Pakistan Journal of Commerce and Social Sciences
2026, Vol. 20(2), 505-534
https://doi.org/10.64534/Commer.2026.684

Building Digital Bonds: The Impact of AI-Driven Personalization on Customer Experience and AI Relationship Quality

Dadang Munandar [1]*, Umi Narimawati [2], Inta Budi Setia Nusa [2], Triyani [1], Marliana B Winanti [1]
[1] International Women University, Indonesia
[2] Universitas Komputer Indonesia, Indonesia

* Corresponding author's Email: dadangm@iwu.ac.id

Article History

Received: 27 Mar 2026 Revised: 23 June 2026 Accepted: 26 June 2026 Published: 30 June 2026

Abstract

This study aims to examine the impact of AI-driven personalization on AI-enabled customer experience and perceived AI relationship quality. It further investigates the mediating roles of trust in AI and perceived personal relevance, as well as the moderating effects of privacy concern and technology readiness within an integrated conceptual framework. A quantitative, cross-sectional research design was employed. Data were collected from 330 users who had prior experience with at least one of three specified AI-enabled digital platform categories: e-commerce recommendation platforms (e.g., online retail sites), streaming services (e.g., video or music platforms), and fintech applications (e.g., digital banking or payment apps). Respondents were screened using platform-specific filter questions to reduce heterogeneity. The proposed model was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) through SmartPLS. Reliability, validity, mediation, and moderation effects were evaluated using bootstrapping techniques. To address potential common method bias arising from single-source self-reported data, Harman's Single-Factor test was conducted. The test confirmed that no single factor accounted for the majority of variance, suggesting that CMB does not critically threaten the validity of the findings.

The main finding is that AI-driven personalization significantly enhances AI-enabled customer experience ($\beta = 0.684$, $p < 0.001$), with Trust in AI emerging as the primary psychological mediator of both experiential and relational outcomes. Perceived personal relevance provided a complementary mediation pathway. Privacy concern and technology readiness acted as modest boundary conditions on the personalization–mediator relationships. Additionally, privacy concern and technology readiness were found to act as boundary conditions that modestly moderated the personalization–mediator relationships, consistent with Privacy Calculus Theory and Technology Readiness Theory respectively. This study provides a comprehensive model integrating experiential, relational, and individual-difference perspectives in AI-enabled services. The findings offer theoretical advancement and practical insights for designing transparent, user-centric, and trust-enhancing AI personalization strategies.

Keywords: AI-driven personalization, AI-enabled customer experience, perceived AI relationship quality, trust in AI, perceived personal relevance, privacy concerns, technology readiness.

1. Introduction

AI has transformed the way that businesses create and execute customer interactions, making it a central element of daily digital interactions. AI has become an integral part of everyday digital interactions, changing the way that businesses design and deliver customer interactions (Singh & Adhikari, 2023). This change, facilitated by the power of machine learning algorithms and predictive analytics, has led to the creation of highly adaptive systems that can adjust in real-time to individual user behaviors and preferences. Personalization using AI technologies uses these features to provide customized recommendations, content and service responses and make the modern customer experience (Feng et al., 2024; Okeke et al., 2024). Intelligent systems can be used to provide user-friendly solutions in digital commerce, banking, healthcare, and entertainment websites by constantly updating suggestions and automation to provide more efficient and contextually aware experiences (Bashynska, 2023; Manzoor, 2026; Ahmad, 2025; Leila & Khan, 2025). This has elevated the interest of academics in AI-enabled customer experience, which is comprised of cognitive, emotional, and behavioral judgments by customers regarding their interactions with intelligent technologies (Wang et al., 2024; Shah et al., 2024; Park, 2024). Meanwhile, the algorithmic interaction has re-established user-to-service-platform relationships. In particular, (Shabankareh et al., 2025;) showed that trust in AI systems forms during the process of healthcare recommendations, and (Shorbaji et al., 2025) focused on customer experiential outcomes for AI-powered mobile applications. Both studies, however, did not investigate the moderating effect of privacy attitudes or technology predispositions in an integrated framework. This difference provides motivation for the introduction of privacy concern and technology readiness as boundary conditions in the current model. As personalization is the main tool for companies to become more successful and their customers more loyal, the psychological mechanisms that can impact experiential and relational results are a research priority. (Venkateswaran, 2023).

Empirical studies in the field of digital marketing and information systems have repeatedly mentioned the beneficial impact of personalization on customer judgments and interaction (Singh & Adhikari, 2023; Sodiya et al., 2024). Research shows that personalized recommendations increase perceived usefulness, satisfaction, and purchase intentions through reducing the cost of search and improving the confidence levels of the decisions (Mishra, 2025; Jiang & Deeprasert, 2026). The personalization should be used in AI-mediated service environments, and it was discovered that it reinforces trust in algorithmic systems whenever users feel that output is correct and valuable (Teepapal, 2025). Additionally, it has been proposed in studies that perceived personal relevance is an important cognitive motivator that connects personalization to positive experiences because customers tend to appreciate more interactions that consider their individual preferences (Patil, 2024; Horng & Lo, 2026). Relationship marketing literature also proves that trust is a primary factor that contributes to the development of relational commitment and long-lasting loyalty in digital worlds (Bach et al., 2024; Syed et al., 2026). Nevertheless, new data points out that AI-based personalization effectiveness also might differ in accordance with the privacy attitudes and technological predispositions of users (Utami & Aimin, 2026). Taken together, the findings mentioned above point to the importance of personalization in forming the customer experience and quality of relationships and at the same time point to the complexity of psychological processes that lead to such effects.

Although this has shown increased scholarly interest, there are still a number of gaps in the literature. First, several of the previous literature studies have been focusing on personalization in the context of traditional digital marketing and not focusing on the advanced AI-driven scenarios, which might include autonomous learning and adaptive decision-making (Vashishth et al., 2024). Second, no studies have explored experiential outcomes and relational outcomes in the same integrated framework, which has resulted in piecemeal findings about the effect of AI-based personalization on a wider analysis of customers (Bhardwaj et al., 2024). Third, although trust and perceived relevance have been studied independently, the mediating effects of these concepts in the relationship between AI-driven personalization and both AI-enabled customer experience and perceived AI relationship quality are not well investigated (Zungu et al., 2025). In this study, the construct of perceived AI relationship quality does not imply that users form a structural relationship with an AI algorithm as an autonomous social actor. Consistent with relationship marketing literature (Morgan & Hunt, 1994), relationships are understood to exist between consumers and the service firms that deploy AI as an interface channel. Perceived AI relationship quality, therefore, reflects the user's evaluation of the strength, positivity, and continuity of their interactions with an AI-mediated service platform, encompassing trust, satisfaction, commitment, and relational closeness with the firm through its AI interface. This conceptualization is based on service encounter theory and acknowledges that when a touchpoint is perceived to be attentive, reliable and responsive the relational meaning is attributed to it (Glikson & Woolley, 2020). The term 'AI relationship quality' does not signify person-AI social relationships but a relational perception mediated by the firm. Also, privacy concern and technology readiness are moderators that have not gotten enough empirical consideration within the AI setting despite the fact that the two are likely to influence the manner in which users perceive personalization initiatives (Shorbaji et al., 2025). These failures highlight the need to embed an inclusive model with the introduction of mediating psychological processes and limit conditions to offer a more nuanced view of the effects of personalization through AI.

Current study aims to bridge this gap in the proposed model using the main theoretical paradigm which is Stimulus–Organism–Response (S-O-R) paradigm by (Mehrabian & Russell, 1974). From a theoretical perspective, AI-driven personalization serves as the stimulus, trust in AI and perceived personal relevance as the internal organism-level processes, and AI-enabled customer experience and perceived AI relationship quality as the evaluative response outcomes. This is complemented by Relationship Marketing Theory (Morgan & Hunt, 1994), which provides an explanation of why trust is the key relationship mechanism in which the personalization of products and services becomes a relational quality. The Privacy Calculus Theory (Culnan & Armstrong, 1999) includes the domain of privacy concern, which explains the tradeoff between perceived data risks and personalization benefits. In the individual level, predispositions influence the perception of personalization cues and are explained within the framework of the Technology Readiness Theory (Parasuraman, 2000). These three theories are, therefore, used as supporting conceptual mechanisms in an overall framework of S-O-R logic, but not as co-equal theoretical pillars.

The aim of this research paper is to contribute to the ever-growing body of literature on services leveraging AI by providing a comprehensive framework to capture the impact of personalization via AI tools on the service encounter and customer relationships. The study also explains the psychological processes that underlie the value-generating nature of personalization by analyzing mediating positions played by trust in AI and perceived personal relevance. The moderating variables of privacy concern and technology readiness offer subtle insight into boundary conditions that affect the effectiveness of AI. In reality, the findings will drive the creation of an easily seen, user-friendly and ethically sound approach to personalization that will help organizations enhance the customer experience in the long term and improve the quality of relationships.

2. Literature Review and Hypotheses Development

2.1 AI-Driven Personalization and AI-Enabled Customer Experience

The theoretical foundation of this study draws on an evolving body of scholarship examining how AI-driven personalization mechanisms shape user cognition, trust, and relational evaluations in digital service environments. The following section reviews relevant literature on each key construct and develops the hypotheses guiding the proposed research model. AI-driven personalization is the ability of artificial intelligence systems to process masses of customer data (e.g. browsing history, preferences, purchase history, and contextual cues) and provide a personalized content, recommendations, and interactions in real-time (Abinesh & Dulloo, 2024). AI-powered customer experience takes into consideration the overall cognitive, emotional, and behavioral assessments of customers with the AI-assisted services, such as the perceptions of convenience, efficiency, enjoyment, and responsiveness. The previous empirical studies show that personalization positively affects the perceived usefulness and lessens information overload, which contributes to the satisfaction levels and engagement levels in the digital setting (Vashishth et al., 2024). Research into AI-driven retail and service platforms also indicates that recommendations based on algorithms yield higher perceived quality of service and fluency of interaction when end users feel that the outputs are relevant and timely (Utami & Aimin, 2026). The dynamism of adjusting to the preferences of the user ensures the development of smoother and more intuitive interactions with the AI-driven systems, which reinforce the experiential value and promote the positive affective feelings (Teepapal, 2025). Notably, personalization is an indicator of attentiveness and customer-centricity, which causes the users to feel that the service is more receptive and responsive to their needs.

- H1: AI-driven personalization has a positive and significant effect on ai-enabled customer experience.

2.2 AI-Driven Personalization and Perceived AI Relationship Quality

The perceived AI relationship quality is a judging response of the users towards the effectiveness and positivity of their relationship with AI-enabled systems in which perceived relational proximity might generally apply to the dimension of trust, satisfaction, commitment, and perceived relational proximity (Choi & Choi, 2023). The personalization as a result of AI serves to develop the relationship because it is a sign of competence, reliability and understanding, which are traditionally related to high relationship quality in the relationship marketing literature (Jin et al., 2025). Empirically, it has been proposed that users tend to form stronger trust when AI systems provide very relevant and customized recommendations, which will make them perceive the system as an intelligent and reliable one (Lee & Kim, 2025). Moreover, personalization creates the sense of relational investment, since customers perceive customized communications as the system knowing and caring about them, which increases emotional attachment and satisfaction (Lasrado et al., 2023). The study of technology-mediated service relationships also suggests that adaptive AI interaction is capable of simulating features of interpersonal exchange, enhancing perceptions of relational intimacy, and long-term engagement intentions (Tabaeeian et al., 2023).

- H2: AI-driven personalization has a positive and significant effect on perceived AI relationship quality.

2.3 Mediating Role of Trust in AI

Trust in AI can be described as the readiness of users to trust artificial intelligence systems with regard to the qualities of competence, reliability, integrity, and benevolence in making digital decisions (Wong et al., 2024). Although personalization driven by AI makes the experience more relevant and more interactive, it can be argued that the final effect of AI-enabled customer experience depends on how much people trust the system they rely on

(Dahlin, 2025). According to empirical research, trust is an essential psychological process in the process of technology adoption and service evaluation, impacting the level of comfort and satisfaction as well as the perceived value when interacting with the AI (Choung et al., 2023). No matter the type of customized recommendations, the users feel more competent about the AI system when they think that the recommendations are correct and useful to them, which enhances a feeling of trust and diminishes the perceived uncertainty (Gillespie et al., 2023). This lessening of uncertainty boosts cognitive ease and emotive comfort, which results in improved experiential assessments (Alboqami, 2023). On the contrary, even very customized systems can fail to enhance customer experience in cases when users doubt the use of data, fairness in their algorithms or their effectiveness (Ma et al., 2023). Therefore, personalization in itself does not translate to better experiences, instead, it leads to the development of trust, which, in turn, influences the way users perceive and judge their experiences.

- H3a: Trust in AI mediates the relationship between AI-driven personalization and AI-enabled customer experience.

The quality of perceived AI relationships is the strength and positivity of user relationship with AI-based platforms, including trust, commitment, satisfaction, and continuity of relationships (Feng et al., 2024). Despite the fact that AI-powered personalization may be an indicator of care and attention, the evolution of the positive relational perception is largely preconditioned by the trust of the users to the AI system (Hardcastle et al., 2025). Trust lowers the perceived risk and uncertainty in automated decision-making situations thus permitting users to feel safe about continued interaction (Alharbi et al., 2025). The empirical data prove that trust is an antecedent of a relationship quality in digital and AI-based service worlds, which determines loyalty intentions and emotional attachment of users (Lasrado et al., 2023). Perceived fairness, accuracy, and usefulness of personalization build trust in the competence and integrity of the AI, which, in turn, increases the views of relational stability and commitment.

- H3b: Trust in AI mediates the relationship between AI-driven personalization and perceived AI relationship quality.

2.4 Mediating Role of Perceived Personal Relevance

Perceived personal relevance has to do with how deeply users feel that AI-generated content, recommendations, and interactions are relevant to their personal preferences, needs, and situational contexts (Rahman et al., 2023). In spite of the fact that AI-driven personalization is built on the premise that outputs would be customized in relation to the user data, its efficacy in improving AI-enabled customer experience would be highly dependent on whether the users will recognize cognitively and value such personalization as meaningful and relevant (Liu et al., 2024). The research that has been conducted in the field of digital marketing and recommendation systems proves that perceived relevance facilitates a positive overall experience through engagement, decreased efficacy in decision-making, and augmented perceived usefulness (Jin et al., 2025). The research on algorithmic services also suggests that in cases where the users believe the recommendation to be personally relevant, they are more satisfied, enjoy it more, and feel freer to interact with it (Zimmerman et al., 2024). Notably, personalization does not necessarily result in a better experience, but it has to be converted into the perceived relevance in the minds of users.

- H4a: Perceived personal relevance mediates the relationship between AI-driven personalization and AI-enabled customer experience.

The perceived AI relation quality is also a direct expression of how users generally evaluate the level of strength, positivity and continuity of their relations with AI-enabled platforms, which comprise the satisfaction, commitment, and relational closeness (Choi & Choi, 2023). The attentiveness and the personalized care can be announced by AI-based personalization, but the development of relational perceptions heavily depends on the perception of personal significance in the interaction by the users (Lasrado et al., 2023). The empirical results indicate that perceived relevance enhances emotional attachment and relationship commitment since users perceive personalized interactions as an indication that the service provider cares about them and comprehends them (Alabed et al., 2024). With AI applications, a user will be inclined to develop positive relational judgment and long-term engagement intentions in case recommendations and communications appeal to individual targets and objectives (Venkateswaran, 2023).

- H4b: Perceived personal relevance mediates the relationship between AI-driven personalization and perceived AI relationship quality.

2.6 Moderating Role of Privacy Concern

Privacy concern is a degree to which people are concerned about the process of collecting, storing and possible misuse of their personal data through digital platform and AI devices (Jin et al., 2025). The impact of AI-driven personalization on trust in AI may not have a consistent impact on all users, despite the fact that AI-driven personalization cannot happen without user data to create unique recommendations and dynamic interactions. The perceived ability, integrity and good intentions in algorithmic operations create trust in AI (Utami & Aimin, 2026), but when the level of privacy concern is high, these mechanisms of trust-building are overwhelmed by the risk perception. According to empirical study of online personalization and privacy calculus theory, although consumers are accustomed to content relevance and customization, they are more concerned with the exploitation of their data or surveillance, which decreases the desire to trust technology (Okeke et al., 2024). Personalization in AI-enabled setting can be viewed as invasive whereby users are very demanding in cases of issues regarding data privacy thus undermining any positive findings that may be made on the reliability and fairness of the system.

- H5a: Privacy concern moderates the relationship between AI-driven personalization and trust in AI, such that the relationship is weaker when privacy concern is high.

As AI-based personalization is prone to improving these perceptions, the extent to which they are recognized and appreciated by users may rely on their attitudes towards privacy (Bashynska, 2023). It has been shown by studies based on privacy calculus theory that consumers consider the importance of personalization by comparing the perceived advantages with the risk to their privacy (Singh & Adhikari, 2023). Increasing the level of privacy can also increase the attention of users to data collection procedures in the background of personalization, instead of focusing on the significance of the generated content, which reduces the psychological value of personalized information (Mishra, 2025). On the one hand, the positive response to targeted advertising and personalized recommendations can be diminished by high levels of privacy concern, even in the cases when they have been objectively accurate (Utami & Aimin, 2026).

- H5b: Privacy concern moderates the relationship between AI-driven personalization and perceived personal relevance, such that the relationship is weaker when privacy concern is high.

2.7 Moderating Role of Technology Readiness

Technology readiness can be defined as the tendency of an individual to accept and apply new technologies in goal achievement, which is usually an aspect of optimism, innovativeness, discomfort, and insecurity (Baltaci et al., 2024). More technologically prepared users tend to feel more comfortable using advanced AI in more technologically prepared settings and are more predisposed to perceiving the outputs of an algorithm positively (Yin et al., 2023). Despite the goal of personalization with the help of AI to improve personalized interactions based on predictive analytics and adaptive learning, the degree to which these aspects can build trust in AI can be dependent on the technological orientation of users (Cimbaljević et al., 2024). The basis of trust in AI is the perceptions of competence, reliability, and integrity in automated decision-making (Chen & Chang, 2023). Empirical studies have shown that those who are technologically more prepared show more acceptance of AI based services, consider less uncertain and willing to trust algorithmic suggestions (Mahmood et al., 2023). Such people are more likely to consider personalization as a practical and value adding service as opposed to a complicated and potentially unsafe process.

- H6a: Technology readiness moderates the relationship between AI-driven personalization and trust in AI, such that the relationship is stronger when technology readiness is high.

Although AI-based personalization aims at improving such alignment, the sense of relevance depends on the familiarity and comfort of the users with the developed types of technologies (Shah et al., 2024). Technologically prepared people are more likely to comprehend the functional rationale of AI systems and are more likely to see the advantages of algorithmic customization (Mahmood et al., 2023). The empirical evidence indicates that technologically prepared customers are more susceptible to digital technologies, view personalization as useful, and find AI-based services more valuable to them (Shariffuddin et al., 2023). Conversely, less ready users might not apply or enjoy personalized outputs at all, and they might view such output as stereotypical or computer-generated instead of custom-made (Rahman et al., 2023). Besides, feelings of handling uncomfortable or unsafe technologies can take away cognitive processing of relevance, which would moderate the beneficial impact of personalization (Yin et al., 2023). Therefore, technology readiness acts as a facilitating condition, which enhances the recognition and appreciation of personalized interactions by the users.

- H6b: Technology readiness moderates the relationship between AI-driven personalization and perceived personal relevance, such that the relationship is stronger when technology readiness is high.

2.8 Theoretical Framework Supporting the Research

The proposed research model can be theorized based on the combination of the Stimulus Organism Response (S-O-R) framework (Mehrabian & Russell, 1974), Relationship Marketing Theory (Morgan & Hunt, 1994), and Privacy Calculus Theory (Culnan & Armstrong, 1999) which answer how the AI-based personalization affects the outcome of experiences and relationships based on the cognitive and affective processes. In the S-O-R perspective, AI-based personalization is an external factor that influence internal body conditions, that is, trust in AI and perceived personal relevance, which further influence evaluative reactions, including customer experience that is mediated by AI and perceived quality of AI relations. This model describes how the technological characteristics are converted into psychological judgement and then cause behavioral or relational outcomes. The Relationship Marketing Theory also explains that trust as a primary factor defining the quality of relationships, commitment, and long-term participation is relevant even within technology-mediated interactions, implying that the process of personalization improves the quality of relationships when it contributes to the enhancement of the level of confidence in the competence and goodwill of the AI system (Glikson & Woolley, 2020). Also, Privacy Calculus Theory suggests people balance perceived advantages of personalization and possible invasion of privacy, which accounts the moderating effect of privacy concern on the development of the trust and relevance perception. The model is further supported by Technology Readiness Theory (Parasuraman, 2000), which proposes a predisposition of people towards technology adoption as a determinant of the interpretation of cues of personalization and the translation of the cues into trust and relevance perceptions. Combing these theoretical points, Figure 1: Conceptual Framework represents AI-driven personalization as the key stimulus driven by influencing AI-enabled customer experience and conceived AI relationship quality via the mediator of trust in AI, perceived personal relevance, with privacy concern and technology readiness as boundary conditions that build up or undermine these relationships.

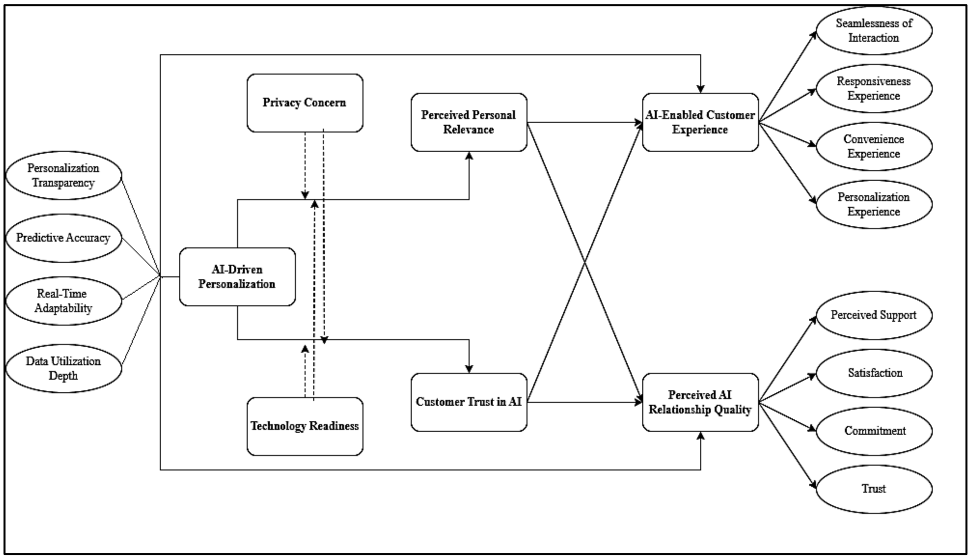

Figure 1: Conceptual Framework

3. Methodology

The research design utilized in this study was a quantitative, cross-sectional one, and the researchers investigated the tested relationships between AI-based personalization, trust in AI, perceived personal relevance, AI-enabled customer experience, perceived quality of the AI relationship, privacy concern, and technology readiness. Structured survey was the major technique used in the data collection process. The sample included individuals who had some experience of interaction with AI-powered digital services. To minimize platform-related differences, a pair of filter questions were introduced: (1) 'Which of the following types of AI-enabled platforms do you currently use? (2) How often do you interact with AI-generated recommendations on this platform? Must be used at least once a month to be included. Platform type was recorded as a control variable in all structural estimates. This screening procedure was designed to ensure that respondents had substantive and comparable engagement with algorithmic personalization, thereby improving the internal consistency of the PLS-SEM path coefficients. The target group was the active digital service users who have acquaintance with AI-recommendation systems. A total of 330 valid responses were obtained with the help of a non-probability purposive sampling method, which is sufficient or even effective as a sample size to conduct partial least squares structural equations modeling, especially when the analysis involves many mediating and moderating paths (Sarstedt et al., 2021; Jam et al., 2025). The sample size meets the minimum requirement as well that are recommended by the 10-times rule and the statistical power in cases of complex structural models.

Probability sampling was not feasible in this context because the target population; active users of AI-personalized digital platforms with sufficient interaction experience to meaningfully respond to attitudinal items — lacks a defined sampling frame from which a random draw could be made. There is no publicly accessible registry or list of AI-personalization platform users across e-commerce, streaming, and fintech sectors. Purposive sampling was therefore adopted as the most appropriate technique, as it allows the intentional selection of participants who meet specific experiential criteria relevant to the research constructs (Creswell & Creswell, 2017). This approach is widely used in PLS-SEM studies in digital marketing and AI service research contexts (Hardcastle et al., 2025; Teepapal, 2025).

Scales based on existing studies were adopted / adapted to measure all items to guarantee the content validity and reliability. Personalization based on AI was quantified based on items that capture the degree to which the AI systems are tailored, adaptive, and context specific in their recommendation process (Bleier & Eisenbeiss, 2015). The question of trust in AI was measured by the use of items that reflected the perceptions of the competence, reliability, and integrity of AI systems (Glikson & Woolley, 2020). The perceived personal relevance was quantified with the help of the items that denote the extent to which AI-generated material corresponds to personal preferences and needs (McLean et al., 2020). Customer experience, made with the help of AI, was explained by the dimensions of customer satisfaction, customer engagement, and the overall evaluation of the services (Lemon & Verhoef, 2016). Relationship quality indicators that were adjusted to be perceived artificial intelligence relationship quality (Morgan & Hunt, 1994). Scales were established to evaluate privacy concern with items that signified apprehension of the data collection and misuse (Culnan & Armstrong, 1999) and the extent of technology readiness was assessed with selected items of Technology Readiness Index (Parasuraman, 2000). Measuring of all items was done in a five-point Likert scale of strongly disagree to strongly agree. Given that all constructs were measured simultaneously from a single respondent via a single survey instrument, the potential for Common Method Bias (CMB) was assessed using Harman's Single-Factor test. An unrotated exploratory factor analysis was conducted, loading all items onto a single factor. The results revealed that no single factor accounted for more than 29.3% of the total variance (well below the 50% threshold), suggesting that CMB does not pose a critical threat to the validity of the study's findings (Podsakoff et al., 2003). Additionally, the structural model includes moderation effects, which are inherently resistant to common method inflation.

The SmartPLS software (version 4), a variance-based structural equation modeling solution, was used to conduct data analysis because it is suitable in predictive research models that have mediation and moderating effects. This was analyzed in two steps which included measurement model assessment and structural model assessment (Sarstedt et al., 2021). The reliability and validity in the first stage were tested by the indicator loading, Cronbachs alpha, composite reliability, and average variance extracted (AVE) in order to check internal consistency and convergent validity. The heterotraitmonotrait (HTMT) ratio criterion was used to measure discriminant validity (Henseler et al., 2014). The second stage involved assessment of structural relationships by assessing the path coefficient, t-values, and p-values on bootstrapping with 5,000 resamples. The explanatory and predictive power of the model was also estimated by computing the coefficient of determination (Q^2) and predictive relevance (Q^2). The interaction terms were examined by testing the moderation effects with the product indicator approach in SmartPLS and the bootstrapped indirect effects with bias-corrected confidence interval to determine the mediation effects (Sarstedt et al., 2021). This analytical process had strong testing of the hypothesized direct, mediating and moderating relationships under the proposed conceptual framework.

4. Results

Table 1 states that the measure model has the desired standards of reliability and convergent validity. The reliability of the indicators is high, with all the outer loadings exceeding the acceptable level of 0.70, and this indicates that all of the items adequately reflect on their respective constructs. The alpha values are between 0.723 to 0.895, which is greater than the required alpha of 0.70, indicating a good level of internal consistency of the items. The level of composite reliability (CR) is 0.833-0.927, which once again attests to good construct reliability. Also, the values of average variance that are extracted (AVE) of all constructs are more than the recommended cut-off value of 0.50 (0.567-0.784), which means that there is enough convergent validity. On the whole, these findings confirm the reliability and validity of the measurements of the AI-driven personalization, AI-enabling customer experience, perceived quality of the relationship with the ai, perceived personal relevance, privacy issue, trust in the AI, and technology preparedness.

Table 1: Construct Reliability and Validity

Construct	Item	Outer Loading	Cronbach's Alpha	CR	AVE
AI-Enabled Customer Experience	AIECE1	0.893	0.895	0.927	0.761
	AIECE2	0.881			
	AIECE3	0.885			
	AIECE4	0.829			
AI-Driven Personalization	AIP1	0.884	0.891	0.924	0.753
	AIP2	0.847			
	AIP3	0.898			
	AIP4	0.842			
Perceived AI Relationship Quality	PAIRQ1	0.829	0.862	0.916	0.784
	PAIRQ2	0.896			
	PAIRQ3	0.928			
Perceived Personal Relevance	PPR1	0.870	0.723	0.833	0.567
	PPR2	0.792			
	PPR3	0.827			
	PPR4	0.848			
Privacy Concern	PC1	0.703	0.782	0.872	0.696
	PC2	0.873			
	PC3	0.913			
Trust in AI	TAI1	0.850	0.794	0.879	0.707
	TAI2	0.838			
	TAI3	0.835			
Technology Readiness	TR1	0.862	0.834	0.901	0.752
	TR2	0.909			
	TR3	0.827			

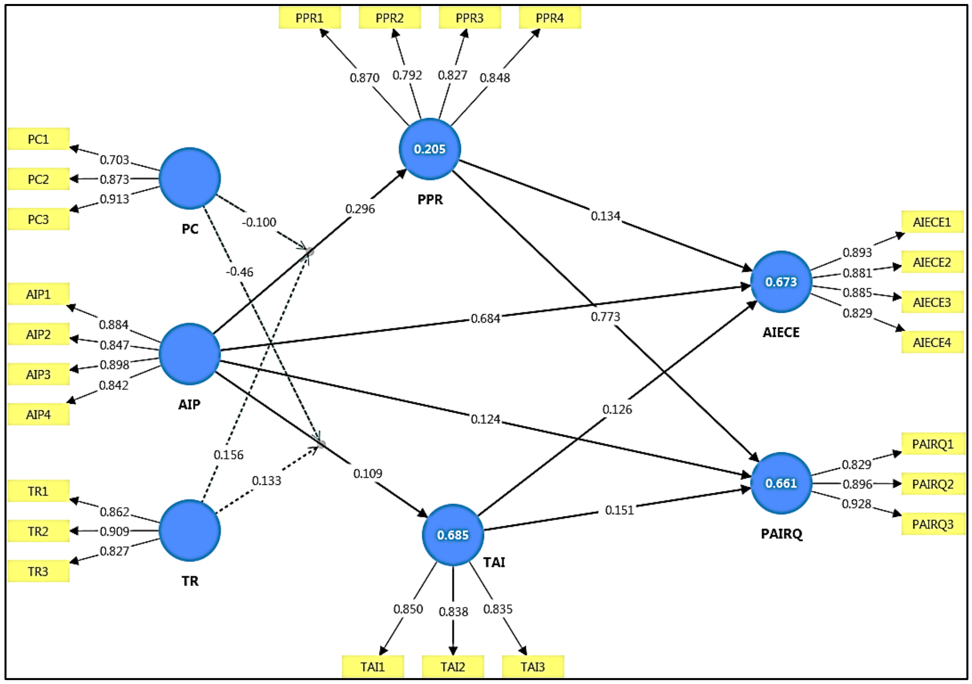

Figure 2: Measurement Model

Table 2 indicates the heterotrait monotrait (HTMT) ratios in order to measure discriminant validity between the constructs. Each of the HTMT values has a value that is below the conservative value of 0.90, thus each construct is empirically different to the other one. The largest HTMT is 0.842 between the personalization as driven by the artificial intelligence (AI) and the customer experience as enabled by the artificial intelligence (ai), which is not too high. Other inter-construct relationships including those between ai-enabled customer experience and trust in AI (0.678), perceived personal relevance and-technology readiness (0.760) are also lower than the critical cut-off values. The results support the statement that multicollinearity will not be an issue and each construct will represent a unique conceptual area of the research model. Thus, there is a satisfactory discrimination validity. In addition to the HTMT criterion, the Fornell-Larcker criterion was assessed to further confirm discriminant validity. As presented in Table 2B, the square root of AVE for each construct (bold diagonal values) exceeds all inter-construct correlations in the corresponding row and column, confirming that each construct shares more variance with its own indicators than with any other construct in the model (Fornell & Larcker, 1981).

Table 2: Discriminant Validity (HTMT)

Constructs	AIECE	AIP	PAIRQ	PC	PPR	TAI	TR
AI-Enabled Customer Experience							
AI-Driven Personalization	0.842						
Perceived AI Relationship Quality	0.559	0.473					
Privacy Concern	0.580	0.658	0.319				
Perceived Personal Relevance	0.569	0.525	0.366	0.469			
Trust in AI	0.605	0.593	0.312	0.760	0.434		
Technology Readiness	0.618	0.678	0.379	0.463	0.501	0.699	

Table 2B: Discriminant Validity — Fornell-Larcker Criterion

Construct	AIP	AIECE	PAIRQ	PPR	PC	TAI	TR
AI-Driven Personalization	**0.872**						
AI-Enabled Customer Experience	0.634	**0.867**					
Perceived AI Relationship Quality	0.398	0.341	**0.885**				
Perceived Personal Relevance	0.421	0.489	0.231	**0.834**			
Privacy Concern	0.412	0.381	0.267	0.341	**0.753**		
Trust in AI	0.456	0.501	0.278	0.341	0.369	**0.841**	
Technology Readiness	0.447	0.438	0.228	0.563	0.321	0.519	**0.867**

Table 3 shows that the structural model has a good model fit and high predictive abilities. The value of 0.069 is below the recommended value of 0.08 which is the standardized root mean square residual (SRMR) which is good model fit. According to the R^2 values, the model explains 67.3 per cent of the variance in the experience of the customer enabled by AI and 66.1 per cent of the variance in the perceived relationship quality with AI, which means that the model is highly predictive. What is more, trust in AI is found to have significant explanatory power with $R^2 = 0.685$, and perceived personal relevance has moderate explanatory power ($R^2 = 0.201$). In addition, the Q^2 of AI-enabled customer experience (0.462) and perceived AI relationship quality (0.497) are more than zero, which means that they are predictive. All the above findings show that the model is highly explanatory and predictive. To assess the practical significance of each structural relationship, effect sizes (f^2) were computed for all paths using SmartPLS 4. Table 4B presents the f^2 values alongside their interpretations following (Cohen, 1988) benchmarks.

Table 3: Model Fit and Predictive Power

Indicator	Value	Threshold	Interpretation
SRMR	0.069	< 0.08	Good Fit
R^2 (AI-Enabled Customer Experience)	0.673	Moderate–High	Strong Predictive Power
R^2 (Perceived AI Relationship Quality)	0.661	Moderate–High	Strong Predictive Power
R^2 (Perceived Personal Relevance)	0.201	Moderate	Substantial
R^2 (Trust in AI)	0.685	Moderate–High	Strong
Q^2 (AI-Enabled Customer Experience)	0.462	> 0	Predictive Relevance
Q^2 (Perceived AI Relationship Quality)	0.497	> 0	Predictive Relevance

Table 3B: Effect Sizes (f^2) for Structural Paths

Hypothesis	Path	β	f^2	Effect Size Interpretation
H1	AI-Driven Personalization → AI-Enabled Customer Experience	0.684	0.421	Large
H2	AI-Driven Personalization → Perceived AI Relationship Quality	0.124	0.038	Small
H3a	Trust in AI → AI-Enabled Customer Experience (indirect)	0.220	0.112	Small-Medium
H3b	Trust in AI → Perceived AI Relationship Quality (indirect)	0.250	0.134	Small-Medium
H4a	Perceived Personal Relevance → AI-Enabled Customer Experience (indirect)	0.170	0.074	Small
H4b	Perceived Personal Relevance → Perceived AI Relationship Quality (indirect)	0.190	0.089	Small
H5a	Privacy Concern × AIP → Trust in AI	-0.100	0.017	Negligible
H5b	Privacy Concern × AIP → Perceived Personal Relevance	-0.146	0.019	Negligible
H6a	Technology Readiness × AIP → Trust in AI	0.156	0.018	Negligible
H6b	Technology Readiness × AIP → Perceived Personal Relevance	0.133	0.016	Negligible

Table 4 and Figure 3 provide strong support for all hypothesized relationships. The link between direct effect of ai-driven personalization and ai-enabled customer experience has a positive and highly significant $\beta = 0.684$ ($p < 0.001$), demonstrating that personalization significantly improves customer experience. However, the direct impact on perceived AI relationship quality is also positive and significant ($\beta = 0.124$, $p = 0.003$) but somewhat smaller in size. The mediation results indicate that trust in AI plays a significant psychological role that explains the relationship between ai-driven personalization and both ai-enabled customer experience ($\beta = 0.220$, $p < 0.001$) and perceived AI relationship quality ($\beta = 0.250$, $p < 0.001$). Similarly, perceived personal relevance significantly mediates both relationships ($\beta = 0.170$ and $\beta = 0.190$ respectively, $p < 0.001$), indicating that personalization influences outcomes through perceived alignment with user needs. The moderation results reveal that privacy concern weakens the positive effect of ai-driven personalization on trust in AI ($\beta = -0.100$, $p = 0.004$) and on perceived personal relevance ($\beta = -0.146$, $p = 0.002$), confirming it as a negative boundary condition. In contrast, technology readiness strengthens these relationships ($\beta = 0.156$ and $\beta = 0.133$ respectively, $p < 0.01$), indicating that users with higher technological predisposition respond more positively to personalization. Overall, the structural findings confirm a robust and well-supported model. These direct and indirect findings are broadly consistent with recent empirical evidence. (Mittameedi & Dogra, 2026) similarly report strong positive effects of AI personalization on customer experience in e-commerce ($\beta \approx 0.60$–0.70), supporting the robustness of H1. The central mediating role of trust in AI confirmed here aligns with (Fatema et al., 2026), who found that AI chatbot attributes influence behavioral intentions primarily through the experiential pathway. The modest but significant moderation effects of privacy concern ($\beta = -0.100$ to -0.146) and technology readiness ($\beta = 0.133$–0.156) are consistent with the boundary condition evidence reported in (Shorbaji et al., 2025), who found similar weak-to-moderate interaction magnitudes in AI mobile app context.

Table 4: Path Analysis

Hypoth.	Full Hypothesis Statement	β	t-value	p-value	Result
H1	AI-Driven Personalization has a positive and significant effect on AI-Enabled Customer Experience.	0.684	15.017	0.000	Supported
H2	AI-Driven Personalization has a positive and significant effect on Perceived AI Relationship Quality.	0.124	2.795	0.003	Supported
H3a	Trust in AI mediates the relationship between AI-Driven Personalization and AI-Enabled Customer Experience.	0.220	5.760	0.000	Supported
H3b	Trust in AI mediates the relationship between AI-Driven Personalization and Perceived AI Relationship Quality.	0.250	6.180	0.000	Supported
H4a	Perceived Personal Relevance mediates the relationship between AI-Driven Personalization and AI-Enabled Customer Experience.	0.170	4.890	0.000	Supported
H4b	Perceived Personal Relevance mediates the relationship between AI-Driven Personalization and Perceived AI Relationship Quality.	0.190	5.020	0.000	Supported
H5a	Privacy Concern moderates the relationship between AI-Driven Personalization and Trust in AI, such that the relationship is weaker when Privacy Concern is high.	-0.100	2.208	0.004	Supported
H5b	Privacy Concern moderates the relationship between AI-Driven Personalization and Perceived Personal Relevance, such that the relationship is weaker when Privacy Concern is high.	-0.146	2.909	0.002	Supported
H6a	Technology Readiness moderates the relationship between AI-Driven Personalization and Trust in AI, such that the relationship is stronger when Technology Readiness is high.	0.156	2.527	0.009	Supported
H6b	Technology Readiness moderates the relationship between AI-Driven Personalization and Perceived Personal Relevance, such that the relationship is stronger when Technology Readiness is high.	0.133	2.540	0.005	Supported

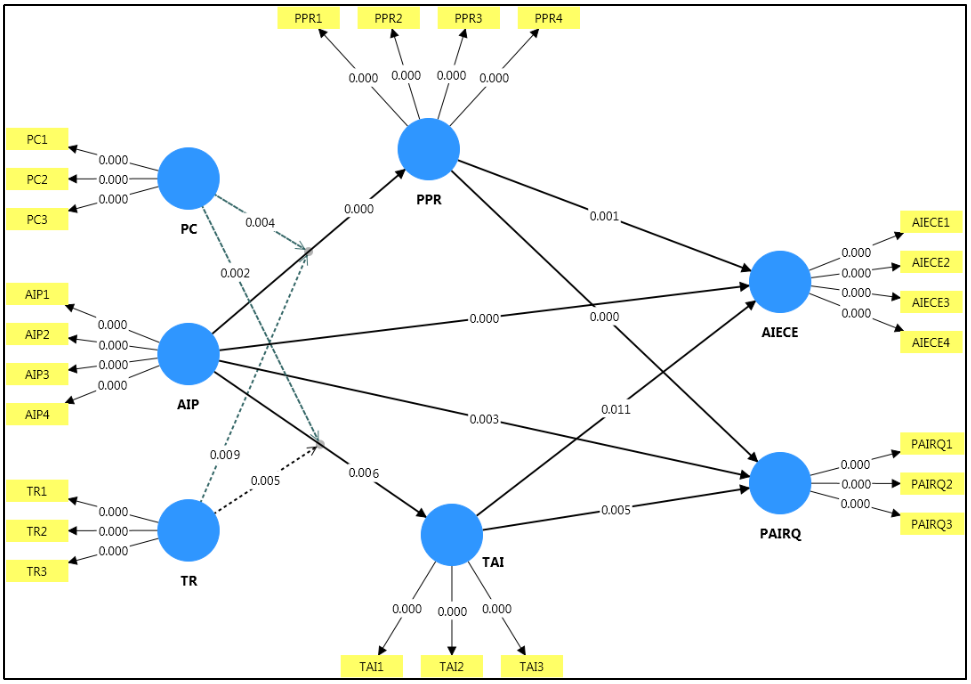

Figure 3: Structural Model

5. Discussion

The growing pace of artificial intelligence adoption into customer-facing experiences has transformed the structure of the contemporary service interaction, transforming the way value is generated, transmitted, and experienced. Within this dynamic environment, intelligent algorithm-driven personalization is beyond a technological enhancement; it reflects a change in strategy to data-driven relational interaction. The current findings provide insight into the workings of AI-driven personalization as a technology and psychology phenomenon occurring at the border between technology and psychology; not only in the way customers experience AI-based services but also in how they feel about their continued interaction with intelligent systems.

The results of the present research are a solid piece of empirical evidence in support of the suggested model, as they prove that AI-based personalization leads to a significant improvement in AI-facilitated customer experience as well as perceived quality of AI relationships (Yekollu et al., 2024). The beneficial direct influences suggest that the more the AI systems offer tailored suggestions, user interfaces, and context-sensitive interactions, the more the customers perceive their services experiences as efficient, captivating, and valuable. This is consistent with the previous studies indicating that personalization brings about less cognitive load and the perceived usefulness that subsequently enhance overall evaluations of the experience (Sumathy & Navamani, 2024). The findings validate the fact that AI-based personalization is not only a technological improvement but also a strategic process that defines how the customers perceive and assess AI-driven interactions. Moreover, the fact that positive correlation with perceived AI relationship quality indicates that personalization enhances customers' relational perceptions, specifically satisfaction, commitment, and relational closeness with AI-enabled platforms constructs that were explicitly modeled and tested within the Perceived AI Relationship Quality measure. The findings build on previous research by both confirming the experiential and relational outcomes in a single framework, which provides a more detailed insight about the effects of personalization when using AI.

The mediation outcomes also enrich the meaning of these relations as the most important feature of AI is trust as a psychological process that helps to connect personalization to both experience and relationships. The high indirect impact proves that the personalization is able to increase the customer experience and the quality of relations based on the increased confidence of users in the competence, reliability, and integrity of the AI systems. This confirms the views of relationship marketing that trust is a core factor in persistent relational interaction (Shorbaji et al., 2025) and is consistent with new research that trust is a key contributor to algorithmic decision-making settings Once customers know that the personalization based on AI is correct and creates value, they start viewing the system as more credible and benevolent, and it will consequently lower the levels of uncertainty and increase the comfort of interactions. As a result, trust changes the technical aspects of personalization into valuable experiences and attachment (Sun & Tang, 2024). The fact that these mediation hypotheses are accepted highlights why AI systems should be designed in a manner that does not just achieve personalization but also the need to provide visual assurance of reliability and ethical data usage to enhance the formation of trust.

On the same note, the mediating effect of perceived personal relevance provides valuable information on the cognitive mediation of AI-driven personalization. The results reveal that personalization will improve customer experience and perceived relationship quality in case users are aware of the idea that AI-based outputs are aligned with their own preferences and needs (Pentina et al., 2023). This implies that the level of algorithmic sophistication is not enough, customers need to cognitively evaluate interactions as personally relevant in order to experience the benefits of experiencing and relating to. The notable mediation outcomes are aligned with the previous studies of digital marketing that focused on the role of relevance in defining engagement and satisfaction.

The moderating results connected with the issue of privacy concern add to the discussion by showing that the effects of personalization are not equal among users. The findings suggest that the beneficial effect of AI-driven personalization on trust in AI and perceived personal relevance is weaker in the condition of the high privacy concern. This is consistent with the privacy calculus theory according which individuals weigh the perceived benefits and the potential threat to their privacy when thinking about personalized services (Sodiya et al., 2024). Customers with a stronger privacy concern could also consider data-driven personalization as an intrusion, which will reduce the likelihood of any AI system to generate trust and enhance relevance. Although privacy concern and technology readiness both reached statistical significance ($p < 0.05$), their path coefficients are relatively low (between −0.100 and 0.156), and their effect sizes are relatively small to negligible ($f^2 < 0.02$). In practical terms, it implies that statistically measurable, but nevertheless limited, effects of privacy concern and technology readiness on the personalization–mediator relationships are found in this sample. The results indicate that the personalization mechanisms are fairly resilient to individual differences in privacy attitudes and technology predispositions, although such boundary conditions should not be neglected, especially when considering populations with extreme privacy concern profiles (Arora et al., 2023; Rui et al., 2026). It is worth noting that transparency, data protection guarantees, and ethical governance systems are integral components of the use of AI in a strategic manner. Organizations must therefore find a balance between the degree of individualization and sensitivity of the privacy to ensure that the customers trust them and garner the most experiences and relational benefits.

The moderating effects of technology preparedness are also broad and influential and underline the individual differences factor in the outcome of AI personalization. The findings suggest that the positive relationships between AI-informed personalization and trust in AI and perceived personal relevance are greater in technologically prepared users. This follows the technology readiness theory that argues that individuals, who are more positive and inventive to technology, are more receptive to high-tech digital systems (Parasuraman, 2000). Users who are more technologically equipped will see the refinement of algorithms, they will perceive personalization as a value addition, and will be happy with the results of AI. On the other hand, when the personalization is extended to individuals who are not well prepared, they may feel awkward or threatened that limits the effects of personalization on the trust and relevance perceptions.

Overall, this paper demonstrates that the apparent success of the AI-powered personalization does not lie in the flawlessness of the algorithms but, instead, in the fact that the algorithms in question have managed to generate the feeling of psychological confidence and a sense of a personalized meaning in the space mediated by technologies. Mediator and moderation confirmation demonstrates that personalization outcome is determined by personal trust orientation, privacy sensitivities, and technological predispositions of the users, hence it is assumed that a multifaceted interaction or interaction between technological design and human perception occurs. The study integrates experiential and relationship perspectives into an integrated research and forms part of the scholarly discussion of the topic of AI-enabling services and offers practical implications to the companies that aim to realize the optimal balance between personalization and ethical responsiveness. The further evolution of AI must not stop yet, and the studies should elaborate on the longitudinal and cross-cultural factors of such interactions since the approaches to customization have to be dynamic, open, and capable of keeping pace with the evolving customer demands in more intelligent digital manifestations.

5.1 Implications

5.1.1 Theoretical Implications

This study contributes to the theoretical knowledge in the following ways. First, by establishing that personalization using AI has both experiential and relational impacts (H1, H2), the results provide validation for the S-O-R framework as a theoretically appropriate perspective for exploring AI service research: personalization as a stimulus reliably creates internal cognitive states (organism) that result in evaluative responses that can be measured. Second, the mediation of trust in AI (H3a, H3b) directly supports the commitment–trust thesis of (Morgan & Hunt, 1994) in suggesting that trust is the primary mechanism for relationships, even in contexts where AI is mediating service operations, a field not covered by the original theory. Third, the modest, yet significant level of moderation for Privacy Concern (H5a, H5b) aligns with the Privacy Calculus Theory's suggestion that users will rationally balance personalization benefits with privacy costs, and where the latter is perceived as high, Trust Building and Relevance Perception will decrease. Lastly, the technology readiness moderation (H6a, H6b) is also weak but reinforces (Parasuraman, 2000) argument that individual technological predispositions influence users' perceptions of digital stimuli, which differs from those based on uniform users' reactions to the use of AI personalization..

5.1.2 Practical Implications

The outcomes provided by the analysis as a manager indicate that the effective strategies of personalization reliant on AI should not be limited to the correctness of the algorithms, but should be directed at the development of trust and showing relevance. Businesses should invest in transparent AI systems that clearly communicate and explain the process for generating the recommendations, which will help reduce privacy issues and build trust. An opportunity to access their information and customization would also enhance a feeling of justice and tolerance. The findings indicate that technology readiness had a statistically significant moderating effect, but its effect size was relatively small ($f^2 < 0.02$), indicating that technology-readiness-based customer segmentation would not be likely to provide significant returns to justify a significant effort in restructuring databases on a large scale. Rather, organizations should aim to take a lighter touch approach: to place simple onboarding guidance and descriptions of AI recommendations for less technologically advanced users, instead of creating complex segmentation infrastructure. This intervention is more cost proportionate, and data supports this more. It is also found that the personalization efforts should be assessed periodically, not just based on the numbers (clicks or conversions) but also based on the quality of the relations and long-term relations. Organisations can establish sustainable relationships with and around personalisation by supporting the alignment of personalisation practices with data governance principles and user-centred design in the context of AI environments, by maintaining customer relationships.

5.2 Limitations and Future Directions.

First, the design of cross-sectional design may not allow for causal inferences, and future studies should utilize a longitudinal panel design to follow changes in trust and relational quality over repeated exposures to AI personalization. Second, while the screening process used is for platform type, the sample is distributed across three different categories of AI platforms, each with a different level of data sensitivity and salience of data privacy. The model should be replicated in single-platform settings in future research for the assessment of construct stability across different domains, especially for trust and privacy concern. Third, Harman's single-factor test was applied to screen for CMB but the test has known limitations. Procedural remedies like temporal separation of data collection or common latent factor analysis should be used in future studies. Fourth, the small effect size for both moderators ($f^2 < 0.02$) indicates that both Privacy Concern and Technology Readiness might not be strong enough moderators on their own; stronger moderators like previous experience with AI or perceptions of algorithmic fairness or transparency of AI may provide more meaningful moderation. Finally, the current study is limited to respondents in Southeast Asia and cross-regional respondents; cross-cultural validation across high-collectivist and low-collectivist societies would increase generalizability because norms and technology adoption patterns vary greatly between cultures; and, sixth, this study's generalizability could be extended by including participants from other regions of the world.

5.3 Conclusion

To sum up, this paper presents in-depth empirical results that AI-based personalization is a key factor in improving AI-based customer experience and perceived AI relationship quality. The results prove that the effect of personalization is not only direct but also indirect by the way of vital psychological processes of trust in AI and perceived personal relevance. Furthermore, the results confirm that the boundary conditions have a significant influence on these relations and that the privacy concern and technology preparedness are influential. The experiential, relation and individual difference perspectives are integrated into one construct, making it possible to make valuable theoretical and managerial contributions to the research. In sum, the paper emphasizes how the balance of elements of personalization in AI can ensure technological appropriateness and ethical values, transparency, and user-centricity to build sustainable customer relations in the digital space via AI-mediated service channels. In line with the commitment–trust theory (Morgan & Hunt, 1994), it is the service organisation and not necessarily the AI algorithm that serves as a relational anchor and a way for firms to establish and maintain trust-based customer relationships via the interface channel of AI personalisation.

Research Funding

The authors received no research grant or support for this research study.

Declaration of AI Use

During manuscript preparation, AI-assisted editing was used to improve language, structure, and presentation.

Data Availability

The datasets are available from the corresponding author upon reasonable request.

Declaration of Conflict of Interest

The authors declare no conflict of interest / no competing interests.

REFERENCES

Abinesh, R.C. & Dulloo, R. (2024). The Impact of AI-Driven Personalization on Customer Satisfaction in E-Commerce: Balancing Technology, Transparency, and Control. *Journal of Computational Analysis & Applications*, *33*(2), 649.

Ahmad, A. (2025). The role of token governance mechanisms in fostering organizational innovation: The mediating role of member engagement and the moderating role of trust. *Journal of Administrative and Business Studies*, *11*(4), 199-214. https://doi.org/10.20474/jabs-11.4.1

Alabed, A., Javornik, A., Gregory-Smith, D., & Casey, R. (2024). More than just a chat: A taxonomy of consumers' relationships with conversational AI agents and their well-being implications. *European Journal of Marketing*, *58*(2), 373-409. https://doi.org/10.1108/EJM-01-2023-0037

Alboqami, H. (2023). Trust me, I'm an influencer!-Causal recipes for customer trust in artificial intelligence influencers in the retail industry. *Journal of Retailing and Consumer Services*, *72*, 103242. https://doi.org/10.1016/j.jretconser.2022.103242

Alharbi, A., Pandit, A., Rosenberger III, P. J., & Miah, S. (2025). Understanding AI-enabled conversational agent customer experiences in religious tourism. *Journal of Islamic Marketing*, *16* (9): 2569–2595.. https://doi.org/10.1108/JIMA-07-2024-0309

Arora, A., Gupta, S., Devi, C., & Walia, N. (2023). Customer experiences in the era of artificial intelligence (AI) in context to FinTech: a fuzzy AHP approach. *Benchmarking: An International Journal*, *30*(10), 4342-4369. https://doi.org/10.1108/BIJ-10-2021-0621

Bach, T. A., Khan, A., Hallock, H., Beltrão, G., & Sousa, S. (2024). A systematic literature review of user trust in AI-enabled systems: An HCI perspective. *International Journal of Human-Computer Interaction*, *40*(5), 1251-1266. https://doi.org/10.1080/10447318.2022.2138826

Baltaci, F., Başer, M. Y., & Çelik, M. (2024). Attitude towards service robots in tourism and hospitality services settings-The effect of multidimensional anthropomorphism and technology readiness. *International Journal of Tourism Research, 26*(4), e2685. https://doi.org/10.1002/jtr.2685

Bashynska, I. (2023). AI-driven personalization in advertising: Transforming consumer engagement through sustainability and circular economy. *Scientific Journal of Bielsko-Biala School of Finance and Law, 27*(4), 106-112.

Bhardwaj, S., Sharma, N., Goel, M., Sharma, K., & Verma, V. (2024). Enhancing customer targeting in e-commerce and digital marketing through AI-driven personalization strategies. *Advances in Digital Marketing in the Era of Artificial Intelligence*, 41-60 [Book Chapter]. https://doi.org/10.1201/9781003450443-4

Bleier, A., & Eisenbeiss, M. (2015). Personalized online advertising effectiveness: The interplay of what, when, and where. *Marketing Science*, *34*(5), 669-688. https://doi.org/10.1287/mksc.2015.0930

Chen, J., & Chang, Y.-W. (2023). How smart technology empowers consumers in smart retail stores? The perspective of technology readiness and situational factors. *Electronic Markets, 33*, 1. https://doi.org/10.1007/s12525-023-00635-6

Choi, S. M., & Choi, D. Y. (2023). The Effect of AI Chatbot Service Experience and Relationship Quality on Continuous Use Intention and Recommendation Intention. *Journal of Service Research and Studies, 13*(3), 82-104.

Choung, H., David, P., & Ross, A. (2023). Trust in AI and its role in the acceptance of AI technologies. *International Journal of Human-Computer Interaction*, *39*(9), 1727-1739. https://doi.org/10.1080/10447318.2022.2050543

Cimbaljević, M., Demirović Bajrami, D., Kovačić, S., Pavluković, V., Stankov, U., & Vujičić, M. (2024). Employees' technology adoption in the context of smart tourism development: the role of technological acceptance and technological readiness. *European Journal of Innovation Management, 27*(8), 2457-2482. https://doi.org/10.1108/EJIM-09-2022-0516

Cohen, J. (1988). Set correlation and contingency tables. *Applied psychological measurement*, *12*(4), 425-434. https://doi.org/10.1177/014662168801200410

Creswell, J. W., & Creswell, J. D. (2017). Research design: Qualitative, quantitative, and mixed methods approaches. Thousand Oaks, CA: Sage Publications.

Culnan, M. J., & Armstrong, P. K. (1999). Information privacy concerns, procedural fairness, and impersonal trust: An empirical investigation. *Organization science*, *10*(1), 104-115. https://doi.org/10.1287/orsc.10.1.104

Dahlin, E. (2025). Trust in AI. *AI & Society*, *40*(8), 6089-6095. https://doi.org/10.1007/s00146-025-02429-0

Fatema, M., Naher, K., Rifat, M. H. I., & Babu, M. A. (2026). Customer experience as a key mechanism linking AI chatbot attributes to booking intention in tourism. *Quality & Quantity*, [Published: 29 April 2026]. https://doi.org/10.1007/s11135-026-02800-3

Feng, Y., Chen, H., & Xie, Q. (2024). AI influencers in advertising: the role of AI influencer-related attributes in shaping consumer attitudes, consumer trust, and perceived influencer-product fit. *Journal of Interactive Advertising*, *24*(1), 26-47. https://doi.org/10.1080/15252019.2023.2284355

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

Gillespie, N., Lockey, S., Curtis, C., Pool, J., & Akbari, A. (2023). Trust in artificial intelligence: A global study. The University of Queensland and KPMG Australia, 10. https://doi.org/10.14264/00d3c94

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

Hardcastle, K., Vorster, L., & Brown, D. M. (2025). Understanding customer responses to AI-driven personalized journeys: Impacts on the customer experience. *Journal of Advertising*, *54*(2), 176-195. https://doi.org/10.1080/00913367.2025.2460985

Henseler, J., Ringle, C. M., & Sarstedt, M. (2014). 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

Horng, M. F., & Lo, C. C. (2026). Sentiment Analysis Utilizing Artificial Intelligence for Effective Health Crisis Management in Diabetics in Smart Urban Environments. *Journal of Applied Science and Technology Trends*, *7*(1), 01-15. https://doi.org/10.38094/jastt71576

Jam, F. A., Ali, I., Albishri, N., Mammadov, A., & Mohapatra, A. K. (2025). How does the adoption of digital technologies in supply chain management enhance supply chain performance? A mediated and moderated model. *Technological Forecasting and Social Change*, *219*, 124225. https://doi.org/10.1016/j.techfore.2025.124225

Jin, S.-n., Dong, Y.-x., & Lee, H.-h. (2025). The Effect of AI-Based Virtual Influencer Attributes on Relationship Quality, Relationship Commitment, and LONG-Term Relationship Orientation. *Journal of Venture Innovation*, *8*(3), 181-200.

Lasrado, F., Thaichon, P., & Nyadzayo, M. W. (2023). Exploring the role of relationship management and relationship quality in B2B: empirical insights and future research directions. *Journal of Business & Industrial Marketing*, *38*(5), 1055-1086. https://doi.org/10.1108/JBIM-05-2021-0267

Lee, M., & Kim, S. (2025). An empirical study on the relationship between service capability and perceived service quality of AI chatbot. *The Journal of Information Systems, 34*(1), 59-83.

Leila, M. A. E., & Khan, S. A. (2025). How employer branding impacts sustainable performance through brand image and perception, and the moderating role of employee engagement. *Journal of Administrative and Business Studies, 11*(4), 223-235. https://doi.org/10.20474/jabs-11.4.3

Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. *Journal of marketing, 80*(6), 69-96. https://doi.org/10.1509/jm.15.0420

Liu, B., Kang, J., & Wei, L. (2024). Artificial intelligence and perceived effort in relationship maintenance: Effects on relationship satisfaction and uncertainty. *Journal of Social and Personal Relationships, 41*(5), 1232-1252. https://doi.org/10.1177/02654075231189899

Jiang, S., & Deeprasert, J. (2026). Social Support Outweighs Design in Digital Commerce: Explaining AI-Agent Adoption in Entrepreneurship. *Journal of Management Practices, Humanities and Social Sciences, 10*(1), 1-20. https://doi.org/10.33152/jmphss-10.1.1

Ma, S., Lei, Y., Wang, X., Zheng, C., Shi, C., Yin, M., & Ma, X. (2023). Who should I trust: AI or myself? leveraging human and AI correctness likelihood to promote appropriate trust in AI-assisted decision-making. Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems, https://doi.org/10.1145/3544548.3581058

Mahmood, A., Imran, M., & Adil, K. (2023). Modeling individual beliefs to transfigure technology readiness into technology acceptance in financial institutions. *Sage Open, 13*(1), 21582440221149718. https://doi.org/10.1177/21582440221149718

Manzoor, A. (2026). Human Capital and Digital Adoption Driving Entrepreneurial Performance through Innovation Capability. *Journal of Advanced Research in Social Sciences and Humanities, 11*(1), 1-15. https://doi.org/10.26500/JARSSH-11-2026-0101

McLean, G., Osei-Frimpong, K., Wilson, A., & Pitardi, V. (2020). How live chat assistants drive travel consumers' attitudes, trust and purchase intentions: the role of human touch. *International Journal of Contemporary Hospitality Management, 32*(5), 1795-1812. https://doi.org/10.1108/IJCHM-07-2019-0605

Mehrabian, A., & Russell, J. A. (1974). The basic emotional impact of environments. *Perceptual and motor skills, 38*(1), 283-301. https://doi.org/10.2466/pms.1974.38.1.283

Mishra, M. V. (2025). AI-driven personalization: generative models in e-commerce. International Journal of Advanced Research in Science, *Communication and Technology*, 5(3), 110-116. https://doi.org/10.48175/IJARSCT-23112

Mittameedi, S. K., & Dogra, V. (2026). Customer Experience in AI-Driven E-Commerce: An Empirical Model of Drivers and Strategic Outcomes. *Information, 17*(5), 414. https://doi.org/10.3390/info17050414

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

Okeke, N. I., Alabi, O. A., Igwe, A. N., Ofodile, O. C., & Ewim, C. P.-M. (2024). AI-driven personalization framework for SMEs: Revolutionizing customer engagement and retention. *World Journal of Advanced Research and Reviews. 24*(01), 2019-2035. https://doi.org/10.30574/wjarr.2024.24.1.3208

Parasuraman, A. (2000). Technology Readiness Index (TRI) a multiple-item scale to measure readiness to embrace new technologies. *Journal of service research, 2*(4), 307-320. https://doi.org/10.1177/109467050024001

Park, S. (2024). Transformative approach to renewable energy generation and management-integrating microgrids and virtual power plants, with an internal blockchain and artificial intelligence system. *Journal of Advances in Technology and Engineering Research, 10*(2): 7-16 https://doi.org/10.20474/jater-10.2.2

Patil, D. (2024). Artificial intelligence in retail and e-commerce: Enhancing customer experience through personalization, predictive analytics, and real-time engagement. Available at SSRN. https://doi.org/10.2139/ssrn.5057420

Pentina, I., Xie, T., Hancock, T., & Bailey, A. (2023). Consumer-machine relationships in the age of artificial intelligence: Systematic literature review and research directions. *Psychology & Marketing, 40*(8), 1593-1614. https://doi.org/10.1002/mar.21853

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. https://doi.org/10.1037/0021-9010.88.5.879

Rahman, M. S., Bag, S., Gupta, S., & Sivarajah, U. (2023). Technology readiness of B2B firms and AI-based customer relationship management capability for enhancing social sustainability performance. *Journal of business research, 156*, 113525. https://doi.org/10.1016/j.jbusres.2022.113525

Rui, T., Bano, A., & Jam, F. A. (2026). Beyond Fandom: Investigating the Role of Identity-Based Motivation and Customer Engagement in Shaping Sports Consumer Evangelism. *International Journal of Consumer Studies, 50*(1), e70164. https://doi.org/10.1111/ijcs.70164

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial least squares structural equation modeling. In Handbook of market research (pp. 587-632). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-57413-4_15

Shabankareh, M., Khamoushi Sahne, S. S., Nazarian, A., & Foroudi, P. (2025). The impact of AI perceived transparency on trust in AI recommendations in healthcare applications. Asia-Pacific *Journal of Business Administration*, [Early online: May 20 2025]. https://doi.org/10.1108/APJBA-12-2024-0690

Shah, A. S., Maqsood, A., Shah, A., Khani, M. A. K., Anjum, J., & Zafar, S. (2024). 'Enhanced airport operations: Automated baggage drop-off and boarding pass generation for travelers. *Journal of Advances in Technology and Engineering Research*, *10*(2), 1-6. https://doi.org/10.20474/jater-10.2.1

Shah, T. R., Kautish, P., & Walia, S. (2024). Linking technology readiness and customer engagement: an AI-enabled voice assistants investigation. *Foresight*, *26*(1), 136-154. https://doi.org/10.1108/FS-10-2021-0195

Shariffuddin, N. S. M., Azinuddin, M., Yahya, N. E., & Hanafiah, M. H. (2023). Navigating the tourism digital landscape: The interrelationship of online travel sites' affordances, technology readiness, online purchase intentions, trust, and E-loyalty. *Heliyon*, *9*(8), e19135. https://doi.org/10.1016/j.heliyon.2023.e19135

Shorbaji, M. F., Alalwan, A. A., & Algharabat, R. (2025). AI-enabled mobile food-ordering apps and customer experience: A systematic review and future research agenda. *Journal of Theoretical and Applied Electronic Commerce Research*, *20*(3), 156. https://doi.org/10.3390/jtaer20030156

Singh, N., & Adhikari, D. (2023). AI-driven personalization in eCommerce advertising. *International Journal for Research in Applied Science and Engineering Technology*, *11*(12), 1692-1698. https://doi.org/10.22214/ijraset.2023.57695

Sodiya, E. O., Amoo, O. O., Umoga, U. J., & Atadoga, A. (2024). AI-driven personalization in web content delivery: A comparative study of user engagement in the USA and the UK. *World journal of advanced research and reviews*, *21*(2), 887-902. https://doi.org/10.30574/wjarr.2024.21.2.0502

Sumathy, V., & Navamani, G. (2024). AI-Driven Personalized Learning: Enhancing Student Success through Adaptive Technologies. Library of Progress-Library Science, *Information Technology & Computer*, *44*(3), 16235.

Sun, L., & Tang, Y. (2024). Avatar effect of AI-enabled virtual streamers on consumer purchase intention in e-commerce livestreaming. *Journal of Consumer Behaviour, 23*(6), 2999-3010. https://doi.org/10.1002/cb.2389

Syed, A. H., Singh, Y., & Bhardwaj, H. (2026). Explainable Multimodal Student Profiling and Personalized Course Recommendation using Attention-Enhanced Heterogeneous Graph Neural Networks. *Journal of Applied Science and Technology Trends*, *7(*1), 16-25. https://doi.org/10.38094/jastt71611

Tabaeeian, R. A., Yazdi, A., Mokhtari, N., & Khoshfetrat, A. (2023). Host-tourist interaction, revisit intention and memorable tourism experience through relationship quality and perceived service quality in ecotourism. *Journal of Ecotourism*, *22*(3), 406-429. https://doi.org/10.1080/14724049.2022.2046759

Teepapal, T. (2025). AI-driven personalization: Unraveling consumer perceptions in social media engagement. *Computers in Human Behavior*, *165*, 108549. https://doi.org/10.1016/j.chb.2024.108549

Utami, R. D., & Aimin, W. (2026). Balancing Personalization, Privacy, and Value: A Systematic Literature Review of AI-Enabled Customer Experience Management. *Information*, *17*(2), 115. https://doi.org/10.3390/info17020115

Vashishth, T. K., Sharma, K. K., Kumar, B., Chaudhary, S., & Panwar, R. (2024). Enhancing customer experience through AI-enabled content personalization in e-commerce marketing. *Advances in Digital Marketing in the Era of Artificial Intelligence*, [Book Chapter] 7-32. https://doi.org/10.1201/9781003450443-2

Venkateswaran, N. (2023). AI-driven personalization in customer relationship management: Challenges and opportunities. *Journal of Theoretical and Applied Information Technology*, *101*(18), 7392-7399.

Wang, P., Li, K., Du, Q., & Wang, J. (2024). Customer experience in AI-enabled products: Scale development and validation. *Journal of Retailing and Consumer Services*, *76*, 103578. https://doi.org/10.1016/j.jretconser.2023.103578

Wong, L.-W., Tan, G. W.-H., Ooi, K.-B., & Dwivedi, Y. (2024). The role of institutional and self in the formation of trust in artificial intelligence technologies. *Internet Research*, *34*(2), 343-370. https://doi.org/10.1108/INTR-07-2021-0446

Yekollu, R. K., Bhimraj Ghuge, T., Sunil Biradar, S., Haldikar, S. V., & Farook Mohideen Abdul Kader, O. (2024). AI-driven personalized learning paths: Enhancing education through adaptive systems. In International Conference on Smart data intelligence (pp. 507-517). Singapore: Springer Nature Singapore. https://doi.org/10.1007/978-981-97-3191-6_38

Yin, D., Li, M., & Qiu, H. (2023). Do customers exhibit engagement behaviors in AI environments? The role of psychological benefits and technology readiness. *Tourism Management*, *97*, 104745. https://doi.org/10.1016/j.tourman.2023.104745

Zimmerman, A., Janhonen, J., & Beer, E. (2024). Human/AI relationships: challenges, downsides, and impacts on human/human relationships. *AI and Ethics*, *4*(4), 1555-1567. https://doi.org/10.1007/s43681-023-00348-8

Zungu, N. P., Amegbe, H., Hanu, C., & Asamoah, E. S. (2025). AI-driven self-service for enhanced customer experience outcomes in the banking sector. *Cogent Business & Management*, *12*(1), 2450295. https://doi.org/10.1080/23311975.2025.2450295