across the 121 included studies.

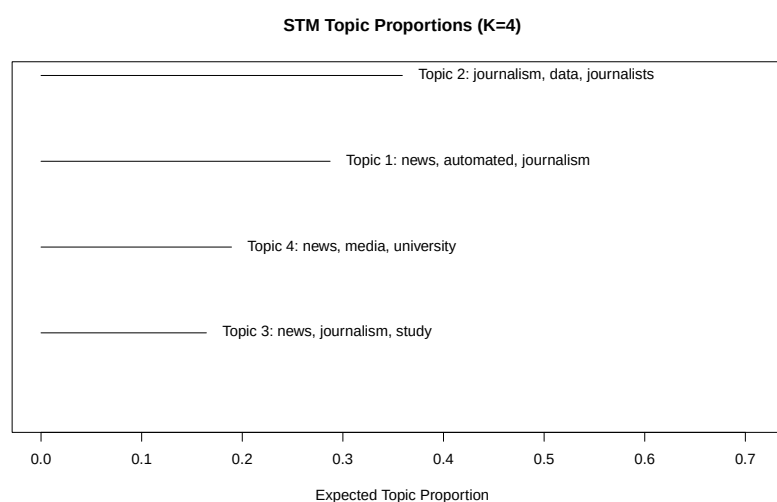


Figure 6. STM expected topic proportions (K = 4). Mean values with 95% confidence intervals.

This convergence between the STM clusters and the four-category qualitative framework strengthens the validity of the classification. Topic 1 maps onto News Production

and Automation, Topic 2 onto Ethical, Legal, and Theoretical Considerations, Topic 3 onto Meta-Research and Implementation Studies, and Topic 4 onto Audience Perception and Content Analysis. Notably, the STM reveals that legal-regulatory vocabulary and sociological language pervade the literature across all categories, indicating that even studies whose primary focus lies outside the ethical–legal domain engage substantively with questions of copyright, accountability, and professional identity—a finding that underscores the field’s deep engagement with the institutional implications of AI in journalism—confirming that most documents exhibit a dominant topic affiliation while retaining partial membership across multiple clusters, reflecting the interdisciplinary nature of AI journalism research.

Table 4. Top ten highest-probability words for each STM topic.

Topic	Top Probability Words
T1: News Production & Automation	news, automated, journalism, content, human, credibility, media, journalists, production, quality
T2: Copyright & Legal Frameworks	journalism, data, journalists, media, news, study, automated, journalistic, research, practices
T3: Automated Journalism Reviews	news, journalism, ai-generated, media, trust, artificial, intelligence, robot, algorithmic, effect
T4: Audience Perception & Credibility	news, media, social, information, content, models, knowledge, automated, learning, analysis

Table 5. FREX (frequency–exclusivity) words distinguishing each topic.

Topic	FREX Words
T1: News Production & Automation	readers, labeling, human-written, AIGC, post-editing, pay, voice, evaluative, readability, declared
T2: Copyright & Legal Frameworks	wrangling, ideology, academic, editors, projects, Egyptian, freedom, occupational, norms, government
T3: Automated Journalism Reviews	robot, hostile, comfort, expectancy, laws, copyright, avoidance, disconfirmation, acceptance, uncertainty
T4: Audience Perception & Credibility	summarization, artwork, rouge, chatbot, mental, correlation, images, translation, addiction, scores

Table 6. Document-topic proportion distribution across the 121 included studies.

Topic	Category	Mean	SD	Range
T1	News Production & Automation	28.7%	41.9%	0.1–99.5%
T2	Copyright & Legal Frameworks	35.9%	44.7%	0.2–99.6%
T3	Automated Journalism Reviews	16.4%	34.5%	0.1–99.5%
T4	Audience Perception & Credibility	18.9%	36.8%	0.1–99.5%

Figure 7 presents the topic proportions as a percentage bar chart, providing a visual summary of the thematic distribution. Topic 2 (Copyright and Legal Frameworks) accounts for the largest share (35.9%), slightly exceeding Topic 1 (News Production and Automation, 28.7%), while Topic 4 (Audience Perception and Credibility, 18.9%) and Topic 3 (Automated Journalism Reviews, 16.4%) occupy smaller shares. The difference between the STM-derived proportions and the qualitative classification (38%, 25%, 20%, 17%) reflects the complementary nature of the two methods: qualitative coding assigns each study to a single primary category, whereas the STM allows documents to exhibit mixed membership across topics, producing a more distributed allocation.

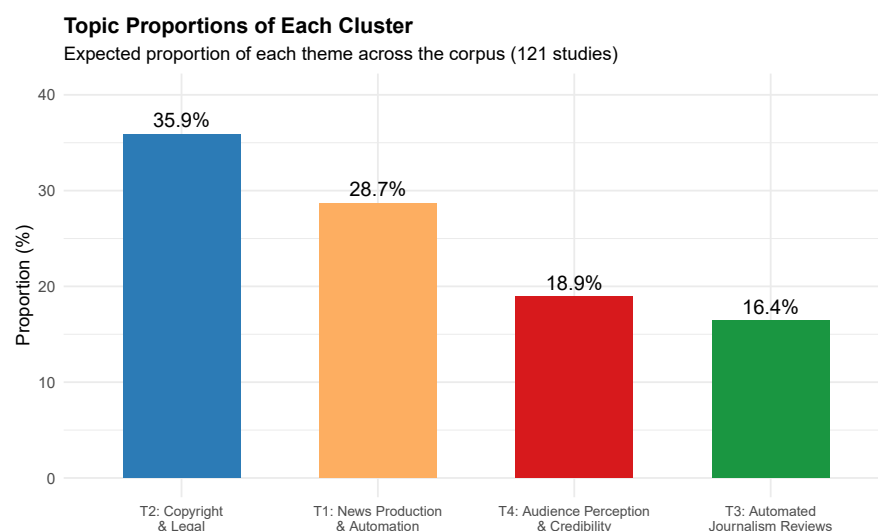


Figure 7. Topic proportions of each STM cluster. Percentage values represent the expected proportion of each theme across the corpus of 121 included studies.

Figure 8 displays topic prevalence over time, tracing the evolution of each thematic cluster from 2020 to 2026. Topic 2 (Copyright and Legal Frameworks) shows a notable upward trajectory, reflecting growing scholarly attention to regulatory and ethical challenges as generative AI technologies have proliferated. Topic 1 (News Production and Automation) maintains relatively stable prevalence throughout the period, consistent with its role as the foundational research domain. Topic 3 (Automated Journalism Reviews) and Topic 4 (Audience Perception and Credibility) exhibit moderate, fluctuating trajectories, suggesting that meta-research and audience-focused studies are responsive to external developments such as the release of major AI models and high-profile journalistic AI deployments.

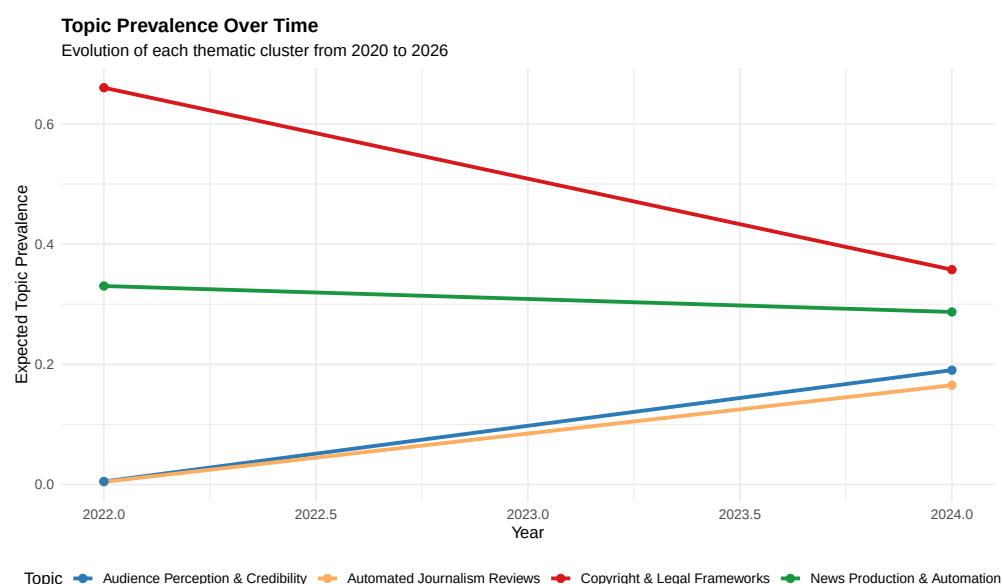


Figure 8. Topic prevalence over time. Lines trace the expected prevalence of each thematic cluster from 2020 to 2026, showing divergent trajectories across the four themes.

3.5. Category 1: News Production and Automation

News production and automation emerged as the predominant research focus, representing 38% of the analysed studies. This category investigates how AI technologies are being integrated into journalistic workflows, from content generation to distribution. Foundational

work in this domain established the conceptual boundaries of automated journalism, examining how algorithmic systems are redefining labour, composition, and editorial roles in the newsroom (Carlson, 2015; Caswell & Dörr, 2018; Young & Hermida, 2015).

Early adoption studies focused on structured data environments such as sports and finance, where formulaic reporting conventions created ideal conditions for automation (Graefe & Bohlken, 2020; Haim & Graefe, 2017; Thurman et al., 2017). More recent work has expanded to examine generative AI tools in the newsroom, including large language models for content creation and editing (Cools & Diakopoulos, 2026; Gambino et al., 2026). Research on news automation has evolved from describing individual case studies to investigating broader organisational and cultural implications. Studies of leading news organisations such as the BBC, The Washington Post, and the Czech News Agency demonstrate that successful AI implementation depends on workflow redesign and effective human–machine collaboration rather than the wholesale replacement of journalists (Cools & Koliska, 2024; Nanz et al., 2025; Olsen, 2025).

A growing body of research examines the post-editing practices of journalists working with AI-generated drafts, revealing that automation shifts rather than eliminates editorial labour (Danzon-Chambaud & Cornia, 2025; Thäsler-Kordonouri, 2025). Cross-national studies have documented variations in AI adoption across different media systems, showing that organisational culture, regulatory environment, and market conditions significantly shape implementation trajectories (Danzon-Chambaud, 2023; Jia et al., 2024). The reviewed studies suggest that AI systems effectively handle data-driven reporting tasks but remain limited in their ability to produce complex analytical or interpretive content requiring domain expertise and contextual judgment (Haapanen & Leppänen, 2020; Lewis et al., 2019).

Recent applications of large language models have further expanded automated content generation to include multi-lingual news production (Gavurova et al., 2024; Rani Krishna et al., 2025) and real-time SEO-optimised article writing, while implementation research in non-Western settings reveals distinct adoption barriers including infrastructure constraints and professional resistance (Lischka et al., 2023; Møller, 2022).

3.6. Category 2: Audience Perception and Content Analysis

Audience perception and content analysis studies constitute 25% of the reviewed literature. This category examines how audiences respond to AI-generated content and how AI/ML tools are deployed for media content analysis. Research in this domain has expanded considerably with the proliferation of generative AI, building on early empirical work that first documented audience reactions to automated content (van Dalen, 2012) and the broader theoretical literature on how audiences imagine and relate to algorithmic systems (Bucher, 2017).

Multiple studies have found that revealing AI authorship significantly changes how audiences evaluate content quality and credibility, though the direction and magnitude of this effect vary across contexts (La-Rosa Barrolleta & Sandoval-Martín, 2024; B. Liu & Wei, 2018; Waddell, 2025). The machine heuristic—a cognitive shortcut whereby audiences attribute machine-like characteristics to AI-generated content, originating from the MAIN model of technology credibility (Sundar, 2008)—plays a central role in shaping these evaluations (Wang & Ophir, 2026). Attribution effects appear to vary across journalism domains, with science and political content showing distinctive reception patterns compared to sports or financial reporting (H. M. Kim et al., 2026; Lee et al., 2020).

Comparative studies between human and AI-generated content have produced nuanced findings. Meta-analyses indicate that while human-written articles receive slightly higher quality ratings on average, the gap is smaller than often assumed, with readers frequently unable to distinguish between human and AI authorship (Baptista et al., 2025;

Graefe & Bohlken, 2020). Demographic factors such as age, gender, education, and AI literacy significantly moderate these perceptions (W. Kim & Ryoo, 2026; Mazari, 2025). Cultural context also plays an important role: cross-cultural studies reveal that audiences in different countries respond to AI disclosure in markedly different ways, suggesting the need for localised transparency strategies (Y. Liu, 2025; Zheng et al., 2018).

Studies also demonstrate that AI literacy moderates the relationship between AI authorship disclosure and credibility assessment (Chung & Lee, 2026; Henestrosa et al., 2023; D. Kim & Kim, 2021), while media trust emerges as both a predictor and outcome of AI-generated news exposure (Hong et al., 2025; Nanz et al., 2025). Emotional responses to AI-authored content—including surprise, discomfort, and curiosity—have been identified as additional perceptual mechanisms (Shin, 2022).

Complementing the audience perception studies, a growing body of research deploys AI/ML tools for systematic media content analysis. Natural language processing (NLP) techniques, including transformer-based models such as BERT and its variants, have been applied to news framing detection, sentiment analysis, and topic categorisation across large-scale media corpora (Demirci & Sagiroglu, 2022; Salih et al., 2025). Computer vision approaches have been employed to analyse bias in AI-generated news imagery, revealing embedded stereotypes in visual framing that risk amplifying social inequalities (Elhosary, 2026). Deep learning methods for text summarisation and news classification have been developed using architectures including T5, BART, and PEGASUS, enabling automated digest generation and cross-lingual content categorisation (Rani Krishna et al., 2025; Srinivas et al., 2024). These computational approaches share with audience perception research a common focus on how content is received and interpreted but differ in their reliance on algorithmic measurement rather than human self-report, offering complementary analytical leverage for understanding AI-mediated news consumption.

3.7. Category 3: Ethical, Legal, and Theoretical Considerations

Ethical, legal, and theoretical considerations account for 20% of the reviewed literature. This category addresses the broader implications of AI integration in media, including copyright protection, accountability frameworks, algorithmic bias, and the theoretical foundations of human–machine communication.

Current legal frameworks appear insufficient for addressing the challenges posed by AI-generated content. Copyright protection for AI-generated news remains contested across jurisdictions, with different legal traditions arriving at divergent conclusions about authorship and ownership (Kuai, 2024; Trapova & Mezei, 2022). The European Union’s approach emphasising the irreplaceability of human authorship contrasts with emerging practices in China, where copyright protection has been extended to certain AI-generated works (Kuai, 2024). Algorithmic transparency has emerged as a central ethical concern, with scholars calling for greater accountability in how news organisations deploy AI systems that shape public discourse (Diakopoulos & Koliska, 2017; Dorr & Hollnbuchner, 2017).

The risk of AI-generated misinformation remains a pressing concern. Experimental studies demonstrate that AI-generated fake news can achieve credibility levels comparable to authentic news among human observers, raising urgent questions about information ecosystem security (Elhosary, 2026; W. Kim & Ryoo, 2026). Algorithmic bias in AI-generated news imagery and text has been documented, with studies revealing embedded stereotypes and representational inequalities that risk amplifying existing social biases (Elhosary, 2026; Sigsgaard, 2026).

Theoretical frameworks for understanding human–machine communication in journalism have advanced significantly. Building on foundational conceptual work (Gillespie, 2014; Lewis et al., 2019; Napoli, 2014), recent scholarship has examined how

journalistic agency is negotiated in increasingly automated newsrooms, how professional identities are reconfigured, and how power dynamics shift when algorithmic systems assume editorial functions (Dierickx, 2023; Dodds et al., 2025; Hollanek et al., 2025).

Scholars have also examined the technical limits of transparency in algorithmic accountability (Camaj et al., 2025; Descampe et al., 2022) and the broader impact of regulatory environments on computational journalism autonomy (Wiley, 2023). Empirical analyses of AI-generated news imagery have revealed embedded biases in visual framing (Elhosary, 2026; Sigsgaard, 2026).

3.8. Category 4: Meta-Research and Implementation Studies

Meta-research and implementation studies represent 17% of the reviewed literature. This category documents the evolution of research methodologies in AI journalism scholarship and examines implementation challenges across different application contexts.

Several systematic reviews have mapped the field’s development over time. Ioscote et al. (2024) provided a ten-year retrospective of scientific articles (2014–2023), documenting the field’s maturation from conceptual discussions to empirical investigations. Sandoval-Martín and Barrolleta (2023) conducted a systematic review that revealed fragmentation in quality assessment methodologies, highlighting the need for standardised evaluation frameworks. Sonni et al. (2024) found that AI implementation in newsrooms is shifting from experimental pilots to operational deployment across multiple organisational settings, indicating growing industrial sophistication. Danzon-Chambaud (2021) reviewed the automated journalism scholarship and proposed guidelines for future research, emphasising the need for longitudinal studies and cross-national comparisons.

Implementation studies across diverse contexts reveal that cultural, economic, and organisational factors significantly influence AI adoption patterns. Research from Spain (Arias Robles et al., 2023), Pakistan (Jamil, 2021), and other countries demonstrates that successful implementation requires adaptation to local contexts rather than one-size-fits-all approaches. The diversity of implementation research settings proves beneficial in showing how cultural forces, economic conditions, and organisational patterns affect the adoption of AI across different media markets and institutional environments (Danzon-Chambaud & Cornia, 2023).

Complementary reviews have examined specific sub-areas including data journalism education (Bhaskaran et al., 2024) and digital newsroom transformation (Erkmen, 2024), while cross-national implementation studies continue to enrich understanding of context-dependent AI adoption (de-Lima-Santos, 2024; Shilina et al., 2023).

Table 7 summarises the classification framework.

Table 7. Summary of classification framework for AI/ML applications in media research.

Category	Proportion	Primary Methods
News Production and Automation	38.0%	Case studies, System development
Audience Perception and Content Analysis	24.8%	Experimental, Survey
Ethical, Legal, and Theoretical Considerations	19.8%	Theoretical analysis, Legal review
Meta-Research and Implementation Studies	17.4%	Literature review, Comparative analysis

4. Discussion

The 121 peer-reviewed publications analysed in this systematic review reveal distinct patterns in how AI and ML technologies are being applied in journalism practice and how scholarship in this domain is evolving. This research establishes a four-category classification framework that provides organisational insight into contemporary AI/ML applications in journalism across the 2020–2026 timeframe, addressing our first research

objective of systematically identifying and categorising primary applications. The framework reveals a clear hierarchy of research attention: news production and automation dominates, accounting for 38%, followed by audience perception and content analysis at 25%, ethical and legal considerations at 20%, and meta-research and implementation studies at 17%. These proportions reflect both industry-driven research priorities and the maturing trajectory of the field.

4.1. *The Primacy of News Production Research*

The predominance of news production and automation research reflects the tangible impact of AI technologies on journalistic practice. Our findings confirm that AI implementation in newsrooms has progressed from experimental projects to operational integration across major media organisations (Cools & Koliska, 2024; Nanz et al., 2025; Olsen, 2025). Findings indicate that successful adoption depends on workflow redesign and human-machine collaboration rather than automation for its own sake (Cools & Koliska, 2024; Thäsler-Kordonouri & Barling, 2025). The evidence indicates that structured data environments such as sports and finance remain the most fertile ground for automation (Graefe & Bohlken, 2020; Haim & Graefe, 2017), while generative AI tools are expanding the scope of what can be automated to include aspects of editorial judgment previously considered exclusively human (Cools & Diakopoulos, 2026; Gambino et al., 2026).

A critical insight from this category is that automation transforms rather than eliminates journalistic labour. Post-editing of AI-generated drafts has emerged as a distinct professional practice, requiring new competencies that blend editorial expertise with technical literacy (Danzon-Chambaud & Cornia, 2025; Thäsler-Kordonouri, 2025). Cross-national comparisons reveal that adoption trajectories are shaped by organisational culture, regulatory frameworks, and market conditions, suggesting that universal implementation models are unlikely to succeed (Danzon-Chambaud, 2023; Jia et al., 2024). The field would benefit from longitudinal studies that track how these organisational adaptations evolve as AI technologies continue to develop.

4.2. *Methodological Fragmentation and the Need for Standardisation*

Addressing our second and third research objectives, this review reveals significant methodological heterogeneity across the four categories. News production research predominantly employs case studies and qualitative approaches, while audience perception studies favour experimental designs. This methodological diversity reflects the interdisciplinary nature of the field but also indicates fragmentation that hinders cumulative knowledge building (Ioscote et al., 2024; Sandoval-Martín & Barrolleta, 2023).

A persistent weakness across all categories is the inadequate reporting of validation procedures. Many studies fail to specify how their findings were validated, and those that do often rely on small or homogenous samples. This limitation is particularly concerning given the high-stakes nature of AI deployment in news production, where errors can have significant societal consequences. The call for standardised quality assessment frameworks is not merely an academic concern but a practical necessity for ensuring the reliability of research that informs industry practice and policy (Danzon-Chambaud, 2021; Sandoval-Martín & Barrolleta, 2023).

Multiple studies confirm that revealing AI authorship significantly influences audience evaluations, though the direction and magnitude of this effect vary considerably across contexts (La-Rosa Barrolleta & Sandoval-Martín, 2024; B. Liu & Wei, 2018; Waddell, 2025). The machine heuristic—whereby audiences attribute machine-like characteristics of objectivity and accuracy to AI-generated content—plays a central mediating role (Wang & Ophir, 2026). Cultural context emerges as a critical moderator: audiences in

different countries respond to AI disclosure in markedly different ways, reflecting varying levels of technological trust, media literacy, and prior exposure to AI systems (Y. Liu, 2025; Zheng et al., 2018). This finding has direct implications for media organisations operating across multiple markets, as it suggests that transparency strategies must be locally adapted rather than globally applied.

4.3. Ethical and Legal Gaps

The evaluation of ethical, legal, and theoretical considerations reveals important deficiencies in current frameworks, particularly regarding copyright and authorship protection. Copyright protection for AI-generated news remains contested across jurisdictions, with the European Union's anthropocentric approach contrasting with more permissive regimes in China (Kuai, 2024; Trapova & Mezei, 2022). These legal uncertainties create practical challenges for news organisations seeking to deploy AI systems while managing intellectual property risk. Algorithmic transparency has emerged as a central ethical concern, with scholars documenting how the opacity of AI decision-making processes can undermine accountability in news production (Diakopoulos & Koliska, 2017; Dorr & Hollnbuchner, 2017).

The risk of AI-generated misinformation remains a pressing concern. Experimental evidence demonstrates that AI-generated content can achieve credibility levels comparable to authentic news, raising urgent questions about information ecosystem security (Elhosary, 2026; W. Kim & Ryoo, 2026). Algorithmic bias in AI-generated news imagery and text has been documented, with studies revealing embedded stereotypes that risk amplifying existing social inequalities (Elhosary, 2026; Sigsgaard, 2026). These findings underscore the need for robust ethical frameworks that are integrated into the design and deployment of AI systems rather than treated as afterthoughts.

4.4. Toward an Integrated Theoretical Framework

Drawing on the convergent evidence from qualitative thematic analysis, STM, and bibliometric network analysis, Figure 9 proposes an integrated theoretical framework that maps the relationships among the four categories and identifies key moderating mechanisms. The framework positions AI and ML technologies as exogenous drivers (LLMs, NLG systems, computer vision, generative AI) that enable transformation across the news production pipeline. News production and automation research (Category 1) constitutes the entry point: technological capabilities determine the scope and nature of automation in content generation, workflow integration, and editorial decision-making.

From news production, two pathways emerge. First, AI-generated content reaches audiences, triggering perceptual and evaluative responses captured in the audience perception and content analysis category (Category 2). Second, the deployment of automated systems raises legal and regulatory questions that are the focus of the ethical, legal, and theoretical considerations category (Category 3). Two critical moderators condition the audience pathway: cultural context, which shapes how different populations interpret and respond to AI-generated content (Y. Liu, 2025; Zheng et al., 2018), and disclosure and attribution practices, which influence whether audiences apply the machine heuristic—attributing machine-like characteristics of objectivity and accuracy to AI-generated outputs—or engage in more critical evaluation (Sundar, 2008; Wang & Ophir, 2026). Notably, the STM analysis reveals that legal-regulatory vocabulary and institutional-sociological discourse pervade the literature across all four categories, indicating that the ethical–legal domain functions as a discursive backbone of the field rather than a separate thematic silo.

Both the audience perception and ethics categories feed into meta-research and implementation studies (Category 4), which synthesise empirical evidence, document field-level patterns, and generate methodological guidance. This meta-level analysis produces feed-

back loops that inform news production practices: systematic reviews identify best practices and persistent gaps, implementation studies reveal context-specific barriers and enablers, and methodological standards progressively raise the quality floor for the entire field.

The framework advances prior theoretical work in two respects. First, it moves beyond static typologies of AI journalism research (Ioscote et al., 2024; Sandoval-Martín & Barrolleta, 2023) by specifying directional relationships and feedback mechanisms among categories. Second, it identifies the machine heuristic (from Sundar’s MAIN model (Sundar, 2008)) and cultural context as empirically grounded moderators that explain variance in audience responses, directly extending the agency dimension of the MAIN model to the specific context of AI-generated news. The framework generates testable propositions: (a) disclosure practices moderate the relationship between AI-generated news production and audience trust, with transparent attribution reducing the machine heuristic’s influence; (b) cultural context moderates the acceptability of automation in different journalistic domains, with societies characterised by higher uncertainty avoidance showing greater resistance to automated content (W. Kim & Ryoo, 2026); and (c) the strength of feedback from meta-research to practice depends on institutional mechanisms for knowledge transfer between academia and industry.

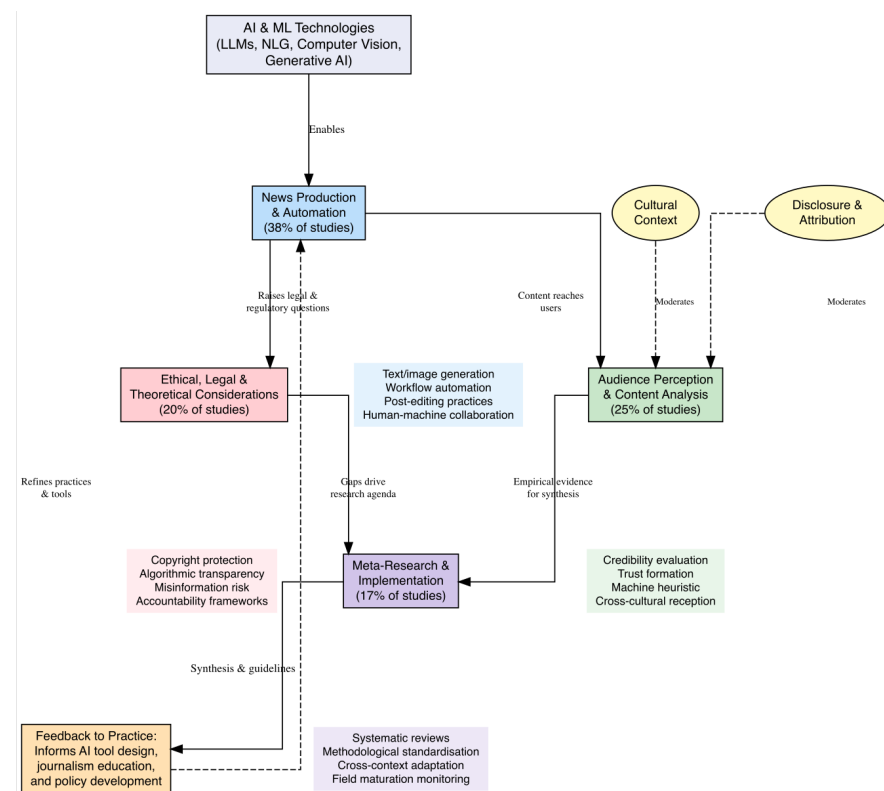


Figure 9. Integrated theoretical framework of AI/ML applications in journalism research. The model identifies four interconnected research domains, two key moderating mechanisms (cultural context and disclosure/attribution practices), and feedback loops from meta-research to practice. Percentage values indicate the proportion of studies in each category based on qualitative classification.

4.5. Field Maturation and Persistent Challenges

Meta-research studies document the field’s evolution from conceptual discussions in earlier periods to increasingly sophisticated empirical investigations (Ioscote et al., 2024; Sonni et al., 2024). The growing number of systematic reviews and bibliometric analyses indicates a field that is self-reflexively examining its own development, a hallmark of academic maturation (Danzon-Cham baud, 2021; Sandoval-Martín & Barrolleta, 2023). However, this maturation is uneven. Implementation studies reveal that AI adoption

patterns differ substantially across media markets, with research concentrated in Western contexts and limited evidence from the Global South (Arias Robles et al., 2023; Jamil, 2021; Shah et al., 2024; Zulqarnain et al., 2026). The dominance of case studies from major news organisations in developed countries limits our understanding of how AI technologies are being adopted in smaller outlets, local journalism, and developing media markets.

Our proposed four-category framework addresses the fourth research objective by providing a structured approach for understanding how AI/ML technologies are being integrated into journalism and media research methodologies. The framework reveals key insights: a disproportionate focus on news production applications suggests industry-driven research priorities; complex interactions between categories indicate that developments in one area—such as new automation capabilities—have ripple effects on audience perception, ethical considerations, and implementation practices. The significant methodological variation across categories reflects the field's interdisciplinary nature but also highlights the urgent need for standardised evaluation approaches.

4.6. Future Research Directions

Responding to our fifth research objective, our analysis identifies several priority areas for future investigation. First, longitudinal studies tracking AI systems and their impact over time are urgently needed to understand the sustainability and evolution of automation practices. Second, cross-cultural research that systematically includes perspectives from the Global South is essential for developing globally applicable theoretical frameworks. Extending this methodology to under-represented media markets—particularly in Latin America, Africa, and South Asia—would test the generalisability of our findings across distinct regulatory, cultural, and technological contexts. Third, the development of standardised validation protocols and quality assessment instruments would significantly strengthen the field's methodological rigour. Fourth, as generative AI technologies continue to evolve rapidly, research must address emerging challenges around multi-modal content generation, AI accountability, and the reconfiguration of professional roles in increasingly automated newsrooms (Dierickx, 2023; Dodds et al., 2025; Hollanek et al., 2025). Fifth, future research should incorporate a gender perspective, examining both the gender composition of authorship in AI journalism research and potential gender biases in AI-mediated news production, algorithmic curation, and audience reception.

In summary, our analysis addresses all five research aims by performing the following processes: (1) developing a four-category classification framework for AI/ML applications; (2) evaluating methodological approaches across categories and identifying validation gaps; (3) assessing limitations including geographical concentration and ethical framework deficiencies; (4) proposing an integrated framework that maps relationships between categories; and (5) examining how AI/ML methods are transforming journalism and media research practices and identifying priority directions for future work.

5. Managerial and Practical Implications

The findings of this review carry significant implications for media practitioners, educators, and policymakers. For media organisations, the findings suggest that successful AI integration depends on workflow redesign and human-machine collaboration rather than automation-driven cost reduction (Cools & Koliska, 2024; Nanz et al., 2025; Olsen, 2025). Implementation strategies should prioritise incremental deployment, allowing for organisational learning and cultural adaptation. The emergence of post-editing as a distinct professional practice (Danzon-Chambaud & Cornia, 2025; Thäsler-Kordonouri, 2025) suggests that newsrooms need to invest in training programmes that equip journalists with the skills to work effectively with AI-generated content while maintaining editorial standards. Furthermore,

the finding that audience perceptions of AI-generated content vary significantly across cultural contexts (Y. Liu, 2025; Zheng et al., 2018) underscores the importance of locally adapted transparency strategies rather than one-size-fits-all disclosure approaches.

For educators, the findings underscore the urgent need to integrate AI literacy into journalism curricula. As AI tools become embedded in news production workflows, journalists require not only technical competency but also critical understanding of algorithmic bias, transparency, and ethical considerations (Dodds et al., 2025; Hollanek et al., 2025). Educational institutions should develop interdisciplinary programmes that combine computational methods with journalistic ethics and media theory to prepare students for hybrid roles in increasingly automated newsrooms.

For policymakers, this review highlights critical regulatory gaps in copyright protection for AI-generated content, accountability frameworks for algorithmic decision-making, and standards for AI transparency in news production (Diakopoulos & Koliska, 2017; Kuai, 2024; Trapova & Mezei, 2022). The risk of AI-generated misinformation and algorithmic bias (Elhosary, 2026; W. Kim & Ryoo, 2026) demands coordinated policy responses that balance innovation with public interest protections. Policies should also support workforce adaptation through reskilling initiatives that preserve journalistic quality and ethical standards in increasingly automated news environments.

6. Limitations

Several limitations of the reviewed literature and the review methodology should be acknowledged. First, the reliance on Scopus and Web of Science as primary databases, combined with the restriction to English-language publications, may have excluded relevant research published in other languages or indexed in regional databases. Although the sample includes studies from diverse geographical contexts, the overrepresentation of research from Spain, the United States, and the United Kingdom suggests that findings from other regions may be underrepresented.

Second, most studies in the reviewed corpus employ cross-sectional designs, providing valuable correlational data but limiting causal inferences about the relationship between AI implementation and journalistic outcomes. The few experimental studies offer stronger evidence for causal effects but typically examine short-term responses to controlled stimuli rather than naturalistic newsroom engagement over time. Longitudinal investigations remain relatively scarce, creating a significant gap in understanding how AI adoption trajectories evolve.

Third, measurement inconsistencies present a methodological challenge across the reviewed literature. Studies vary considerably in how they operationalise key constructs such as “AI adoption,” “automation,” “audience trust,” and “credibility.” This heterogeneity complicates direct comparisons across studies and may partially explain divergent findings. Similarly, validation procedures vary widely, with some research employing established instruments while others use adapted scales with limited psychometric documentation.

Fourth, sampling limitations are particularly noteworthy. Despite the growing body of work on AI in journalism, male participants and non-Western populations are underrepresented in many audience perception studies. The concentration of news production case studies in major Western news organisations limits understanding of how AI technologies are adopted in smaller outlets, local journalism, and developing media markets.

Fifth, the rapid evolution of AI technologies during the study period (2020–2026) presents a challenge for cross-temporal comparisons. Studies from the early part of this period examined fundamentally different technological capabilities than those published more recently, particularly following the emergence of large language models. The field’s

rapid development means that some findings may already be dated, and the long-term implications of recent technological advances remain uncertain.

Finally, the classification framework, while grounded in the literature and independently validated by the STM (optimal $K = 4$), organises studies across partially overlapping analytical dimensions. Audience perception and content analysis, though thematically convergent, employ different methodological traditions (experimental/survey vs. computational/text-analytic). Meta-research and implementation studies operate at different levels of analysis (field-level vs. organisational). Some studies could reasonably be placed in multiple categories, and the quantitative proportions reported should be understood as indicative distributions that capture thematic affinities rather than rigid partitions. Additionally, formal quality assessment of individual studies was not conducted due to the substantial methodological heterogeneity of the included studies, which span experiments, surveys, case studies, content analyses, and system development papers; no single quality assessment instrument would be appropriate across all designs. Future research should address these limitations through more diverse sampling strategies, longitudinal designs, standardised measurement protocols, and improved channels for knowledge exchange between academia and industry.

7. Conclusions

This systematic review has provided comprehensive insights into the integration of AI and ML technologies in journalism practice by analysing 121 peer-reviewed publications spanning 2020 to 2026. Through a multi-method approach combining qualitative thematic analysis, structural topic modelling, and bibliometric network analysis, we have developed a four-category classification framework that organises a rapidly expanding field into coherent thematic areas: news production and automation, audience perception and content analysis, ethical and legal considerations, and meta-research and implementation studies.

Several key findings emerge from this synthesis. First, news production and automation dominates the research landscape, reflecting the tangible impact of AI on journalistic practice, though the field is evolving from descriptive case studies toward more sophisticated empirical investigations examining organisational, cultural, and ethical dimensions. Second, audience perception research has matured considerably, with the machine heuristic—originating from Sundar’s MAIN model—consistently identified as a central mediating mechanism, and with cultural context and disclosure practices emerging as critical moderators of how audiences evaluate AI-generated content. Third, ethical and legal frameworks lag behind technological developments, with copyright protection for AI-generated news remaining contested across the European Union, the United States, and China, creating uncertainty for practitioners and policymakers. Fourth, the STM analysis revealed that legal-regulatory vocabulary and institutional-sociological discourse pervade the literature across all categories, indicating that the field’s engagement with the institutional implications of AI is not confined to a single thematic area but functions as a shared discursive backbone.

This study makes a significant theoretical contribution by developing an integrated framework that maps the directional relationships among the four research domains, identifies cultural context and disclosure practices as key moderating mechanisms, and generates testable propositions for future investigation. The framework advances beyond static typologies by specifying how developments in automation capabilities cascade through audience perception, raise ethical questions, and inform meta-research synthesis, with feedback loops that progressively refine journalistic practice.

Looking forward, the field must address several critical challenges. Longitudinal studies tracking AI systems and their societal impacts over time are urgently needed. Cross-

cultural research systematically including perspectives from underrepresented regions is essential for developing globally applicable theoretical frameworks. The development of standardised validation protocols and quality assessment instruments would significantly strengthen methodological rigour. As generative AI technologies continue to evolve, researchers must grapple with emerging questions about multi-modal content verification, algorithmic accountability, and the reconfiguration of professional roles in increasingly automated news production environments.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
ML	Machine Learning
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
NLP	Natural Language Processing
LLM	Large Language Model
STM	Structural Topic Model

References

- Alivi, M. A., Ghazali, A. H. A., Tamam, E., & Osman, M. N. (2021). Motives to use online news and the impact on satisfaction with the government and vote choice. *Electronic Government, an International Journal*, 17(1), 55–74. [\[CrossRef\]](#)
- Anderson, C. W. (2013). Towards a sociology of computational and algorithmic journalism. *New Media & Society*, 15(7), 1005–1021.
- Aria, M., & Cuccurullo, C. (2017). bibliometrix: An R-tool for comprehensive science mapping analysis. *Journal of Informetrics*, 11(4), 959–975. [\[CrossRef\]](#)
- Arias Robles, F., Marín-Sanchiz, C. R., Abellán-Mancheño, A., & García-Avilés, J. A. (2023). Transparency in informative content . An analysis of methods in Spanish data journalism (2019–2022). *Analisi-Quaderns de Comunicació i Cultura*, 68, 97–116.
- Baptista, J. P., Rivas-de-Roca, R., Gradim, A., & Pérez-Curiel, C. (2025). Human-made news vs AI-generated news: A comparison of Portuguese and Spanish journalism students' evaluations. *Humanities and Social Sciences Communications*, 12(1), 567. [\[CrossRef\]](#)

- Bartleman, M., Schapals, A. K., & Dubois, E. (2026). Generative AI and the new landscape of automated journalism: A systematized review of 185 studies (2012–2024). *Journalism and Media*, 7(1), 39. [\[CrossRef\]](#)
- Bhaskaran, H., Kashyap, G., & Mishra, H. (2024). Teaching data journalism: A systematic review. *Journalism Practice*, 18(3), 722–743.
- Broussard, M. (2016). Big data in practice: Enabling computational journalism through code-sharing and reproducible research methods. *Digital Journalism*, 4(2), 266–279.
- Bucher, T. (2017). The algorithmic imaginary: Exploring the ordinary affects of facebook algorithms. *Information, Communication & Society*, 20(1), 30–44. [\[CrossRef\]](#)
- Camaj, L., Lanosga, G., & Martin, J. (2025). A global perspective on data journalism materiality: Knowledge production across public transparency infrastructure environments. *Digital Journalism*, 13(3), 418–437.
- Carlson, M. (2015). The robotic reporter: Automated journalism and the redefinition of labor, compositional forms, and journalistic authority. *Digital Journalism*, 3(3), 416–431.
- Caswell, D., & Dörr, K. (2018). Automated Journalism 2.0: Event-driven narratives: From simple descriptions to real stories. *Journalism Practice*, 12(4), 477–496.
- Chung, J., & Lee, J. (2026). AI byline, human content: Exploring how source and message framing shape news perception. *Computers in Human Behavior*, 179, 108949. [\[CrossRef\]](#)
- Coddington, M. (2015). Clarifying journalism's quantitative turn: A typology for evaluating data journalism, computational journalism, and computer-assisted reporting. *Digital Journalism*, 3(3), 331–348.
- Cools, H., & Diakopoulos, N. (2026). Uses of generative AI in the newsroom: Mapping journalists' perceptions of perils and possibilities. *Journalism Practice*, 20(3), 878–896.
- Cools, H., & Koliska, M. (2024). News automation and algorithmic transparency in the newsroom: The case of the Washington post. *Journalism Studies*, 25(6), 662–680. [\[CrossRef\]](#)
- Danzon-Chambaud, S. (2021). A systematic review of automated journalism scholarship: Guidelines and suggestions for future research. *Open Research Europe*, 1, 4. [\[CrossRef\]](#) [\[PubMed\]](#)
- Danzon-Chambaud, S. (2023). Automated news in practice: A cross-national exploratory study. *Open Research Europe*, 3, 95. [\[CrossRef\]](#)
- Danzon-Chambaud, S., & Cornia, A. (2023). Changing or reinforcing the “rules of the game”: A field theory perspective on the impacts of automated journalism on media practitioners. *Journalism Practice*, 17(2), 174–188.
- Danzon-Chambaud, S., & Cornia, A. (2025). The cultural capital you need to work with automated news: Not only “your beautiful piece of work”, but also “patterns that emerge”. *Journalism*, 26(12), 2581–2598.
- de-Lima-Santos, M. F. (2024). The entanglements between data journalism, collaboration and business models: A systematic literature review. *Digital Journalism*, 12(2), 256–281.
- Demirci, S., & Sagioglu, S. (2022). TwitterBulletin: An intelligent and real-time automated news categorization tool for twitter. *Journal of Universal Computer Science (JUCS)*, 28(4), 345–377. [\[CrossRef\]](#)
- Descampe, A., Massart, C., Poelman, S., Standaert, F. X., & Standaert, O. (2022). Automated news recommendation in front of adversarial examples and the technical limits of transparency in algorithmic accountability. *AI and Society*, 37(1), 67–80.
- Diakopoulos, N., & Koliska, M. (2017). Algorithmic transparency in the news media. *Digital Journalism*, 5(7), 809–828.
- Dierickx, L. (2023). News automation, materialities, and the remix of an editorial process. *Journalism*, 24(3), 654–670.
- Dierickx, L., Opdahl, A. L., Khan, S. A., Lindén, C. G., & Guerrero Rojas, D. C. (2024). A data-centric approach for ethical and trustworthy AI in journalism. *Ethics and Information Technology*, 26(4), 64. [\[CrossRef\]](#)
- Dodds, T., Vandendaele, A., Simon, F. M., Helberger, N., Resendez, V., & Yeung, W. N. (2025). Knowledge silos as a barrier to responsible AI practices in journalism? Exploratory evidence from four dutch news organisations. *Journalism Studies*, 26(6), 740–758. [\[CrossRef\]](#)
- Dorr, K. N., & Hollnbuchner, K. (2017). Ethical challenges of algorithmic journalism. *Digital Journalism*, 5(4), 404–419.
- Elhosary, M. (2026). Pixels of prejudice: Decoding embedded biases in ai-generated news imagery and their implications for visual journalism-toward an algorithmic-mediated visual framing. *Journalism & Mass Communication Quarterly*, 103(2), 430–461.
- Erkmen, O. (2024). Data Journalism: A systematic literature review. *Journalism Studies*, 25(1), 58–79.
- Gambino, O. J., García Mendoza, C. V., Hernandez Minutti, B., Zapata-Manilla, C. M., Bernal-Trani, M. A., & Calvo, H. (2026). A modular approach to automated news generation using large language models. *Information*, 17(4), 319. [\[CrossRef\]](#)
- Gavurova, B., Skare, M., Hynek, N., Moravec, V., & Polishchuk, V. (2024). An information-analytical system for assessing the level of automated news content according to the population structure—A platform for media literacy system development. *Technological Forecasting and Social Change*, 200, 123161. [\[CrossRef\]](#)
- Gillespie, T. (2014). The relevance of algorithms. In T. Gillespie, P. J., Boczkowski, & K. A. Foot (Eds.), *Media technologies: Essays on communication, materiality, and society* (pp. 167–194). MIT Press.
- Graefe, A., & Bohlken, N. (2020). Automated journalism: A meta-analysis of readers' perceptions of human-written in comparison to automated news. *Media and Communication*, 8(3), 50–59. [\[CrossRef\]](#)

- Haapanen, L., & Leppänen, L. (2020). Recycling a genre for news automation: The production of valtti the election bot. *AILA Review*, 33(1), 67–85. [\[CrossRef\]](#)
- Haim, M., & Graefe, A. (2017). Automated news: Better than expected? *Digital Journalism*, 5(8), 1044–1059. [\[CrossRef\]](#)
- Henestroza, A. L., Greiving, H., & Kimmerle, J. (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. [\[CrossRef\]](#)
- Hollanek, T., Peters, D., Drage, E., & Hernandez, R. (2025). AI, journalism, and critical AI literacy: Exploring journalists' perspectives on AI and responsible reporting. *AI and Society*, 40(8), 6393–6405. [\[CrossRef\]](#)
- Hong, J. W., Chang, H. C. H., & Tewksbury, D. (2025). Can AI become Walter Cronkite? Testing the machine heuristic, the hostile media effect, and political news written by artificial intelligence. *Digital Journalism*, 13(4), 845–868.
- 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. [\[CrossRef\]](#)
- Jamil, S. (2021). Increasing accountability using data journalism: Challenges for the Pakistani journalists. *Journalism Practice*, 15(1), 19–40.
- Jia, C., Riedl, M. J., & Woolley, S. (2024). Promises and perils of automated journalism: Algorithms, experimentation, and “teachers of machines” in China and the United States. *Journalism Studies*, 25(1), 38–57. [\[CrossRef\]](#)
- Kim, D., & Kim, S. (2021). A model for user acceptance of robot journalism: Influence of positive disconfirmation and uncertainty avoidance. *Technological Forecasting and Social Change*, 163, 120448. [\[CrossRef\]](#)
- Kim, H. M., Lee, E. J., Park, J. W., & Walter, N. (2026). Synthetic news, natural doubts? A meta-analysis of credibility perceptions of AI-generated news. *Cyberpsychology Behavior and Social Networking*, 29(5), 281–288. [\[CrossRef\]](#) [\[PubMed\]](#)
- Kim, W., & Ryoo, Y. (2026). The literacy paradox: How AI literacy amplifies biases in evaluating AI-generated news articles. *International Journal of Information Management*, 86, 102992. [\[CrossRef\]](#)
- 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 and Society*, 26(9), 5150–5168. [\[CrossRef\]](#)
- La-Rosa Barrolleta, L. A., & Sandoval-Martín, T. (2024). Artificial intelligence versus journalists: The quality of automated news and bias by authorship using a Turing test. *Anàlisi: Quaderns de Comunicació i Cultura*, 70, 15–36. [\[CrossRef\]](#)
- Lee, S., Nah, S., Chung, D. S., & Kim, J. (2020). Predicting AI News credibility: Communicative or social capital or both? *Communication Studies*, 71(3), 428–447. [\[CrossRef\]](#)
- Lewis, S. C., Guzman, A. L., & Schmidt, T. R. (2019). Automation, journalism, and human–machine communication: Rethinking roles and relationships of humans and machines in news. *Digital Journalism*, 7(4), 409–427. [\[CrossRef\]](#)
- Lischka, J. A., Schaetz, N., & Oltersdorf, A. L. (2023). Editorial technologists as engineers of journalism's future: Exploring the professional community of computational journalism. *Digital Journalism*, 11(6), 1026–1044. [\[CrossRef\]](#)
- Liu, B., & Wei, L. (2018). Reading machine-written news: Effect of machine heuristic and novelty on hostile media perception. *Lecture Notes in Computer Science*, 10901, 307–324. [\[CrossRef\]](#)
- Liu, Y. (2025). Culture or industry: Chinese and American young journalists' usage and perception of AI and Gen-AI. *Journalism Practice*, 1–20. [\[CrossRef\]](#)
- Mazari, N. (2025). Unpacking public trust in ai-generated news: Constructing and validating a three-factor measurement tool. *Moscow University Journalism Bulletin*, 2025(6), 53–79.
- Møller, L. A. (2022). Between personal and public interest: How algorithmic news recommendation reconciles with journalism as an ideology. *Digital Journalism*, 10(10), 1794–1812. [\[CrossRef\]](#)
- Nanz, A., Binder, A., & Matthes, J. (2025). AI in the newsroom: Does the public trust automated journalism and will they pay for it? *Journalism Studies*, 26(14), 1745–1764. [\[CrossRef\]](#)
- Napoli, P. M. (2014). Automated media: An institutional theory perspective on algorithmic media production and consumption. *Communication Theory*, 24(3), 340–360. [\[CrossRef\]](#)
- Oh, C., Choi, J., Lee, S., Park, S., Kim, D., Song, J., Kim, D., Lee, J., & Suh, B. (2020, April 25–30). *Understanding user perception of automated news generation system*. 2020 CHI Conference on Human Factors in Computing Systems, Honolulu, HI, USA.
- Olsen, G. R. (2025). Enthusiasm and alienation: How implementing automated journalism affects the work meaningfulness of three newsroom groups. *Journalism Practice*, 19(2), 304–320. [\[CrossRef\]](#)
- Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., ... Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, 372, n71. [\[CrossRef\]](#) [\[PubMed\]](#)
- Rani Krishna, K. M., Somasundaram, K., Arulmozhivarman, P., Immanuel, S. A., & Rajkumar, E. R. (2025). Deep learning for text summarization using NLP for automated news digest. *Scientific Reports*, 15(1), 36343. [\[CrossRef\]](#) [\[PubMed\]](#)
- Roberts, M. E., Stewart, B. M., Tingley, D., Lucas, C., Leder-Luis, J., Gadarian, S. K., Albertson, B., & Rand, D. G. (2014). Structural topic models for open-ended survey responses. *American Journal of Political Science*, 58(4), 1064–1082. [\[CrossRef\]](#)

- Salih, M. I., Mohammed, S. M., Ibrahim, A. K., Ahmed, O. M., & Haji, L. M. (2025). Fine-tuning BERT for automated news classification. *Engineering, Technology & Applied Science Research*, 15(3), 22953–22959. [\[CrossRef\]](#)
- Sandoval-Martín, T., & Barrolleta, L. L. R. (2023). Research on the quality of automated news in international scientific production: Methodologies and results. *Cuadernos.Info*, 55, 114–136.
- Shah, M. H. A., Alivi, M. A., Dharejo, N., Dayo, F., Khoso, I. A., & Shah, A. (2024). Explaining journalist interns' concerns using AI technology in media workspace in Pakistan. *Pakistan Journal of Life & Social Sciences*, 22(2). [\[CrossRef\]](#)
- Shilina, M. G., Volkova, I. I., Bombin, A. Y., & Smirnova, A. A. (2023). Artificial journalism: The reverse of human-machine communication paradigm. Mapping the field of AI critical media studies. *Rudn Journal of Studies in Literature and Journalism*, 28(4), 757–768. [\[CrossRef\]](#)
- Shin, D. (2022). Expanding the role of trust in the experience of algorithmic journalism: User sensemaking of algorithmic heuristics in Korean users. *Journalism Practice*, 16(6), 1168–1191. [\[CrossRef\]](#)
- Sigsgaard, M. E. (2026). Striking the (im)balance—A review of the relative prevalence of meta-ethical models in AI journalism research. *Journalism*, 27(3), 757–775. [\[CrossRef\]](#)
- Sonni, A. F., Hafied, H., Irwanto, I., & Latuheru, R. (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(4), 1554–1570. [\[CrossRef\]](#)
- Srinivas, B., Bagadi, L., Darimireddy, N. K., Prasad, P. S., Satrupalli, S., & Kumar, A. (2024). Deep learning-based modified transformer model for automated news article summarization. *Facta Universitatis, Series: Electronics and Energetics*, 37(2), 261–276. [\[CrossRef\]](#)
- Sundar, S. S. (2008). The MAIN model: A heuristic approach to understanding technology effects on credibility. In M. J. Metzger, & A. J. Flanagan (Eds.), *Digital media, youth, and credibility* (pp. 73–100). MIT Press.
- Thäsler-Kordonouri, S. (2025). Refining automated news? The role of journalistic post-editing in shaping reader perceptions. *European Journal of Communication*, 40(5), 471–490. [\[CrossRef\]](#)
- Thäsler-Kordonouri, S., & Barling, K. (2025). Automated journalism in UK local newsrooms: Attitudes, integration, impact. *Journalism Practice*, 19(1), 58–75. [\[CrossRef\]](#)
- Thurman, N., Dörr, K., & Kunert, J. (2017). When reporters get hands-on with robo-writing: Professionals consider automated journalism's capabilities and consequences. *Digital Journalism*, 5(10), 1240–1259.
- 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. [\[CrossRef\]](#)
- van Dalen, A. (2012). The algorithms behind the headlines: How machine-written news redefines the core skills of human journalists. *Journalism Practice*, 6(5–6), 648–658.
- Waddell, T. F. (2025). The effects of AI attribution, source priming, and story topic polarization on news credibility. *Digital Journalism*, 1–18. [\[CrossRef\]](#)
- Wang, R., & Ophir, Y. (2026). Behind the black box: The moderating role of the machine heuristic on the effect of transparency information about automated journalism on hostile media bias perception. *Journalism*, 27(1), 103–121. [\[CrossRef\]](#)
- Wiley, S. K. (2023). The grey area: How regulations impact autonomy in computational journalism. *Digital Journalism*, 11(6), 889–905. [\[CrossRef\]](#)
- Young, M. L., & Hermida, A. (2015). From Mr. and Mrs. outlier to central tendencies: Computational journalism and crime reporting at the Los Angeles Times. *Digital Journalism*, 3(3), 381–397.
- Zheng, Y., Zhong, B., & Yang, F. (2018). When algorithms meet journalism: The user perception to automated news in a cross-cultural context. *Computers in Human Behavior*, 86, 266. [\[CrossRef\]](#)
- Zulqarnain, W., & Alivi, M. A. (2025). AI in media professions: Trends, challenges, and professional norms; a systematic literature review (2024–2025). *Journal of Media Horizons*, 6(7), 834–846.
- Zulqarnain, W., Alivi, M. A., & Zulqarnain, A. (2026). Selective resistance and strategic adoption: Professional culture and AI integration in a Global South media ecosystem. *Future Business Journal*, 12(1), 118. [\[CrossRef\]](#)

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