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Role of Artificial Intelligence in Shaping Consumer Demand in E-Commerce

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Abstract: The advent and incorporation of technology in businesses have reformed operations across industries. Notably, major technical shifts in e-commerce aim to influence customer behavior in favor of some products and brands. Artificial intelligence (AI) comes on board as an essential innovative tool for personalization and customizing products to meet specific demands. This research finds that, despite the contribution of AI systems in e-commerce, its ethical soundness is a contentious issue, especially regarding the concept of explainability. The study adopted the use of word cloud analysis, voyance analysis, and concordance analysis to gain a detailed understanding of the idea of explainability as has been utilized by researchers in the context of AI. Motivated by a corpus analysis, this research lays the groundwork for a uniform front, thus contributing to a scientific breakthrough that seeks to formulate Explainable Artificial Intelligence (XAI) models. XAI is a machine learning field that inspects and tries to understand the models and steps involved in how the black box decisions of AI systems are made; it provides insights into the decision points, variables, and data used to make a recommendation. This study suggested that, to deploy explainable XAI systems, ML models should be improved, making them interpretable and comprehensible.

Keywords: artificial intelligence; automation; e-commerce; machine learning; big data; customer relationship management (CRM)

1. Introduction

Technological advancement continues to create new opportunities for people across a variety of industries [1]. Technology helps to improve the efficiency, quality, and cost-effectiveness of the services provided by businesses. However, technological advancements can be disruptive when they make conventional technologies obsolete. Neha et al. [1] assert that cloud computing, blockchain, and AI are the current developments that may create new opportunities for entrepreneurs. The computer systems are also influencing and improving interactions between consumers and business organizations. Thus, the shift towards the improved use of technology has led to the creation of intelligent systems that can manage and monitor business models with reduced human involvement. AI systems that demonstrate an ability to meet consumers' demands in different sectors are necessary for the current economy [2]. AI plays a critical role in monitoring the business environment, identifying the customers' needs, and implementing the necessary strategies without or with minimal human intervention. Thus, it bridges the gap between consumers' needs and effective or quality services.

Therefore, AI is modifying the economic landscape and creating changes that can help consumers and entrepreneurs to reap maximum benefits. It is gaining popularity in businesses, especially in business administration, marketing, and financial management [3]. AI creates new opportunities that result in notable transformations in the overall economic systems. For instance, it causes the rapid unveiling of big data patterns and improved product design to meet customers' specifications and

preferences [1]. E-commerce is the major beneficiary of the increased use of AI to improve services' efficiency and quality.

AI helps in reducing complications that may result from human errors. Thus, although AI may reduce employment opportunities, its benefits to organizations are immense.

Notably, AI is a formidable driving force behind the development and success of e-commerce. In e-commerce, AI systems allow for network marketing, electronic payments, and management of the logistics involved in availing products to the customers. Di Vaio et al. [3] note that AI is becoming increasingly vital in e-commerce food companies because it maintains the production sites' hygienic conditions and ensures safe food production. It also helps in maintaining high levels of cleanliness of the food-producing equipment.

The automated systems collect, evaluate, and assess data at a rapid rate compared to human beings. AI helps e-commerce to capture the business trends and the changing market needs of customers. Therefore, the customers' increased convenience leads to increased satisfaction and balancing of the demand and supply mechanisms.

Kumar and Trakru [4] report that AI allows e-commerce to develop new ideas on satisfying the consumers' needs and keep up with the changing preferences and choices. Human intelligence may often be limited in carrying out some tasks in e-commerce, including predicting demand and supply chain mechanisms. AI simulates and extents human intelligence to address the rising challenges in e-commerce [5]. For instance, Soni [6] established that AI helps e-commerce platforms to manage and monitor their customers. Through AI, a business can gather a wide range of information and evaluate customers to ensure that quality services are offered to them. This helps e-commerce platforms understand the factors that influence their current and potential clients' purchasing behaviors. It improves the interactions between the e-commerce companies and their customers through chatbots and messengers. E-commerce companies use automation processes to eliminate redundancies in their operations. Kitchens et al. [7] state that AI allows for automated responses to questions raised by the customers. However, Kumar and Trakru [4] warn of potential threats and challenges to customers and e-commerce that limit the efficiency and effectiveness of AI in meeting the business expectations. Consequently, it is necessary to explore opportunities and challenges in light of changing consumer demands in e-commerce.

1.1. Statement of the Problem

Even though AI systems have revolutionized e-commerce, courtesy of the wide range of functionalities such as video, image and speech recognition, natural language, and autonomous objects, a range of ethical concerns have been raised over the design, development, and deployment of AI systems. Four critical aspects come into play: fairness, auditability, interpretability and explainability, and transparency. The estimation process via such systems is considered the 'black box' as it is less interpretable and comprehensible than other statistical models [8]. Bathaee [9] identifies that there are no profound ways of understanding the decision-making processes of AI systems. The black box concept implies that AI predictions and decisions are similar to those of humans. However, they fail to explain why such decisions have been made. While AI processes may be based on perceivable human patterns, it can be imagined that understanding them is similar to trying to determine other highly intelligent species. Because little can be inferred about the conduct and intent of such species (AI systems), especially regarding their behavior patterns, issues of the degree of liability and intent of harm also come into play. The bottom line revolves around how best to guarantee transparency to redeem trust among the targeted users within e-commerce spaces [9].

1.2. Proposed Solution

The main aim of the current study is to lay the foundation for a universal definition of the term explainability. AI systems need to adopt post hoc machine learning methods that will make them more interpretable [10]. While there is a wide range of taxonomic proposals on the definition and

classification of what should be considered 'explainable' in regards to AI systems [10], it is contended that there is a need for a uniform blueprint of the definition of the term and its components. To address the main objective, which is solving the black box problem, this research proposes the employment of XAI models. XAI models feature some level of explainability approached from various angles, including interpretability and transparency. Even though the current research recognizes the prevalence of studies under the topic and consults widely within the area, it goes a step ahead to offer a solution to the existing impasse, as seen in divided scientific contributions concerning what constitutes the concept of 'explainability'. In this regard, the article will contribute to the state of the art by establishing a more uniform approach towards research that seeks to create evidence based XAI models that will address ethical concerns and enhance business practices.

1.3. Overview of the Study

The current article provides a critical outline of key tenets of AI and its role in e-commerce. The project is structured into six main sections, which are the introduction, review of the literature, proposed method, results, discussion, and conclusion. The introduction part of the project provides an overview of the research topic 'role of AI in shaping consumer in E-commerce,' a statement of the problem and the proposed solution. Section 2 examines the available literature on artificial intelligence techniques, including sentimental analysis and opinion mining, deep learning, and machine learning. It also examines the AI perspective in the context of shaping the marketing strategies that have been adopted by businesses. Section 3 discusses the methodology used to explore the research question. It identifies the research approach (word cloud analysis), sources of data (Neural Information Processing Systems (NIPS), and Cognitive Science Society (CSS)). Section 3 also details data analysis techniques, which include corpus analysis and concordance analysis. The results section provides the outcomes of the analyzed data, particularly the corpus generated from the word cloud. Some of the software, such as the Voyant Tools, was used to reveal the most prominent words. A concordance analysis table was also generated, in the results section, for the term 'explainability'. Section 5 provides a detailed discussion of the outcome of the research as well as the key observations made regarding opaque systems, interpretable systems, and comprehensible systems. The overall outcome of the study and implications for future research are provided in the conclusion section.

2. Artificial Intelligence Techniques

2.1. Sentimental Analysis and Opinion Mining

Communication between a business organization and customers occurs through user-generated content on websites and social media. The views of clients expressed on Twitter, Instagram, and Facebook can impact the service providers' image and reputation. The sentimental analysis involves methodologies that help companies evaluate the meaning of online content and develop strategies that can improve customer loyalty [7]. Thus, sentimental analysis refers to an automation process that helps customers to extract emotions from customers' online content by processing unstructured data and creating models to extract information from it [11,12]. It helps managers or decision-makers to understand customers' responses towards particular topics, and it helps to determine if the event is neutral, positive, or negative. There is a minor difference between sentimental analysis and opinion planning. Opinion planning focuses on extraction and analyzing customers' opinions while searching for clients' expressions or words and analyzing them. Opinion mining involves using predefined rules to establish rules based on automated systems that analyze data [13]. It helps in the classification and investigation of customers' behavior and attitudes towards an event, a brand, company services, and products. Twitter is one platform that contains relevant information and hashtags that have been followed by large numbers of people [14].

Sentimental analysis or opinion mining classifies customer emotions into three levels: the sentence level, document level, and entity level.

Natural language processing (NLP) is a fundamental technique for promoting sentimental analysis. It is a sub-domain in AI that focuses on understanding the unstructured content found on social media platforms and organizing it to make it easier for sentimental analysis [13]. It helps the computer-aided system to assess and understand the various languages spoken by customers. NLP is also a key component in opinion mining [13]. It helps people process a large amount of information from unstructured data by analyzing the sentence structures and computing it into the sentence or document level using linguistic databases such as treebanks and WordNet [14]. Besides, sentiment polarity from user-generated texts can be classified using various approaches: a semantic approach, machine learning, lexical-based analysis, and a statistical approach [14]. These approaches help to eliminate unnecessary noise or information such as URLs, slang, and abbreviations, thus, they decrease the size of the dataset. Therefore, through sentimental analysis and opinion mining, customers can understand the type of shopping experience they are likely to have in a particular enterprise based on customers' views or opinions on social media platforms.

2.2. Related Work

2.2.1. Deep Learning

The rapid increase in cross-border e-commerce (CBEC) and demand for international logistics have rendered third-party logistics (3PL) obsolete because they can meet the current requirements of CBEC [12]. The random arrival of goods or products creates a big challenge. The deep-learning method avoids these challenges through the optimization and demand forecasting process [12]. It helps e-commerce companies identify the best advertisements to use, understand customers' intentions, and optimize products' delivery. Deep learning also supports decision making in a logistics service capacity.

2.2.2. Machine Learning

Machine learning techniques use machine learning algorithms to control data processing by classifying linguistic data and presenting it in vector form [14]. The machine learning techniques help e-commerce businesses to detect anomalies in the products and prices. They also help the companies track assets in warehouses and improve their pages or websites' rankings. Machine learning algorithms help e-commerce companies to learn from the derived data and create solutions to challenges they may be experiencing. Thus, machine learning models are used to solve various economic issues.

2.3. AI Perspective

Davenport et al. [15] assert that AI has great potential in shaping the marketing strategies adopted by businesses. AI redefines business models and sales processes to address the changing macro-business environment. The impact of AI is substantial in customer behavior. Soni et al. [5] argue that the changes brought about by AI in e-commerce aim at enhancing customer experience through improved systems that bridge the gap between the business and consumers. Companies in e-commerce face the challenge of addressing the continually changing customer expectations. Businesses are crafting ways to remain competitive by going beyond merely delivering what customers demand. Soni [5] postulates that the appropriateness of the time and channels of delivery are central in customer service. A business that seems to be eliminating the customer's pain associated with purchasing processes will attract more consumers by expanding its market share. Such a business relies on machine learning to develop a model that enhances efficiency based on available information regarding the market and nature of the competition.

Marketing is a crucial component of the business as it convinces customers to prefer some products from individual enterprises to others. Tussyadiah and Miller [16] observe that AI has great potential in redefining marketing in the present and future. AI comes with new and dynamic marketing strategies with entirely new and improved ways of reaching out to customers. AI allows for attitudinal

segmentation making marketing strategies more sustainable. Additionally, AI ensures a comprehensive approach to understanding customer behavior hence tailoring marketing to win over individual buyers in e-commerce [17]. For instance, AI, as applied in marketing, supports changing user interfaces across platforms accessed by the customers, hence increasing their likelihood to purchase a given product. The hyper-personalization of marketing supported by AI is one critical aspect that influences customer's demand in e-commerce. Davenport et al. [15] stress the association between marketing and customer's purchasing behavior. On the contrary, Kachamas et al. [18] warn against a blanket belief that AI in marketing leads to increased consumer demand. Instead, the authors point out the complexities associated with AI in marketing. Customers remain exposed to malicious activities that may lead to a breach of information, thereby harming them. On the other hand, AI is quickly evolving, and businesses' strategies in e-commerce to attract customers become obsolete fast. The use of AI in marketing may mislead marketers, leading to unrealistic expectations. The study points out that AI comes with the concepts of perceived usefulness (PU) and perceived ease of use (PEOU), which may not necessarily be the case. Therefore, it is necessary to note the issues in using macro-levels of business operations before rolling out the market operations [16]. Adadi and Berrada [19] argue that, with the advent of AI, society is shifting towards a more algorithmic system characterized by the wide use of ML techniques. With this unprecedented advancement, an essential aspect of AI systems is that they have been deemed to lack transparency. Indeed, the BlackBox nature of Machine Learning (ML) systems allows unexplainable but powerful predictions to occur. When AI systems make predictions without explanations, they are bound to cause difficulties when there is a need to detect inappropriate decisions. Thus, organizations are exposed to biased data, incorrect decision making, and unsuitable modeling techniques in the algorithm lifecycle.

As AI systems are getting powerful, sophisticated and pervasive, the techniques for troubleshooting and monitoring them lag behind their adoption, leading to many risks that affect consumers. Marketing measurements are still one-dimensional. AI analytics continue to run statistical methods that are single-sided. They are based on unidirectional feedback and responses such as click-through purchase, customer responses, etc. While such traditional metrics are useful for gauging customer behavior, they are static and slow. Additionally, they do not reveal the real picture of consumers—that is, they are shallow. For example, in most cases, drilling down into consumer behavior is usually done through segmentation and clustering, which tends to be descriptive and outdated. While such analytics tend to reveal interesting consumer findings, the outcomes are always non-dynamic and contextually unsafe, and inappropriate for use to inspire actionable insight to influence the customer's daily activities and how they interact with the business. Arrieta et al. [10] echo similar findings; the dangers of using black-box systems are that they elicit unjustifiable decisions or those that do not allow the acquisition of detailed explanations of the target customer's behavioral patterns. This becomes an issue in a world where customers expect relevance, since they are not static in their thinking, interests, and needs.

Even though AI systems are highly precise, if they cannot explain why a given customer responds the way they did, it becomes difficult to gain insight that can generate contextually significant action. XAI presents as a solution to the problem of static AI data. Notably, with fully explainable AI, businesses can conduct dynamic analytics generating contextually relevant data. XAI is concerned with the issues revolving around trustworthiness. XAI mostly revolves around the evaluation of the moral and ethical standards of an ML. Thus XAI seeks to overcome the dangerous practice of "accepting" outcomes blindly, whether by necessity or by choice. Therefore, by implementing XAI models, analysts provide an output that can be understood to support rational human decision-making.

Additionally, analysts can easily assess decisions made by clients and users of AI systems to determine if they are rational—that is, if the decisions incorporate reasoning and do not conflict with legal or ethical norms. As echoed in the chorus voices across ML studies, there is an increased demand for ethical AI, thus pointing to the need for XAI models. However, as argued by Arrieta et al. [10], there is a lack of a novel framework that brings together previous works in the field as well as covering conceptual

propositions with a unified focus on the users of XAI. Thus, this research proposes a comprehensive framework for defining what comprises XAI, paving the way for large-scale implementation.

3. Proposed Method

Figure 1 below is an overview of the proposed method used in the study. In the research approach, the researcher utilized word cloud analysis. Data were collected from two databases, namely Cognitive Science Society and Neural Information Processing Systems. Finally, the collected data were analyzed through normalization of the frequency of the 'explainability' term, Voyant analysis, and concordance analysis.
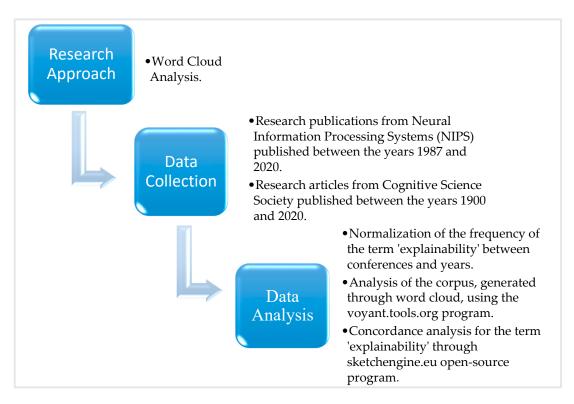

Research Approach
- Word Cloud Analysis.

Data Collection
- Research publications from Neural Information Processing Systems (NIPS) published between the years 1987 and 2020.
- Research articles from Cognitive Science Society published between the years 1900 and 2020.

Data Analysis
- Normalization of the frequency of the term 'explainability' between conferences and years.
- Analysis of the corpus, generated through word cloud, using the voyant.tools.org program.
- Concordance analysis for the term 'explainability' through sketchengine.eu open-source program.

Figure 1. A flowchart of the proposed method.

3.1. Research Approach

This research utilized a word cloud analysis to investigate the research problem and question. A word cloud analysis is a research approach where a visual representation of a word is generated based on its frequency [20]. In this approach, the image of the word generated becomes larger the more the term appears within the analyzed text. This research approach is appropriate for this study, given that the main purpose was to investigate the significance of the term 'explainability' within AI research databases and determine how the concept has been defined. According to Doran et al. [21], terms such as interpretability have been widely applied in research publications despite unclear definitions. Thus, through the word cloud analysis, the researcher was able to assess relevant terms in AI databases whose researchers rely on machine-learning-driven techniques to approach their study objectives. Therefore, the method was effective in identifying the focus of the written materials being assessed by highlighting the frequency of word use for a basic understanding of data as described by McNaught and Lam [22].

Additionally, compared to other methods of textual analysis, the word cloud analysis was the most appropriate for this study. For instance, in comparing word clouds to the user interface with a search box, Sinclair and Cardew-Hall [23] found that participants tended to prefer the search box to fill specific terms; however, they favored word clouds more when it came to dealing with open-ended

tasks. Kuo et al. [24] found similar results and argued that word clouds are an essential technique for giving impressions of the information in a query list. The overall conclusion is that word clouds are a useful visualization tool for communicating the overall textual picture [20].

3.2. Data Collection

Data used in this study were the linguistic corpora obtained from conference proceedings whereby research articles and peer-reviewed papers were evaluated. Data were gathered from the Neural Information Processing Systems (NIPS), with the target being a range of research publications from 1987 to 2020. Additionally, research papers from the Cognitive Science Society from between 1900 and 2020 (accessed via an open-source managed by the University of California) were obtained for analysis. These two ML communities were chosen for their richness in AI-based information [21]. Moreover, the wide information available makes it possible to analyze the trends in using the term explainability and the related concepts.

3.3. Data Analysis

The data analysis involved conducting a shallow assessment for the term 'explanation'. The frequencies were normalized between conferences and years, after which the plots in Figure 2a,b were derived. Figure 2a is a frequency plot for the term explainability obtained from the Cognitive Science Society database. Figure 2b is the frequency plot obtained from the Neural Information Processing Systems (NIPS) database searches. The voyant.tools.org program was used to analyze the corpus, generated through the word cloud analysis, to establish a connection between the words and, consequently, generate meaning. The researcher also utilized the sketchengine.eu open-source program to generate the concordance of the term 'explainability'.

4. Results

The word cloud plots (Figure 2a,b) are an easy way of understanding the composition of the 'explainability' concept and the related semantic meaning across the ML-driven databases chosen for this study. Here, essential words were perceived as those that first appeared in a 20-word window following a search of the term 'explanation'; such words also had a frequency above the average level. In Figure 2a, it is evident that the corpus reveals the prominent words as use, explanation, model, and emotion. Other notable words are learn and the system. The corpus (in Figure 2b) shows well-known words as model, learn, use, and data. Other prominent words are method, task, infer, and image. There are also essential words such as decision and prediction appearing within the 20-word window. Thus, the AI community in Figure 2a describes the term explainability as being related to words such as use, explanation, and model, among others, suggesting an emphasis on using system models that enhance learning, explanation, decision making, and prediction. The implication (in Figure 2b) is that the term explainability could be taken to mean using models that allow learning, ease of inference, and prediction, among others.

The corpus generated from the word cloud (in Figure 2a) reveals that the 20 most prominent words are as follows: system, explanation, model, emotion, learn, use, study, train, method, predict, data, estimate, control, result, show, decision, interpret, design, variance, image). Analyzing this corpus to formulate a connection between the words and generate meaning using voyant-tools.org (an open-source corpus analysis program) revealed that the most prominent words, as seen in Figure 3, were as follows: control; data; decision; design; emotion.

(**a**) Word Cloud 1   (**b**) Word Cloud 2

Figure 2. Frequency plot for the term explainability results, (**a**) word cloud 1 and (**b**) word cloud 2.
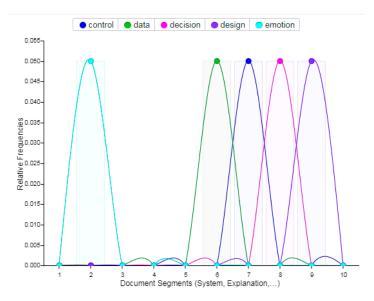
Figure 3. Word cloud 1 analysis.

Many meaningful sentences in the context of responsible XAI can, therefore, be formed from combining these words. For example, the words could be brought together to imply 'a design of data control that enhances decision making' or 'designing and controlling data in such a way that enhances emotion and decisions'. The corpus from word cloud 2 reveals 20 words as the most prominent (model, use, learn, data, method, predict, behavior, task, perform, base, show, infer, image, algorithm, propose, optimal, object, general, explain, network). Voyant analysis revealed that five words were the most prominent words: action; algorithm, base, behavior, data, and explain, as seen in Figure 4 below.
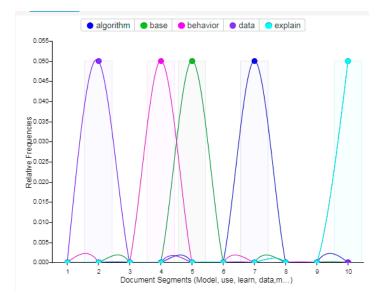

Figure 4. Word cloud 2 analysis.

Possible sentences from this word combination include: 'an algorithm that explains data behavior' or 'an algorithm behavior that is based on data explanation'. Additionally, upon looking for the concordance of the term 'explainability' in sketchengine.eu (an open-source program that analyses how real users of a given language use certain words), some terms emerged as critical definitional terms of the word: predictability, verifiability, user feedback, information management, data insights, analytics, determinism, understanding, and accuracy, as seen in Figure 5 below.

		Details	Left context	KWIC	Right context	
1	☐	ⓘ evo-art.org	ur primary levels and explicate their nonhomomorphic interlevel relations. </s><s>	**Explainability**	of emergence in relation to determinism and predictability is considered. </s><s> R	📋
2	☐	ⓘ juii.net	called empathy), as that's the precondition of finding help for people. </s><s> But	**explainability**	does not mean that every kind of behavior is "good", i.e. has a right to stay unchan	📋
3	☐	ⓘ iapa.org.au	s that it takes to actually apply analytics – data restrictions, model accuracy versus	**explainability**	, inter-departmental politics etc. </s><s> I subsequently started my tenure at SAS i	📋
4	☐	ⓘ jmsmith.org	the most profound truths and one that we should meditate seriously on. </s><s> "	**Explainability**	" and "rationality" are both good things...at its core, the irrationality and inexplicabili	📋
5	☐	ⓘ usemp-project.e...	ltimedia content shared by OSN users and is designed for interactive use and with	**explainability**	as a core requirement. </s><s> User assistance tools – that provide the users with	📋
6	☐	ⓘ usemp-project.e...	spective, translated into user control over automated processing and work towards	**explainability**	of obtained results. </s><s> As explained in Section 1.1.1, we discriminate betwee	📋
7	☐	ⓘ wise.io	and your next best action. </s><s> And in some industries, such as credit scoring,	**explainability**	of predictions can even be a regulatory requirement. </s><s> Most advanced mach	📋
8	☐	ⓘ usemp-project.e...	<s> Emphasis will be put on integrating user feedback in the USEMP tools and on	**explainability**	of the extraction processes in order to facilitate the adoption of the tools by the use	📋
9	☐	ⓘ usemp-project.e...	ds adapted to personal information management, with focus on user feedback and	**explainability**	in order to ensure fast adoption by the users. </s><s> S4 . Improve the manageme	📋
10	☐	ⓘ global-systems-...	h mappings should enjoy a number of features, including: clarity and conciseness,	**explainability**	, formal verifiability, and the ability of adapting to an enormous number of possible	📋
11	☐	ⓘ vukcevic.net	ents. </s><s> In one step of their modelling process, they do a trade-off between '	**explainability**	' and 'predictability'. </s><s> Specifically, they chose a model that was easier to int	📋
12	☐	ⓘ josemalvarez.es	mmenders based on optimizing a global cost function keeping advantages such as	**explainability**	and handling new users while improving accuracy </s><s> a set of extensions to e	📋
13	☐	ⓘ degreedays.net	the point of the site is to generate degree days for you , making the simplicity and	**explainability**	of the calculation process irrelevant. </s><s> So, when we can't use the Integratior	📋
14	☐	ⓘ opossem.org	ncy curves are trivial. </s><s> And if a social scientist felt compelled for reasons of	**explainability**	to discretize the analysis, then I certainly agree that doing an extreme-groups analy	📋
15	☐	ⓘ blackstone.name	s quite willing to replace the judgment of doctors with this net. </s><s> This lack of	**explainability**	is a practical problem for applications involving people, but it is not an argument de	📋
16	☐	ⓘ blackstone.name	n argument demonstrating that the net cannot understand. </s><s> Indeed, lack of	**explainability**	is to be expected if the net does understand. </s><s> The point is, understanding c	📋
17	☐	ⓘ bostoncommons.n...	s><s> At times it can be difficult to meet a company?s Data Science goal of model	**explainability**	– or data insights provided by the model – if the Data Scientist has not done a good	📋
18	☐	ⓘ wittgensteinrep...	and necessary condition; to these relations are added the claims of reducibility and	**explainability**	. </s><s> A supervening property or fact can be reduced to the property or fact on	📋
19	☐	ⓘ gfzk-leipzig.de	d by Klaus Werner </s><s> In closed systems, concepts like responsibility, justice,	**explainability**	create the desire to withdraw from instrumentalized inventions. </s><s> Abundance	📋
20	☐	ⓘ madm.eu	Further, the utilization of SentiBank features shows high potential for detection and	**explainability**	of such content. </s><s> Overall, multi-modal feature fusion can achieve an improv	📋

Figure 5. Concordance analysis for the term 'Explainability'.

5. Discussion

The findings from the results highlight critical tenets regarding the concept of explainability in AI. From the results, it is evident that specific keywords were prominently featured compared to others. Notably, words such as 'use', 'explanation', and 'model', as highlighted in Figure 2, confirm increased usability. The findings are key in addressing the shortcoming of the whole concept of explainability as reported by Soni et al. [5]. Similar results are reported in the case of Figure 3, which identifies notable words such as 'use', 'model', 'learn', and 'data'. The analysis reveals that the AI communities approach the concept of explainability differently, but with some general resemblance. The term is used to assist in evaluating the mechanism of machine language systems, such as understanding the working of the system, yet, at other times, to relate to concepts of particular inputs like determining how a given input was mapped to an output. From the analysis, certain key observations were made.

5.1. Opaque Systems

Mainly, this refers to a system where mapping inputs to outputs are not visible to the user. It can be perceived as a mechanism that only predicts an input, without stating why and how the predictions are made. Opaque systems exist, for example, when closed-source AI systems are licensed by an organization where the licensor prefers to keep their workings private. Additionally, black-box methodologies are categorized as opaque because they use algorithms that do not give insight into the actual reasoning for the system mapping of inputs to outputs [21].

5.2. Interpretable Systems

This refers to AI systems where clients cannot see, understand, and study how mathematical concepts are used to map inputs to the output. Thus, related issues include transparency and understanding. Regression models are considered interpretable, for instance, in comparing covariate heights to determine the significance of each aspect to the mapping. However, deep neural networks' functioning may not be interpretable, especially regarding the fact that input features are mostly based on automatic non-linear models [21].

5.3. Comprehensible Systems

Comprehensible AI models emit symbols without the use of inputs. These symbols are mostly words and allow the user to relate input properties to the outputs. Thus, the user can compile and understand the symbols relying on personal reasoning and knowledge about them. Thus, comprehensibility becomes a graded notion, with the extent of clarity being the difficulty or ease of use. The required form of knowledge from the user's side relates to the cognitive intuition concerning how the output, inputs, and symbols relate to each other [21]. Interpretable and comprehensible systems are improvements over opaque systems. The concept of interpretation and comprehension are separate: interpretation mostly relies on the transparency of system models, whereas comprehension requires emitting symbols that allow a user to reason and think [21]. Most present-day AI systems can produce accurate output but are also highly sophisticated if not outright opaque, making their workings incomprehensible and difficult to interpret. As part of the efforts to renew user trust in AI systems, there are calls to increase system explainability.

There is an increasing need to enhance user confidence in AI systems [25]. User confidence and trust are cited as the primary reasons for pursuing explainable AI. System users seek explanations for various reasons—to manage social interactions, assign responsibility, and persuade others. A critical aspect of explainable AI is that it creates an opportunity for personalized human–computer interaction. Instead of the brick and mortar models of decision-making techniques that cannot be understood or interpreted by humans, explainability ensures that the customer journey through machine learning and AI systems is modeled in a way that mimics human interactions. There is a need for machine learning to explain why and how individual recommendations or decisions are made [26]. The implication is that

consumers' activity on AI systems will be complemented to make better and accurate decisions faster. Thus, organizations will be able to leverage customer value. When giving advice, recommendations, or even descriptive aspects, looking for justifications and reasons behind the recommended action is important. It is not enough to predict or suggest outcomes as the best or the preferred action without showing connections between the data and the factors involved to arrive at the decisions [26].

McNaught and Lam [22] state that most people have the perception that a doctor is 'a kind of black box' who transforms symptoms of illnesses and related test outcomes into the best diagnosis for treatment. Doctors deliver diagnostic recommendations to patients without explaining why and how they arrived at such decisions. Mostly, doctors use high-level indicators or symptoms (which, in the context of AI systems, denote system symbols). However, when handling a patient, the doctor should be like a comprehensible model. When interacting with medical staff and other physicians, the doctor may be like an interpretable model. Other doctors will interpret the technical analysis like an analyst would do to a ML system to ensure that the decisions arrived at are backed up by the reasonable assessment of the evidence provided.

Thus, XAI ensures that the information provided is accurate and personalized, to engage with targeted users in the most optimal manner [26]. In this way, XAI will increase the offer's relevance, thus enhancing user engagement and interest. Additionally, XAI will offer aspects that drive predicted outcomes, allowing real-time adjustment of primary business aspects to optimize gains and corporate outcomes. Transparency and reasoning will contribute to a decrease in abandoned products and an increase in order value, and thus higher revenue and conversion rates. Therefore, this research proposes implementing XAI frameworks that possess the following features: interpretability and comprehensibility. However, responsible XAI is more than just the ML features: user-related aspects of external AI features that should be considered are trust, fairness, confidence, ethics, and safety, as highlighted in So [27]. Moreover, the actual meaning of XAI is dependent on the perspective of the user, as highlighted by So [27] in Figure 6. As illustrated in Figure 6, XAI utilizes customer data to support the process of decision-making, with the impact being witnessed in improved business outcomes.
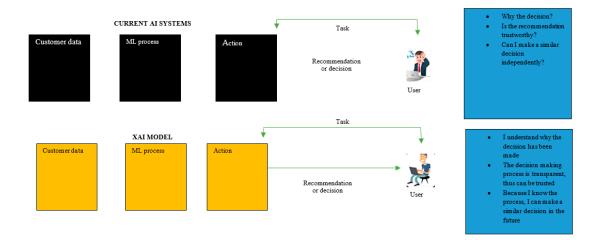

Figure 6. An analogy showing the differences between present-day AI and XAI models.

6. Conclusions

The study's main purpose was to lay the foundation for a universal definition of the term 'explainability'. The analyzed data from the word cloud plots revealed that the term 'explainability' is mainly associated with words such as model, explanation, and use. These were the most prominent words exhibited in the corpus generated from the word cloud. In the corpus from word cloud 1, they include emotion, design decision, data, control, image, variance, interpret, decision, show, result, control, estimate, data, predict, method, train, study, use, learn, model, explanation, and system.

In corpus word cloud 2, they include model, use, learn, data, method, predict, behavior, task, perform, base, show, infer, image, algorithm, propose, optimal, object, general, explain, network. After the Voyant analysis was conducted, the most prominent words that appeared on word cloud 1 included control, data, decision, design, and emotion, while in word cloud 2, they included algorithm, base, behavior, data, and explain. When the words obtained from the Voyant analysis were combined, they provided specific meanings of the word 'explainability'. The main definitions obtained from the combination of the most frequent words include 'an algorithm that explains data behavior' or 'an algorithm behavior that is based on data explanation' or 'a design of data control that enhances decision making' or 'designing and controlling data in such a way that enhances emotion and decisions'.

The application of AI in e-commerce stands to expand in the future, as businesses are appreciating their role in influencing consumer demands. The rapid development of research technology and increased access to the internet present e-commerce businesses with an opportunity to expand their various platforms. Notably, the influence of AI in e-commerce spills over to customer retention and satisfaction. The customers are at the center of the changes and adoption of AI in e-commerce. Hence, e-commerce can further develop contact with customers and establish developed customer relationship management systems.

The researcher of this study has made an effort to provide a critical outline of the key tenets of AI and its role in e-commerce, as well as a comprehensive insight regarding the role of AI in addressing the needs of consumers in the e-commerce industry. Even though the study has attempted to provide a universal meaning of 'explainability', the actual impact of AI on consumers' decisions is not yet clear, considering the notion of the "black box", i.e., if the decisions arrived at cannot be explained and the reasons behind such actions given, it will be difficult for people to trust AI systems. Therefore, there is a need for future studies further to examine the need for explainable AI systems in e-commerce and find solutions to the 'black box' issue.

For future research, this study may serve as a 'template' for the definition of an explainable system that characterizes three aspects: opaque systems where users have no access to insights that define the involved algorithmic mechanism; interpretable systems where users have access to the mathematical algorithmic mechanism, and comprehensible systems where users have access to symbols that enhance their decision making.

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