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AI and Brand Management: Evaluating the Role of Artificial Intelligence in Shaping Brand Perceptions

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The development and implementation of new technology in corporate settings have resulted in widespread operational changes across all sectors. Notably, significant changes in the technical infrastructure of e-commerce are being made with the intention of swaying consumer behavior in favor of particular products and companies. The use of artificial intelligence (AI) emerges as a critical component of the innovative toolkit required for the personalization and customization of products to fulfill particular requirements. The findings of this study indicate that despite the contribution of AI systems to e-commerce, the question of whether or not they are ethically sound remains a problematic one, particularly with relation to the idea of explainability. In order to get a comprehensive comprehension of the concept of explainability, as it has been applied by researchers in the field of AI, the research utilized word cloud analysis, voyance analysis, and concordance analysis as their respective methods of investigation. This research was inspired by a corpus analysis, and it establishes the framework for a uniform front. As a result, it contributes to a scientific breakthrough that aims to develop models of Explainable Artificial Intelligence (XAI). XAI is a subfield of machine learning that examines and attempts to comprehend the models and methods involved in how the "black box" judgments of AI systems are formed. It offers insights into the decision points, factors, and data that are utilized in the process of making a suggestion. According to the findings of this study, explainable ML models need to be developed so that they can be interpreted and comprehended before they can be used in XAI systems.

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

1. Introduction

In the ever-evolving landscape of business and marketing, brands stand as crucial assets. They represent not just products or services but embody a promise, an identity, and a set of values that customers can relate to. Building and maintaining a positive brand perception has always been a critical endeavor for organizations. However, in the digital age, this endeavor has taken on a new dimension, where the power of Artificial Intelligence (AI) has emerged as a formidable ally in shaping brand perceptions.

AI is transforming the way brands interact with consumers, analyze market trends, and understand their customers' needs. This transformation is not only driven by technological advancements but is also a response to the changing dynamics of consumer behavior in a digital world. Consumers are increasingly engaging with brands through online platforms, social media, e-commerce websites, and digital marketing campaigns. In this digital space, AI has demonstrated its capability to interpret, analyze, and respond to consumer interactions in a manner that was previously inconceivable.

This paper seeks to shed light on the pivotal role that AI plays in the realm of brand management. It explores how AI-driven technologies are influencing, shaping, and enhancing brand perceptions in several dimensions. One of the primary focal points is the use of AI in creating a more personalized and engaging brand-consumer relationship. AI-powered chatbots and virtual assistants have extended the reach of brands by providing 24/7 support, answering queries, and addressing customer concerns, thus enhancing customer satisfaction and overall brand perception.

Furthermore, AI's ability to analyze consumer sentiment, coupled with natural language processing, allows brands to monitor and respond to the voice of the customer in real-time. This not only fosters a sense of authenticity but also builds trust and loyalty. By tailoring content and recommendations to individual preferences through AI-driven personalization, brands can create immersive experiences that capture and retain customer attention.

In addition to these consumer-facing applications, AI also plays a pivotal role in optimizing brand management behind the scenes. AI-driven data analytics and machine learning help brands discern trends, customer preferences, and market fluctuations. This information is invaluable for refining brand strategies, product development, and marketing campaigns to better align with the ever-changing market dynamics.

As we delve into the multifaceted relationship between AI and brand management, we must not forget the ethical considerations that come with AI implementation. This paper also touches upon issues of data privacy, transparency, and algorithmic biases and highlights the need for responsible AI usage in brand management.

1.1 Problem Statement:

Despite the fact that artificial intelligence systems have completely transformed the way in which online business is conducted thanks to a vast array of features including video, picture, and speech recognition, natural language, and autonomous objects, a number of ethical concerns have been raised about the design, development, and deployment of AI systems. Fairness, auditability, interpretability and explainability, and transparency are the four essential components that come into play here. The estimation process that is performed by such systems is referred to as the "black box" because it is less capable of being interpreted and comprehended than the estimation processes performed by other statistical models. According to Bathaee, there are no profound methods for comprehending the decision-making processes of AI systems. The idea of a "black box" in AI suggests that the predictions and choices made by the technology are comparable to those made by humans. But they don't bother to explain why such decisions were reached in the first place. Despite the fact that AI processes might be founded on human patterns that are observable by humans, it is conceivable that comprehending them will be comparable to attempting to understand other highly intelligent species. The crux of the matter is determining how to most effectively ensure transparency in order to win back the trust of the people who are being targeted within e-commerce environments.

1.2 Proposed Solution:

The primary objective of the research being conducted right now is to produce a universally acceptable definition of the word "explainability." It is necessary for AI systems to implement post hoc machine learning techniques so that they can become more interpretable [10]. Although there is a wide variety of taxonomic ideas on the definition and classification of what should be regarded 'explainable' in relation to AI systems [10], it is argued that there is a need for a standard blueprint of the definition of the term and its components. This is due to the fact that there is a wide range of taxonomic recommendations on the definition and classification of what should be considered 'explainable' in relation to AI systems. The utilization of XAI models is what is suggested to accomplish the primary goal of this research, which is to find a solution to the "black box" dilemma. Models built using XAI have some degree of explainability, which may be handled from a variety of different viewpoints, including interpretability and transparency. In spite of the fact that the current study acknowledges the existence of previous research on the subject and conducts a broad range of consultations within the field, it goes one step further to offer a solution to the existing deadlock, which can be seen in the divided scholarly contributions concerning what constitutes the idea of "explainability."

Organisation of the paper: A critical overview of AI and e-commerce is provided in this article. The article explores how AI influences company marketing techniques. Section 2 discuss about the literature survey and section 3 Key study methods include word cloud analysis and data sources from NIPS and CSS. In Section 3, data analysis methods will be covered, including corpus and concordance analysis. The findings section presents the studied data, including the word cloud corpus result. The software Voyant Tools was used to identify the most important terms. We created a concordance analysis table in the results section for the phrase ‘explainability’. Section 5 discusses the research findings and key observations focused on opaque, interpretable, and intelligible systems. Results and future research implications are presented in the conclusion section.

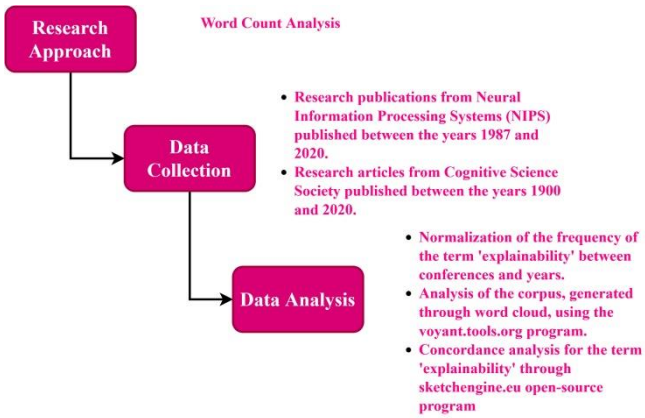
2. Literature Review

The rise of cross-border e-commerce (CBEC) and international logistics has made third-party logistics (3PL) obsolete since they can meet current CBEC criteria [12]. Random product arrivals are difficult. The deep-learning strategy uses optimization and demand forecasting to overcome these issues [12].
This tool aids e-commerce enterprises in determining effective advertising, comprehending customer intent, and optimizing product delivery. Deep learning aids logistical decision-making also. According to Davenport et al. [15], AI has significant potential to influence commercial marketing tactics. AI transforms company models and sales processes to adapt to evolving macro-environments. AI significantly affects customer behavior. According to Soni et al. [5], AI in e-commerce aims to improve customer experience by connecting businesses and consumers through improved processes. Companies in e-commerce must adapt to evolving client expectations. Businesses are evolving to stay competitive by going beyond meeting client demands. Soni [5] argues that customer service relies on timely and effective distribution methods.
A business that reduces customer suffering during purchase will increase market share and attract more customers. A business uses machine learning to create an efficient model based on market and competitive data.
Effective marketing is essential for businesses to persuade customers to choose specific products over others. According to Tussyadiah and Miller [16], AI has the ability to transform marketing in the future. New dynamic marketing segmentation from AI makes marketing techniques more sustainable. AI enables marketers to adapt marketing to individual purchasers in e-commerce by comprehensively knowing customer behavior [17]. AI in marketing can improve user interfaces across platforms, boosting customer likelihood to acquire a product. AI-supported hyper-personalization of marketing is crucial for influencing customer demand in e-commerce. Davenport et al. [15] emphasize the link between marketing and client purchase behavior. Contrarily, Kachamas et al. [18] caution against the assumption that AI in marketing boosts consumer demand. Instead, the writers highlight the challenges of AI in marketing. Customers are vulnerable to harmful activity that could result in data breaches and harm. However, AI is rapidly advancing, making e-commerce techniques for customer acquisition obsolete. AI marketing may mislead and create unreasonable expectations. The study suggests that AI may not always be associated with perceived usefulness (PU) and perceived ease of use (PEOU). It is important to consider macro-level difficulties in business operations before implementing market operations [16]. According to Adadi and Berrada [19], AI is leading to a move towards a more algorithmic society that utilizes ML approaches. AI systems have been described as lacking transparency due to their rapid growth. The BlackBox characteristic of Machine Learning (ML) systems enables powerful but unexplained predictions. When AI systems anticipate without explanations, they can hinder detecting improper decisions. Organizations face prejudice, poor decision-making, and inappropriate modeling methodologies during the algorithm lifespan.
As AI systems become more powerful and widespread, advanced troubleshooting and monitoring tools lag behind their adoption, posing threats to users. Marketing measures remain one-dimensional. Single-sided statistical approaches are still used in AI analytics. They rely on unidirectional feedback, such as click-through purchases and customer reactions. Traditional metrics are important for measuring client behavior, but they are static and slow. Additionally, they lack a complete understanding of consumers, making them superficial. Typically, consumer behavior is analyzed by segmentation and grouping, which might be outdated and descriptive. Analytics can provide valuable consumer insights, but they are not dynamic and contextually hazardous, making them unsuitable for influencing customer behavior and company interactions. Arrieta et al. [10] agree that black-box systems can lead to unjustified conclusions or lack of detailed explanations of customer behavior patterns. This is a challenge in a world where customers expect relevance due to their ever-changing interests and needs.
AI systems are accurate, but without understanding client responses, they struggle to provide contextually relevant action.
XAI addresses static AI data. Fully explainable AI enables enterprises to generate contextually relevant data through dynamic analytics. XAI focuses on trustworthiness issues. XAI focuses on assessing the moral and ethical norms of ML. XAI aims to eliminate the risk of blindly accepting outcomes, whether by necessity or choice. Thus, XAI models enable analysts to generate clear outputs for rational human decision-making.
Analysts can evaluate the rationality of decisions made by customers and users of AI systems, ensuring they follow legal and ethical norms. Research indicates a growing demand for ethical AI, emphasizing the

necessity for XAI models. Arrieta et al. [10] present a proposition that focuses on XAI users. Hence, this research provides a thorough foundation for defining XAI, enabling widespread application. No new paradigm exists that integrates past research and introduces innovative customer outreach tactics. AI allows attitude

I. PROPOSED SYSTEM

The following diagram, labeled "Figure 1," provides an overview of the proposed strategy that was applied in the study. Word cloud analysis was one of the methodologies that the researcher used in the research process. The Cognitive Science Society and the Neural Information Processing Systems databases were mined for information, and the results are presented here. In the final step of the analytic process, the data that had been gathered were subjected to normalization of the frequency of the phrase "explainability," Voyant analysis, and concordance analysis. In the course of this research, a word cloud analysis was applied in order to analyze the research topic and query.



A study method known as a word cloud analysis is one in which a word is formed depending on the frequency with which it is used [20]. This methodology is appropriate for this study given that the primary purpose was to investigate the significance of the term "explainability" within AI research databases and determine how the concept has been defined. Within this methodology, the size of the word generated increases proportionally to the number of times the term appears within the analyzed research. According to Doran et al. [21], concepts like interpretability have been commonly used in research publications despite the fact that their definitions are not entirely clear. Therefore, the researcher was able to evaluate important terms in AI databases through the use of the word cloud analysis. These databases are maintained by AI researchers who rely on methodologies driven by machine learning to approach their study aims. Because of this, the method was successful in identifying the primary topic of the written materials that were being evaluated by highlighting the frequency of word use for a fundamental understanding of the data as indicated by McNaught and Lam. In addition, in comparison to various other approaches to the analysis of text, the word cloud analysis proved to be the most suitable for this particular investigation. For instance, Sinclair and Cardew-Hall [23] observed that participants tended to prefer the search box to complete specific terms; nevertheless, they chose word clouds more when it came to dealing with open-ended activities. This was discovered after comparing word clouds to the user interface with a search box. Similar findings were reported by Kuo et al. [24], who stated that word clouds are a vital method for conveying perceptions of the information included in a query list. The overall conclusion is that word clouds are a valuable visualization tool for presenting the overall picture that is painted by the textual content [20].

2.1 Data Collection:

The evaluation of research articles and papers that were peer-reviewed was done with the help of linguistic corpora that were gathered from conference proceedings. These data were used in this study. The Neural Information Processing Systems (NIPS) served as the source for the data that was collected, and the research articles that spanned the years 1987 to 2020 served as the target. In addition, research papers that were published by the Cognitive Science Society between the years 1900 and 2020 were gathered for the purpose of analysis. These publications could be accessible through an open source that was controlled by the University of California.

These two ML communities were selected because of the abundance of AI-related information that they provide [21]. In addition, the wealth of information that is currently accessible makes it possible to conduct an investigation of the shifting patterns of usage of the term explainability and the notions that are associated with it.

2.2 Data Analysis:

In the process of analyzing the data, we did a cursory investigation into the meaning of the word "explanation."

After standardizing the frequencies across conferences and years, the plots shown in Figure 2a and 2b were created as a result of this process. The Cognitive Science Society database was used to compile the information shown in figure 2a, which is a frequency plot for the phrase "explainability." The frequency plot that was derived from the searches conducted on the Neural Information Processing Systems (NIPS) database is depicted in figure 2b. In order to construct a connection between the words and, as a result, generate meaning, the voyant.tools.org application was utilized to conduct an analysis of the corpus, which was produced as a result of the word cloud study. The concordance of the word 'explainability' was also produced by the researcher with the use of the open-source sketchengine.eu tool.

(**a**) word cloud 1 **b**) word cloud 2.

Figure 2: Frequency plot for the term explain ability results, (**a**) word cloud 1 and (**b**) word cloud 2.

3. Result And Disscution

The word cloud plots (Figure 2a,b) provide a straightforward method for comprehending the composition of the 'explainability' notion as well as the associated semantic meaning across the ML-driven databases that were selected for this investigation. In this case, we determined that crucial terms were those that came up first in a 20-word frame after conducting a search for the term "explanation." These words also had a frequency that was higher than the normal level. It is clear from looking at Figure 2a that the corpus reveals the most common words to be "use," "explanation," "model," and "emotion." Other words worth mentioning are learn and the system. Words such as model, learn, use, and data may be found in the corpus, which is depicted in Figure 2b. Method, task, infer, and image are a few additional words that stand out. Within the 20-word span, you'll also find important words like "decision" and "prediction," among others. Therefore, the AI community, as shown in Figure 2a, describes the term explainability as being related to concepts such as usage, explanation, and model, amongst others. This suggests that an emphasis should be placed on the use of system models that promote learning, explanation, decision making, and prediction. The implication, which can be found in Figure 2b, is that the term "explainability" could be considered to suggest utilizing models that allow learning, ease of inference, and prediction, amongst other things.

The corpus that was obtained from the word cloud can be seen in Figure 2a, and it 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, and picture). An open-source corpus analysis program called voyant-tools.org was used to perform an analysis of this corpus to generate meaning and form connections between the words. The results of this study showed that the most prominent words were control, data, decision, and design, as shown in Figure 3.

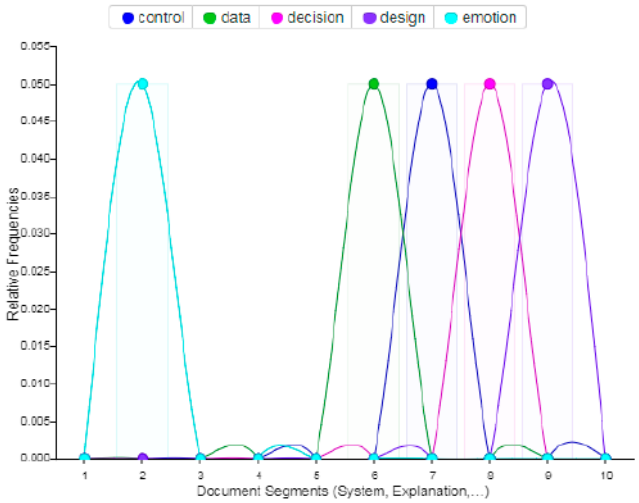


Figure 3: Word cloud 1 analysis.

Combining these terms, therefore, allows for the formation of a large number of relevant phrases within the context of responsible XAI. For instance, the combination of the two phrases could suggest "a design of data control that enhances decision making" or "designing and controlling data in such a way that enhances emotion and decisions."

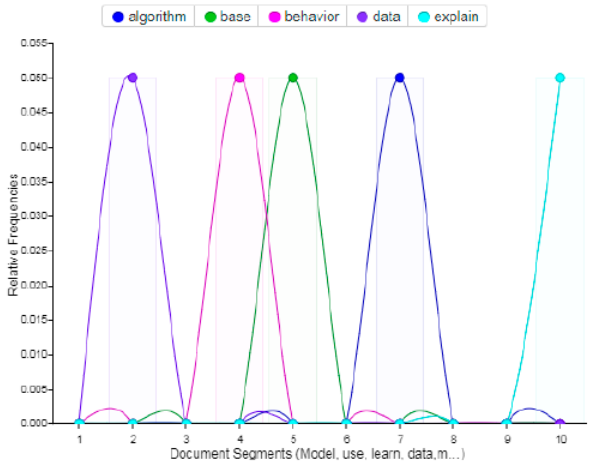


Figure 4: Word cloud 2 analysis

The corpus from word cloud 2 suggests that there are 20 words that are the most prominent. These words include model, use, learn, data, method, predict, behavior, task, perform, base, demonstrate, infer, picture, algorithm, propose, optimal, object, general, explain, and network. According to the findings of the Voyant research, the five most common words are "action," "algorithm," "base," "behavior," "data," and "explain." This is illustrated in Figure 4, which can be found below.

Potential sentences derived from this word combination encompass phrases such as 'an algorithm that elucidates the behavior of data' or 'an algorithmic behavior that is predicated upon the explanation of data'. Furthermore, when examining the concordance of the term 'explainability' in sketchengine.eu, a software tool that analyzes the usage of specific words by actual users of a particular language, several terms emerged as crucial in defining the concept. These terms include predictability, verifiability, user feedback, information management, data insights, analytics, determinism, understanding, and accuracy, as depicted in Figure 5.

The results of this study shed light on important principles related to the concept of explainability in artificial intelligence.

The analysis of the data reveals that certain keywords were more prominently utilized in comparison to others.

Significantly, the terms 'usage', 'explanation', and 'model', as indicated in Figure 2, provide evidence of enhanced usability. The results are crucial in addressing the limitations of the overall idea of explainability,

as documented by Soni et al. [5]. Comparable findings are observed in the instance of Figure 3, whereby noteworthy terms such as 'use', 'model', 'learn', and 'data' are identified. The analysis demonstrates that the AI communities adopt varying approaches to the concept of explainability, albeit with certain overarching similarities. The word is employed to facilitate the assessment of the operational principles of machine language systems, encompassing comprehension of system functionality. Additionally, it is occasionally employed to refer to the examination of specific inputs, namely the process of ascertaining the mapping of a given input to an output. Based on the analysis conducted, several significant observations were identified. This usually refers to a system that hides input-output mapping.

The mechanism anticipates input without explaining why or how it does so. Opaque systems occur when an enterprise licenses closed-source AI technologies and chooses to keep their workings confidential. According to [21], black-box techniques are opaque as they use algorithms that do not reveal the reasoning behind the system mapping of inputs to outputs. Comprehensible AI models emit symbols without inputs. These symbols, primarily words, let users connect input qualities to outputs. The user can interpret symbols using personal logic and knowledge.

The level of clarity determines the ease of usage, making comprehensibility a graded concept. User knowledge must include cognitive intuition about the relationship between output, inputs, and symbols [21]. Clear and understandable systems outperform opaque ones. The concepts of interpretation and understanding are distinct: interpretation relies on system model transparency, whereas comprehension requires symbols for user reasoning [21]. Modern AI systems are often complex and difficult to understand, despite producing correct results. To restore consumer trust in AI systems, there is a push to improve system explainability.

Increased user confidence in AI systems is needed [25]. User confidence and trust are key drivers for achieving explainable AI. System users seek explanations for social interactions, accountability, and persuasion. A key benefit of explainable AI is tailored human-computer interaction.

Explainability integrates machine learning into the customer journey, replacing traditional decision-making processes that are incomprehensible to humans.

According to McNaught and Lam [22], many consumers view doctors as a black box that uses symptoms and test results to determine the optimal treatment plan. Patients are not informed of the reasoning behind doctors' diagnostic recommendations. Most clinicians employ high-level signs or symptoms, which in AI systems represent system symbols. However, doctors should act as comprehensible models when interacting with patients. In interactions with medical personnel and colleagues, doctors may serve as interpretable models. To ensure that decisions are supported by evidence, other clinicians will analyze technical analysis like they would a machine learning system.

XAI ensures precise, tailored information for effective engagement with targeted users [26]. Using XAI will improve the relevancy of the offer, leading to increased user engagement and interest. Additionally, XAI will enable real-time adjustments to major business components for optimal benefits and corporate outcomes. Transparency and rationality can reduce abandoned products, raise order value, and boost revenue and conversion rates. This research suggests creating XAI frameworks with interpretability and comprehensibility capabilities. However, responsible XAI goes beyond ML:

Important user-related characteristics of external AI features include trust, fairness, confidence, ethics, and safety (So, 27). The meaning of XAI varies based on the user's perspective, as shown in Figure 6 by So [27]. Figure 6 shows how XAI uses consumer data to inform decision-making, leading to greater business outcomes and better understanding of individual suggestions [26]. It implies that.

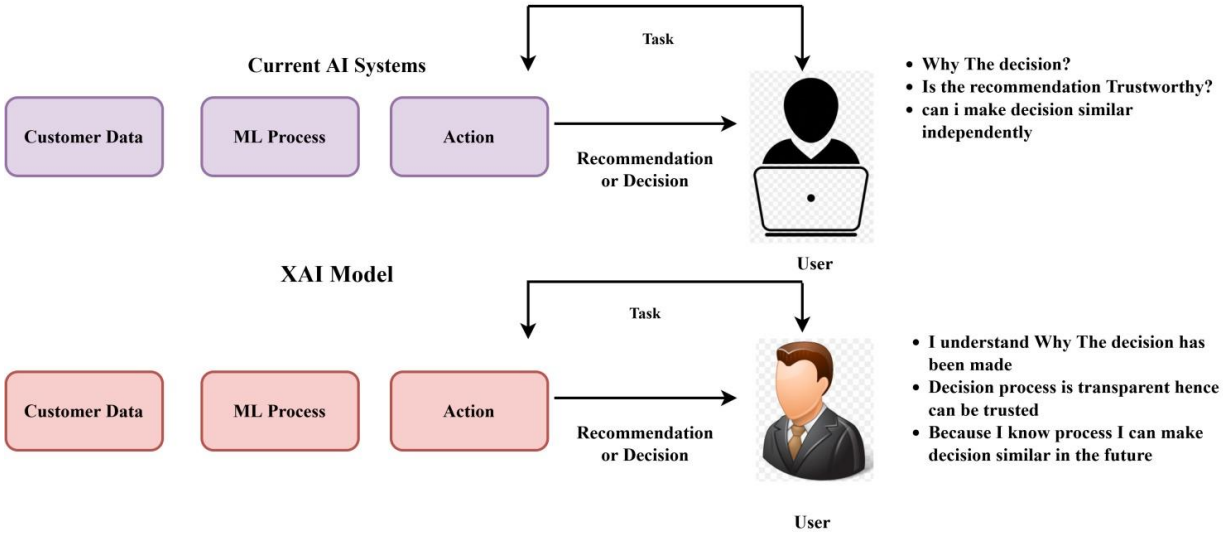


Figure 5: The differences between present-day AI and XAI models.

4. Conclusion

The study aimed to establish a common definition of the term 'explainability'. The data from word cloud plots indicates that 'explainability' is mostly linked to words like model, explanation, and use. These words dominated the corpus created from the word cloud. Word cloud 1 corpus includes emotion, design choice, data, control, image, variance, interpretation, decision, result, control, estimate, data, predict, method, train, study, use, learn, model, explanation, and system. Corpus Word Cloud 2 includes: model, use, learn, data, method, predict, behavior, task, perform, base, demonstrate, infer, picture, algorithm, propose, optimal, object, general, explain, network. The Voyant analysis revealed that the top terms on word cloud 1 were control, data, decision, design, and emotion, while word cloud 2 had algorithm, base, behavior, data, and explanation. Combining the words from Voyant analysis revealed specific meanings for the word 'explainability'. Combining the most common words yields definitions such as 'an algorithm that explains data behavior', 'an algorithm behavior based on data explanation', 'a design of data control that enhances decision making', and 'designing and controlling data to enhance emotion and decisions'.

The use of AI in e-commerce is expected to grow as businesses recognize its impact on consumer needs. The rapid advancement of research technology and internet availability offer e-commerce enterprises the chance to expand their platforms. AI in e-commerce impacts client retention and satisfaction. E-commerce AI adoption is driven by customers. E-commerce is able to enhance client communication and construct customer relationship management solutions.

This report provides a critical overview of AI and its function in e-commerce, as well as a full understanding of how AI may meet consumer expectations in the business. Although the study aims to define 'explainability', the impact of AI on consumer decisions remains unclear. The concept of the "black box"—inability to explain decisions and provide reasons—makes it challenging for people to trust AI systems. Future studies should investigate the necessity for explainable AI systems in e-commerce and discover solutions to the 'black box' issue.

In future research, this study can serve as a template for defining an explainable system with three aspects: opaque (no access to algorithmic mechanism insights), interpretable (access to mathematical algorithm), and comprehensible (access to symbols for decision-making).

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