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AI-driven personalization: Unraveling consumer perceptions in social media engagement

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ABSTRACT

This study advances our understanding of the impact of personalized stimuli driven by artificial intelligence on consumer engagement in social media marketing. The research develops and examines an extensive S-O-R model, linking AI stimuli to customer perceptions of trust, privacy concerns, perceived usefulness, and, consequently, consumer engagement. Structural equation modeling was utilized to examine the gathered data and evaluate the hypotheses. The results confirm the hypothesis that AI-enabled personalization positively influences trust, privacy concerns, and perceived usefulness. Trust and perceived usefulness positively impact consumer engagement, while privacy concerns do not. Unexpectedly, AI-enabled personalization doesn't significantly affect customer engagement. By exploring the mediating roles of consumer perceptions, the results emphasize perceived utility and trust as a significant mediating factor, underscoring its crucial contribution to fostering positive interactions between users and technology. The research extends the SOR model in understanding AI's impact on consumer engagement, emphasizing trust and perceived usefulness as crucial mediators. For practical implications, businesses in social media marketing should prioritize trust-building, enhance user experience, address privacy concerns, and adopt a customer-centric approach. These insights provide valuable guidance for navigating AI driven personalization dynamics in social media marketing.

1. Introduction

Rapid technological advancements have significantly changed the field of marketing over the past few decades. The rise of Web 2.0, known for user-generated content, has led to a shift in marketing to a more intricate and ever-changing landscape with the development of Web 3.0, focused on data-driven strategies (Erragcha & Romdhane, 2014). Data-driven marketing has undergone a gradual evolution, leveraging technological advancements such as data analytics, machine learning, web analytics, social media analytics, virtual reality, augmented reality, and chatbots for customer support. These advancements have allowed marketers to refine their strategies and customize their responses to meet the needs of consumers. This evolution has facilitated personalization, automation, data analysis, predictive analytics, and improved consumer experiences and engagement (Bag et al., 2021; Krishen et al., 2021; Sakas et al., 2023).

Technological developments in retail have greatly influenced the industry through the emergence of dynamic multichannel and omnichannel strategies (Jin & Shin, 2020). Major online retail platforms such as, eBay, alibaba, amazon, rakuten, and booking.com, along with popular social media like twitter, facebook, and instagram, have driven the social digitalization of retail businesses. Digital technology has transformed marketing by reducing regulatory barriers, resulting in significant cost savings, and enabling personalized promotional campaigns for individual clients (Bag et al., 2021).

In the e-commerce industry, companies utilize artificial intelligence (AI) platforms to extract valuable customer insights by analyzing patterns in customer behavior, data, and feedback (Krishnan et al., 2002). These platforms have become indispensable for monitoring shifting consumer behaviors and preferences, often replacing or complementing traditional marketing methods. Customer relationship management (CRM), social interactions and media, digital content marketing, e-WOM, digital marketing analytics, and virtual marketing communities are all important tools for meaningful consumer engagement (Gołąb-Andrzejak, 2023).

Moreover, integrating AI into digital marketing has transformed consumer-brand interactions and shopping experiences. AI enables digital marketers to automate processes, create personalized

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advertisements, optimize campaigns, and track results, thereby improving efficiency and effectiveness (Huang & Rust, 2020). AI in the digital market has already been used by businesses to better meet customer needs and preferences by personalizing emails, social media postings, websites, and other marketing communication devices (Haleem et al., 2022). Content personalization, through customized content and targeted advertising, has emerged as a key driver of engagement, enabling more effective digital marketing strategies.

Digital technology and AI greatly influence how consumers behave and make purchasing decisions (Bag et al., 2022). Personalization is essential for connecting with, engaging, and co-creating with customers. Additionally, it is crucial in fostering positive attitudes and reinforcing interpersonal connections (Payne, Dahl, & Peltier, 2021a). Contemporary marketing segmentation strategies heavily rely on collecting and analyzing preference and behavior data. This includes data from sources like Facebook (e.g., likes, shares), Google searches, and mobile app usage (Ma & Sun, 2020).

Although digital marketing can improve user experiences and build consumer-brand connections, it also presents challenges regarding privacy issues in digital marketing approaches (Gao & Liu, 2022; Roggeveen et al., 2021). Nevertheless, this study's primary goal is to investigate how AI driven personalization affects consumer perceptions and engagement within the context of digital marketing. Understanding consumer attitudes is crucial as new technology like AI-driven personalization continues to evolve in digital marketing. This information is essential for marketers adapting to the evolving digital environment.

There is a significant knowledge gap exists regarding how consumer perception affects AI-driven personalization and its connection to customer engagement in digital marketing. (Ameen et al., 2021; Andrzejak, 2023). This research fills this gap by examining consumers' perceptions of AI-driven personalization in digital marketing content across various platforms and their level of engagement. Furthermore, it contributes to strategic marketing research by bridging the divide between AI-driven marketing practices and academic studies, improving our comprehension of how AI-enabled personalization impacts consumer engagement. Therefore, our inquiry seeks to exploring three specific research questions.

RQ1. What impact does AI-enabled personalization in online marketing, specifically on social media platforms, have on the awareness of customer perceptions (trust, privacy concerns, perceived usefulness) and consumer engagement?

RQ2. How does AI-enabled personalization affect user engagement across social media platforms?

RQ3. Do customer perceptions of trust, privacy concerns, and perceived usefulness mediate the relationship between AI-enabled personalization and customer engagement?

2. Theoretical and literature review

2.1. Stimulus organism response (SOR) model

The SOR model is a widely used model for examining how external stimuli impact an individual's cognitive and emotional processes before influencing their behavior (Mehrabian & Russell, 1974; Tang and Zhang, 2018). In this framework, the stimulus (S) acts as an antecedent, while the organism (O) functions as mediating processes bridging the gap between the stimulus and behavioral responses (R) (Bag et al., 2022; Gao et al., 2023).

Within these mediating processes, it is essential to consider consumers' emotional states, encompassing factors like pressure, feelings of happiness or joy (pleasure), a sense of stimulation (arousal), and a perception of control or influence over the mediator (dominance) (Sung et al., 2021). The SOR model has been utilized in different areas such as marketing, service management, and information systems, offering insights into how technological and environmental factors influence human responses (Gao et al., 2023).

The SOR model used in this study states that customer perceptions in social network platforms serve as the organism, contributing to improved customer engagement through behavioral responses. In today's digital age, the SOR model remains highly relevant. In artificial intelligence systems, data serves as stimuli, driving synthesis and enabling the system to learn and adapt, facilitating efficient and appropriate responses, whereas traditional computer systems rely on static, predefined instructions (programs) without adaptive learning (Perez-Vega et al., 2021).

Organizations are utilizing AI-enabled personalization as cognitive stimuli, tailoring content to individual preferences, thereby enhancing their marketing capabilities. This alignment with the SOR framework highlights how customers perceived of digital marketing act as the organism influencing online customer engagement behaviors. To provide a comprehensive understanding, we will now review relevant literature on this topic.

2.2. Artificial intelligence (AI) driven personalization

In the field of online marketing, artificial intelligence (AI) is increasingly recognized for its ability to drive personalized experiences tailored to individual consumer preferences and behaviors. As companies around the globe continue to advance in AI, machine learning, and deep learning technologies, the role of AI in comprehending and responding to consumers is becoming increasingly vital. According to Kaplan and Haenlein (2019), artificial intelligence (AI) is characterized by its ability to comprehend and learn from outside data, as well as adapt to meet specific objectives. Specifically, AI-driven personalization in digital marketing aims not only to identify opportunities and comprehend customer behaviors but also to establish meaningful connections with consumers (Krishen et al., 2021). This form of personalization extends beyond traditional marketing approaches, offering superior strategies, models, processes, and services that influence customer behaviors (Huang & Rust, 2020). Moreover, while the objective of AI in digital marketing is to enhance rather than replace human judgment, its ability to customize products according to individual customer needs can significantly impact sales outcomes (Campbell et al., 2020).

Furthermore, AI's role in facilitating engagement marketing by leveraging data from previous customer interactions enhances value creation and influence across the customer journey (Payne et al., 2021a). Specifically, in social media marketing, AI-driven personalization enables the customization of content and precise targeting of audience segments, drawing from a diverse range of data sources such as search browsing patterns, purchase histories, and demographic information. However, it's crucial to acknowledge the potential pitfalls of personalization, including the risk of negative consumer reactions if it encroaches on individual choices or privacy (Roggeveen et al., 2021).

2.3. Consumer perceptions

In this dynamic digital environment, trust, privacy concerns, and perceived usefulness are important factors influencing how consumers perceive and engage in online and social media marketing that uses AI to personalize content for them. The stimulus organism response (SOR) model states that a consumer's emotional state affects their perception. It is essential for businesses to properly understand the complex connections among these components regardless of whether they expect to successfully survive the rapidly changing landscape of digital marketing.

- *Trust*

Trust is a multifaceted and crucial concept that holds significant importance across various fields, particularly in e-commerce and artificial intelligence (AI). In both domains, trust is a fundamental factor in ensuring success. According to Ha and Stoel (2009) and Ameen et al. (2021), trust can be defined as an attitude characterized by confident belief that potential vulnerabilities in a risky online situation will not be maliciously exploited. This definition emphasizes how trust influences how customers behave in online interactions and transactions.

Consumers' confidence in online retailers and internet technology plays an important role in how they make decisions, impacting their perceptions of safety and security while making online purchases (Ha & Stoel, 2009). Uncertainty about the safety and security of digital platforms significantly contributes to customer unwillingness to make purchases online (Gefen & Straub, 2003). Previous studies have shown that users' trust in the online platform significantly influences their confidence in participation in social commerce (Li, 2019).

Moreover, trust becomes even more complicated when it comes to AI-driven personalization, fundamentally reshaping consumers' perceptions and interactions with content. It extends beyond trusting the technology and the brand of the retailer; it also encompasses having confidence in the objectives and processes behind AI-generated content (Huang et al., 2022). Consequently, we consider trust to be an essential factor in understanding consumer perceptions of digital online marketing and how it influences consumer involvement with AI-enabled personalization.

- *Privacy concern*

Leveraging customer personal information is a powerful tool for companies, enabling them to create precise and targeted marketing campaigns that strengthen relationships with and retain customers. This data-driven approach enhances targeting and relevance, resulting in increased engagement and brand affinity (Maduku et al., 2023). Benefits from customer relationships are offset, however, by growing concerns about confidentiality and information security.

Gutierrez et al. (2019) define privacy as the ability to control and manage access to different areas of one's social and private spaces, such as information privacy, interpersonal relationships, physical boundaries, and psychological states. Individual attitudes and beliefs about privacy can vary depending on the situation and have significant consequences on how people share their data. Consumer perceptions of privacy play a pivotal role in determining their willingness to disclose information when interacting with websites or online platforms. Negative perspectives can arise from increased concerns regarding data collection, storage, and possible exploitation of personal data (Alzaidi & Agag, 2022). As data collection of customer expands, businesses of all sizes face challenges from the growing number of security breaches. The privacy issues significantly affect how willing customers are to use social media platforms for shopping and sharing information. (Maduku et al., 2023; Swani et al., 2021). However, despite privacy concerns, earlier studied have shown that customers are still willing to embrace personalized online marketing campaigns in order to enjoy their advantages. (Swani et al., 2021).

Therefore, AI-enabled personalization in interactive marketing holds the potential for advantages, but it also carries the risk of negative reactions if it constrains choices or violates individuals' privacy. Therefore, we consider privacy and security to be crucial elements in comprehending how consumers engage in online marketing and investigating their influence on consumer behavior in AI-driven personalization.

- *Perceived Usefulness*

According to Davis (1989), perceived usefulness refers to consumers' belief that technology will enhance their effectiveness, performance, or productivity in job-related tasks. This study examines how consumers view the relevance and value of AI-driven personalized content that is customized to their specific needs (Gao & Liu, 2022). Customers automatically see AI-driven personalization as valuable when they believe it to be useful and convenient. This perception of value serves as a key driver behind their acceptance and utilization of personalized marketing strategies (Sadriwala & Sadriwala, 2022). Prior studies have suggested that consumer attitudes regarding the adoption of new technology are significantly influenced by perceived usefulness (Na et al., 2022).

Moreover, there is empirical evidence to support the strong positive correlation between marketing innovation and the perceived usefulness of artificial intelligence (Maduku et al., 2023; Sadriwala & Sadriwala, 2022). in the competitive e-commerce landscape, businesses need to communicate the tangible benefits of AI-driven personalization to attract customers and improve their digital marketing efforts. Consequently, perceived usefulness emerges as an important factor influencing consumer behavior within the realm of AI and digital marketing. After examining the current literature, we propose the following hypothesis.

H1. AI-enabled personalization significantly impacts customer trust perceptions.

H2. AI-enabled personalization significantly affects customer perceptions regarding privacy concerns.

H3. AI-enabled personalization significantly impacts customer perceptions of perceived usefulness.

2.4. Consumer engagement

Customer engagement extends into the digital context, particularly on social networking websites within e-tailer platforms, where users interact with businesses and express their preferences through online comments and reviews (Kannan, 2017). This engagement is measured through consumer interactions such as likes, shares, and comments on posts, providing valuable insights through data analytics tools. Being engaged in social media is crucial for companies as it enables them to access a larger customer base. LinkedIn, Facebook, Instagram (IG), and Twitter are popular social media platforms for evaluating customer engagement with online business campaigns (Bag et al., 2022). According to Bag et al. (2022), consumer engagement refers to methods, processes, and technological applications that enable ongoing interaction with prospective clients across various channels.

Digital marketing tools play a significant role in enabling businesses to engage with online customers (Pantano & Vannucci, 2019). However, effectively engaging consumers through social media requires a deep insight of target markets, compelling content, and a thoughtful approach (So et al., 2021). Additionally, in today's digital marketing context, AI systems have become essential tools for businesses. However, their efficacy depends on consumer acceptance (Kaplan & Haenlein, 2019). This necessitates consumers acknowledging and agreeing with AI suggestions before fully embracing the system. With AI's capacity to gather and analyze data, it assists businesses in tailoring marketing campaigns, fundamentally altering consumer interactions with organizations. The transformation in customer engagement has a profound impact on stakeholders' psychological states throughout the entire process of developing, producing, and consuming products or services, ultimately influencing the co-creation of value (Gao et al., 2023).

Customer engagement involves a wide range of activities, including interactions on social media, active participation in loyalty programs, and sustained interest in a company's products or services. This increased level of engagement not only enhances a company's financial performance but also increases customer satisfaction, brand loyalty, and growth and innovation opportunities (Kumar & Kalse, 2021). Therefore, hypotheses are proposed.

H4. Customer trust perceptions significantly impact customer engagement.

H5. Customer privacy concern perceptions significantly influence customer engagement.

H6. Perceived usefulness significantly impacts customer engagement.

H7. AI-enabled personalization significantly affects customer engagement.

2.5. Mediating mechanisms

Van der Heijden et al. (2003) investigate the impact of perceived risk and perceived ease of use on attitudes on online purchasing attitude. The researchers identified these factors as crucial in understanding individuals' intentions to make online purchases. In our study's conceptual framework, we build upon this insight and propose that AI-enabled personalization's impact on consumer engagement is mediated through three key factors: trust, privacy concerns, and perceived usefulness. This perspective aligns with previous studies (Adamson & Shine, 2003; Lucas & Spider, 1999; Vijayasarathy, 2004) that have emphasized the essential role of consumer perceptions as mediating variables in technology adoption. Expanding on this concept, Ahn et al. (2003) highlighted the positive effects of online attributes, such as informational and system quality, on perceived usefulness and ease of use. Similarly, Sung et al. (2021) conducted research demonstrating that incorporating AI-powered advanced technological capabilities significantly enhances the consumer experience, leading to positive attitudes and engagement. Our current research, we draw upon these established connections and introduce trust as a mediating factor. We believe that trust plays a crucial role in connecting AI-driven personalization and user opinions, serving as a driving force in the complex network of perceived user friendliness, perceived utility, and attitudes towards customer interaction. Our research goal is to comprehend how AI-driven personalization influences customer engagement on social media platforms, with trust, privacy concern, and perceived usefulness as mediators. Therefore, hypotheses are proposed.

H8. AI-enabled personalization and customer engagement are mediated by customer trust perceptions.

H9. AIenabled personalization and customer engagement are mediated by customer privacy concern perceptions.

H10. AI-enabled personalization and customer engagement are mediated by customer perceived usefulness.

3. Methods

3.1. Data collection procedure

This research adopted a quantitative approach to gather primary data through survey questionnaires. Convenience sampling was used in the study in selecting participants. Google Forms facilitated the creation of the survey questionnaire, with participants providing feedback using a five-point rating scale. The majority of participants in this research comprised lecturers and college students. A total of 245 questionnaires were returned via the online survey. There were 245 appropriate replies considered for the final analysis. A sample size that is appropriate for the number of variables being examined is crucial for multivariate analysis. According to Hair et al. (2006) and Sekaran and Bougie (2016) suggest that a common range for the sample size is between 100 and 250 respondents. In this study, there were 5 constructs and 16 measuring items, indicating the minimum sample size should be at least 160 respondents. This range ensures sufficient statistical power to detect significant relationships among the variables in the construct model.

3.2. Measurement scales

In this study, we examined 16 constructs derived from previously published studies: AI-enabled personalization (Lalicic & Weismayer, 2021), consumer perception of trust (Sharma et al., 2021), perception of privacy concerns (Gao et al., 2018), perceived usefulness (Ashfaq et al., 2020), and consumer engagement (Hollebeek et al., 2014). A rating scale, with response options ranging where '1′ indicating totally disagree and a '5′ indicates totally agree, was adopted to assess all constructs.

3.3. Validity and reliability

To assess the validity of each construct, we conducted a sampling adequacy test and sphericity test in exploratory factor analysis. The KMO value resulted 0.916, which was higher than the suggested threshold of 0.9, and sphericity test's significant result ($p < 0.001$), indicating that the sampling was appropriate for factor analysis. Principal component analysis with varimax orthogonal rotation method was used to extract 18 observe variables in factor analysis. Following this analysis, we assessed the convergent validity using the AVE and CR metrics, which are shown in Table 1. Factor loadings ranged from 0.64 to 0.88, and all latent variables showed an AVE value greater than 0.5, indicating satisfactory convergence (Hair et al., 2017).

We used Cronbach's alpha coefficient test (Cronbach, 1951) to evaluate the survey questionnaire's internal consistency reliability. According to Nunnally (1978), a reliability score of at least 0.70 is considered acceptable. Table 1 shows that the latent variables have alpha values that fall between 0.826 and 0.914. The variables are being reliably measured by the questionnaire, as these values surpass the 0.7 threshold.

Table 2 presents the mean, standard deviation (SD), and a discriminant validity matrix. We applied the Fornell-Larcker criterion to assess latent variables and mitigate potential multicollinearity concerns. According to this criterion, the values on the upper right diagonal of the matrix should surpass correlations with other variables, ideally equaling or greater than the AVE's square root. This process confirms the discriminant validity of our constructed model (Fornell & Larcker, 1981).

4. Results

4.1. Sampling

Table 3 presents the participant information, derived from survey data that that were processed using statistical tools.

The sample for this study consisted of 245 respondents, comprising 148 males (60.41%) and 96 females (39.59%). A significant proportion of the respondents were aged between 21 and 30 years olds (42%), had education levels below a bachelor's degree or were college students (77.87%), and earned a monthly salary of less than 10,000 baht. Most of the participants were Thai (78.27%) and reported spending over 5 h daily on social media (40.57%). They used various social media platforms, including Facebook (80%), Instagram (60%), TikTok (56.55%), Line (45.49%), and WeChat (36.88%). Additionally, all participants had experience with multiple online shopping platforms, such as Shopee (74.59%) and Lazada (60.65%).

4.2. Empirical testing of the hypothesized model

The evaluation of model fit involved several key metrics, each associated with recommended thresholds (Hair et al., 2017). The model's fit was evaluated using the following metrics: chi-squared ratio to degrees of freedom ($\chi^2/\text{df} \leq 3$), Root Mean Square Residual (RMR ≤ 0.08), approximation's root mean squared error (RMSEA ≤ 0.08), comparative fit (CFI ≥ 0.9), incremental fit (IFI ≥ 0.9), Normed Fit (NFI ≥ 0.9), and Tucker Lewis (TLI ≥ 0.9) (Hair et al., 2017). The results are displayed in Table 4, demonstrating the measurement model was in good alignment with the data.

The results of the fitting test indicated that both the measurement

Table 1
Exploratory factor analysis and reliability analysis.

Factors/Items	Cronbach's α	CR	AVE	Factor Loading
AI enable Personalization in social media	**0.882**	**0.80**	**0.57**	
Artificial intelligence (AI) systems on popular social media platforms such as Line, Facebook, Instagram, Twitter (X), and TikTok often present content that matches your personal needs and preferences.				0.757
Artificial intelligence (AI) technology on social media platforms, they often present content, discounts, or promotions that match your interests and personal preferences.				0.812
Artificial intelligence (AI) systems built into social media platforms improve your user experience.				0.705
Perception: Privacy concern	**0.826**	**0.85**	**0.65**	
You are unsure about the safety of storing personal information on social media platforms that use artificial intelligence (AI) systems.				0.725
You are worried that your privacy information will not be safe because artificial intelligence (AI) systems may access your information and use it without your permission.				0.844
You are concerned about protecting your information. When you know that there is an AI system on the social media platforms you regularly use				0.855
Perceptions: Trust	**0.853**	**0.81**	**0.59**	
The social media platforms you are using are trusted and reliable source of online information.				0.742
You believe that the content on social media platforms is accurate.				0.887
Social media content can meet your needs.				0.674
Perception: Perceived usefulness	**0.914**	**0.85**	**0.59**	
Social media platforms have easy-to-use instructions that are customized to your interests.				0.647
Using social media platforms is convenient and can be used anywhere, anytime.				0.781
Using social media platforms allows you to find a wider range of information.				0.846
Using these social media platforms allows you to do many things faster.				0.800
User engagement	**0.829**	**0.69**	**0.57**	
Social media platform content stimulates your interest, that lead you to press Like and share the content.				0.808
You press Like on the social media platform that matches your preferences.				0.688
You will recommend or share content that matches your preferences with friends and family.				0.777

model and the structural model fit well; the measurement model's chi-square ratio to degrees of freedom (CMIN/DF) was 2.16. Furthermore, the recommended threshold of 0.9 was exceeded by the Normed Fit Index (NFI), Incremental Fit Index (IFI), Tucker-Lewis Index (TLI), and Comparative Fit Index (CFI) values, which were 0.927, 0.96, 0.939, and 0.9598, respectively. For the measurement model, the Root Mean Square Error of Approximation (RMSEA) value was 0.069, which is likewise within an acceptable range. These models were appropriate for further path analysis and satisfied the suggested fitting criteria. Table 4 shows how well the structural model's results fit as well. The model and path coefficients are shown in Fig. 1, and the results show that relationships are statistically significant with p-values less than 0.001.

4.3. Hypothesis testing

This study used the maximum likelihood method with analysis of moment structures (AMOS) to assess the credibility of the proposed structural model. Hypothesis acceptance was determined by a C.R. (t-value) greater than 1.96 with a significance level below 0.05. Two separate tests were conducted to examine the relationships and mediation of the hypotheses. The first test assessed hypotheses H1 to H7 for direct relationships. The second test aimed to test the mediation hypothesis on H8 to H10 using a bootstrapping procedure and a user-defined route in the estimand command.

Significant impacts are shown by the path analysis results, which are shown in Table 5. AI-enabled personalization exhibited a positive influence on trust perception ($\beta = 0.58$, $t = 2.07$, $p < 0.001$), privacy concern perception ($\beta = 0.63$, $t = 9.02$, $p < 0.001$), and perceived usefulness perception ($\beta = 0.77$, $t = 12.28$, $p < 0.001$), offering substantial support for H1, H2, and H3. Furthermore, the findings indicate that trust perception significantly influences consumer engagement ($\beta = 0.392$, $t = 4.16$, $p < 0.001$), providing support for H4. However, the perception of privacy concerns did not significant impact consumer engagement ($\beta = 0.001$, $t = 0.10$, $p = 0.992$), thus not supporting hypothesis H5. Perceived usefulness was found to significantly affect consumer engagement ($\beta = 0.392$, $t = 3.55$, $p < 0.001$), supporting H6. However, hypothesis 7 was not supported, suggesting that AI-enabled personalization did was not statistically significant customer engagement ($\beta = 0.176$, $t = 1.27$, $p = 0.20$).

4.3.1. Mediation analysis

To examine the mediation effect of consumer perceptions of trust on the relationship between AI-enabled personalization and customer engagement, a mediation analysis was conducted using 5000 bootstrapping samples and a 95% bias-corrected confidence interval (CI).

The analysis, detailed in Table 6, reveals a notable indirect effect on trust as a mediator between AI-enabled personalization and customer engagement (H8: $\beta = 0.26$, $p = 0.03$). Table 5 also shows that trust is strongly influenced by AI-enabled personalization (AI_P) ($\beta = 0.72$, $p < 0.001$), and that trust has a significant influence on customer engagement (CE) ($\beta = 0.39$, $p < 0.001$). These results imply that the relationship between AI-enabled personalization and customer engagement is fully mediated by trust, thus confirming the support for H8.

Table 6 presents the results, which show that the indirect influence of AI-enabled personalization on customer engagement, mediated by consumer privacy concerns, was not statistically significant (H9: $\beta = 0.001$, $p = 0.977$). As shown in Table 5, the direct effect of AI-enabled personalization (AI_P) had a significant influence on privacy concern ($\beta = 0.63$, $p < 0.001$). On the other hand, the effect of privacy concern on customer engagement (CE) ($\beta = 0.001$, $p = 0.992$) was not statistically significant. These findings suggest that consumer perceptions of privacy concern only partially mediate the correlation among AI-enabled personalization and engagement of customer. Therefore, H9 was not supported.

In the relationship between AI-enabled personalization (AI_P) and customer engagement (CE), the results presented in Table 6 indicate a significant indirect effect on perceived usefulness (H10: $\beta = 0.23$, $p = 0.01$). In addition, the direct effect of AI_P on perceived usefulness ($\beta = 0.77$, $p < 0.001$), and the subsequent impact of perceived usefulness on CE ($\beta = 0.33$, $p < 0.001$), were both found to be statistically significant. These results indicate that consumer perceptions of perceived usefulness fully mediate the link between AI-enabled personalization and customer engagement. Therefore, H10 was supported.

Table 2
Discriminant Validity (Fornell- Larcker criterion).

Factors	Mean (SD)	AI-enable	Privacy Concern	Trust	Perceived usefulness	Engagement
AI-enable Personalization	**3.68 (1.08)**	**0.755**				
Perception: Privacy concern	**3.72 (1.76)**	0.611	**0.806**			
Perceptions: Trust	**3.44 (0.98)**	0.693	0.440	**0.768**		
Perception: Perceived usefulness	**3.93 (0.94)**	0.736	0.548	0.684	**0.768**	
User Engagement	**3.66 (1.01)**	0.698	0.462	0.737	0.731	**0.75498**

Note: Diagonal elements in bold (AVE square roots).

Table 3
Descriptive statistics.

Items	*Variables*	*Percentage*	*Items*	*Variables*	*Percentage*
Gender	*Male*	*60.25*	*Occupation*	*College student*	*74.18*
	Female	*39.75*		*Employee*	*6.97*
Nationality	*Thai*	*78.27*		*Unemployed*	*18.85*
	China	*18.45*	*Social media*	*Facebook*	*80.00*
	Indonesia	*3.28*	*Account*	*Instagram (IG)*	*60.00*
Age	*18–20*	*36.10*		*Twitter (X)*	*8.60*
	21–30	*42.20*		*Lazada*	*60.65*
	31–40	*8.20*		*Shopee*	*74.59*
	41–50	*9.90*		*TikTok*	*56.55*
	More than 50	*3.69*		*WeChat*	*36.88*
Education	*> bachelor's degree*	*77.87*		*QQ*	*16.39*
	Bachelor's degree	*12.30*		*Line*	*45.49*
	< bachelor's degree	*9.83*	*Time spends*	*> 1*	*21.72*
Salary (THB)	*> 10,000*	*60.30*	*on social media*	*1–2*	*29.10*
	10,001–20,000	*13.60*	*hour per day*	*3–4*	*8.61*
	20,001–40,000	*16.00*		*> 5*	*40.57*
	> 40,000	*10.10*			

Note: n = 245.

Table 4
Model fit indices.

Model	χ^2/df	RMR	RMSEA	NFI	IFI	TLI	CFI
Measurement model Structural model	2.167 2.331	0.049 0.055	0.069 0.074	0.927 0.918	0.96 0.95	0.939 0.939	0.959 0.951

Note: Recommend index χ^2/df $\leq$ 3, RMR $\leq$0.08, RMSEA $\leq$0.08, NFI $\geq$0.90, IFI $\geq$0.90, TLI $\geq$ 0.90, CFI $\geq$0.90.

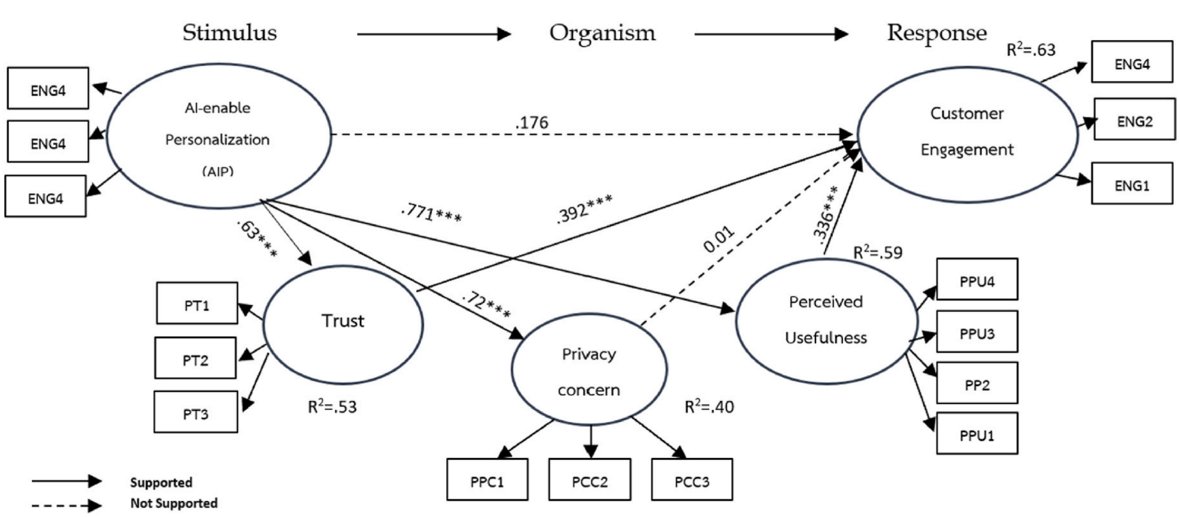

Fig. 1. Structure model.

5. Discussions

This empirical study seeks to explore the influence of AI driven personalization on businesses operating on social media platforms, focusing on its influence on customer perceptions of trust, privacy concerns, perceived usefulness, and consumer engagement. Our findings highlight the intricate relationship between AI-driven personalization and consumer behavior, adding valuable insights to the current literature.

Our findings support the hypothesis that AI-enabled personalization

Table 5
Summary of finding.

Hypotheses	Relationship	β	SE	CR	*P*-value	Results
H1	Trust ← AI_P	0.72	0.064	10.66	***	Supported
H2	Privacy ← AI_P	0.63	0.072	9.02	***	Supported
H3	UseF ← AI_P	0.77	0.061	12.28	***	Supported
H4	CE ← Trust	0.39	0.092	4.16	***	Supported
H5	CE ← Privacy	0.001	0.066	0.010	0.992	Not supported
H6	CE ← UseF	0.336	0.088	3.55	***	Supported
H7	CE ← AI_P	0.176	0.126	1.27	0.202	Not supported

Note: **AI_P** = AI enable Personalization, **Trust** = Perception on trust, **Privacy** = Perception on privacy concern, **UseF** = Perception on perceived usefulness, **CE** = Consumer Engagement, SE = Standardized Error, C.R. = Critical Ratio. ***p < 0.001, **p < 0.01, *p < 0.05.

Table 6
Findings from mediation analysis.

Hypotheses	Relationship	Indirect Effect	SE	Percentile Bootstrap 95%		*P*-value	Results
				Lower Bound	Upper Bound		
H8	AI_P → Trust → CE	0.260**	0.86	0.108	0.451	0.003	Supported (Full Mediation)
H9	AI_P → Privacy → CE	0.001	0.68	−0.138	0.135	0.977	Not Supported (No Mediation)
H10	AI_P → UseF → CE	0.236**	0.86	0.073	0.393	0.010	Supported (Full Mediation)

Note: *n* = 5000 (bootstrap), AI_P = AI enable Personalization, Trust = Perception on trust, Privacy = Perception on privacy concern, UseF = Perception on perceived usefulness, CE = Consumer Engagement, SE = Standardized Error, C.R. = Critical Ratio, ***p < 0.001, **p < 0.01, *p < 0.05.

significantly affects consumer trust, privacy concerns, and perceived usefulness, which aligns with previous studies by Bag et al. (2021) and Krishen et al. (2021). Trust and perceived usefulness emerge as critical factors in influencing consumer engagement, underscoring their essential role in how users interact with personalized content. While Gao and Liu (2022) identified privacy concerns as a significant factor impacting consumer engagement, our study suggests otherwise. This discrepancy could be attributed to differences in research methodologies or evolving consumer attitudes towards privacy. This unexpected finding indicates that while privacy is a concern, it may not be as influential in shaping consumer behavior within the context of AI-driven personalization as previously thought.

Remarkably, the study finds that AI-driven personalization does not exert a significant direct impact on customer engagement. Previous studies, such as those by Alzaidi and Agag (2022), have suggested that consumers generally trust products they discover on social media. However, our study highlights the complex nature of this relationship, indicating that trust alone may not be sufficient to drive engagement. This divergence may result from the specific nature of AI applications examined or variations in user behavior across different social media platforms. Future research should explore the relationship between AI-driven personalization, consumer trust, and engagement across a broader range of digital contexts.

Privacy concerns pose a potential threat to the effectiveness of AI-enabled personalization by potentially deterring consumers from sharing data necessary for personalized experiences (Aguirre, Mahr, Grewal, de Ruyter, & Wetzels, 2015). Despite the lack of a clear correlation between privacy concerns and engagement, it raises critical questions about the personalization-privacy paradox, where consumers may feel dissatisfied despite the perceived benefits of personalization (Canhoto et al., 2023). This paradox presents a challenge for marketers, who must carefully balance offering valuable personalization with respecting consumer privacy.

Moreover, our study emphasizes the importance of perceived usefulness in driving consumer engagement (Liu & Tao, 2022). Customers' perceptions of the usefulness of AI-driven personalization greatly influence how they value and engage with it. However, the lack of a direct impact of AI-enabled personalization on customer engagement suggests that other factors, such as content quality, user experience, or brand loyalty, may play a more substantial role in fostering engagement.

6. Implications

This study enhances our understanding of AI's influence on consumer engagement by examining how consumer perceptions mediate the relationship between AI-enabled personalization and customer engagement. Trust and perceived usefulness have emerged as significant mediators in this relationship, highlighting the complexities of consumer interactions with AI technologies. These findings contribute to both academic knowledge and practical applications by offering insights into the mediating factors and providing guidance for organizations seeking to leverage AI-enabled personalization to enhance consumer engagement.

For academic.

1. This research extends the Stimulus-Organism-Response (SOR) model by illustrating how AI stimuli impact consumer engagement, providing a robust framework for future studies in AI and consumer behavior contexts. The integration of AI as a stimulus provides a novel perspective, encouraging further exploration of AI's role in shaping consumer responses.
2. Recognizing trust and perceived usefulness as key mediators provides valuable insights into the fundamental processes that influence the relationship between AI-enabled personalization and customer engagement. These findings can inform future theoretical developments by encouraging the exploration of additional mediators or moderators that may further clarify consumer behavior in AI-driven scenarios.
3. The finding that privacy concerns do not significantly mediate the relationship between AI personalization and engagement challenges existing assumptions. This opens new research avenues, encouraging scholars to delve deeper into understanding privacy perceptions in AI-enabled personalization and their varying impacts across different demographic groups and cultural contexts.

For practitioners.

1. Companies should prioritize building consumer trust and emphasizing the perceived usefulness of AI applications in their e-commerce strategies. By enhancing these aspects, businesses can positively influence user experiences and foster stronger consumer

engagement, leading to increased brand loyalty and customer retention.

2. The study highlights a potential AI-personalization-privacy paradox, where efforts to personalize, content may inadvertently lead to privacy concerns. Practitioners must carefully balance personalization with robust privacy protection measures to avoid negative user experiences and dissatisfaction. Maintaining this balance is essential to preserving customer confidence and averting possible objections.
3. Recognizing the mediating effects of trust and perceived usefulness, businesses should adopt a customer-centric approach to AI implementation. This involves ensuring transparency in AI processes, reliability in AI-generated content, and clear communication of the practical benefits of AI applications to users. By aligning AI strategies with consumer needs and expectations, companies can enhance engagement and drive long-term success.

6.1. Limitation

This study acknowledges a number of limitations that may impact the general interpretation and application of the findings. Addressing these constraints in future research could lead to a more comprehensive understanding of AI-enabled personalization and its effects on consumer behavior. First, the study's time constraints resulted in a relatively small sample size, which may limit the generalizability of the results (Chen & Zhang, 2019). Moreover, the sample predominantly comprised university students aged 18–22 years, which limited the results' generalizability. In order to enhance both the validity and significance of the results, future studies ought to aim to incorporate a more extensive and diverse group of participants. Second, this study exclusively examines consumer perceptions related to trust, privacy concerns, and perceived usefulness. While these factors are critical, other psychological variables such as motivation, learning, and lifestyle (Li & Wang, 2018) also play significant roles in shaping consumer behavior. Future studies could explore these additional factors to provide a more holistic understanding of consumer engagement in AI-driven environments. Third, the cross-sectional nature of this study limits its ability to capture the long-term effects of AI-enabled personalization on consumer engagement. To gain deeper insights, future research should consider longitudinal studies that observe user behavior over an extended period. This approach could reveal causal relationships and offer a better understanding of how social media platforms and AI technologies evolve and impact marketing strategies over time. Finally, while this study provides valuable insights into the general impact of AI-enabled personalization, the effects may vary across different social media platforms. Future research could focus on platform-specific studies to uncover unique dynamics and tailor marketing strategies to the characteristics of each platform.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

References

Adamson, I., & Shine, J. (2003). Extending the new technology acceptance model to measure end user information systems satisfaction in a mandatory environment: A bank's treasury. *Technology Analysis & Strategic Management, 15*(4), 441–455.

Aguirre, E., Mahr, D., Grewal, D., de Ruyter, K., & Wetzels, M. (2015). Unraveling the personalization paradox: The effect of information collection and trust-building strategies on online advertisement effectiveness. *Journal of Retailing, 91*(1), 34–49.

Ahn, T., Ryu, S., & Han, I. (2003). The impact of the online and offline features on the user acceptance of internet shopping malls. *Electronic Commerce Research and Applications, 3*(4), 405–420.

Alzaidi, M. S., & Agag, G. (2022). The role of trust and privacy concerns in using social media for e-retail services: The moderating role of COVID-19. *Journal of Retailing and Consumer Services, 68*, Article 103042.

Ameen, N., Tarhini, A., Reppe, A., & Anand, A. (2021). Customer experiences in the age of artificial intelligence. *Computers in Human Behavior, 114*, Article 106548.

Andrzejak, E. G. (2023). AI-Powered digital transformation: Tools, benefits and challenges for marketers – case study of LPP. *Procedia Computer Science, 219*, 397–404.

Ashfaq, M., Yun, J., Yu, S., & Loureiro, S. (2020). I, chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents. *Telematics and Informatics, 54*, Article 101473. https://doi.org/10.1016/j.tele.2020.101473

Bag, S., Sivarajah, U. S., Kumari, A., Giannakis, M., & Chowdhury, A. H. (2022). Journey of customers in this digital era: Understanding the role of artificial intelligence technologies in user engagement and conversion. *Benchmarking: An International Journal, 29*(7), 2074–2098.

Campbell, C., Sands, S., Ferraro, C., Tsao, H. Y. J., & Mavrommatis, A. (2020). From data to action: How marketers can leverage AI. *Business Horizons, 63*(2), 227–243.

Canhoto, A. I., Keegan, B. J., & Ryzhikh, M. (2023). Snakes and ladders: Unpacking the personalisation-privacy paradox in the context of AI-enabled personalisation in the physical retail environment. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-023-10369-7

Chen, Y., & Zhang, Y. (2019). Understanding customer engagement in mobile social commerce: A social influence perspective. *International Journal of Information Management, 49*, 366–377.

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika, 16*, 297–334. https://doi.org/10.1007/BF02310555

Davis, F. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*, 319–340.

Erragcha, N., & Romdhane, R. (2014). New faces of marketing in the era of the web: From marketing 1.0 to marketing 3.0. *Journal of Research in Marketing, 2*(2), 137–142.

Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research, 18*(3), 382–388.

Gao, L., Li, G., Tsai, F., Gao, C., Zhu, M., & Qu, X. (2023). The impact of artificial intelligence stimuli on customer engagement and value co-creation: The moderating role of customer ability readiness. *The Journal of Research in Indian Medicine, 17*(2), 317–333.

Gao, Y., & Liu, H. (2022). Artificial intelligence-enabled personalization in interactive marketing: A customer journey perspective. *The Journal of Research in Indian Medicine*, 2040–7122.

Gefen, D., & Straub, D. (2003). Managing user trust in B2C e-services. *E-Service Journal, 2* (2), 7–24.

Gołąb-Andrzejak, E. (2023). AI-Powered digital transformation: Tools, benefits and challenges for marketers–case study of LPP. *Procedia Computer Science*, (219), 397–404.

Gutierrez, N., Freundschuh, S., & Ahn, G. (2019). From privacy to control: Reconceptualizing a complex construct in an age of information disclosure. *Journal of the Association for Information Science and Technology, 70*(10), 1090–1100.

Ha, S., & Stoel, L. (2009). Consumer e-shopping acceptance: Antecedents in a technology acceptance model. *Journal of Business Research, 62*, 565–571.

Hair, J., Black, W., Babin, B., Anderson, R., & Tatham, R. (2006). *Multivariate data analysis* (6th ed.). Upper Saddle River, NJ: 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.). Thousand Oaks, CA: Sage Publications Inc.

Haleem, A. J., Mohd, M., Qadri, A., Singh, R. P., & Suman, R. (2022). Artificial intelligence (AI) applications for marketing: A literature-based study. *International Journal of Intelligent Networks, 3*, 119–132.

Hollebeek, L., Glynn, M., & Brodie, R. (2014). Consumer brand engagement in social media: Conceptualization, scale development and validation. *Journal of Interactive Marketing, 28*. https://doi.org/10.1016/j.intmar.2013.12.002

Huang, R., Kim, M., & Lennon, S. (2022). Trust as a second-order construct: Investigating the relationship between consumers and virtual agents. *Telematics and Informatics, 70* (101811), 1–12.

Huang, M. H., & Rust, R. T. (2020). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science, 49*(1), 30–50.

Jin, B. E., & Shin, D. C. (2020). Changing the game to compete: Innovations in the fashion retail industry from the disruptive business model. *Business Horizons, 63*(3), 301–311.

Kannan, P. K. (2017). Digital marketing: A framework, review and research agenda. *International Journal of Research in Marketing, 34*(1), 22–45.

Kaplan, A., & Haenlein, M. (2019). Siri, siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons, 62*(1), 15–25.

Krishen, A. S., Dwivedi, Y. K., Bindu, N., & Kumar, K. S. (2021). A broad overview of interactive digital marketing: A bibliometric network analysis. *Journal of Business Research, 131*, 183–195.

Kumar, A., & Kalse, A. (2021). Usage and adoption of artificial intelligence in SMEs. *Materials Today: Proceedings*.

Lalicic, L., & Weismayer, C. (2021). Consumers' reasons and perceived value co-creation of using artificial intelligence-enabled travel service agents. *Journal of Business Research, 129*, 891–901.

Li, X. (2019). Understanding Chinese consumers' trust in social commerce: An exploratory study. *Information Systems Frontiers, 21*(1), 229–243.

Li, H., & Wang, Y. (2018). Understanding the influence of hedonic motivation on consumer engagement in social commerce: An empirical study. *Information & Management, 55*(8), 980–991.

Liu, K., & Tao, D. (2022). The roles of trust, personalization, loss of privacy, and anthropomorphism in public acceptance of smart healthcare services. *Computers in Human Behavior, 127*(8), Article 107026.

Lucas, J. H. C., & Spider, V. K. (1999). Technology use and performance: A field study of broker workstations. *Decision Sciences, 30*(2), 291–310.

Ma, L., & Sun, B. (2020). Machine learning and AI in marketing – connecting computing power to human insight. *International Journal of Research in Marketing, 37*(3), 481–504.

Maduku, D. K., Mpinganjira, M., Rana, N. P., Thusi, P., Ledikwe, A., & Mkhize, N. H. (2023). Assessing customer passion, commitment, and word-of-mouth intentions in digital assistant usage: The moderating role of technology anxiety. *Journal of Retailing and Consumer Services, 71*(103208), 1–13.

Mehrabian, A., & Russell, J. A. (1974). *An approach to environmental psychology*. MIT Press.

Na, S., Heo, S., Han, S., Shin, Y., & Roh, Y. (2022). Acceptance model of artificial intelligence (AI)-Based technologies in construction firms: Applying the technology acceptance model (TAM) in combination with the technology–organisation–environment (TOE) framework. *Buildings, 12*(90), 1–17.

Pantano, E., & Vannucci, V. (2019). Who is innovating? An exploratory research of digital technologies diffusion in retail industry. *Journal of Retailing and Consumer Services, 49*, 297–304.

Payne, E. M., Dahl, A. J., & Peltier, J. (2021a). Digital servitization value co-creation framework for AI services: A research agenda for digital transformation in financial service ecosystems. *The Journal of Research in Indian Medicine, 15*(2), 200–222.

Perez-Vega, R., Kaartemo, V., Lages, C. R., Razavi, N. B., & M€annist€o, J. (2021). Reshaping the contexts of online customer engagement behavior via artificial intelligence: A conceptual framework. *Journal of Business Research, 129*, 902–910.

Roggeveen, A. L., Grewal, D., Karsberg, J., Noble, S. M., Nordfält, J., Patrick, V. M., & Olson, R. (2021). Forging meaningful consumer-brand relationships through creative merchandise offerings and innovative merchandising strategies. *Journal of Retailing, 97*(1), 81–98.

Sadriwala, M. F., & Sadriwala, K. F. (2022). Perceived usefulness and ease of use of artificial intelligence on marketing innovation. *International Journal of Innovation in the Digital Economy, 13*(3), 10.

Sakas, D. P., Reklitisa, D. P., Giannakopoulosa, N. T., & Trivellas, P. (2023). The influence of websites user engagement on the development of digital competitive advantage and digital brand name in logistics startups. *European research on management and business economics, 29*(100221), 1–18.

Sekaran, U., & Bougie, R. (2016). *Research methods for business: A skill-building approach* (7th ed.). West Sussex: Wiley & Sons.

Sharma, S., Singh, S., Kujur, F., & Das, G. (2021). Social media activities and its influence on customer-brand relationship: An empirical study of apparel retailers' activity in India. *Journal of Theoretical and Applied Electronic Commerce Research, 16*(4), 602–617.

So, K. K. F., Wei, W., & Martin, D. (2021). Understanding customer engagement and social media activities in tourism: A latent profile analysis and cross-validatio. *Journal of Business Research, 129*, 474–483.

Sung, C., Bae, S., Han, D., & Kwon, O. (2021). Consumer engagement via interactive artificial intelligence and mixed reality. *International Journal of Information Management, 60*, Article 102382.

Swani, K., Milne, G. R., & Slepchuk, A. N. (2021). Revisiting trust and privacy concern in consumers' perceptions of marketing information management practices: Replication and extension. *Journal of Interactive Marketing, 56*, 137–158.

Van Der Heijden, H., Verhagen, T., & Creemers, M. (2003). Understanding online. Purchase intentions: Contributions from technology and trust perspectives. *European Journal of Information Systems, 12*(1), 41–48.

Vijayasarathy, L. R. (2004). Predicting consumer intentions to use on-line shopping: The case for an augmented technology acceptance model. *Information & Management, 41*(6), 747–776.

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The author would also like to add the following declaration:

Declaration of Generative AI in Scientific Writing

During the preparation of this work, the author used ChatGPT (OpenAI) for language editing and improving readability. After using this tool, the author reviewed and edited the content as needed and take full responsibility for the final version of the manuscript.

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