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A Review Of Mediating And Moderating Mechanisms Shaping Consumer Trust And Loyalty In Digital Marketing

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Abstract
This paper offers an integrative overview of mediating and moderating influence which determines consumer trust and loyalty in the context of an AI-driven digital marketing setting. Based on the Stimulus-Organism-Response (S-O-R) model and theory known as privacy calculus, the paper uses the synthesis of recent empirical studies of recommendation systems, chatbots, and predictive models. The perceived personalization quality, customer satisfaction, privacy risk, and perceived control can be defined as the key mediating variables that play a critical role in defining how the AI systems impact the user trust and the behavioral loyalty. Moreover, these effects are also shown to be moderated by some variables such as the sensitivity to privacy, type of product, and brand reputation such that these effects lead to a cue-consistent behavior at some levels but cue-shifted behavior at other levels of consumer groups. The offered conceptual framework combines them in order to provide the comprehensive view on how AI technologies might strengthen the consumer relationships or impede them. Its results have practical implications to be used by marketers, AI designers, and polymakers interested in ethical, personalized, and user-centric digital marketing strategies. The review helps to develop the knowledge base because of describing the psychological and situation-related aspects of interactions between AI and consumers; due to the discussed issues, the consideration may be used in developing AI systems in which the primary concern is the level of their integrity, user control, and the long-term promotion of their loyalty.
Keywords: *Artificial intelligence, Consumer trust, Digital marketing.*

1. INTRODUCTION

The spread of artificial intelligence (AI) technologies has drastically changed digital marketing environments shifting the ways in which brands communicate to consumers. AI provides a possibility of automating and personalizing marketing processes with the help of recommendation systems, chatbots, and predictive analytics. Such technologies enable marketers to present custom messages, enhance user experience, and boost their efficiency (Davenport et al., 2020; Chatterjee et al., 2021). With the development of AI tools, digital marketing is becoming more and more quantifiable and data-driven; this means that it is driven by data that is used to make a prediction of consumer behavior and targeted campaigns are executed in a way that they are optimal in terms of engagement and conversion. These are some of the advantages of AI application in digital marketing, but this topic of AI integration is complicated because it involves issues of consumer-trust, data-privacy and choice. Consumer resistance to AI may be triggered by its own characteristics because what gives AI its power giving the ability to collect and process personal information and make decisions based on that information (Belanche et al., 2020). Research indicates that AI may raise issues of privacy and undermine the sense of personal information control, with this concurrently raising satisfaction and loyalty by delivering a sense of personalized experiences (Binns et al., 2018; Awad & Krishnan, 2006). Trust has thus become a meaningful construct when it comes to the decision-making over the consumer acceptance of artificial intelligence technologies in the marketing setting. Trust formations in AI mediated interactions are a complex process and depend on various factors, such as the quality of perceived user satisfaction, perceived personalization, risk perceptions, and so forth. Studies of this kind have demonstrated that both usefulness and perceived transparency can lead to increased trust, whereas the sense of privacy invasion and what might be called transparency or the lack of transparency of algorithm can decrease it (Lankton et al., 2015; Jiang et al., 2021). Furthermore, the above relationships may be subject to moderation by factors like a person being sensitive to privacy or the setting of the product, as well as brand reputation, which further complicates the mechanisms of developing trust and loyalty (Toufaily et al., 2021). These mediating and moderating mechanisms are the key to the marketers who want to implement AI in an advisable and effective manner. The current paper will meet this demand through a broad overview of the body of research on the topic of AI in digital marketing, and specifically, its impact on consumer trustfulness and loyalty. In particular, it is a synthesis of empirical evidence that was conducted concerning the ability of AI to personalize and provide recommendation algorithms and chatbot communication, as well as key variables underlying what mediates and moderates their effects on consumer perceptions and behavior are identified. This paper provides a better understanding of the psychological and contextual factors of consumer trust strengthening and weakening by analyzing the prerequisites of both. These results present important implications to digital marketers, artificial intelligence developers and policymakers who are interested in encouraging a high level of trust among users, practicing good data ethics and developing consumer loyalty over the long-term as our world becomes more AI-driven.

2. Theoretical foundations

There is need to have a healthy theoretical base that would be primarily associated with understanding the subtle nature of how AI (artificial intelligence) influences consumer trust and consumer loyalty in digital marketing. This part discusses in detail two commonly accepted frameworks which were hitherto used in this field regarding much empirical research, the Stimulus-Organism-Response (S-O-R) framework, and Privacy Calculus Theory.

2.1. Stimulus-Organism-Response (S-O-R) Model

The S-O-R model was actually created in environmental psychology, but there has been a substantial adaptation in the study of consumer behavior to look at the effect of environmental stimuli as the external stimulus that affects cognitive and emotional processes within an individual that, in turn, leads to the behavioral outcome (Mehrabian & Russell, 1974). In digital marketing practice, stimuli that are found in AI-enabled tools include recommendation systems, chatbots, and targeted advertisements. These technologies communicate with the psychological mechanisms of users, including their perceptions of usefulness, trust, satisfaction, and control which, further, determine the results, i.e., loyalty, engagement or avoidance (Chang et al., 2020; Kim & Forsythe, 2008). The S-O-R model is also dynamic, thus rendering it especially well adapted to recording the multi-phased effect of AI. As an example, the AI-powered customization may be a favorable prompt that improves customers perception on the brand relevance (organism) and, subsequently, raise the repetitive buying behavior (response). The same stimulation could however trigger negative organismic reactions like discomfort or relation to privacy issues in case it approaches the cognitive predispositions and experience of the consumer (Pantano et al., 2021). Furthermore, researchers have suggested refined S-O-R frameworks with the further multiplication of mediators, including emotional engagement and cognitive trust especially in AI agent-based and algorithmic individualization (Gursoy et al., 2019). These elaborate models assist in understanding the difference in results realized when AI technologies are applied on various product categories, consumer segments and platforms.

2.2. Privacy calculus theory

Another important dimension to focus on the consumer trust in AI systems is the Privacy Calculus Theory. In this theory, people make a rational cost-benefit analysis when they consider disclosing their individual information over the internet. When these realized benefits (e.g., personalized services, time savings) overcome the perceived risks (e.g., data misuse, surveillance), users are willing to trade off their data in exchange of personalized services (Dinev & Hart, 2006; Xu et al., 2011). Such a trade-off is especially relevant in marketing where it is easy to hide the personal data collected and the algorithmic processes guiding such an inference. Consumer use of AI technologies that function to collect profiling and predictive data on consumer behaviour could find it harder to interpret the usage of their information, which is a critical issue of fairness and accountability (Martin & Murphy, 2017). Research also demonstrates that despite the positive effects of personalization, privacy sensitivity might decrease trust and the readiness to engage in cases where it proves desirable (Bleier & Eisenbeiss, 2015). The additional extrapolations of Privacy Calculus Theory include such variables as the level of privacy concerns about the individual, the brand- or publisher-related trust, and technological literacy (Li et al., 2010). These variables assist in understanding why different segments of demographics and psychographics may look at the same AI application differently. An example is ones that know how to deal with digital eco-system are unlikely to mind exchanging some data about themselves in order to receive an AI-powered recommendation, whereas older users will be hesitant towards such an exchange (Smith et al., 2011). A combination of S-O-R model and Privacy Calculus Theory offers a strong dual-paradigm to study the role played by AI in developing consumer trust and loyalty. The latter provides a description of rational analyses undertaken by consumers when it comes to exchanging data, whereas the former explains cognitive and emotional treatment of stimuli. Combined, these theories construct the base of researching the mediating and moderating variables under discussion in this review.

3. METHODOLOGY

This paper uses narrative literature review approach in a bid to understand the processes by which artificial intelligence (AI), impacts consumer trust and loyalty in digital marketing. The main purpose of the review is to summarize the current empirical and conceptual studies to provide an integrative knowledge about the mediating and moderating factors that influence the consumer reaction to AI-driven tools, namely, recommendation systems, chatbots, and predictive analytics. Such a manner is especially appropriate because the topic under consideration is rather broad and interdisciplinary with references to marketing, psychology, data privacy, and information systems. Narrative reviews differ with systematic reviews or meta-analyses in their strict focus of features of inclusion; also, diverse studies based on different research traditions or the highlighting of quantitative influences of effect (Baumeister and Leary, 1997; Green et al., 2006). This form of flexibility allows incorporating both theoretical and empirical contributions of all sorts and thus promote a more sophisticated conceptual system. Academic databases were used to retrieve the relevant literature and these databases include Scopus, Web of Science, ScienceDirect, and Google Scholar. The keywords that were used in the search included AI in digital marketing, consumer confidence and artificial intelligence, chatbots and customer loyalty, recommendation systems and privacy and personalization and consumer satisfaction. All the research articles that were identified were restricted to peer-reviewed ones issued between 2010 and 2024 and analyzing the application of AI technologies in consumer-related marketing. Studies that had neither mediating nor moderating variables of relationship with either consumer trust or consumer loyalty were excluded. The papers that did not contain the dimensions of engagement of consumers, regardless of being technical in nature, or that did not address aspects of performance of the technical system or the analytic perspective on the business side were excluded. A systematic review of each of the identified articles was performed in order to obtain the related insights concerning the type of AI application, the type of personal data involved, the criteria of user evaluation (e.g., perceived usefulness and intrusiveness) and behavioral outcomes (e.g., purchases, repeat visits or trust formation). The thematic analysis of these insights allowed diagnosing some consistent trends across the contexts, as well as deviations associated with the type of industry, the complexity of technology, or the specifics of the audience. The works that used extensively popular theories like Stimulus-Organism-Response (S-O-R) framework and privacy calculus theory were given specific significance because of the theoretical stability that was applied throughout the analysis. Despite the failure to implement a quantitative scoring grid to assess methodological quality in this review, it follows the principles of an academic narrative review, i.e., it prioritizes empirical rigour, reviewed literature, and coherence of ideas (Ferrari, 2015). All the studies were analyzed in terms of applicability to trust-loyalty dynamic and the contribution to informing about the role of mediators and moderators of AI-driven marketing. To further increase transparency and replicability of the review process, a research matrix was created to keep a catalogue of studies and make comparisons between the studies. As with all narrative reviews, this method has its limitations such as a possibility of researcher bias in choosing studies and interpreting them. In addition, there is a possibility that the relevant literature could have been unintentionally missed since the search that was included was extensive; however, it could not cover all the databases, key word differences, or language of the publication. However, narrative review study is the best study methodology in synthesis of a conceptually and methodologically wide field. It gives a baseline interpretation of the way AI technologies are transforming the consumer-brand relationship; it presents a future guideline of empirical studies.

4. Types of artificial intelligence in digital marketing

Artificial intelligence (AI) solutions are now important tools available in the contemporary form of digital marketing that provides an opportunity to optimize and maximize customer interaction, service delivery, as well as customization of content. Those of the AI that are most applicable to the consumer-facing marketing initiatives are recommendation systems, chatbots, and predictive models. All these technologies use user information to provide them with the customized experience according to their taste, and many times in real-time. The privacy and trust concerns of the consumers can be increased, however, due to the same data-driven personalization that is the foundation of such technologies, so it is crucial to learn more about how various AI-based apps work and how they will influence how a particular client views them. The most popular AI tool in digital marketing is perhaps the recommendation system. These are used to examine the user behavior, buying history and web surfing trends to propose services or products that would suit as per a person's taste. Examples of companies that have applied and proved the successive usefulness of recommendation engines in pushing sales and heightening engagement after customizing content feeds include Amazon, Netflix, and Spotify (Ricci et al., 2015). In terms of consumer trust, the appropriately designed recommendation systems have the capacity to improve the perceived relevance and decrease the choice overload, thereby endearing satisfaction and brands loyalty (Adomavicius & Tuzhilin, 2005). Nevertheless, in situations when recommendations can be seen as overbearing or inappropriately suited to users, the skepticism and even resistance reaction may be observed especially in high-privacy-sensitive users (Bleier & Eisenbeiss, 2015). The chatbot is another mode of AI that has gained so much popularity in digital marketing. Natural language processing (NLP) and machine learning algorithms allow chatbots to give a user an impression of talking to a person. Customers are turning to such virtual assistants to support customer service, place an order, or even find a product. Modern chatbots have the potential to present customers with 24-hour support, minimize wait times, and save money spent on operations retaining a unified brand voice (Gnewuch et al., 2017). In numerous scenarios, customers will enjoy the effectiveness and quick reaction of AI chatbots, where the conversation is smooth and the system can comprehend and find a solution to complicated requests. However, emotional intelligence and personalization have weaknesses that may lower user satisfaction, and some users report the feeling of discomfort when they understand they are talking to a machine (Chaves & Gerosa, 2021). In such a way, the credibility of the chatbot interaction may frequently rely on the clarity of the system, the correctness of its feedback, as well as on the capability to demonstrate the level of supposed empathy. A much more mathematical use of AI is predictive modeling, which is aimed at predicting consumer behavior based on the existing model of the past and the current information. Such models are useful when it comes to lead scoring, dynamic pricing, how to manage inventory, and how to optimize campaigns. Predictive analytics can be used in marketing by determining the probability of a customer to buy a good, the flavour of offers to attract a customer, or the time at which a user is most likely to churn (Wedel & Kannan, 2016). Although in most cases these tools work in the background, their effect may be experienced through extremely individualized offers or dynamic web site displays. Effectiveness of predictive modeling, on the consumer level, depends on a subtleness and technique of its usage. Overuse of predictions may induce a sense of surveillance, and that has a bad effect on trust, whereas a context-aware application has been more widely accepted and well-liked by individuals (Martin & Murphy, 2017). In each of these uses of AIs, the extent and privacy of personal information used becomes a focal point in determining consumer response. Biometric or financial data is usually more invasive than behavioral data such as clickstream data and time-on-site. Nevertheless, even the processing of various low-sensitivity data may generate very detailed user specifications, which begs the question of transparency, informed consent and mischievous use of data (Acquisti et al., 2016). These issues are particularly relevant in marketing ecosystems powered by AI since data gathering, algorithmic treatments and customization are fast and increasingly, transparent to the human user. Finally, the form of artificial intelligence applied in a marketing setting also plays a decisive role in the way the consumers carry out their judgement concerning trust, control and value. The technologies that deliver and offer relevant, respectful, and contextually right communications are more likely to promote positive user engagements and longtime loyalty. On the one hand weak privacy or performance weaknesses on the part of AI system could jeopardise the very relationships they are meant to influence.

5. Mediating variables

Mediating variables play an imperative role in the determination of the impacts of artificial intelligence (AI) technologies on consumer trust and loyalty in digital marketing. Mediation is the manner because of which the independent variable (which in the present context is the AI applications) influence a dependant result (in this case, consumer loyalty) through an intervening mechanism. There are a number of mediators that have been found in the AI-driven marketing environment which are perceived personalization quality, customer satisfaction, perceived privacy risk and the perceived control. Such variables become critical in case one has to explain the reasons due to which AI in some instances may improve the relationships between consumers and brands, and similarly in other cases break them. One of the most reported mediators in the AIs literature regarding marketing is perceived personalization quality. It is the opinion of the consumer of judging the effectiveness that a system delivers a content, recommendation or communication that fits their preferences. The recommended approach to effect personalization is utilization of AI-driven recommendation engines, as well as dynamic content generators that would take advantage of behavioral data, as well as fine-grained contextual signals (Tam & Ho, 2006). In the case of accurate and context-sensitive systems consumers tend to feel that they are better understood and appreciated and that has the potential of increasing engagement and emotional attachment towards the brand (Arora et al., 2008). Indeed, some studies show that the perceived personalization quality highly mediates the connection between AI applications and trust because it determines the quality of the per-ceived system competence and relevance (Bleier & Eisenbeiss, 2015).

The important mediating role is played by customer satisfaction, too. Satisfaction is mostly thought of as a positive affective outcome due to meeting the consumer expectations in and/or following a service encounter (Oliver, 1999). In the AI context, satisfaction is anything that leads most effectively to efficient service delivery, lessening of the burden of making choices, or beneficial chats with chatbots and recommendation systems. Once the consumers are convinced that these AI tools bring value to them, their satisfaction and attitude towards them surge, which results in stronger brand loyalty and brand advocacy (Chattaraman et al., 2023). Moreover, satisfaction could strengthen faith as it would denote the brand as competent and eager to abide by its customers. The role of satisfaction as a mediator of the relationship between AI-enabled services and trust, as well as loyalty, has been confirmed in several empirical studies, mainly in the luxury retail and e-commerce industries (Gursoy et al., 2019). The mediator perceived privacy risk is a two-edged sword. Although AI increases personalization of services, there are times when it necessitates huge amounts of information as well as profiling. This may cause consumer distrust on the ways their personal data are utilized, deposited, and even distributed. The perceived privacy risk implies how the consumers feel threatened that using the AI technologies can cost them their data misuse or surveillance (Xu et al., 2011). Under such circumstances, there could be the feeling of excessive danger, even though someone is practicing a top-quality personalization, as it might not be enough to generate credibility. Conversely, as privacy risks are viewed comparatively low such as through visible data policies or good anonymization methods, the probability of AI technologies bringing about trust and future interaction increases (Lwin et al., 2007). Accordingly, the connection between personalization and consumer trust can be mediated by concerns of privacy and increase or nullify the planned advantages of AI. Perceived control is another prominent mediator as it relates to the ability of a consumer to control how his or her data are exploited and how the AI systems work with the person. The need to control increases the psychological comfort associated with reduced vulnerability in interaction with an algorithmic decision-maker (Lankton et al., 2015). The more a user believes that personalization can be tailored, the ability to opt-out of data collection, or having insight into AI suggestion creation, the lower the chances of a system being viewed as user-centric (Binns et al., 2018). On the other hand, seen through the decision-making process of AI systems as a black box hiding its logic or restricting input, familiarity with AI systems also reduces the sense of control, undermining the trust-building process. A number of papers revealed that perceived control mediates the AI impacts on satisfaction and trust, can serve as a precursor to long-term consumer stays, as well as play a secondary role between satisfaction and trust (Jung et al., 2021). Collectively, these mediating variables can provide a multifaceted view of how AI technologies stimulate consumer-trust and consumer-loyalty on the psychological level. Quality AI technology should not be a mere piece of functionality, but it should be well thought-out to understand what users need, feel and worry about. These mediating relationships are additionally dependent on the presence of the contextual variables, including product category, brand reputation, and playing norms, and some of them are discussed in the following section.

6. Moderating variables

Although mediating variables promote understanding of how relations between artificial intelligence (AI) applications and consumer trust and loyalty happen, moderating variables help discover when and by which persons these associations are stronger and weaker. Moderators do not push through the causal effect where they rather change the magnitude or direction relating AI technology to consumer outcomes. Among the most significant moderators in the literature relating to the AI-centric digital marketing, one may note privacy sensitivity, the nature of the product, and brand reputation. These aspects add contextual and individual variability, and in that way, they contribute to a situation and explain why some consumers respond and behave differently when faced with AI applications. Perhaps the most established digital marketing literature moderator is the privacy sensitivity. It is defined as the extent of concern that people have regarding the retrieval and utilization of their personal details (Xu et al., 2008). Privacy-sensitive consumers will further investigate the AI frameworks that monitor, process, and react to their actions and behaviors such as those whose AI algorithms work in opaque manner or without data protection policy. These people might see even an adequately performed personalization as an invasion or manipulation, which lowers the level of trust and activity (Awad & Krishnan, 2006). On the other hand, low privacy sensitive consumers will tend to trade data usage marketing with convenience, or the quality-of-service delivery. The moderating impact of privacy sensitivity has been established in various research particularly in domains that include recommender systems and algorithmic targeting (Bleier & Eisenbeiss, 2015). Product type is also another key moderator. The categories of different products induce different degrees of consumer involvement, emotionalization, and risk perception and change the acceptance of AI interventions. As an example, customers might be a little bit more open to AI personalization in the case of buying low-involvement/hedonic purchases, fashion, entertainment, or fast food, than with high-involvement/utilitarian services, such as financial services, or healthcare (Kim & Kim, 2022). AI algorithms making skincare suggestions may be moderately (or even eagerly) accepted as a convenient solution and a new development, whereas the other type of AI capable of recommending something in the realm of health diagnostics may be regarded with suspicions. Perceived relevance and intrusiveness are also subject to product type. Consumers might be willing to use human workers instead of AI in risky situations because they tend to need empathy, moral judgment, and faith in judgment (Chatterjee et al., 2021). Thus, it is vital to study how the factor of product type can moderate the relationship between consumer expectations and psychological needs and AI capabilities. Another moderating factor is brand reputation as it assumes a crucial part in determining the consumer trust in AI-enabled services. Customers would easily agree to AI interventions of brands that they consider as trustworthy, innovative, or customer focused. The good reputation of a brand can lower the perceived risk more because it can be used as a heuristic personality that makes one confident in the fairness and accuracy of the AI system (Pavlou & Fygenson, 2006). A study demonstrates that credible brands can enjoy more leeway to apply use of the arising technologies, such as AI chatbots and automated personalization tools, to particular customers (Nguyen & Simkin, 2022).

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Conversely, less familiar or newer brands would be doubted, no matter how well AI system performs, and clarity of transparency and its ethical protection, is not conveyed. Other moderators are demographic variables that are age, technological literacy, and cultural background. Digital natives as the younger consumers are usually more tolerant to AI-mediated interactions and not shy about sharing data (Smith et al., 2011). AI functionality will be supported more readily by technologically versed consumers, not by those with less expertise concerning algorithmic systems, who are likely to treat algorithmic decisions as random or unjust. The cultural norms are also present since societies are divided according to their attitudes to automation, data exchange, and institutions trust (Hofstede, 2001). All these moderating variables convey the idea that the efficacy of AI in marketing is not the same in every scenario or in relation to every buyer. Customized suggestion, which has an augmenting effect on trust in one sense, can search it in another, depending on issues of user privacy, to the type of product at issue, or to the brand reputation. It is important to identify, and take into consideration, these moderators in order to develop AI-based strategies that are not merely technically sound, but also situational and context-appropriate, as well as ethically sensitive.

7. Key studies provided through empirical evidence

The overview of the recent empirical papers shows that there is a stable interest in the effects of AI technologies on consumer trust and loyalty in the terms of specific psychological mechanisms. The methodologies of such studies involve various theoretical frameworks: Stimulus-Organism-Response (S-O-R) model, privacy calculus theory, and they rely both on survey-based structural equation modeling and experiment types. They also focus and emphasize on a few recurring mediators including customer satisfaction, trust and perceived quality of personalization and key moderators including privacy sensitivity, brand reputation, and product category. The multidimensional character of the application of AI is echoed by the variety of its contexts, (exotic) luxury fashion, social media, recommender systems, and e-commerce platforms. Whereas some examine relational perspectives on AI, others look into how AI-loyalty imperfect relationships are mediated by trust and engagement. Overall, these studies confirm the theoretical perspective offered in this review and offer empirical support to the mediating/moderating pathways presented above. Short summary table with significant empirical contributions which were used as the basis of this review is provided below.

Table 1: key studies contributed for the significance of evidence

Study	Context and AI type	Mediators	Mediators	Key findings
Chattaraman et al. (2023)	Fusion retail; recommender system and chatbots	Engagement, satisfaction	N/A	AI enhances customer loyalty via satisfaction and engagement in luxury markets.
Gnewuch et al. (2022)	E-brand chatbots services	Trust, experience	N/A	Trust and experience mediate the effect of chatbot service quality on brand loyalty.
Kim & Kim (2022)	Social media platforms; personalized Ai	Usefulness and trust	Privacy	High privacy concerns reduce the effectiveness of personalized AI content.
Xu et al. (2021)	Recommended personalization, recommendation system	Benefits and risks	Privacy	The privacy–personalization paradox is mediated by privacy calculus; users weigh benefits against privacy concerns.

Nguyen & Dholakia (2022)	E-commerce, personalize depends on algorithms.	Experience and brand attachment	Brand reputation and product type	Loyalty is influenced by experiential satisfaction, with stronger effects for reputable brands.

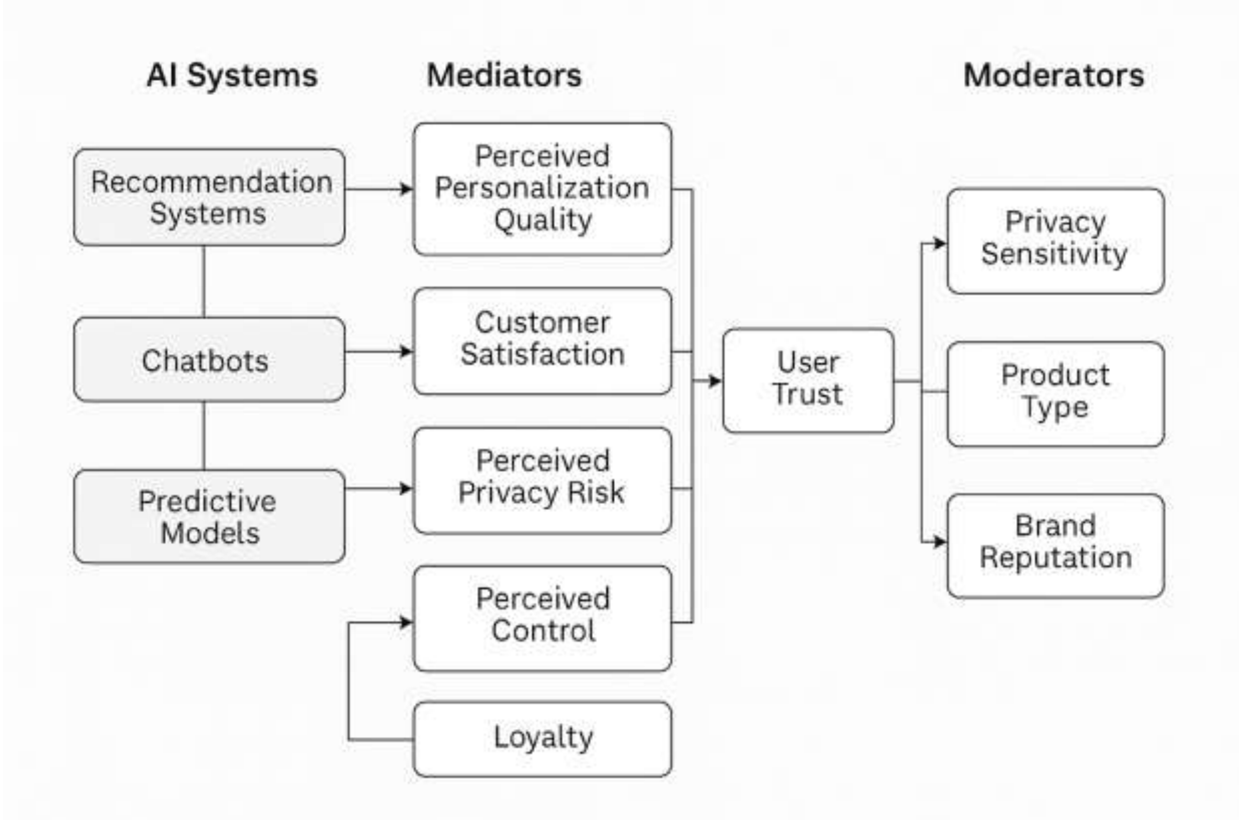

Figure 1: Conceptional framework

9. DISCUSSION

The increased manifestation of artificial intelligence (AI) in the digital marketing campaign creates a shift in nature with regards to the way companies engage consumers, earn their trust and establish long term loyalty. The present review adds to the theoretical and practical knowledge of this change by providing a synthesised conceptual model that determines the mediating and moderating variables that can affect the relationship between AI and trust, and trust and loyalty. Among the most significant conclusions that can be made on the basis of this review, one may state the core role of consumer perception in the determination of the overall efficiency of AI technologies. Although AI systems can be optimized to provide efficiency, personalization, and predictive accuracy, the extent to which they foster trust by users relies on the power of subjective interpretation of functions. AI is not considered in isolation because it is viewed through the prism of satisfaction, the quality of personalization, privacy concerns, and the feeling of control. These mediating variables are strongly psychological and situational, which is why it is important to consider technological capabilities within human expectations and ethical principles in order to be able to help marketers as well as system designers (Lankton et al., 2015; Jung et al., 2021).The fact that perceived quality of personalization can repeatedly serve the role of mediator indicates a key contradiction existing in the AI-driven marketing: consumers want more relevance and convenience but are they still hesitant in the data gathering processes, which would allow companies to create a meaningful personalization practice. This is in line with the larger privacypersonalization paradox, as also witnessed in the online context (Xu et al., 2011). To make AI positively impact on trust, personalization should not only be tailored but also viewed as respectful and non-invasive. The marketer has to adjust the degree of personalization relying on the specifics of the consumer profile and use situational clues, but effective levels of opt-out and clear data transparency terms are necessary. Perceived control and customer satisfaction also turned out to be relevant mediators that play the role of psychological gateways to trust. Once users feel satisfied with the experience of interacting with AI systems and believe that they could make a difference to the ways AI systems have interactions with them, a much higher willingness of re-engagement will be observed. This result supports the fact that previous study focus is on control as a type of psychological empowerment that increases perceived fairness and trustworthiness (Binns et al., 2018). This sense of control may be destroyed by AI systems that butcher decision logic or have restricted user feedback, particularly to consumers who are high in privacy sensitivity. The moderating variables also complicate the AI trust relation. Such a factor as privacy sensitivity, in its turn, changes the perception of the identical AI applications radically. Very sensitive customers can take even a benign personalization campaign as intrusive and the other persons as valuable. Such a variety indicates that generalized AI solutions cannot be employed in a uniform way that would be effective (Bleier & Eisenbeiss, 2015). Product type and brand reputation likewise adjust the consumer responses, so that well established brands get a higher allowance of algorithmic experimentation worry less, and hedonic product classification begets a correspondingly higher allowance of AI powered connection (Nguyen and Dholakia, 2022; Kim and Kim, 2022). These moderators ought to be used to advise strategy on where, how and to whom AI tools are used. In the theoretical perspective, the framework proposed can be considered as the unification of two prevailing theories in consumer behavior studies an array of models: the Stimulus-Organism-Response (S-O-R) paradigm and Privacy Calculus Theory. The combination of these models enables a more elaborate explanation of the impact of AI considering cognitive assessments and affective reactions. Whereas S-O-R describes the process using technological exposure to the behavioral outcome of internal states (e.g., satisfaction, trust), Privacy Calculus describes an economic process that is happening in the mind of consumers when choosing to interact or not with AI systems. The dual-theory framework does not only increase the scope of explanations, but it also presents feasible recommendations to practitioners operating on the question of how to optimize the consumer-AI interface. The practical impacts of this framework are very significant. First, the design of AI should be more transparent among the marketers. Describing the process of generating recommendations, providing data access and option of its correction, and explaining its algorithmic decisions can raise the level of trust and their perceived fairness by users. Second, brands are advised to consider the use of adaptive ranges of personalization- systems that vary depending on the user preference, indicators of behavior or direct feedback. Thirdly, companies need to understand the relevance of brand equity in the moderation of the AI acceptance. On the one hand, a strong brand may cushion against events of negative reception of new or unknown AI tools; on the other hand, a weak or unfamiliar brand may experience enhanced criticism. Lastly, policy implications are also essential. The European Union General Data Protection Regulation (GDPR) and other alternatives in the regulation of AIs globally demand accountability, disclosure of algorithms, and consent among users to automated decision-makers, as well as fair procedures in that respect (European Commission, 2021). The moral implications of ethically aligned practices ever more coincide in the context of the augmented AI in marketing, as follows, namely, such practices are strategically pre-requisite, nonetheless. The inability to consider the nuanced mediators and moderators of trust may result in reputational losses, regulatory fines and customer loss by companies.Overall, the research in this review demonstrates that AI is potentially a potent source of establishing trust and loyalty, but only when applied in a wise and not unethical manner. The proposed framework provides a guideline to traverse this multidimensional landscape as well as establishes the platform on which future research will empirically test and repeat the elements suggested in most industries, in different cultures, and on different tech platforms.

10.CONCLUSION AND IMPLICATIONS

This has provided a new opportunity and challenges in the development of consumer trust and loyalties due to the introduction of artificial intelligence (AI) into digital marketing. In this review, a complete model was presented that displays connections between AI technologies, especially recommendation systems, chatbots, and predictive models, and consumer perceptions mediated by mechanisms like the quality of personalization, satisfaction, risk of privacy breach, and a sense of control. These effects are not general but dependent on some important moderating factors such as privacy sensitivity, type of product, brand image. Central to this is the realization that the extent to which one trusts AI depends not only on the technical performance of said AI but also on how consumers feel and feel about interactions with AI. Those technologies that present personalized and efficient services are able to foster trusting and loyal relations only in case people consider information they provide to be within their control and understand that relations imply respectful and clear communication. However, on the other hand, cascading trust may be lost in case AI systems are either not transparent in their activities or are intrusive in terms of collecting data which is particularly true of users who are more privacy minded.Substantially, the present analysis can enrich academic literature with a multi-dimensional view of the issue concerning AI and consumers, based on the Stimulus-Organism-Response (S-O-R) model augmented with a privacy calculus theory. The findings highlight to practitioners the significance of dynamic personalization, transparent data practice and the use of brand reputation to encourage AI acceptance. The ethical conscience associated with this change is also likely to be of concern to policymakers, who must address an urgency to set up rules and regulations to allow proper transparency in algorithms, user approval, and fair play. With the further development of AI, it is necessary to investigate the presented framework empirically and apply it to different sectors, cultures, and demographic segments in future.To sum it all up, fair weather of AI in digital marketing is becoming less about the abilities of the digital marketing to engage in human enterprises, and more about the perceptions of how it is impacting consumers and making them feel: driven, appreciated, and in command of their online experiences.

REFERENCES

1. Acquisti, A., Brandimarte, L., & Loewenstein, G. (2016). Privacy and human behavior in the age of information. Science, 347(6221), 509–514. https://doi.org/10.1126/science.aaa1465
2. Adomavicius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. IEEE Transactions on Knowledge and Data Engineering, 17(6), 734–749. https://doi.org/10.1109/TKDE.2005.99
3. Arora, N., Dreze, X., Ghose, A., Hess, J. D., Iyengar, R., Jing, B., ... & Shankar, V. (2008). Putting one-to-one marketing to work: Personalization, customization, and choice. Marketing Letters, 19(3), 305–321. https://doi.org/10.1007/s11002-008-9046-z
4. Awad, N. F., & Krishnan, M. S. (2006). The personalization privacy paradox: An empirical evaluation of information transparency and the willingness to be profiled online for personalization. MIS Quarterly, 30(1), 13–28. https://doi.org/10.2307/25148715
5. Baumeister, R. F., & Leary, M. R. (1997). Writing narrative literature reviews. Review of General Psychology, 1(3), 311–320. https://doi.org/10.1037/1089-2680.1.3.311
6. Belanche, D., Casaló, L. V., & Flavián, C. (2020). Frontline robots in tourism and hospitality: Service enhancement or cost reduction? Electronic Markets, 30(2), 611–624. https://doi.org/10.1007/s12525-020-00414-5
7. Binns, R., Veale, M., Van Kleek, M., & Shadbolt, N. (2018). 'It's reducing a human being to a percentage': Perceptions of justice in algorithmic decisions. CHI Conference on Human Factors in Computing Systems Proceedings, 1–14. https://doi.org/10.1145/3173574.3173951
8. Bleier, A., & Eisenbeiss, M. (2015). Personalized online advertising effectiveness: The interplay of what, when, and where. Marketing Science, 34(5), 669–688. https://doi.org/10.1287/mksc.2015.0930
9. Bleier, A., & Eisenbeiss, M. (2015). The importance of trust for personalized online advertising. Journal of Retailing, 91(4), 544–564. https://doi.org/10.1016/j.jretai.2015.07.001
10. Chang, H. H., Fu, C. S., & Jain, H. (2020). Consumer responses to AI recommendation agents: The S-O-R model perspective. International Journal of Information Management, 54, 102200. https://doi.org/10.1016/j.ijinfomgt.2020.102200
11. Chattaraman, V., Kwon, W. S., Gilbert, J. E., & Ross, K. (2023). Enhancing loyalty in luxury fashion with AI: The mediation role of customer relationships. Journal of Retailing and Consumer Services, 71, 103224. https://doi.org/10.1016/j.jretconser.2022.103224

12. Chatterjee, S., Rana, N. P., Tamilmani, K., Sharma, A., & Dwivedi, Y. K. (2021). The role of AI in customer engagement in the digital era: Theoretical perspectives and research agenda. Journal of Business Research, 122, 336–349. https://doi.org/10.1016/j.jbusres.2020.09.038
13. Chaves, A. P., & Gerosa, M. A. (2021). How should my chatbot interact? A survey on human–chatbot interaction design. International Journal of Human–Computer Interaction, 37(8), 729–758. https://doi.org/10.1080/10447318.2020.1841438
14. Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. Journal of the Academy of Marketing Science, 48, 24–42. https://doi.org/10.1007/s11747-019-00696-0
15. Dinev, T., & Hart, P. (2006). An extended privacy calculus model for e-commerce transactions. Information Systems Research, 17(1), 61–80. https://doi.org/10.1287/isre.1060.0080
16. Ferrari, R. (2015). Writing narrative style literature reviews. Medical Writing, 24(4), 230–235. https://doi.org/10.1179/2047480615Z.000000000329
17. Gnewuch, U., Morana, S., & Maedche, A. (2017). Towards designing cooperative and social conversational agents for customer service. Proceedings of the International Conference on Information Systems (ICIS).
18. Green, B. N., Johnson, C. D., & Adams, A. (2006). Writing narrative literature reviews for peer-reviewed journals: Secrets of the trade. Journal of Chiropractic Medicine, 5(3), 101–117. https://doi.org/10.1016/S0899-3467(07)60142-6
19. Gursoy, D., Chi, C. G., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. International Journal of Information Management, 49, 157–169. https://doi.org/10.1016/j.ijinfomgt.2019.03.008
20. Hofstede, G. (2001). Culture's consequences: Comparing values, behaviors, institutions, and organizations across nations (2nd ed.). Sage Publications.
21. Jiang, Y., Bhatnagar, N., & Ghose, S. (2021). Perceived value of AI-powered personalization in e-commerce: The role of perceived intrusiveness and trust. Journal of Retailing and Consumer Services, 61, 102549. https://doi.org/10.1016/j.jretconser.2021.102549
22. Jung, J., Hur, W. M., & Yoon, H. J. (2021). Understanding the effects of AI-based service quality on customer satisfaction and loyalty: The mediating role of perceived control. Technological Forecasting and Social Change, 168, 120767. https://doi.org/10.1016/j.techfore.2021.120767
23. Kim, J., & Forsythe, S. (2008). Adoption of virtual try-on technology for online apparel shopping. Journal of Interactive Marketing, 22(2), 45–59. https://doi.org/10.1002/dir.20113
24. Kim, J., & Kim, M. (2022). The role of product type and perceived risk in consumer acceptance of AI recommendations. Journal of Retailing and Consumer Services, 64, 102821. https://doi.org/10.1016/j.jretconser.2021.102821
25. Lankton, N. K., McKnight, D. H., & Tripp, J. (2015). Technology, humanness, and trust: Rethinking trust in technology. Journal of the Association for Information Systems, 16(10), 880–918. https://doi.org/10.17705/1jais.00412
26. Li, Y., Hess, T. J., & Valacich, J. S. (2010). Why do we trust new technology? A study of initial trust formation with organizational information systems. The Journal of Strategic Information Systems, 19(1), 39–71. https://doi.org/10.1016/j.jsis.2010.01.001
27. Lwin, M. O., Wirtz, J., & Williams, J. D. (2007). Consumer online privacy concerns and responses: A power–responsibility equilibrium perspective. Journal of the Academy of Marketing Science, 35(4), 572–585. https://doi.org/10.1007/s11747-006-0003-3
28. Martin, K. D., & Murphy, P. E. (2017). The role of data privacy in marketing. Journal of the Academy of Marketing Science, 45(2), 135–155. https://doi.org/10.1007/s11747-016-0495-4
29. Mehrabian, A., & Russell, J. A. (1974). An approach to environmental psychology. MIT Press.
30. Nguyen, A., & Simkin, L. (2022). Trust and brand credibility in artificial intelligence-driven marketing. Journal of Strategic Marketing 30(6), 515–530. https://doi.org/10.1080/0965254X.2021.1906649
31. Oliver, R. L. (1999). Whence consumer loyalty? Journal of Marketing, 63(4_suppl1), 33–44. https://doi.org/10.1177/00222429990634s105
32. Pantano, E., Pizzi, G., Scarpi, D., & Dennis, C. (2021). Artificial intelligence in retailing: A review. Journal of Business Research, 124, 311–324. https://doi.org/10.1016/j.jbusres.2020.01.057
33. Pavlou, P. A., & Fygenson, M. (2006). Understanding and predicting electronic commerce adoption: An extension of the theory of planned behavior. MIS Quarterly, 30(1), 115–143. https://doi.org/10.2307/25148720
34. Ricci, F., Rokach, L., & Shapira, B. (2015). Recommender systems: Introduction and challenges. In F. Ricci, L. Rokach, & B. Shapira (Eds.), Recommender Systems Handbook (pp. 1–34). Springer. https://doi.org/10.1007/978-1-4899-7637-6_1
35. Smith, H. J., Dinev, T., & Xu, H. (2011). Information privacy research: An interdisciplinary review. MIS Quarterly, 35(4), 989–1016. https://doi.org/10.2307/41409970
36. Tam, K. Y., & Ho, S. Y. (2006). Understanding the impact of web personalization on user information processing and decision outcomes. MIS Quarterly, 30(4), 865–890. https://doi.org/10.2307/25148757
37. Toufaily, E., Ricard, L., Perrien, J., & Parent, M. (2021). Trust in digital service encounters: A systematic literature review of trust antecedents. Journal of Service Theory and Practice, 31(2), 175–197. https://doi.org/10.1108/JSTP-01-2020-0015
38. Wedel, M., & Kannan, P. K. (2016). Marketing analytics for data-rich environments. Journal of Marketing, 80(6), 97–121. https://doi.org/10.1509/jm.15.0413