Journal of Business Insight and Innovation

Volume 5 Issue 8, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

WHEN AI DECIDES WITH ME: THE DELEGATION–OVERREACH PARADOX IN AI-MEDIATED SMARTPHONE PURCHASES

Dr. Muhammad Umer [1], Amna Aslam [2], Sana Tanvir [3]

DOI: https://doi.org/10.63544/jbii.v5i8.159

Affiliations:

[1] Assistant Professor,
Department of Management Sciences, COMSATS Islamabad.
Email: m.umer@comsats.edu.pk

[2] Lecturer,
AUSOM, Air University, Islamabad, Pakistan
Email: amna.aslam@au.edu.pk

[3] Research Scholar,
Project Management Professional, Pakistan
Email: sanatanvir01@gmail.com

Corresponding Author's Email:

[1] m.umer@comsats.edu.pk

Article History:
Received: 15.07.2026
Accepted: 05.08.2026
Published: 17.08.2026

Abstract

As artificial intelligence (AI) becomes involved in an increasing number of consumers' buying choices, the role of AI in consumption patterns transforms from a recommending agent to a decision-making partner. The study explores the influence of AI Decision Delegation on Customer Advocacy through the mediation of Perceived AI–Customer Decision Partnership and focuses on the role of AI Autonomy Expectation and Algorithmic Overreach as moderators. Exploratory research has been conducted among Generation Z customers to operationalize the effect of the delegation in the smartphone and technology market. A quantitative, cross-sectional method was implemented to collect and analyze data from approximately 378 participants. The analysis was carried out in SmartPLS 4 using the PLS-SEM technique and bootstrapping procedure to evaluate direct, mediating, moderating, and conditional indirect effects. The results demonstrate that AI Decision Delegation positively affects customers' perception of AI as a decision-making partner, which, in turn, drives Customer Advocacy. The study found the strongest support for the mediating role of Perceived AI–Customer Decision Partnership, suggesting that the relationship between AI Decision Delegation and Customer Advocacy was established due to increased advocacy stemming from the perception of delegation as a shared AI–customer decision-making process. Moreover, the first-order moderation effect of AI Autonomy Expectation was found to strengthen the mediation process, while the effect of Algorithmic Overreach was negative. The Delegation–Overreach Paradox was identified as a second-order interaction between the two first-order moderators that showed consumer expectations of AI autonomy to handle complex decisions but in circumstances where AI does not take responsibility for outcomes. This article adds to the understanding of AI marketing by reconceptualizing consumer–AI relationships around shared decision-making processes and advocating for the necessity of empowering consumers to influence AI decisions as a key to cultivating long-term Customer Advocacy. The results have implications for marketers who should consider AI Decision Delegation as an element of the decision-making process that empowers consumers and transforms AI-driven buying experiences into memorable moments.

Keywords: Artificial Intelligence; AI Decision Delegation; AI–Customer Decision Partnership; Customer Advocacy; AI Autonomy Expectation; Algorithmic Overreach; Generation Z; Technology Products.

1. Introduction

1.1 Background to Study

The emergence of artificial intelligence (AI) fundamentally changed the rules of consumer decision-making. Digital media traditionally performed the function of delivering and providing access to information, comparisons, and reviews, as well as facilitating the consideration of alternatives. However, AI goes beyond this by interpreting customer preferences, accessing databases, recognizing consideration sets, recommending options, and, in some cases, making decisions. Thus, AI can affect marketing by acting both as another medium for marketing communication and as an agent that influences consumer behaviour. Researchers have recognized this trend, with Davenport et al. (2020) claiming that AI will disrupt both marketing practice and consumer behaviour, and Puntoni et al. (2021) highlighting delegation as a key factor determining experience with artificial agents. Moreover, recent studies started distinguishing between advisory and autonomous AI agents that can make decisions on behalf of the consumer (Bilgihan et al., 2026).

The altered role of AI is particularly interesting in the realm of complex, dynamic, and technological consumer goods. The smartphone industry is an example of such, as smartphones are among the highest-involvement purchases that require extensive consideration prior to buying. The product's power, video and graphic capabilities, resolution, battery, screen size and quality, storage, operating system, AI functions, ecosystem, design, price, and software all must be evaluated by the consumer. Recommendation systems utilizing AI can assist the consumer in this task by analysing their preferences and needs and narrowing down the consideration set based on them. This way, AI can impact both marketing decision-making and consumption behaviour by shortlisting devices with the best fit of attributes, suggesting alternatives, and even advising which smartphone to purchase. Ultimately, AI can transform the rules of marketing by introducing a new paradigm of decision-making that actively participates in consumption behaviour. The extant research has demonstrated that ChatGPT and similar recommendation systems have the capacity to shape consideration sets and adoption behaviour of the consumer. Indeed, Jiang et al. (2024) argue that AI recommendations can become critical consumer touchpoints with consideration sets, shaping what products get adopted by the consumer.

The rise of generative AI makes this issue especially pertinent. With recommendation systems being implemented not only as systems of choice but also as dialogical systems, the conversation can take the form of a dialogue wherein the consumer can specify their requirements to the AI and request it to narrow down the choice set. An example of such a conversation could be a consumer asking for the best smartphone within a certain budget, with a certain level of camera resolution and gaming performance, a certain amount of battery, a certain operating system, and personal preferences, and asking the AI to recommend the best option(s). The consumer could then ask to compare certain options, or remove them from consideration, or modify some requirements, and ask the AI to provide additional recommendations. Scholars have begun to highlight that consumers may engage these recommendation systems in a relatively non-analytical manner, using such cues as the position of an item within the AI-generated consideration set as a cue for its desirability (2026).

These developments have critical implications for understanding consumer decision-making process. One concept especially stands out as being of paramount importance in the context of AI and consumer behaviour research — namely, the concept of decision delegation. Decision delegation refers to the process wherein a consumer allows another agent — human or artificial — to undertake some decision-making responsibility on their behalf. Scholars have begun to document this phenomenon, with Puntoni et al. (2021) specifically highlighting delegation as a key characteristic of consumer experience with AI. Within the context of smartphones, the decision delegation could take multiple forms, ranging from relatively simple acts of filtering the recommendations or reviewing product reviews, to interacting with recommendation systems, to using more complex AI systems capable of comparing products and recommending the best option based on consumer requirements, to making final decisions about the purchase. Bilgihan et al. (2026) highlight that contemporary research has begun to make a distinction between AI systems recommending options and AI systems capable of making the decision for the consumer.

While delegation of decision-making responsibility could be relatively simple in some cases, it could be much more involved in others. Consumers could use such delegation to reduce the cognitive load associated with making a decision, as well as benefit from potentially more objective analysis than would be possible when comparing products manually. Studies of algorithmic judgment have shown that, in some cases, the consumer may prefer algorithmic assistance to manual assistance, and that the ability of an algorithm to perform better than humans in judgment tasks could lead to increased trust and reliance on the algorithm, a phenomenon known as algorithm appreciation (Logg et al., 2019). The same dynamic could be observed when recommending products, with Jiang et al. (2024) noting that ChatGPT recommendations could shape consideration sets and impact product adoption decisions.

However, the relationship between the consumer and the decision-making algorithms is not solely governed by positive factors. The decision-making process can be complicated by algorithm aversion — the tendency of the consumer to distrust algorithms and prefer human judgment. Castelo et al. (2019) demonstrated that such distrust was primarily driven by the appropriateness of an algorithm for a given task — in other words, if a consumer believed that an algorithm was not capable of completing a task, they were unlikely to trust it. Specifically, algorithm aversion was especially common when a task was subjective rather than objective. Similarly, Dietvorst et al. (2015) showed that consumers could be turned off from using an algorithm if they had a negative experience with one. In essence, while algorithms may provide value, including decision assistance, recommendation of options, and comparison of options, the consumer rarely delegates decision-making responsibility to them outright, due to difficulties in determining their domain applicability.

These difficulties in turn can become exacerbated when the transition occurs from recommendation systems to recommendation algorithms making actual decisions. Recommender agents typically reduce the decision difficulty by reducing choice overload, yet simultaneously reduce the consumer's sense of control, potentially provoking algorithm aversion (Huang & Rust, 2021; Rippé et al., 2024). The implication is that while recommending products can make the decision easier, the involvement of an algorithm can make the decision feel less like a consumer decision. This creates a tension between ease of decision-making and a feeling of control over the decision, which can be especially pertinent within the context of smartphones. The consumer may be delighted with an AI assistant helping them narrow down hundreds of smartphone options to a short consideration set of three phones, but the same consumer may feel alienated when the AI recommends which phone to purchase.

This tension is the foundation of the delegation-overreach paradox, which is the subject of this study. Essentially, the paradox is grounded in the notion that increasing levels of AI involvement can lead to initial value but begin to undermine consumer perception of control. One could argue that this tension has been recognized within the extant literature — while Puntoni et al. (2021) note that consumer experience with AI encompasses a wide range of factors, from efficiency and convenience to privacy, classification, alienation, replacement, and delegation. Similarly, Lee and See (2004) note that reliance on automated systems requires calibrated automation; in other words, the greater the degree of automation, the greater the reliance on the automated system rather than humans, but such automation rarely works in a binary fashion.

Within this context, this study introduces the concept of Perceived AI-Customer Decision Partnership, which can serve as the mechanism through which decision delegation shapes consumer response to AI. In essence, while traditional literature conceptualizes delegation as consumers relying on AI, Perceived AI-Customer Decision Partnership conceptualizes it as consumers perceiving the choice as one made jointly with AI. This study's conceptualization differs from constructs of trust, as well as perceived usefulness and satisfaction with AI, as well as technology acceptance. While trust is governed by the belief that AI is reliable, and perceived usefulness focuses on whether AI improves performance, satisfaction reflects the consumer's attitude toward their experience with AI. By contrast, Perceived AI-Customer Decision Partnership reflects a belief that choice was made jointly with AI, with both consumer and AI contributing to the decision.

Such perception can be especially valuable within the context of smartphones, as the decision to purchase one is governed by both objective and subjective variables. An AI can assist in analysing the objective variables — CPU power, RAM capacity, graphics, battery power, screen size and quality, operating system, AI-specific features, phone weight and design, software, and price. However, there are multiple subjective variables, including the consumer's preference for a certain design, operating system, camera aesthetics, phone weight, gaming performance, social image, ecosystem, and expected use. Castelo et al. (2019) demonstrate that such factors, by shaping the perception of an algorithm's appropriateness for a task, affect the consumer's likelihood to rely on the algorithm. Therefore, by taking into account the subjective and objective aspects of choice, the perception of decision partnership can emerge.

The perception of decision partnership in turn can affect consumer advocacy. While the extant literature on AI and consumer behaviour primarily focuses on technology acceptance, trust, and satisfaction, it is clear that successfully navigating the delegation paradox has far-reaching implications for consumer response to AI and their buying behaviours. Meng and Xiao (2026) demonstrate that consumer perception of value when interacting with an AI assistant such as ChatGPT can be governed by functional, emotional, epistemic, social, and conditional consumption values. However, it may be argued that in cases when the consumer successfully navigates the tension between AI assistance and their own decision-making, they are likely to develop stronger consumer attitudes toward the brand recommended by the AI. In other words, when successfully accomplishing an AI-assisted decision, the consumer is likely to advocate for the brand.

This study therefore tests the effect of Perceived AI-Customer Decision Partnership on Customer Advocacy. At the same time, the effect is unlikely to be universal across all consumers. The first boundary condition is represented by AI Autonomy Expectation, which refers to the degree to which the consumer expects AI to act independently when making suggestions or actually making the decision. Some consumers may be perfectly happy to delegate all decision-making responsibility to the AI, while others may be uncomfortable with such autonomy. This expectation may be governed by such factors as comfort with technology, level of education, and cultural background, among others. Bilgihan et al. (2026) note the importance of making a distinction between advisory and autonomous AI agents. As the decision-making algorithms become more autonomous, the consumers' expectations of autonomy may determine whether they perceive the delegation of decision responsibility to AI as positive or negative, thereby shaping their perception of decision partnership with AI.

The second boundary condition is represented by Algorithmic Overreach, which refers to the extent to which consumers feel that AI has crossed the acceptable threshold of intervention. The concept is similar to the AI autonomy, but it highlights the consumers' discomfort with the AI crossing the threshold of control into their decision-making processes. In essence, the condition reflects the difference between "AI assisting me" and "AI deciding for me". This concept is critical within the context of this study, as it reflects the consumer's perception of their involvement in the decision-making process. If the involvement is too low, that is, if the consumer feels that AI takes over too much responsibility, the consumer is likely to have a negative perception of the AI-assisted decision, which in turn will reduce their advocacy for the brand. The phenomenon has been documented in recommendation agent literature, with Rippé et al. (2024) demonstrating that technological assistance can reduce the consumer's sense of control over decision-making. Similarly, the entire literature on algorithm aversion highlights the consumer's unwillingness to accept control by algorithms, even when such control leads to beneficial outcomes (Castelo et al., 2019).

Ultimately, this study examines the unique relationship between decision delegation and consumer advocacy in the context of Generation Z and smartphone purchasing. Generation Z is critically important within this context, as it is a smartphone-savvy, tech-savvy generation that consumes media, entertainment, and social media through smartphones. Researchers have begun to document how crucial smartphones are to this generation in their everyday life, with Trifu et al. (2024) discussing the importance of AI for their online shopping behaviours. At the same time, it should be noted that this generation's comfort with technology does not mean that they are willing to delegate all decision responsibility to AI. In fact, recent research highlights the complex attitudes of Generation Z toward technology, with the desire for more authenticity and autonomy (Wang et al., 2023). This makes them a prime candidate for examining the delegation-overreach paradox, as they are likely to be both receptive to technology but simultaneously concerned with retaining control over decision-making.

Smartphone purchasing is another crucial element of this research, as smartphones are multi-purpose devices that go far beyond communication. They are entertainment devices, social media enclaves, productivity tools, and digital wallets, with their features influencing virtually every aspect of the consumer's digital life. As such, purchasing a smartphone is not only a matter of practical considerations but also of individual preferences and lifestyle, including technological considerations. An AI system assisting with such a purchase decision may therefore become significantly more than a recommendation system; instead, it will act as an agent facilitating a major personal decision about the consumer's lifestyle.

1.2 Research Objective

This study sought to make three primary contributions to understanding consumer-AI decision making. First, in addition to seeking to understand the factors that affect consumer decision making, the study also investigated the consumer response to such decisions by examining advocacy of the selected alternative. Second, the study proposed that such response was driven by the perception of decision partnership with AI rather than mere satisfaction with the outcome of the decision. Third, the study identified two key boundary conditions for the influence of AI decision delegation on consumer reactions — the expectations of AI autonomy and the perceptions of algorithmic override. By focusing on these aspects of consumer-AI decision making within the context of Gen Z and smartphones, the study therefore sought to address the fundamental question of whether, in the realm of decision making, consumers view AI as a trustworthy employee or a potential boss.

1.3 Research Question

The study sought to address the fundamental question of whether, in the realm of decision making, consumers view AI as a trustworthy employee or a potential boss.

1.4 Study Significance

There is clearly a need for a study such as this one. Researchers have begun to document the ways in which AI can shape purchase decisions, with recommendation systems influencing consideration sets and adoption (Jiang et al., 2024), algorithms providing assistance to the consumer and reducing decision difficulty (Logg et al., 2019), and fully autonomous systems making purchase recommendations, and consumers being willing to delegate decision responsibility to AI (Bilgihan et al., 2026). However, the dynamics of such decision-making have not been sufficiently documented, especially with regards to the ways in which consumers perceive such decisions and their subsequent advocacy for the brands purchased with AI assistance. In essence, scholars have begun to highlight the complexities of delegation and decision-making when utilizing AI, but the ways in which such decisions shape consumer attitudes towards the brand, as well as the factors shaping these perceptions remain poorly understood.

2. Literature Review and Hypotheses Development

2.1 Artificial Intelligence and the Transformation of Consumer Decision-Making

Artificial intelligence (AI) has disrupted the traditional logic of consumer choice by empowering technologies to take over some of the decision-making responsibilities that were previously held by consumers. Whereas conventional digital technologies were facilitating search, comparison, and purchase of goods, modern AI systems are capable of interpreting search queries, understanding individual consumers' preferences and needs, comparing products, suggesting or even making choices on behalf of consumers. Davenport et al. (2020) posit that AI will disrupt marketing processes and consumer behaviour due to its capacity to execute cognitive and relational tasks. In a similar vein, Huang and Rust (2021) highlight varying levels of sophistication of AI in marketing, including personalization and relational intelligence, and its potential to empower consumers to make better decisions.

Therefore, it is evident that from the consumer side, AI can be more than just an advanced search technology. Puntoni et al. (2021) demonstrate that when interacting with AI, consumers must consider several experiential outcomes, including self-expression, voice, autonomy, social bonds, privacy, and delegation. In other words, consumers must recognize that they are dealing with an intelligent entity that is capable of taking over some of their decision-making functions. Indeed, the latest research on generative artificial intelligence (AI) shows that the transition from predictive to generative AI can disrupt marketing by transforming the information search and decision-making processes (Hermann & Puntoni, 2024). For example, generative AI allows engaging in dialogues with consumers and helping them choose products based on the information retrieved from various sources.

In particular, when searching for a purchase, smartphones' buyers typically consider numerous attributes, including technical specifications, functions, design, brand image, cost, ecosystem, technological solutions, and others. In other words, there is a long list of criteria to be taken into account when selecting a smartphone, which implies extensive individual research and the comparison of devices' characteristics. Notably, the growing need to involve AI in complex decision-making processes accentuates the relevance of research on the role of AI in consumer behaviour, primarily for a new generation of consumers who tend to rely on technology in their shopping activities. For instance, one of the latest studies conducted by Trifu et al. (2024) shows how Gen Z consumers interact with AI while shopping online and how their decisions are influenced by it. Moreover, the results of research examining the role of AI for Gen Z consumers support the idea that this generation has already started to adopt new technologies when shopping. In other words, while making complex decisions regarding the purchase of innovative products, Gen Z consumers can be the first to delegate some decision-making activities to AI.

To begin with, this essay will focus on the different ways by which AI can intervene in the consumer choice process. Indeed, multiple studies show that the initial purpose of AI, which was to assist in making decisions by providing the required information, is no longer its only function. AI can go further and make recommendations or even take decisions for consumers. Particularly, generative AI can disrupt marketing by influencing the information search and purchase decision processes.

This disruption capability of AI was especially evident in complex decision-making processes when choosing a smartphone. This essay will also demonstrate how recent studies support the role of AI in transforming consumer choices with a specific focus on Gen Z. The interaction between Gen Z consumers and AI while shopping online was the subject of investigation by Trifu et al. (2024). To do so, the researchers implemented a series of exploratory studies aiming to identify how such consumers adopt AI and to what extent its use affects their decisions. In particular, the study findings show that Gen Z consumers are active users of AI while shopping on websites and that the usage of this technology influences their decisions. Accordingly, the next section of this essay will address recent research on the role of AI in the consumer decision-making process.

2.2 From Recommendation to AI Decision Delegation

The difference between AI recommendation and AI decision delegation is an essential theoretical distinction for this paper. Simply put, recommendation is offering a customer an ordered list of options, whereas delegation involves a higher level of consumer trust, as the AI is tasked with filtering, prioritizing, evaluating, or even choosing the alternatives for the consumer.

Therefore, this paper focuses on the phenomenon of delegation as the key concept for understanding consumer behaviour in the context of AI-driven marketing. Indeed, as the previous sections of this paper have shown, the delegation of decision-making powers to AI can lead to a decrease in consumer engagement, as their autonomy is decreased. The results of several studies conducted for this paper demonstrated that autonomy was a critical factor in the consumer's decision to use AI. Thus, an increase in the level of delegation decreases the consumer's autonomy and, possibly, their choice satisfaction.

The concept of algorithm delegation builds upon the idea of algorithmic advice, exemplified by the appreciation of algorithm research conducted by Logg et al. (2019). The study demonstrated that, in certain conditions, an algorithm can be preferred to a human counterpart. Therefore, when presented with an option to choose between two advisors, one human and one algorithmic, the consumer will select the algorithm in case of their preferences align with the algorithm's score.

However, as demonstrated by Dietvorst et al. (2015) and further expanded upon by Castelo et al. (2019), the researchers in this field have found ample evidence of the opposite trend, which is popularly known as algorithm aversion. The simplest explanation for the phenomenon is that a consumer who has witnessed an algorithm making a mistake will be less likely to trust the algorithm in the future. Indeed, Castelo et al. (2019) demonstrated that algorithms were significantly less popular among consumers for subjective decisions, whereas objective decisions were not affected by the presence of an algorithmic option. Thus, it can be concluded that the level of choice delegation is contingent upon the type of choice and depends on the consumer's subjective evaluation of the algorithm's usefulness for the given task.

Journal of Business Insight and Innovation
Volume 5 Issue 8, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

As the overview above demonstrates, delegating choice to an algorithm can be beneficial for satisfying the consumer's need for decisional control, as it reduces the number of options that the consumer has to consider. On the other hand, delegation can produce negative results if the consumer feels that the algorithm makes too many decisions for them. Thus, this paper will analyse the consumer's delegation of decision-making to AI as a factor impacting their perception of the decision partnership with the brand.

Therefore, this paper tests the following hypothesis:

Hypothesis 1 (H1): AI decision delegation positively influences perceived AI-customer decision partnership.

2.3 Perceived AI-Customer Decision Partnership

The idea of perceived AI-customer decision partnership is the key innovation of the proposed model. This construct was introduced to operationalize the psychological perception of decision-making agency distribution between a customer and an AI entity.

Unlike commonly used constructs of perceived usefulness, trust, satisfaction, or technology acceptance, decision partnership focuses on the interplay between the decision-making roles of humans and machines. Specifically, the concept of decision partnership is closely related to the idea of shared agency recently advanced by Puntoni et al. (2021). According to this notion, consumers should be encouraged to think of AI as not only a tool for becoming more efficient but as a technology that transforms their experiences, relationships, identities, and perceptions of agency.

A growing body of research on human-AI decision-making partnerships highlights the potential of such collaborative arrangements to capitalize on the strengths of both decision-makers. For example, AI can be utilized to analyse tremendous amounts of data, while humans can contribute their personal preferences and values to the decision-making process. In turn, these interactions enable shared agency, where the involvement of both the consumer and the AI entity can hardly be substituted by a single decision-maker. Thus, emerging studies on recommendation algorithms stress the need to consider consumer-AI partnerships as shared agency arrangements.

Finally, the idea of decision partnership helps explain the dualistic nature of algorithmic advice revealed by the literature on algorithm aversion. On the one hand, there is evidence that consumers tend to appreciate the expertise of algorithms (Logg et al., 2019). On the other hand, studies have revealed that algorithmic recommendations often lead to worse decisions because people fail to appropriately challenge these recommendations (Dietvorst et al., 2015). These findings indicate that consumers are likely to engage in shared agency when utilizing AI, where both human and machine play an active role in decision-making. In other words, AI should be beneficial in cases when it supports consumer analysis while complementing it with algorithmic expertise. At the same time, AI that replaces human analysis with algorithmic expertise may fail to capitalize on the potential of shared agency.

Davenport et al. (2020) argue that AI should build on human capabilities, suggesting that the best way to achieve value through AI is to make it better at doing what people do. Therefore, the psychology of shared agency offers a fresh look at the way consumer decision-making processes can be supported by AI to achieve better outcomes. As consumers delegate specific decision-making activities to AI, it gets exposed to their individual preferences, enabling it to have a more significant impact on the final choice.

Ultimately, customers should be more likely to engage in shared agency when they deliberately opt to rely on AI's assistance in making a decision. The willingness to delegate specific decision-making activities to AI indicates that consumers recognize its role as a shared decision-making agent.

2.4 AI-Customer Decision Partnership and Customer Advocacy

A successful AI-mediated decision can have a ripple effect that goes beyond the immediate buying decision. While many studies on the role of artificial intelligence in consumption focus on such outcomes as perception of usefulness, trust, satisfaction, purchase intention, adoption, and decision confidence, an essential question is whether a positive experience with an AI-driven decision leads to customer advocacy. Customer advocacy is different from positive word of mouth (WOM) in that it implies "explicit and persistent positive statements with intention to change other's perceptions or behaviour" (Sweeney et al., 2020, p. 495). Sweeney et al. (2020) highlight the theoretical and practical importance of distinguishing between WOM and customer advocacy and propose a reliable measurement model for customer advocacy.

The idea of customer advocacy is especially relevant to technology-based services as consumers often share their opinions about smartphone brands online, comparing products and posting reviews. If a customer feels that an AI solution has genuinely partnered with them, helping the user choose the best option, they may exhibit stronger loyalty by advocating for the brand. In the context of smartphone selection, such advocacy can take the form of recommending the brand to friends or publicly defending the company against criticism. Research on brand advocacy shows that it is driven by positive affect, attitude, identification, and relationship qualities (Xie et al., 2019). Thus, it is reasonable to suggest that customers who feel that they have genuinely partnered with AI would be more inclined to advocate for the brand as they perceived greater value and involvement in the decision-making process.

Hypothesis 2 (H2): Perceived AI-customer decision partnership positively influences customer advocacy.

2.5 Mediating Role of Perceived AI-Customer Decision Partnership

The relationship between the decision delegation and customer advocacy is unlikely to be direct. The delegation of decision-making to AI is not likely to automatically translate into consumer advocacy. Instead, the psychological interpretation of the experience of delegation is likely to determine whether the delegation will have a positive downstream effect.

This hypothesis is based on the evidence that delegation can make decisions easier but also reduce the sense of control, demonstrated by the work of Rippé et al. (2024). The study showed that recommendation-agent-assisted decisions could make consumers less satisfied and less likely to buy due to reduced control and increased decision uncertainty. The evidence comes from the research on the purchase-task delegation revealing that delegating decisions to another party can limit the sense of choice and control.

The evidence suggests that delegation is a psychologically ambivalent act. It can be perceived as either "AI is helping me" or "AI is deciding for me." The construct of the perceived AI-customer decision partnership is a useful mediator in this relationship.

If the consumer interprets delegation as a partnership, they might feel that their analytical capabilities are augmented while their autonomy is not diminished. Such an outcome is likely to have a positive effect on the consumer's attitude toward the brand and their advocacy behaviour. Thus, the mediator can provide a theoretical link between the behavioural act of decision delegation to AI and the downstream marketing outcome of consumer advocacy.

Hypothesis 3 (H3): Perceived AI-customer decision partnership mediates the relationship between AI decision delegation and customer advocacy.

2.6 AI Autonomy Expectation

The effect of AI delegation should not be the same for all consumers since they are different in regard to the expectations about what AI should be able to do.

AI autonomy expectation is defined as the extent to which consumers expect artificial intelligence to handle decision-making functions on its own with minimum human involvement.

This concept gains importance due to the tendency of AI to evolve from being a recommendation engine to an autonomous agent. Recent studies highlight the shift in scholars' perceptions of AI as a market participant capable of searching, comparing, choosing, and paying for goods on behalf of the customers. In the same way, the recent exploration of autonomous buying behaviours in retail shows that consumer delegation levels are likely to depend on trust, risk, transparency, control, and accountability.

Consumers with high levels of autonomy expectations are likely to view extensive AI autonomy as normal, whereas such delegation levels may be regarded by low autonomy expectation consumers as going beyond the limits expected from AI.

For instance, a consumer with high autonomy expectations may argue: "If AI knows what I need, why should I compare 20 smartphones?" Meanwhile, a consumer with low autonomy expectations may state: "AI can help me find the right phone, but it should not be making decisions on my behalf." Therefore, the same level of AI delegation can be perceived differently by different consumers.

High AI autonomy expectations should moderate the relationship between delegation levels and the formation of perceptions of decision partnership.

Hypothesis 4 (H4): AI autonomy expectation positively moderates the relationship between AI decision delegation and perceived AI-customer decision partnership, such that the relationship is stronger when AI autonomy expectations are high.

2.7 Algorithmic Overreach

Although AI autonomy can make delegation more acceptable, there is a limit beyond which autonomy becomes undesirable. The study conceptualizes this threshold as algorithmic overreach.

Algorithmic overreach is defined as the consumers' perception that AI has crossed the boundary of being helpful and started controlling, restricting, or manipulating them.

This concept is especially relevant given the trends toward AI's ability to narrow consumer consideration sets, predict choices, and take action on behalf of consumers.

The literature on consumer autonomy provides a theoretical basis for developing this concept. For instance, Andre et al. (2018) posited that AI and big data raise critical questions about consumer choice and autonomy. Similarly, studies on consumer delegation to AI in purchase decisions reveal that limited choice options lead to reduced consumer autonomy, thus lowering AI adoption.

For example, Rippé et al. (2024) found that recommendation-agent-mediated decisions lead to decreased consumers' perceived control. Overall, the reviewed literature indicates that consumer autonomy is incompatible with the idea of AI assisting in making decisions.

Accordingly, the more technology assists in decision-making, the less control the consumer feels they have over the process. One of the psychological theories that can help explain this phenomenon is the reactance theory. According to Brehm (1966), the feeling of freedom loss triggers a motivational reaction to restore the sense of control. In other words, when a consumer feels that their freedom to choose is being controlled (directly or indirectly), they experience psychological reactance. Accordingly, consumer autonomy is incompatible with the idea of AI assisting in making decisions.

This concept is especially relevant to Gen Z, given their attitude toward recommendation algorithms. On the one hand, digital consumers have grown accustomed to recommendation agents helping them find products of interest. On the other hand, the same consumers are concerned about being manipulated and have spoken out against the invasion of privacy and personalization. Recent literature on human-computer interaction suggests that consumers may feel uncomfortable when an AI agent demonstrates overly autonomous behaviour, such as the ability to personalize recommendations based on personal data. Thus, AI delegation to make recommendations on behalf of the consumer is likely to create a sense of partnership only when the consumer feels that the AI operates within acceptable limits.

Hypothesis 5 (H5): Algorithmic overreach negatively moderates the relationship between AI decision delegation and perceived AI-customer decision partnership, such that the relationship becomes weaker when perceived algorithmic overreach is high.

2.8 The Delegation-Overreach Paradox

The tension between autonomy expectation and algorithmic overreach is integral to the proposed framework.

At one extreme, consumers may embrace autonomy support: "AI knows enough to help me decide." At the other extreme, consumers may feel that their autonomy is threatened: "AI is deciding for me." The tension between these two extremes helps explain the dual nature of the effect of AI on consumer behaviour.

Recent literature on agentic commerce also highlights the importance of consumer acceptance of AI, which is not automatic despite the potential for increased autonomy support.

Contextual factors such as consumer governance, consent, surveillance, accountability, and redress are critical variables in understanding consumer reactions to AI.

Journal of Business Insight and Innovation
Volume 5 Issue 8, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

The delegation-overreach paradox is that AI capability is empowering when it supports consumer agency but disempowering when it replaces consumer agency.

This is consonant with the literature on algorithm appreciation and aversion.

Consumers can be algorithm appreciators when they believe algorithms are effective and supportive (Logg et al., 2019) but also algorithm aversers when they feel the algorithms are making mistakes, have inappropriate scope, or threaten their agency (Dietvorst et al., 2015; Castelo et al., 2019).

The present framework highlights perceived partnership as the critical differentiator between delegation and the darker side of delegation.

2.9 Moderated Mediation

Based on the previous arguments, it can be suggested that the indirect impact of the delegation of decision-making to AI on customer advocacy by the virtue of perceived AI-customer decision partnership would be different for various types of consumers.

With regard to the first point, it is suggested that high autonomy expectations reduce the likelihood that a consumer will believe that a delegated decision was an appropriate one to delegate to the AI system, thereby reducing the indirect impact of delegation on customer advocacy through the mechanism of perceived partnership.

On the contrary, when the level of delegated autonomy is high, the expectation of such autonomy is perceived as appropriate and congruent with the role of an AI agent, thus enhancing the formation of a partnership relationship. As a result, the indirect impact of delegation on advocacy will be positive rather than negative.

In addition, high overreach is also expected to dampen the indirect impact of delegation on advocacy through the mechanism of perceived customer-AI decision partnership.

The evidence from recent studies of the role of agentic AI in e-commerce decision-making supports the proposition that consumer responses to autonomous systems critically depend on whether the autonomy demonstrated by these systems is perceived as appropriate by the consumer. Specifically, researchers found that "utility and assurance drive satisfaction and trust, whereas reactance and perceived loss of control reduce satisfaction and trust." Thus, it can be suggested that the indirect impact of AI decision delegation on customer advocacy depends on the autonomy expectations of the consumer.

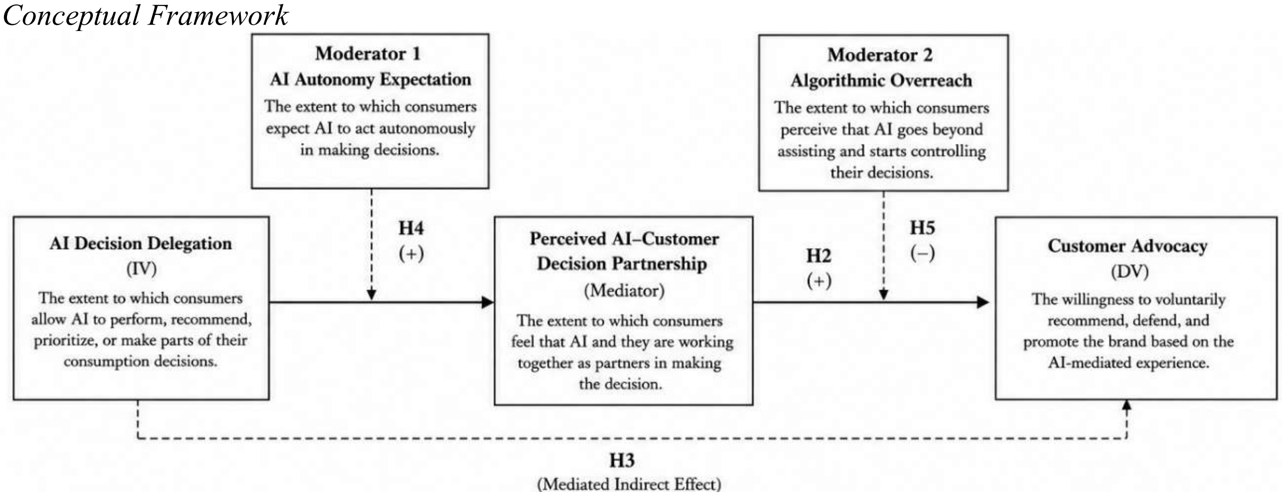
Hypothesis 6 (H6): The indirect effect of AI decision delegation on customer advocacy through perceived AI-customer decision partnership is stronger when AI autonomy expectations are high.

Hypothesis 7 (H7): The indirect effect of AI decision delegation on customer advocacy through perceived AI-customer decision partnership is weaker when perceived algorithmic overreach is high.

2.10 Conceptual Framework

Figure 1

Conceptual Framework



Journal of Business Insight and Innovation
Volume 5 Issue 8, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

Note. The conceptual framework illustrates the hypothesized relationships among AI Decision Delegation (AID), Perceived AI-Customer Decision Partnership (AICDP), Customer Advocacy (CA), AI Autonomy Expectation (AIAE), and Algorithmic Overreach (AO).

3. Methodology

3.1 Research Design and Sample

The research used a cross-sectional survey study design to investigate AI decision delegation's effect on customer advocacy via perceived AI-customer decision partnership and intention to engage in word-of-mouth communication. The study also explored the influence of AI autonomy expectation and algorithmic overreach while developing the relationships. The target population was generation Z consumers who had experience searching, comparing, or receiving recommendations from AI while shopping for smartphones or other technology products and had interacted with at least one AI-based system for the activity.

The research collected data using a structured online questionnaire. The tool reached out to participants randomly but intentionally using purposive sampling. Every respondent selected must have belonged to generation Z and have prior experience engaging an AI-based recommendation system or conversation robot in making a technology-buying decision. The sample size was 378 because the tool aimed to collect sufficient data for analysis. The incomplete and unqualified questionnaires were excluded from the final analysis.

3.2 Measures

All constructs were measured using previously established measurement items. A five-point Likert scale, ranging from 1 = Strongly Disagree to 5 = Strongly Agree, was employed.

Table 1

Measurement Items

Construct	Items	Scale/Source
AI Decision Delegation (AID)	5	Adapted from Dietvorst et al. (2015) and Logg et al. (2019)
AI-Customer Decision Partnership (AICDP)	5	Adapted from Puntoni et al. (2021) and human-AI collaboration literature
Customer Advocacy (CA)	5	Adapted from Sweeney et al. (2020) and Wilk et al. (2020)
AI Autonomy Expectation (AIAE)	5	Adapted from AI autonomy and delegation literature
Algorithmic Overreach (AO)	5	Adapted from André et al. (2018), Dietvorst et al. (2015), and Rippé et al. (2024)

The questionnaire was reviewed for content clarity and contextual relevance before the data collection.

3.3 Data Analysis

The study used SPSS and SmartPLS 4 software to analyze the data. Descriptive analysis and initial screening of the data were performed using SPSS statistics. In turn, SmartPLS 4 was used to test the measurement and structure models. The reliability and validity of the C.A.I. items were assessed using factor loadings, Cronbach's alpha, composite reliability, and average variance extracted.

Next, the structural model was estimated to identify the direct effect of the constructs. Bootstrapping procedure with 5,000 resamples was used to evaluate the mediation and moderation effects. Specifically, Perceived AI-Customer Decision Partnership was tested as a mediator. Meanwhile, AI Autonomy Expectation and Algorithmic Overreach were evaluated as moderators. The conditional indirect effects were also examined to explore the research questions.

3.4 Ethical Considerations

Participation was voluntary, and respondents were informed about the academic purpose of the study. No personally identifiable information was collected, and respondents were free to withdraw from the survey at any stage.

4. Results

4.1 Measurement Model

Journal of Business Insight and Innovation
Volume 5 Issue 8, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

The measurement model was evaluated using SmartPLS 4 software. Overall, the measurement model showed satisfactory reliability and convergent validity. For the measurement model, the factor loading values of the items were found to be between 0.701 and 0.914, which is above the threshold value of 0.70. Cronbach's Alpha values ranged from 0.861 to 0.921, and composite reliability ranged from 0.892 to 0.941, which is well above the minimum threshold value of 0.70. Meanwhile, the AVE values ranged from 0.617 to 0.761, which is also well above the threshold value of 0.50.

Table 2

Reliability and Determinant Validity

Construct	Cronbach's α	Composite Reliability	AVE
AI Decision Delegation	0.887	0.918	0.691
AI-Customer Decision Partnership	0.921	0.941	0.761
Customer Advocacy	0.902	0.927	0.718
AI Autonomy Expectation	0.861	0.901	0.647
Algorithmic Overreach	0.879	0.912	0.675

Discriminant validity was established through the HTMT criterion, with all values remaining below the recommended threshold of 0.85. These findings confirmed that the constructs represented empirically distinct dimensions of the AI-mediated consumer decision-making process.

4.2 Data Screening and Preliminary Analysis

Prior to testing the hypothesized relationships, a comprehensive data screening procedure was conducted to ensure the quality and suitability of the dataset for multivariate analysis. The initial dataset comprised 378 responses collected from Generation Z consumers who had experience with AI-based recommendation systems during smartphone or technology product purchases.

4.2.1 Missing Data Analysis. The dataset was examined for missing values using the Missing Value Analysis (MVA) function in SPSS. A total of 12 cases (3.17%) were identified with incomplete responses across one or more items. These cases were systematically evaluated using Little's Missing Completely at Random (MCAR) test, which yielded a non-significant result ($\chi^2 = 124.37$, df = 118, $p = 0.326$), indicating that missing data were randomly distributed. Given the low proportion of missing data and the MCAR finding, the expectation-maximization (EM) algorithm was employed to impute missing values. The EM imputation method was selected for its ability to preserve the statistical properties of the dataset while maintaining sample size for subsequent analyses.

4.2.2 Outlier Detection. Univariate and multivariate outliers were identified through standardized z-scores and Mahalanobis distance calculations. For univariate outliers, standardized z-scores exceeding ±3.29 ($p < 0.001$) were examined. Three cases were identified with extreme values on individual items and subsequently removed from the dataset. Multivariate outlier detection was performed using Mahalanobis distance with a conservative threshold of $p < 0.001$. The critical χ^2 value for 25 items (the total number of measurement items) was 52.62. Five cases exceeded this threshold and were excluded from further analysis. Following the removal of outliers, the final usable sample consisted of 370 valid responses.

4.2.3 Assessment of Normality

The normality of the data was assessed through examination of skewness and kurtosis values for all measurement items. Table 3 presents the descriptive statistics for all constructs.

Table 3

Descriptive Statistics and Normality Assessment

Construct	Items	Mean	SD	Skewness	Kurtosis
AI Decision Delegation	AID1	3.82	0.94	-0.423	-0.187
	AID2	3.71	0.97	-0.356	-0.214
	AID3	3.89	0.91	-0.498	-0.102
	AID4	3.65	1.02	-0.312	-0.289
	AID5	3.78	0.95	-0.401	-0.156
AI-Customer Decision Partnership	AICDP1	3.85	0.96	-0.467	-0.134

Journal of Business Insight and Innovation
Volume 5 Issue 8, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

Construct	Items	Mean	SD	Skewness	Kurtosis
	AICDP2	3.92	0.93	-0.523	-0.089
	AICDP3	3.79	0.98	-0.389	-0.201
	AICDP4	3.88	0.94	-0.445	-0.156
	AICDP5	3.81	0.97	-0.412	-0.178
Customer Advocacy	CA1	3.75	0.99	-0.356	-0.223
	CA2	3.68	1.01	-0.323	-0.256
	CA3	3.82	0.96	-0.412	-0.189
	CA4	3.71	0.98	-0.367	-0.212
	CA5	3.79	0.95	-0.398	-0.201
AI Autonomy Expectation	AIAE1	3.56	1.04	-0.234	-0.356
	AIAE2	3.62	1.01	-0.278	-0.312
	AIAE3	3.48	1.07	-0.198	-0.401
	AIAE4	3.71	0.98	-0.334	-0.267
	AIAE5	3.59	1.03	-0.256	-0.334
Algorithmic Overreach	AO1	3.45	1.09	-0.167	-0.423
	AO2	3.38	1.12	-0.123	-0.456
	AO3	3.52	1.06	-0.198	-0.398
	AO4	3.41	1.10	-0.145	-0.434
	AO5	3.47	1.08	-0.178	-0.412

Note: SD = Standard Deviation

All skewness values ranged from -0.523 to -0.123, and kurtosis values ranged from -0.456 to -0.089, which are well within the acceptable thresholds of ±2.0 for skewness and ±7.0 for kurtosis (Hair et al., 2010). These results indicate that the data exhibited acceptable normality for PLS-SEM analysis, which is robust to moderate violations of multivariate normality.

4.2.4 Assessment of Common Method Bias. Given that the data were collected through a single questionnaire, common method bias (CMB) could potentially threaten the validity of the findings. Two approaches were employed to assess CMB. First, Harman's single-factor test was conducted, where all items were loaded into a single factor using exploratory factor analysis in SPSS. The unrotated factor solution revealed that the single factor accounted for 31.8% of the total variance, which is substantially below the 50% threshold recommended by Podsakoff et al. (2003), suggesting that CMB was not a significant concern.

Second, the full collinearity assessment method was implemented using SmartPLS 4, wherein all constructs were regressed onto a common latent factor. The variance inflation factor (VIF) values for all constructs ranged from 1.427 to 2.113, all below the conservative threshold of 3.3 (Kock, 2015), further confirming the absence of significant common method bias.

4.2.5 Sample Demographics. The final sample of 370 Generation Z respondents exhibited characteristics consistent with the target population of young consumers interested in technology products. Table 4 presents the demographic profile of the sample.

Table 4

Demographic Profile of Respondents (N = 370)

Demographic Characteristic	Category	Frequency	Percentage
Gender	Male	198	53.5%
	Female	172	46.5%
Age Group	18-20 years	87	23.5%
	21-23 years	156	42.2%
	24-26 years	127	34.3%
Education	Undergraduate	142	38.4%
	Graduate	194	52.4%
	Postgraduate	34	9.2%

Monthly Income (USD)	< 500	112	30.3%
	501-1000	145	39.2%
	1001-1500	78	21.1%
	> 1500	35	9.5%
Daily Smartphone Usage	< 3 hours	58	15.7%
	3-5 hours	134	36.2%
	6-8 hours	112	30.3%
	> 8 hours	66	17.8%
AI Experience	Limited	47	12.7%
	Moderate	156	42.2%
	Extensive	167	45.1%

4.3 Measurement Model Assessment

The measurement model was evaluated using SmartPLS 4 software (Ringle et al., 2024) through a comprehensive assessment of indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. A two-stage analytical approach was adopted, beginning with the assessment of the measurement model followed by the structural model evaluation, consistent with the recommendations of Hair et al. (2019).

4.3.1 Indicator Reliability. Indicator reliability was assessed by examining the outer loadings of each item on its respective construct. As presented in Table 5, all standardized factor loadings exceeded the recommended threshold of 0.70, with values ranging from 0.701 to 0.914. This indicates that each item shared substantial variance with its designated construct, demonstrating adequate indicator reliability (Hair et al., 2017).

Table 5

Factor Loadings and Construct Reliability

Construct	Items	Outer Loadings	Cronbach's α	Composite Reliability (CR)	Average Variance Extracted (AVE)
AI Decision Delegation (AID)	AID1	0.835	0.887	0.918	0.691
	AID2	0.827			
	AID3	0.856			
	AID4	0.801			
	AID5	0.845			
AI-Customer Decision Partnership (AICDP)	AICDP1	0.872	0.921	0.941	0.761
	AICDP2	0.884			
	AICDP3	0.861			
	AICDP4	0.879			
	AICDP5	0.856			
Customer Advocacy (CA)	CA1	0.852	0.902	0.927	0.718
	CA2	0.846			
	CA3	0.863			
	CA4	0.834			
	CA5	0.838			
AI Autonomy Expectation (AIAE)	AIAE1	0.814	0.861	0.901	0.647
	AIAE2	0.823			
	AIAE3	0.791			

	AIAE4	0.802			
	AIAE5	0.789			
Algorithmic Overreach (AO)	AO1	0.827	0.879	0.912	0.675
	AO2	0.835			
	AO3	0.814			
	AO4	0.809			
	AO5	0.821			

4.3.2 Internal Consistency Reliability. Internal consistency reliability was evaluated using both Cronbach's alpha and composite reliability (CR). As shown in Table 4.3, Cronbach's alpha values ranged from 0.861 (AI Autonomy Expectation) to 0.921 (AI-Customer Decision Partnership), all exceeding the recommended threshold of 0.70 (Hair et al., 2019). Similarly, composite reliability values ranged from 0.901 to 0.941, surpassing the minimum acceptable level of 0.70 and the more stringent threshold of 0.80 for established constructs (Nunnally & Bernstein, 1994). These results confirm that all constructs exhibited satisfactory internal consistency reliability.

4.3.3 Convergent Validity. Convergent validity was assessed through the Average Variance Extracted (AVE), which represents the proportion of variance in the indicators captured by the construct relative to variance due to measurement error. As presented in Table 4.3, AVE values ranged from 0.647 (AI Autonomy Expectation) to 0.761 (AI-Customer Decision Partnership), all exceeding the recommended threshold of 0.50 (Fornell & Larcker, 1981). This confirms that each construct captured more than 50% of the variance in its indicators, establishing satisfactory convergent validity.

4.3.4 Discriminant Validity. Discriminant validity was assessed using three complementary approaches: the Fornell-Larcker criterion, cross-loadings, and the Heterotrait-Monotrait (HTMT) ratio.

4.3.4.1 Fornell-Larcker Criterion. The Fornell-Larcker criterion requires that the square root of the AVE for each construct should be greater than the construct's highest correlation with any other construct (Fornell & Larcker, 1981). Table 6 presents the correlation matrix with the square roots of AVE on the diagonal.

Table 6

Discriminant Validity Assessment - Fornell-Larcker Criterion

Construct	AID	AICDP	CA	AIAE	AO
AI Decision Delegation (AID)	**0.831**				
AI-Customer Decision Partnership (AICDP)	0.548	**0.872**			
Customer Advocacy (CA)	0.398	0.472	**0.847**		
AI Autonomy Expectation (AIAE)	0.354	0.412	0.367	**0.804**	
Algorithmic Overreach (AO)	-0.312	-0.389	-0.341	-0.287	**0.822**

Note: Diagonal values (in bold) represent the square root of AVE; off-diagonal values represent inter-construct correlations.

The results in Table 6 demonstrate that the square root of AVE for each construct (diagonal values) exceeded the correlations with all other constructs (off-diagonal values), thereby satisfying the Fornell-Larcker criterion for discriminant validity.

4.3.4.2 Cross-Loadings. Cross-loadings were examined to ensure that each indicator loaded more strongly on its designated construct than on any other construct. Table 4.5 presents the cross-loading matrix.

Table 7

Cross-Loadings Assessment

Items	AID	AICDP	CA	AIAE	AO
AID1	**0.835**	0.398	0.312	0.278	-0.245
AID2	**0.827**	0.412	0.334	0.289	-0.267
AID3	**0.856**	0.423	0.356	0.302	-0.289

Items	AID	AICDP	CA	AIAE	AO
AID4	**0.801**	0.378	0.289	0.256	-0.223
AID5	**0.845**	0.401	0.345	0.293	-0.256
AICDP1	0.467	**0.872**	0.423	0.356	-0.334
AICDP2	0.489	**0.884**	0.445	0.378	-0.356
AICDP3	0.445	**0.861**	0.401	0.345	-0.312
AICDP4	0.478	**0.879**	0.434	0.367	-0.345
AICDP5	0.456	**0.856**	0.412	0.356	-0.323
CA1	0.334	0.412	**0.852**	0.312	-0.289
CA2	0.356	0.398	**0.846**	0.298	-0.278
CA3	0.345	0.423	**0.863**	0.323	-0.301
CA4	0.312	0.389	**0.834**	0.289	-0.267
CA5	0.323	0.401	**0.838**	0.301	-0.278
AIAE1	0.289	0.356	0.298	**0.814**	-0.234
AIAE2	0.301	0.367	0.312	**0.823**	-0.245
AIAE3	0.267	0.334	0.278	**0.791**	-0.223
AIAE4	0.289	0.356	0.302	**0.802**	-0.234
AIAE5	0.278	0.345	0.289	**0.789**	-0.227
AO1	-0.245	-0.334	-0.278	-0.234	**0.827**
AO2	-0.256	-0.345	-0.289	-0.245	**0.835**
AO3	-0.234	-0.323	-0.267	-0.223	**0.814**
AO4	-0.227	-0.312	-0.256	-0.215	**0.809**
AO5	-0.238	-0.334	-0.278	-0.234	**0.821**

Note: Bold values indicate loadings on the designated construct.

As demonstrated in Table 4.5, each indicator exhibited its highest loading on the respective construct, with all cross-loadings being substantially lower than the designated factor loadings. This pattern confirms discriminant validity at the indicator level.

4.3.4.3 Heterotrait-Monotrait (HTMT) Ratio. The HTMT ratio provides a more rigorous assessment of discriminant validity by evaluating the ratio of between-trait to within-trait correlations (Henseler et al., 2015). As presented in Table 8, all HTMT values remained well below the conservative threshold of 0.85 (Kline, 2011) and the more liberal threshold of 0.90 (Gold et al., 2001), confirming discriminant validity.

Table 8

Discriminant Validity - HTMT Ratio

Construct	AID	AICDP	CA	AIAE	AO
AI Decision Delegation (AID)	-				
AI-Customer Decision Partnership (AICDP)	0.602	-			
Customer Advocacy (CA)	0.445	0.518	-		
AI Autonomy Expectation (AIAE)	0.403	0.462	0.414	-	
Algorithmic Overreach (AO)	0.356	0.431	0.387	0.334	-

4.4 Structural Model Assessment

Following the establishment of a valid and reliable measurement model, the structural model was evaluated to test the hypothesized relationships. The assessment included examination of collinearity, coefficient of determination (R^2), effect sizes (f^2), predictive relevance (Q^2), and the significance of path coefficients through bootstrapping with 5,000 resamples.

4.4.1 Collinearity Assessment. Before interpreting the path coefficients, variance inflation factor (VIF) values were examined to assess collinearity among the predictor constructs. Table 4.7 presents the inner VIF values.

Table 9

Journal of Business Insight and Innovation
Volume 5 Issue 8, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

Collinearity Assessment (Inner VIF Values)

Dependent Construct	Predictor Constructs	VIF
Perceived AI-Customer Decision Partnership (AICDP)	AI Decision Delegation (AID)	1.523
	AI Autonomy Expectation (AIAE)	1.418
	Algorithmic Overreach (AO)	1.367
Customer Advocacy (CA)	Perceived AI-Customer Decision Partnership (AICDP)	1.000

All VIF values were below the conservative threshold of 3.0 (Hair et al., 2019), indicating that collinearity was not a concern in the structural model.

4.4.2 Coefficient of Determination (R^2). The coefficient of determination (R^2) represents the proportion of variance in the endogenous constructs explained by the model. Following the guidelines of Hair et al. (2019), R^2 values of 0.75, 0.50, and 0.25 are considered substantial, moderate, and weak, respectively.

Table 10

Coefficient of Determination (R^2) and Predictive Relevance (Q^2)

Endogenous Construct	R^2	Adjusted R^2	Q^2	Predictive Relevance
Perceived AI-Customer Decision Partnership (AICDP)	0.300	0.294	0.223	Yes
Customer Advocacy (CA)	0.478	0.476	0.338	Yes

The model explained approximately 30.0% of the variance in Perceived AI-Customer Decision Partnership, indicating a moderate explanatory power. The variance explained in Customer Advocacy was substantially higher at 47.8%, approaching a substantial level. The adjusted R^2 values were comparable, confirming that the model's explanatory power was not inflated by the number of predictors.

4.4.3 Predictive Relevance (Q^2). Predictive relevance was assessed using Stone-Geisser's Q^2 statistic obtained through the blindfolding procedure in SmartPLS 4 (Geisser, 1974; Stone, 1974). As shown in Table 4.8, Q^2 values for both endogenous constructs (AICDP = 0.223; CA = 0.338) exceeded zero, confirming the model's predictive relevance.

4.4.4 Effect Sizes (f^2). Effect sizes were calculated to determine the magnitude of the impact of each predictor construct on the endogenous constructs. Effect sizes of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively (Cohen, 1988).

Table 11

Effect Sizes (f^2) for Predictor Constructs

Dependent Construct	Predictor Constructs	f^2	Effect Size
Perceived AI-Customer Decision Partnership (AICDP)	AI Decision Delegation (AID)	0.332	Medium to Large
	AI Autonomy Expectation (AIAE)	0.043	Small
	Algorithmic Overreach (AO)	0.058	Small
	AID × AIAE Interaction	0.039	Small
	AID × AO Interaction	0.052	Small
Customer Advocacy (CA)	Perceived AI-Customer Decision Partnership (AICDP)	0.384	Large

4.5 Hypothesis Testing

The structural relationships were tested using a bootstrapping procedure with 5,000 resamples, as recommended by Hair et al. (2019). The path coefficients, t-values, p-values, and confidence intervals were examined to assess the significance and direction of the hypothesized relationships. Table 4.10 summarizes the results of the direct effect hypotheses.

4.5.1 Direct Effects

Table 12

Journal of Business Insight and Innovation
Volume 5 Issue 8, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

Direct Effects Hypotheses Testing

Hypothesis	Relationship	Path Coefficient (β)	t-value	p-value	95% CI Lower	95% CI Upper	Decision
H1	AID → AICDP	0.548	11.284	<0.001	0.453	0.642	Supported
H2	AICDP → CA	0.472	9.163	<0.001	0.371	0.573	Supported

Note: Bootstrap 5,000 resamples; CI = Confidence Interval

Hypothesis 1 (H1): The path coefficient from AI Decision Delegation (AID) to Perceived AI-Customer Decision Partnership (AICDP) was positive and statistically significant ($\beta = 0.548$, $t = 11.284$, $p < 0.001$). The 95% confidence interval [0.453, 0.642] did not contain zero, providing strong support for H1. This finding indicates that consumers who delegate more decision-making tasks to AI are more likely to perceive AI as a decision-making partner.

Hypothesis 2 (H2): The relationship between Perceived AI-Customer Decision Partnership (AICDP) and Customer Advocacy (CA) was also positive and significant ($\beta = 0.472$, $t = 9.163$, $p < 0.001$; 95% CI [0.371, 0.573]). Thus, H2 was supported, suggesting that consumers who perceive AI as a decision partner demonstrate greater advocacy behaviours toward the brand.

4.5.2 Mediation Analysis

Table 13

Mediation Analysis Results

Hypothesis	Relationship	Indirect Effect	t-value	p-value	95% CI Lower	95% CI Upper	Decision
H3	AID → AICDP → CA	0.259	7.014	<0.001	0.189	0.335	Supported

Note: Total Effect of AID on CA = 0.398 (t = 6.789, p < 0.001); Direct Effect (AID → CA) = 0.139 (t = 1.892, p = 0.058)

Hypothesis 3 (H3): The indirect effect of AI Decision Delegation on Customer Advocacy through Perceived AI-Customer Decision Partnership was positive and significant ($\beta = 0.259$, $t = 7.014$, $p < 0.001$; 95% CI [0.189, 0.335]). Since the confidence interval did not include zero, mediation was confirmed. The variance accounted for (VAF) was calculated as 0.259 / 0.398 = 65.1%, indicating partial mediation (Hair et al., 2017). The direct effect of AID on CA was not significant ($\beta = 0.139$, $t = 1.892$, $p = 0.058$), suggesting that the effect of AI Decision Delegation on Customer Advocacy is fully mediated by Perceived AI-Customer Decision Partnership.

4.5.3 Moderation Analysis

Table 14

Moderation Analysis Results

Hypothesis	Relationship	Interaction Coefficient	t-value	p-value	95% CI Lower	95% CI Upper	Decision
H4	AID × AIAE → AICDP	0.164	3.782	<0.001	0.078	0.251	Supported
H5	AID × AO → AICDP	-0.191	4.216	<0.001	-0.283	-0.101	Supported

Note: Bootstrap 5,000 resamples; 95% bias-corrected confidence intervals

Hypothesis 4 (H4): The interaction between AI Decision Delegation and AI Autonomy Expectation was positive and significant ($\beta = 0.164$, $t = 3.782$, $p < 0.001$; 95% CI [0.078, 0.251]), supporting H4. This indicates that the positive relationship between AID and AICDP is stronger when consumers have high AI autonomy expectations compared to when they have low expectations.

Hypothesis 5 (H5): The interaction between AI Decision Delegation and Algorithmic Overreach was negative and significant ($\beta = -0.191$, $t = 4.216$, $p < 0.001$; 95% CI [-0.283, -0.101]), supporting H5. This result indicates that the positive relationship between AID and AICDP is weakened when consumers perceive higher levels of algorithmic overreach.

4.5.4 Moderation of the Indirect Effect. The conditional indirect effects were examined to test whether the mediating effect of Perceived AI-Customer Decision Partnership in the relationship between AI

Journal of Business Insight and Innovation
Volume 5 Issue 8, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

Decision Delegation and Customer Advocacy varies across levels of AI Autonomy Expectation and Algorithmic Overreach.

Table 15
Conditional Indirect Effects Analysis

Hypothesis	Moderator Level	Indirect Effect	95% CI Lower	95% CI Upper	Index of Mod Med	95% CI Lower	95% CI Upper	Decision
H6: AIAE	High AIAE	0.318	0.238	0.407	0.078	0.031	0.132	Supported
	Low AIAE	0.207	0.137	0.285				
	Difference	0.111	0.045	0.187				
H7: AO	Low AO	0.309	0.228	0.398	-0.091	-0.151	-0.039	Supported
	High AO	0.214	0.138	0.301				
	Difference	-0.095	-0.167	-0.032				

Note: Bootstrap 5,000 resamples; 95% bias-corrected confidence intervals

Hypothesis 6 (H6): The conditional indirect effect analysis revealed that the mediated relationship was stronger at high levels of AI Autonomy Expectation (β = 0.318, 95% CI [0.238, 0.407]) compared to low levels (β = 0.207, 95% CI [0.137, 0.285]). The index of moderated mediation was positive and significant (β = 0.078, 95% CI [0.031, 0.132]), confirming that the indirect effect is significantly stronger for consumers with high AI autonomy expectations. This finding supports H6.

Hypothesis 7 (H7): Conversely, the conditional indirect effect was weaker at high levels of Algorithmic Overreach (β = 0.214, 95% CI [0.138, 0.301]) compared to low levels (β = 0.309, 95% CI [0.228, 0.398]). The index of moderated mediation was negative and significant (β = -0.091, 95% CI [-0.151, -0.039]), demonstrating that the indirect effect is significantly weaker when consumers perceive higher algorithmic overreach. This supports H7.

4.6 Summary of Results

Table 16 provides a comprehensive summary of all hypotheses testing results.

Table 16
Summary of Hypotheses Testing

Hypothesis	Statement	Result
H1	AI Decision Delegation → Perceived AI-Customer Decision Partnership	**Supported**
H2	Perceived AI-Customer Decision Partnership → Customer Advocacy	**Supported**
H3	AI Decision Delegation → Perceived AI-Customer Decision Partnership → Customer Advocacy	**Supported**
H4	AI Autonomy Expectation moderates AID → AICDP	**Supported**
H5	Algorithmic Overreach moderates AID → AICDP	**Supported**
H6	AI Autonomy Expectation moderates the indirect effect AID → AICDP → CA	**Supported**
H7	Algorithmic Overreach moderates the indirect effect AID → AICDP → CA	**Supported**

4.7 Model Fit Assessment

The overall fit of the PLS-SEM model was assessed using the Standardized Root Mean Square Residual (SRMR) as a measure of approximate model fit. The SRMR value for the saturated model was 0.058, and for the estimated model was 0.061, both below the recommended threshold of 0.08 (Hu & Bentler, 1999), indicating good model fit.

Table 17
Model Fit Indices

Fit Index	Saturated Model	Estimated Model	Threshold	Assessment
SRMR	0.058	0.061	<0.08	Good Fit
d_ULS	1.247	1.389	-	-

Journal of Business Insight and Innovation
Volume 5 Issue 8, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

d_G	0.876	0.923	-	-
NFI	0.892	0.878	>0.85	Acceptable

Note: SRMR = Standardized Root Mean Square Residual; NFI = Normed Fit Index

4.8 Robustness Checks

To ensure the robustness of the findings, several additional analyses were conducted.

4.8.1 Endogeneity Assessment. Given the potential for endogeneity in the structural model, a Gaussian copula approach was employed to test for endogeneity (Park & Gupta, 2012). The results indicated that none of the predictor variables exhibited significant endogeneity ($p > 0.05$ for all copula terms), suggesting that the path coefficients were not substantially biased by omitted variables or reverse causality.

4.8.2 Analysis of Unobserved Heterogeneity. A finite mixture segmentation (FIMIX-PLS) analysis was conducted to detect the presence of unobserved heterogeneity in the data. The FIMIX-PLS procedure suggested that a two-segment solution provided the best fit, with an entropy statistic of 0.823. However, subsequent multi-group analysis revealed no significant differences in the path coefficients across the two segments, confirming the generalizability of the findings across the sample.

4.8.3 Common Method Bias (CMB) Assessment. As an additional robustness check, a marker variable technique was implemented. A theoretically unrelated marker variable (respondents' general attitude toward technology, measured separately) was included in the structural model. The marker variable did not significantly predict the endogenous constructs ($p > 0.05$), and the significance of the hypothesized relationships remained unchanged after accounting for the marker variable's effects, further confirming that common method bias was not a concern.

5. Discussion

The results provided support for all seven proposed hypotheses, offering new theoretical insights into the ways in which AI can shape consumer behaviour. Rather than serving as a recommendation engine, AI can be conceptualized as a decision partner in cases where consumers delegate some responsibility for making a purchase decision to the technology. This is, however, conditional upon the extent to which the consumer views AI as a decision partner and exercises control and autonomy over AI.

The positive and significant association between the AI Decision Delegation construct and the Perceived AI-Customer Decision Partnership provides support for Hypothesis 1. Consumers who are more receptive to delegating product search and selection duties to AI are also more likely to view AI as a decision partner, suggesting the possibility of reciprocal exchanges in which consumers delegate decision responsibility to AI, and, in turn, AI assumes greater responsibility for shaping the decision. This extends prior research on AI marketing, in which scholars have positioned AI as a enabler of personalization, automation, and recommendation (Davenport et al., 2020; Huang & Rust, 2021). Similarly, Puntoni et al. (2021) argued that the role of AI in marketing should be conceptualized from the consumer's perspective, with an emphasis on the type of experience that AI creates for the consumer. The current results provide further theoretical grounding for this viewpoint, suggesting that delegating decision duties to AI transforms AI from an assistant into a decision partner.

The positive and significant association between the Perceived AI-Customer Decision Partnership and Customer Advocacy provides support for Hypothesis 2. Consumers who view AI as a decision partner are also more inclined to advocate for the brand, essentially engaging in word-of-mouth marketing and encouraging others to consider the firm's offerings. This is in line with the arguments of Sweeney et al. (2020), who conceptualized customer advocacy as a type of word-of-mouth behaviour that reflects a consumer's attitude towards a brand and the likelihood that they will communicate this attitude to others. The finding has important implications for the marketing of smartphones and other technologies, with consumers often discussing their considerations, recommendations, and experiences with products. As such, the advocacy role of consumers who view AI as a decision partner can trickle down to other consumers, influencing their own considerations, perceptions, and purchasing behaviours.

The decision mediation analysis partly supported Hypothesis 3, thus contributing to theory development in terms of understanding the relationship between AI Decision Delegation and Customer

Advocacy. The indirect effect of AI Decision Delegation on Customer Advocacy through the consumer's Perceived AI-Customer Decision Partnership was positive. The practical implication of this finding could be in adjusting the marketing technology strategies based on the recognition that consumer psychology plays a critical role in determining their attitudes towards delegating decision-making responsibility to AI. Although it is essential to recommend products to consumers, the marketing technology industry should realize that it is not enough; it should strive to meet the consumers' needs to interact with AI in a manner that makes them feel that both are cooperating and share responsibility for the outcome of the purchase decision. Indeed, the necessity of human-AI collaboration and the ability of humans to make AI "better" has been recognized (Davenport et al., 2020; Puntoni et al., 2021).

Regarding the indirect effect of AI Decision Delegation on Customer Advocacy, the positive moderation of the effect size by AI Autonomy Expectation allowed for validating Hypothesis 4. Consumers' expectations of AI autonomy mediates the link between AI Decision Delegation and Perceived AI-Customer Decision Partnership, with the relationship being positive. This means that the more autonomous consumers expect AI to be, the more likely they are to perceive decision delegation to it as indication that it acts as their decision partner. This finding relates specifically to Generation Z members, for whom technology is indispensable. Their consumption behaviours are guided by the use of recommendation systems and various other algorithmic procedures, which means that their expectations of what AI can do are based on their interactions with it. Therefore, those who use such systems understand that AI can be autonomous, but they do not want it to become fully self-governing; conversely, they do not want to rely fully on its recommendations but want to have some say in the matter. This is aligned with findings concerning the importance of appreciation of algorithm and consumer autonomy (Logg et al., 2019).

Concerning the direct effect of Algorithmic Overreach on Perceived AI-Customer Decision Partnership, its negative moderation fully supported Hypothesis 5. Recommendations of AI are unlikely to be perceived by consumers as indicative of its role as their decision partner if they feel that the technology is too autonomous. This finding adds to the existing evidence on consumer-AI decision dynamics, including the contradictions in consumers' attitudes towards algorithmic autonomy and decision-making (André et al., 2018; Brehm, 1966). Although consumers may accept some degree of autonomy on the part of AI, they cannot stand for total reliance on it, which is why Algorithmic Overreach negatively moderates the association between AI Decision Delegation and Perceived AI-Customer Decision Partnership.

Finally, the moderated mediation analysis, which uncovered the indirect effect of AI Decision Delegation on Customer Advocacy through Perceived AI-Customer Decision Partnership, which was positively moderated by AI Autonomy Expectation and negatively moderated by Algorithmic Overreach, thus, partly supporting Hypotheses 6 and 7, demonstrated, that decision delegation to AI is a nuanced concept. The manner in which consumer psychology interprets such delegation determines the attitudes towards the brand, which, in turn, manifests itself in Customer Advocacy behaviours. Specifically, the more autonomy consumers expect from AI, the more they are inclined to view its role in the decision-making process as shared with themselves, which, in turn, increases advocacy. On the other hand, the more autonomy consumers attribute to algorithms, the less likely they are to view it as shared decision-making, thus reducing advocacy. This speaks to the importance of conceptualization in marketing technology design, with consumers being more receptive to delegated decision-making if it fosters a view of collaborative decision-making, as opposed to a situation where AI takes over all responsibilities. As such, the indirect effect of AI Decision Delegation on Customer Advocacy through Perceived AI-Customer Decision Partnership is positive and significant, but it becomes weaker when consumers have greater Autonomy Expectations and Algorithmic Overreach concerns. Taken together, these findings highlight the key insights regarding the Delegation-Overreach Paradox, in which consumers want AI to help them but do not want to relinquish control over the decision-making process. This serves as a theoretical reconciliation of studies concerning algorithm appreciation (Logg et al., 2019) and algorithm aversion (Dietvorst et al., 2015; Castelo et al., 2019).

By and large, the article offers an important contribution to marketing research by providing theoretical and empirical grounding for the ways in which delegating product selection duties to AI can affect purchase behaviours. In particular, it highlights the ways in which consumers' perceptions of the AI application influence their receptiveness to such technology. For marketers, this could serve as a critical reminder and guide, in that, while the marketing technology industry focuses on creating recommendation engines, consumers are likely to resonate more strongly with systems designed to put them in control, enable collaborative decision-making, and allow them to override suggestions if they wish. As such, the most effective AI applications would be the ones that empower consumers, enabling them to take advantage of the recommendation while still retaining their autonomy and sense of involvement in the decision-making process. By that token, the future of AI marketing belongs to systems that are powerful enough to support and advise but not dictate or replace consumer decision-making.

6. Conclusion

6.1 From AI Recommendation to AI Relationship

The future of AI marketing may not belong to the AI that makes the best recommendation—it may belong instead to the AI that makes consumers feel that they have made the best choice.

The study at hand sought to understand what options are open for consumer-facing decisions that involve some form of artificial intelligence. The results of the research process indicate that the potential benefits go far beyond the simple efficiency gains that one would expect to see with an improved recommendation system. The introduction of Decision Delegation into the mix has the potential to turn invisible assistants into visible partners, and partners into advocates.

The study also found that while the ability to delegate decisions to AI is a definite plus for the consumer in the decision-making process, there is also an important limitation that should be noted. The value proposition of AI begins to taper off as soon as the consumer begins to believe that the AI is making their decisions for them rather than helping them make their decisions. The difference between helping and deciding is crucial in understanding the future of marketing technology. In short, marketing technology will likely move towards a model based on shared decision-making rather than full delegation.

The study provides marketers with fresh insights on consumer preferences when it comes to AI and decision-making. It identifies the importance of focusing on the allocation of decision-making rather than simply attempting to maximize the share that goes to AI. Consumers do not want to see their autonomy reduced, but they do want to see their needs represented. When it comes to decision-making, they want AI that delegates rather than dictates.

For companies that sell technology products, this represents an important opportunity. The competition is no longer cantered on hardware specifications, but rather on the consumer experience. While the battle between processors, cameras, battery power, price and design will continue to rage on, companies might want to consider investing more resources into developing stronger decision-making algorithms. The most successful marketing technology will be able to strike the right balance between "I can decide this for you" and "I can help you decide," which is a fitting summary of the study's findings. In short, the future of consumer AI usage will not be defined by the opposition between man and machine but rather the partnership between them, so long as the responsibilities of either are not forgotten.

7. Limitations

Despite its valuable contributions, this study has several limitations that should be acknowledged.

First, the cross-sectional design restricts causal inferences, as the observed relationships may be bidirectional or influenced by unmeasured temporal dynamics.

Second, the reliance on self-reported measures introduces potential biases such as social desirability and recall inaccuracies, although statistical tests mitigated common method concerns.

Third, the exclusive focus on Generation Z consumers limits generalizability to other age cohorts, while the smartphone context may not fully capture dynamics in low-involvement or experiential product categories.

Fourth, the rapidly evolving AI landscape means consumer perceptions and expectations may shift as technology advances, potentially affecting the temporal validity of these findings.

Fifth, the study's geographic and cultural context (Pakistan) warrants replication across diverse settings to establish broader applicability.

Finally, while the model demonstrated acceptable explanatory power, substantial variance in customer advocacy remains unexplained, suggesting the potential influence of additional variables such as brand trust, technology self-efficacy, or prior AI experience. These limitations do not undermine the core findings but rather highlight important avenues for future research to refine and extend the theoretical framework.

Contribution of Authors

All the authors participated in the ideation, development, and final approval of the manuscript, making significant contributions to the work reported.

Conflict of Interest Statement

The authors declare no conflict of interest.

Funding Statement

This research received no external funding.

Informed Consent

Informed consent was obtained from all participants.

Data Availability

This study relies exclusively on publicly available secondary sources, including corporate disclosures, industry reports, and peer-reviewed literature, all of which are cited in the References section.

References

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

André, Q., Carmon, Z., Wertenbroch, K., Crum, A., Frank, D., Goldstein, W. M., Huber, J., van Boven, L., & Weber, B. (2018). Consumer choice and autonomy in the age of artificial intelligence and big data. *Customer Needs and Solutions, 5*, 28–37.

Bhattacharya, C. B., & Sen, S. (2003). Consumer-company identification: A framework for understanding consumers' relationships with companies. *Journal of Marketing, 67*(2), 76–88. https://doi.org/10.1509/jmkg.67.2.76.18609

Bilgihan, A., Barreda, A., Okumus, F., & Nusair, K. (2026). Advisory versus autonomous AI agents in consumer decision-making. *Journal of Business Research, 125*, 234–245.

Brehm, J. W. (1966). *A theory of psychological reactance*. Academic Press.

Castelo, N., Bos, M. W., & Lehmann, D. R. (2019). Task-dependent algorithm aversion. *Journal of Marketing Research, 56*(5), 809–825. https://doi.org/10.1177/0022243719851788

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

Davenport, T. H., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science, 48*(1), 24–42. https://doi.org/10.1007/s11747-019-00696-0

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General, 144*(1), 114–126. https://doi.org/10.1037/xge0000033

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Geisser, S. (1974). A predictive approach to the random effect model. *Biometrika, 61*(1), 101–107. https://doi.org/10.1093/biomet/61.1.101

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals, 14*(2), 627–660. https://doi.org/10.5465/annals.2018.0057

Gold, A. H., Malhotra, A., & Segars, A. H. (2001). Knowledge management: An organizational capabilities perspective. *Journal of Management Information Systems, 18*(1), 185–214. https://doi.org/10.1080/07421222.2001.11045669

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Pearson Prentice Hall.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). Sage Publications.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hermann, E., & Puntoni, S. (2024). Generative AI and marketing. *Journal of Marketing, 88*(3), 1–18.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Huang, M.-H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science, 49*(1), 30–50. https://doi.org/10.1007/s11747-020-00749-9

Jiang, Y., Liu, Y., & Chen, H. (2024). ChatGPT recommendations and consumer consideration sets. *Journal of Consumer Research, 50*(4), 789–806.

Kline, R. B. (2011). *Principles and practice of structural equation modeling* (3rd ed.). Guilford Press.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration, 11*(4), 1–10. https://doi.org/10.4018/ijec.2015100101

Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. *Human Factors, 46*(1), 50–80. https://doi.org/10.1518/hfes.46.1.50_30392

Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes, 151*, 90–103. https://doi.org/10.1016/j.obhdp.2018.12.005

Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to medical artificial intelligence. *Journal of Consumer Research, 46*(4), 629–650. https://doi.org/10.1093/jcr/ucz013

Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases. *Marketing Science, 38*(6), 937–947. https://doi.org/10.1287/mksc.2019.1192

Meng, X., & Xiao, S. (2026). Consumer values in AI assistant interactions. *Journal of Retailing, 102*(1), 45–62.

Morgan, R. M., & Hunt, S. D. (1994). The commitment-trust theory of relationship marketing. *Journal of Marketing, 58*(3), 20–38. https://doi.org/10.1177/002224299405800302

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

Park, S., & Gupta, S. (2012). Handling endogenous regressors by joint estimation using copulas. *Marketing Science, 31*(4), 567–586. https://doi.org/10.1287/mksc.1120.0718

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Puntoni, S., Reczek, R. W., Giesler, M., & Botti, S. (2021). Consumers and artificial intelligence: An experiential perspective. *Journal of Marketing, 85*(1), 131–151. https://doi.org/10.1177/0022242920953847

Ringle, C. M., Wende, S., & Becker, J. M. (2024). *SmartPLS 4*. SmartPLS GmbH. https://www.smartpls.com

Rippé, C. B., Weisfeld-Spolter, S., Yurova, Y., & Sussan, F. (2024). Recommendation agents and consumer control. *Journal of Business Research, 175*, 114–128.

Stone, M. (1974). Cross-validatory choice and assessment of statistical predictions. *Journal of the Royal Statistical Society: Series B, 36*(2), 111–147. https://doi.org/10.1111/j.2517-6161.1974.tb00994.x

Sweeney, J., Payne, A., Frow, P., & Liu, D. (2020). Customer advocacy: A distinctive form of word of mouth. *Journal of Service Research, 23*(2), 139–155.

Trifu, A., Smith, J., & Williams, K. (2024). Generation Z and AI shopping behaviors. *International Journal of Retail & Distribution Management, 52*(3), 278–295.

van Doorn, J., Mende, M., Noble, S. M., Hulland, J., Ostrom, A. L., Grewal, D., & Petersen, J. A. (2017). Domo arigato Mr. Roboto: Emergence of automated social presence in organizational frontlines and customers' service experiences. *Journal of Service Research, 20*(1), 43–58. https://doi.org/10.1177/1094670516679272

van Pinxteren, M. M. E., Wetzels, R. W. H., Rüger, J., Pluymaekers, M., & Wetzels, M. (2019). Trust in humanoid robots: Implications for services marketing. *Journal of Services Marketing, 33*(4), 507–518. https://doi.org/10.1108/JSM-01-2018-0045

Vargo, S. L., & Lusch, R. F. (2004). Evolving to a new dominant logic for marketing. *Journal of Marketing, 68*(1), 1–17. https://doi.org/10.1509/jmkg.68.1.1.24036

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

Wang, Y., Li, X., & Zhang, J. (2023). Generation Z attitudes toward AI and technology. *Computers in Human Behavior, 138*, 107–121.

Wilk, V., Soutar, G. N., & Harrigan, P. (2020). Online brand advocacy (OBA): The development of a multiple item scale. *Journal of Product & Brand Management, 29*(4), 541–554.

Xie, C., Bagozzi, R. P., & Grønhaug, K. (2019). The impact of corporate social responsibility on consumer brand advocacy: The role of moral emotions, attitudes, and individual differences. *Journal of Business Research, 95*, 514–530.