

Decoding Consumer Responses to Personalized Marketing: An Empirical Study within the Stimulus–Organism–Response Framework

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Abstract

Personalized marketing is widely used to engage consumers in digital commerce environments, supported by advances in artificial intelligence and data analytics that allow firms to create communication aligned with individual preferences. At the same time, concerns around the handling of individuals' personal information continue to grow, and the psychological processes through which such communication affects purchase intentions are not yet clearly understood. This study uses the Stimulus-Organism-Response (S-O-R) framework to examine how personalized marketing messages influence online purchase intentions through consumers' internal states. Perceived personalization and consumer trust are considered as mediators, while privacy concerns are examined as a moderator. A quantitative approach was adopted using data from 195 online shoppers in India with prior exposure to personalized marketing. The proposed relationships were tested using Partial Least Squares Structural Equation Modeling with SmartPLS 4. The results show that personalized marketing messages significantly improve perceived personalization and trust, which in turn increase purchase intentions. Both direct and indirect effects are observed, indicating multiple pathways through which personalization shapes consumer behavior, while the moderating role of privacy concerns is not significant. The study offers a clearer understanding of personalization effects in digital settings and provides useful insights for designing effective and trustworthy marketing strategies, especially within developing markets such as India.

Categories: Consumer Behavior, Digital Marketing, Marketing Communication

Keywords: personalized marketing, purchase intention, perceived personalization, trust, privacy concerns, online shopping, stimulus–organism–response model

Introduction

The expansion of digital commerce has fundamentally changed how firms interact with consumers ([Ratchford, 2009](#)). The rapid growth of digital commerce further underscores the importance of personalized marketing in contemporary business environments. Recent global estimates project e-commerce sales to exceed USD 8 trillion by 2027, with a significant share of this growth driven by data-driven and AI-enabled personalization strategies ([Statista, 2025](#)). In India, the digital commerce market is also expanding rapidly due to increasing internet penetration, smartphone adoption, and growing digital engagement across online platforms. As digital platforms become more integrated into consumers' daily lives, firms are increasingly relying on personalized marketing strategies to improve customer engagement and strengthen online relationships. Studies indicate that more than 70% of consumers expect personalized experiences from brands, while nearly 80% are more likely to purchase when exposed to personalized content and recommendations ([McKinsey and Company, 2021](#)). These developments highlight the growing role of personalization in shaping consumer behavior and influencing online purchase decisions. At the same time, concerns related to data privacy, security, and the effectiveness of personalization continue to shape consumer responses toward personalized marketing efforts. Therefore, understanding how personalized marketing influences consumer purchase intentions has become increasingly important in contemporary digital environments.

Online platforms collect large volumes of behavioral data, enabling firms to move beyond traditional mass communication and develop marketing messages tailored to individual users (Duch-Brown et al., 2017) (Fulgoni, 2018). Consumers interact with brands across multiple digital touchpoints, including e-commerce websites, mobile apps, and social media platforms. In these environments, marketing communication is increasingly shaped by browsing behavior, prior purchases, and expressed preferences (Tam and Ho, 2006). As a result, standardized promotional messages are becoming less effective, while personalized communication is gaining importance for capturing attention and improving relevance (Bleier et al., 2020). Firms rely on data analytics to determine the content, timing, and delivery of marketing messages (Bhavsar and Tiwari, 2024). Personalization is therefore emerging as a key mechanism through which organizations influence consumer responses and maintain relationships in digital marketplaces (Arora et al., 2008). Advances in technologies such as artificial intelligence (AI), machine learning, big data analytics, and IoT (Internet of Things) have strengthened firms' ability to analyze consumer behavior and anticipate individual preferences (Theodorakopoulos and Theodoropoulou, 2024). These technologies enable marketers to adjust communication in real time, creating adaptive, context-specific marketing messages (Deligiannis et al., 2020). Through automated systems, organizations can optimize not only who receives a message but also how it is delivered across digital platforms (An and Ngo, 2025). However, technological capability alone does not guarantee effectiveness, as consumer responses depend on how personalization is perceived and interpreted.

Existing research suggests that personalized marketing influences purchase intentions through both cognitive and affective mechanisms. Personalized recommendation systems enhance perceived value and usefulness, which in turn increase purchase willingness (Kim et al., 2024). High-quality personalization can also elicit positive emotional responses that support persuasion and decision-making (Pappas et al., 2017). In addition, customized digital interfaces and tailored content shape cognitive evaluations that guide consumer behavior (Bleier and Eisenbeiss, 2015). These findings indicate that personalization operates through perceived relevance rather than mere exposure (Xia and Bechwati, 2008). The Stimulus-Organism-Response (S-O-R) framework, proposed by Mehrabian and Russell (1974), provides a structured theoretical basis for explaining how external stimuli influence internal psychological states, which subsequently guide behavioral responses. In digital commerce contexts, personalized marketing messages serve as stimuli, while perceived personalization and trust constitute organismic states that influence purchase intention. Prior studies applying the S-O-R framework show that personalized messages enhance perceived relevance, satisfaction, and trust, which in turn increase purchase likelihood (Pappas et al., 2017). At the same time, the effectiveness of personalized marketing is shaped by contextual factors. Perceived personalization and trust often mediate the relationship between personalized messages and purchase intention, while privacy concerns influence how consumers interpret personalization efforts (Xu et al., 2011) (Awad and Krishnan, 2006). When personalization is perceived as intrusive or lacking transparency, consumers may respond with skepticism or resistance. This perspective can also be understood through the lens of Privacy Calculus Theory, which holds that consumers weigh the benefits of personalization against potential privacy risks when engaging with digital platforms (Xu et al., 2011).

Although prior studies confirm that personalized marketing influences purchase intentions through internal processes (Pappas et al., 2017), the literature remains fragmented (Chandra et al., 2022). Existing research often examines perceived personalization and trust separately or focuses primarily on direct effects, without integrating these mechanisms into a unified framework (Nobile and Cantoni, 2023). This limits the ability to fully understand how personalization translates into behavioral outcomes in integrated models. In addition, privacy concerns are frequently discussed conceptually but are less often tested as moderating factors in comprehensive empirical models (Awad and Krishnan, 2006) (Xu et al., 2011). Evidence from emerging digital markets also remains limited (Bhavsar and Tiwari, 2024). To address these gaps, this study proposes and empirically tests an integrated S-O-R-based model that examines how personalized marketing messages influence online purchase intention through perceived personalization and trust, while incorporating privacy concerns as a moderator. This study makes three specific contributions. First, it extends S-O-R-based personalization research by integrating perceived personalization and trust into a unified framework, providing a more comprehensive explanation of consumer responses (Pappas et al., 2014). Second, it examines both direct and mediated relationships,

offering evidence of dual pathways through which personalization influences decision-making (Pappas et al., 2017) (Bleier and Eisenbeiss, 2015). Third, it contributes to the personalization-privacy debate by empirically testing privacy concerns as a moderator and highlighting their limited influence in an emerging market context (Xu et al., 2011).

Literature review

Research on personalized marketing, trust formation, privacy concerns, and online purchase behavior provides an important foundation for understanding consumer responses in digital commerce environments (Chandra et al., 2022) (Nobile and Cantoni, 2023). The Stimulus-Organism-Response framework offers a structured basis for examining how external marketing factors influence internal psychological states and subsequent behavioral responses (Mehrabian and Russell, 1974). The framework posits that environmental stimuli shape cognitive and affective evaluations, which in turn guide approach or avoidance behaviors. Its ability to integrate evaluative and emotional processes has led to its extensive use in consumer behavior and digital marketing research (Pappas et al., 2017). In online shopping contexts, marketing communication, platform design, and digital interfaces serve as external stimuli that shape consumer perceptions (Pappas et al., 2014). These perceptions, which represent organismic states, include constructs such as perceived personalization and trust. Behavioral intentions, including purchase intention, constitute the response component. Empirical research demonstrates that the Stimulus-Organism-Response framework effectively explains how online marketing environments influence consumer engagement and decision-making (Eroglu et al., 2001) (Pappas et al., 2017) (Mehrabian and Russell, 1974). Recent studies further suggest that contextual variables, including privacy-related concerns, influence how consumers interpret personalized digital communication (Xu et al., 2011) (Awad and Krishnan, 2006).

Personalized marketing messages are a central driver of contemporary digital commerce. These messages are generated from information on individual preferences, browsing patterns, prior purchases, and contextual data (Tam and Ho, 2006) (Arora et al., 2008). Recent advances in AI and data analytics have enabled firms to deliver tailored content at scale, making personalization a core strategic capability in online marketing (Bhavsar and Tiwari, 2024) (Deligiannis et al., 2020). Empirical evidence indicates that personalized communication attracts more attention and is evaluated more positively than non-personalized messages (An and Ngo, 2025). Research across online retail and digital advertising contexts shows that personalization enhances perceived relevance, reduces information-processing effort, and increases engagement (Tam and Ho, 2006) (Sundar and Marathe, 2010). Recent research highlights that personalized marketing is increasingly driven by AI and predictive analytics, enabling firms to deliver hyper-personalized experiences tailored to individual consumer behavior (Kumar et al., 2019) (Davenport et al., 2020) (Huang and Rust, 2021). AI-driven personalization enables real-time adaptation of marketing content, significantly enhancing customer engagement and conversion outcomes compared with traditional approaches (Lemon and Verhoef, 2016). However, growing reliance on data-driven personalization has also raised concerns about algorithmic bias, ethical data use, and consumer trust (Martin et al., 2017) (Culnan and Bies, 2003). These technological developments further strengthen the role of personalized marketing as a key element within the S-O-R framework.

Despite these advantages, consumers often evaluate personalization through a cost-benefit assessment of perceived benefits and privacy risks, as explained by Privacy Calculus Theory (Dinev and Hart, 2006) (Awad and Krishnan, 2006). The theory holds that individuals weigh the perceived benefits of sharing personal information against potential privacy risks when engaging with digital platforms (Culnan and Armstrong, 1999). In personalized marketing, this trade-off shapes how consumers interpret and respond to tailored communication. This perspective complements the S-O-R framework by explaining how consumers cognitively evaluate personalized stimuli before forming behavioral responses. Within the Stimulus-Organism-Response framework, personalized marketing messages prompt internal evaluations of relevance and fit. When consumers perceive communication as tailored to their preferences, they are more likely to feel recognized and aligned with the brand (Sundar and Kim, 2005) (Komiak and Benbasat, 2006) (Adomavicius et al., 2005). This internal assessment is reflected in perceived personalization, defined as the extent to which consumers believe marketing communication aligns with their individual needs and interests (Tam and Ho, 2006). Although prior studies emphasize the importance of relevance in digital persuasion, fewer investigations integrate personalized marketing messages and perceived personalization within a unified theoretical structure.

H1. Personalized marketing messages positively influence perceived personalization.

Personalized communication also serves as a relational signal. In digital environments marked by uncertainty and information asymmetry, signals of attentiveness and competence help build trust. When marketing messages seem relevant and appropriately tailored, consumers may view them as evidence that the firm understands their preferences and can deliver satisfactory service. Trust in online retailers has consistently been identified as a key determinant of purchasing behavior (Gefen et al., 2003). Research further indicates that non-intrusive personalization strengthens trust perceptions by enhancing perceived competence and benevolence (Pappas et al., 2017). Positioning trust as an organismic response allows examination of how personalized stimuli influence relational confidence.

H2. Personalized marketing messages positively influence consumer trust.

Perceived personalization reflects consumers' subjective evaluation of how well marketing messages align with their personal interests and situational needs (Sundar and Marathe, 2010) (Xu et al., 2008). In online shopping environments, perceived personalization enhances the usefulness of information and reduces decision effort. Consumers exposed to relevant, tailored content report greater engagement and higher satisfaction, which positively influence behavioral intentions (Pappas et al., 2014) (Cavdar Aksoy et al., 2021). From a Stimulus-Organism-Response perspective, perceived personalization serves as a cognitive mechanism that translates external stimuli into behavioral outcomes. Empirical evidence supports a positive association between perceived personalization and purchase intention in digital retail settings (Bhavsar and Tiwari, 2024) (Chandra et al., 2022).

H3. Perceived personalization positively influences purchase intentions.

Trust is another critical psychological mechanism that influences online consumer behavior. In the absence of physical interaction, trust reduces perceived uncertainty and increases confidence in transaction outcomes (Gefen et al., 2003) (McKnight et al., 2002). Consumers who perceive an online platform as reliable and responsible are more likely to make purchases. Within the Stimulus-Organism-Response structure, trust functions as an organismic state that facilitates the translation of marketing stimuli into approach behavior.

H4. Trust positively influences purchase intentions.

Although the Stimulus-Organism-Response framework emphasizes mediated pathways, some stimuli can also elicit direct behavioral responses. In digital contexts, highly relevant, personalized cues delivered at decisive moments may prompt immediate action without extensive cognitive processing. Evidence from online advertising research indicates that personalized messages can directly increase click-through rates and purchasing behavior. This suggests that personalization may influence behavior even without extensive cognitive processing.

H5. Personalized marketing messages positively influence purchase intentions.

Despite the advantages of personalization, concerns about data privacy set important boundary conditions. Privacy concerns refer to individuals' worries about the collection, storage, and use of their personal information. The personalization-privacy paradox captures the tension between consumers' desire for tailored experiences and their concerns about losing control over personal data (Awad and Krishnan, 2006). Individuals with higher levels of privacy concern may approach personalized communication with caution, potentially weakening relational trust and behavioral intentions (Xu et al., 2011). Within the Stimulus-Organism-Response framework, privacy concerns serve as contextual conditions that shape how consumers interpret personalized marketing stimuli and translate trust into action. This underscores the conditional nature of personalization effectiveness, as consumer sensitivity to privacy can alter how marketing stimuli are interpreted. Empirical evidence suggests that privacy sensitivity can moderate the relationship between trust and purchase intention in digital settings (Grimmer and Woolley, 2014) (Cavdar Aksoy et al., 2021). Examining privacy concerns as a moderator rather than a direct predictor offers a more nuanced understanding of personalization effectiveness.

H6. Privacy concerns moderate the relationship between personalized marketing messages and consumer trust.

H7. Privacy concerns moderate the relationship between trust and purchase intentions.

Existing research shows that personalized marketing messages influence purchase intentions through both cognitive and relational mechanisms, and that privacy concerns play an important role in shaping these relationships (Dinev and Hart, 2006) (Bleier and Eisenbeiss, 2015) (Pappas et al., 2014). Integrating perceived personalization and trust within a unified Stimulus-Organism-Response framework offers a structured approach to understanding how personalized digital communication affects consumer behavior in online shopping environments (Figure 1).

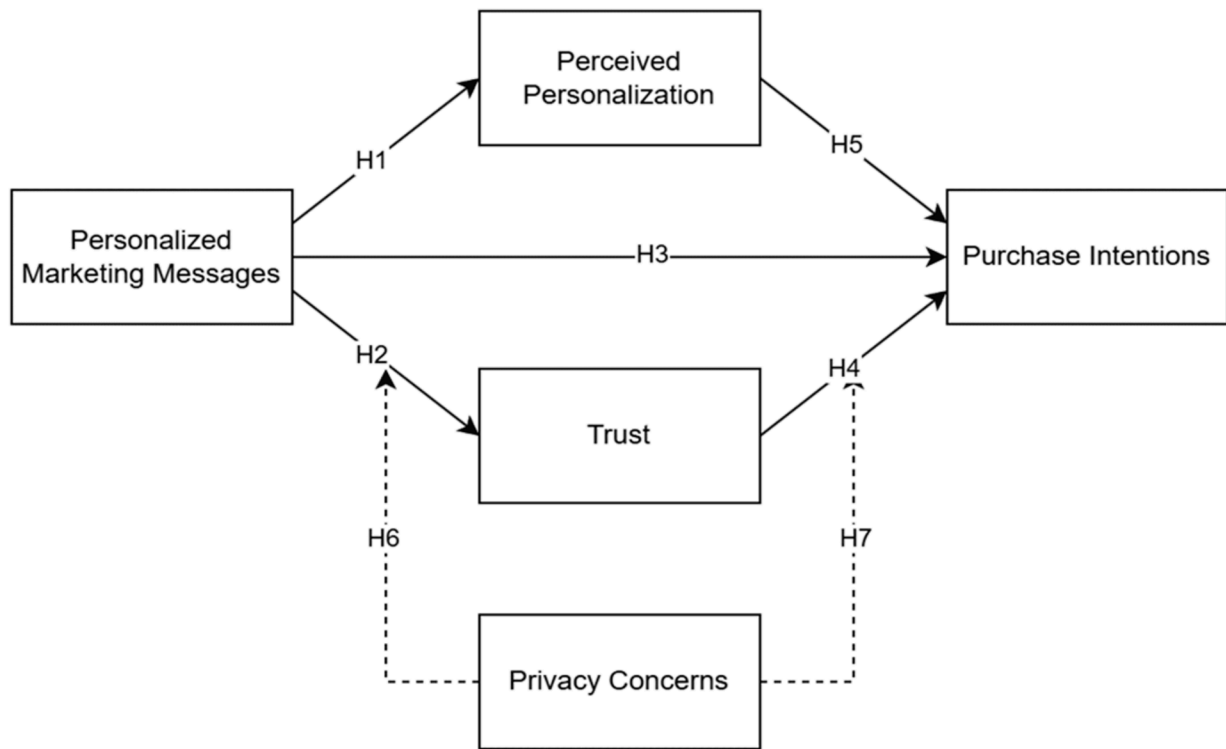


FIGURE 1: Conceptual Framework Based on the Stimulus–Organism–Response Model

Note: Solid arrows represent direct relationships, and dashed arrows indicate moderating effects.
Source: Authors’ own creation

Research Method

Study framework and approach

This study adopted a quantitative, explanatory, cross-sectional research design to examine the relationships among personalized marketing messages, perceived personalization, trust, privacy concerns, and purchase intention in online shopping environments. A survey-based approach was employed to test theoretically derived relationships among multiple latent constructs, consistent with prior research in digital marketing and consumer behavior (Hair et al., 2019) (Sarstedt et al., 2022) (Bryman, 2016). The study was grounded in the Stimulus-Organism-Response (S-O-R) framework, which conceptualizes personalized marketing messages as external stimuli that influence internal psychological states and subsequent behavioral responses (Mehrabian and Russell, 1974). Accordingly, the research design was intended to examine and test theoretically derived relationships among the study constructs rather than merely describe observed patterns. The empirical context focuses on online shopping platforms in India, where consumers are regularly exposed to AI-enabled personalization across e-commerce websites, mobile applications, and social media advertising. India

provides a relevant setting due to the rapid growth of digital commerce and the increasing adoption of data-driven marketing practices. This approach aligns with prior empirical studies examining consumer behavior in digital environments.

Sampling and data collection

Primary data were collected using a structured questionnaire administered via Google Forms. The survey was distributed through digital channels, including WhatsApp, Twitter, LinkedIn, and email, to reach respondents with relevant online shopping experience in India. A purposive sampling approach was used to ensure that participants had prior exposure to personalized digital marketing messages. Initially, 205 responses were collected. After screening for incomplete responses, patterned answers, and inconsistencies, responses that did not meet the study criteria were excluded. The final dataset included 195 valid responses. The adequacy of the sample size is supported by the widely used “10-times rule” (Hair et al., 2017) (Barclay et al., 1995), which recommends that the minimum sample size be at least ten times the maximum number of structural paths directed at any construct. Based on this criterion, the sample size used in this study is sufficient for PLS-SEM analysis. The use of purposive sampling is appropriate because the study focuses on respondents with prior exposure to personalized marketing, ensuring that participants can meaningfully evaluate the constructs under investigation. All subsequent analyses, including descriptive statistics, measurement model assessment, and structural model evaluation, were conducted using the final dataset of 195 valid responses.

Sample characteristics

The demographic characteristics of the respondents are presented in Table 7.

Variable	Category	Frequency	Percentage (%)
Gender	Male	112	57.4
	Female	83	42.6
Age (years)	18–24	92	47.2
	25–34	78	40.0
	35–44	18	9.2
	45–54	7	3.6
Education	12th (Higher Secondary)	14	7.2
	Undergraduate (Bachelor's)	64	32.8
	Postgraduate (Master's)	86	44.1
	Doctorate (PhD)	31	15.9
Employment Status	Student	132	67.7
	Private Sector	32	16.4
	Government/Public Sector Undertaking	12	6.2
	Others	19	9.7
Monthly Income	<₹25,000	64	32.8
	₹25,000–₹50,000	51	26.2
	₹50,000–₹1,00,000	48	24.6
	₹1,00,000–₹2,00,000	20	10.3
	>₹2,00,000	12	6.1
Area of Residence	Urban	138	70.8
	Semi-Urban	39	20.0
	Rural	18	9.2
Online Shopping Frequency	Rarely	18	9.2

	Occasionally	64	32.8
	Frequently	78	40.0
	Very Frequently	35	18.0

TABLE 1: Demographic Profile of Respondents

Source: Authors’ own creation

The sample shows a slightly higher proportion of male respondents than female respondents, indicating a balanced yet mildly male-dominant distribution. A large share of participants falls within the 18-34 age group, reflecting a segment that is actively engaged with digital platforms and online shopping. In terms of education, most respondents hold undergraduate or postgraduate qualifications, suggesting familiarity with digital technologies and online interactions. Students constituted 67.7% of the sample, while the remaining respondents represented diverse occupational backgrounds, including private-sector employees, government/public sector employees, and other professions. This demographic composition should be considered when interpreting the findings and assessing their generalizability. However, all respondents had prior exposure to digital platforms and online shopping environments, which was the primary criterion for inclusion in the study. Income levels are distributed across categories, with a greater concentration in lower- and middle-income groups. Most respondents are from urban areas, reflecting higher digital commerce penetration in such regions. In terms of online shopping behavior, a majority of participants reported shopping either frequently or occasionally, indicating regular exposure to online platforms and personalized marketing communications. Overall, the sample was considered suitable for examining consumer responses to personalized marketing in digital shopping environments.

Measurement instruments

All constructs were measured using multi-item scales adapted from prior studies in the fields of personalized marketing, online consumer behavior, and information systems research to ensure content validity and construct reliability (Churchill, 1979) (DeVellis and Thorpe, 2021). The measurement items were modified to fit the context of online shopping and personalized digital marketing. Personalized Marketing Messages (PMM) were measured using items adapted and contextualized from the personalization literature, particularly Tam and Ho (Tam and Ho, 2006), Xu et al. (Xu et al., 2008), and Pappas et al. (Pappas et al., 2017). These studies emphasize key dimensions of personalization, including content relevance, tailored communication, personalized recommendations, and alignment with users’ interests and preferences in digital environments. Accordingly, the PMM items used in this study assess the extent to which consumers perceive online marketing messages, recommendations, and content as personalized, relevant, and aligned with their interests and prior online behavior.

Perceived Personalization (PP) was assessed using scales adapted from Tam and Ho (Tam and Ho, 2006) and Pappas et al. (Pappas et al., 2017). These items reflect consumers’ perceptions regarding the degree to which online platforms recognize their individual preferences and provide personalized experiences based on prior interactions and behavioral patterns. Trust (TR) was measured using items adapted from Gefen et al. (Gefen et al., 2003) and Pappas et al. (Pappas et al., 2014). These scales have been widely used in e-commerce research to measure consumers’ confidence in online platforms, reliability of personalized communication, and belief that firms handle personal information responsibly. Privacy Concerns (PC) were measured using items adapted from Xu et al. (Xu et al., 2011) and Awad and Krishnan (Awad and Krishnan, 2006). Xu et al. (Xu et al., 2011) examined the personalization-privacy paradox in location-aware marketing and demonstrated how increasing personalization may simultaneously increase perceived benefits and privacy risks. The items used in the present study assess consumers’ concerns regarding data collection, tracking, monitoring, and potential

misuse of personal information in personalized digital environments. Purchase Intention (PI) was measured using established scales adapted from Pappas et al. (Pappas et al., 2014) and Pappas et al. (Pappas et al., 2017). These items capture consumers' willingness and likelihood to make online purchases in response to personalized marketing communication. All items were measured using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree.

Data screening and preliminary analysis

The dataset was screened for missing values, straight-lining responses, and unusual response patterns (Sarstedt et al., 2022). Observations with identical responses across all items were removed. Reverse-coded indicators were checked and recoded for consistency. Multicollinearity was assessed using Variance Inflation Factor (VIF) values, which remained within acceptable limits, indicating that multicollinearity is not a concern (Hair et al., 2017) (Kock, 2015). Common method bias was examined using both procedural and statistical methods. Respondents were assured of anonymity to minimize response bias. Harman's single-factor test showed that the first factor accounted for 28.601% of the total variance, below the recommended threshold of 50% (Podsakoff et al., 2003). These results suggest that common method bias is not a serious issue in this study. Full collinearity VIF values were below the recommended threshold of 3.3, further indicating that common method bias does not significantly affect the results (Kock, 2015).

Analytical approach

The study used PLS-SEM in SmartPLS 4 for data analysis. This method is well suited for analyzing complex models with multiple constructs and for explaining variation in key dependent variables, even with a relatively small sample size. PLS-SEM is appropriate for this study because the model includes both mediation and moderation relationships, and the method does not impose strict distributional assumptions. This makes it suitable for behavioral research settings where data may not follow normal distributions.

The analysis was conducted in two stages. In the first stage, the measurement model was evaluated for indicator reliability, internal consistency, convergent validity, and discriminant validity. In the second stage, the structural model was assessed to test the hypothesized relationships, including path coefficients, explanatory power (R^2), effect sizes, predictive relevance, and moderation effects.

Results And Discussion

Measurement model

The measurement model was evaluated to assess the reliability and validity of the constructs before proceeding to the structural analysis. Indicator reliability was assessed using outer loadings, and most indicators exceeded the recommended threshold of 0.70, indicating acceptable reliability (Hair et al., 2019), as shown in Figure 2. During measurement model refinement, indicators with relatively low outer loadings were removed to improve construct reliability and convergent validity while maintaining theoretical consistency. Specifically, PMM3, PP2, PP4, TR4, PC4, and PI3 were excluded from the final measurement model because their outer loading values did not meet the recommended criteria. Although two retained indicators (PC2 and PMM2) exhibited outer loadings below the recommended threshold of 0.70, they were retained after careful evaluation. According to Hair et al. (2019), indicators with outer loadings between 0.40 and 0.70 may be retained when their removal does not lead to a meaningful improvement in Composite Reliability (CR) or Average Variance Extracted (AVE), provided they are theoretically justified. In the present study, the PC construct achieved a Composite Reliability of 0.791 and an AVE of 0.564, while the PMM construct achieved a CR of 0.811 and an AVE of 0.592, both exceeding the recommended thresholds. Therefore, the inclusion of PC2 and PMM2 did not compromise the reliability or convergent validity of the measurement model, and these indicators were retained for subsequent structural model analysis.

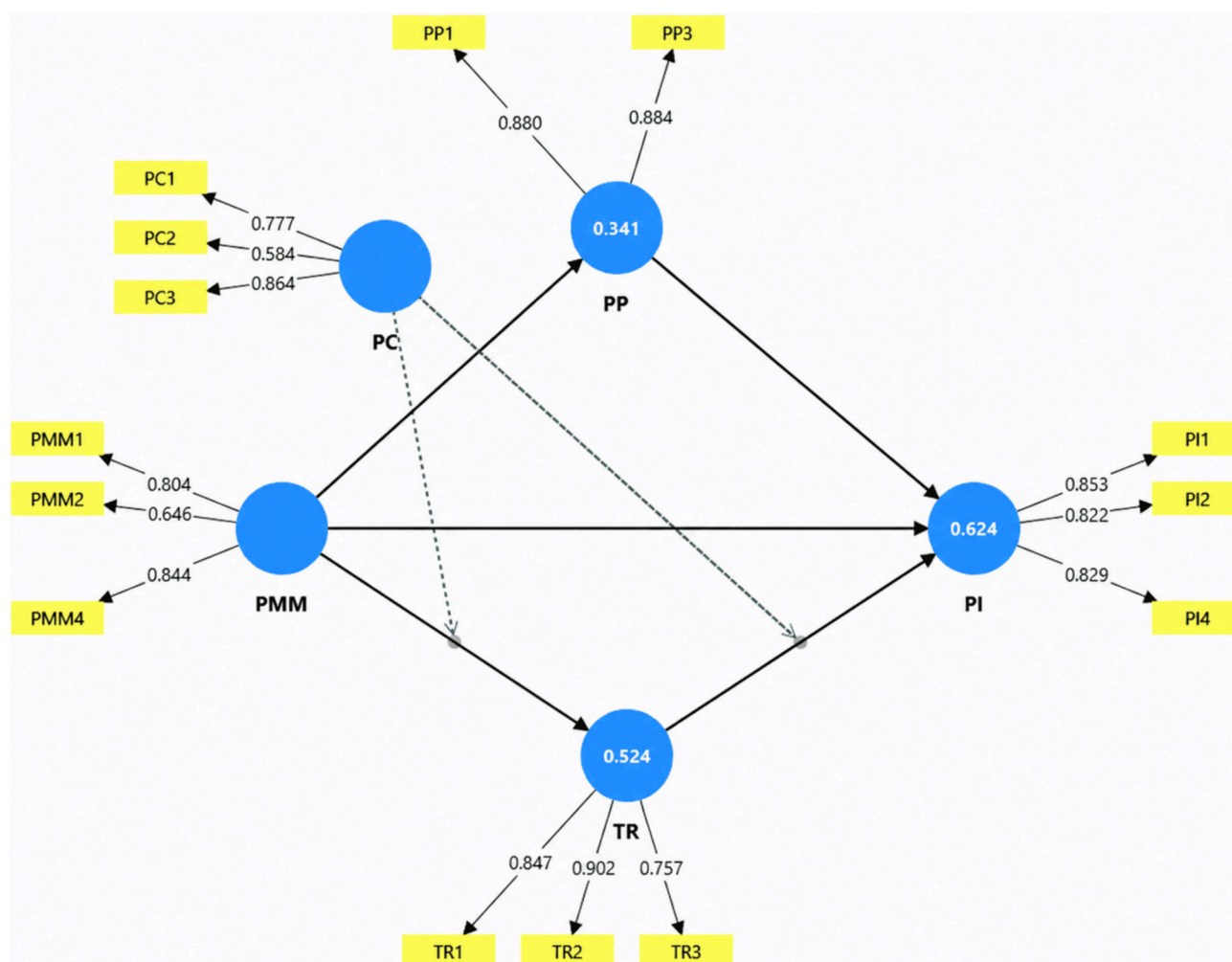


FIGURE 2: Measurement Model with Outer Loadings

Note: PMM = Personalized Marketing Messages; PP = Perceived Personalization; TR = Trust; PI = Purchase Intention; PC = Privacy Concerns

Source: Authors' own creation using SmartPLS 4

Internal consistency reliability was assessed using Cronbach's alpha and composite reliability. CR values exceeded the recommended threshold of 0.70, indicating satisfactory internal consistency (Hair et al., 2017). The detailed results are presented in Table 2. Convergent validity was evaluated using the AVE, and all constructs reported values above 0.50, confirming adequate convergent validity (Hair et al., 2017).

Construct	Cronbach's Alpha	Composite Reliability	AVE
PC	0.639	0.791	0.564
PI	0.784	0.873	0.697
PMM	0.689	0.811	0.592
PP	0.715	0.875	0.778
TR	0.787	0.875	0.701

TABLE 2: Reliability and Convergent Validity

PC = Privacy Concerns; PI = Purchase Intention; PMM = Personalized Marketing Messages; PP = Perceived Personalization; TR = Trust; AVE = Average Variance Extracted.

Source: Authors' own calculations

Discriminant validity was assessed using the Heterotrait-Monotrait ratio (HTMT). All values were below the 0.90 threshold, indicating that the constructs are empirically distinct ([Henseler et al., 2015](#)), as presented in Table 3.

Construct	PC	PI	PMM	PP	TR
PC	—	0.787	0.338	0.471	0.895
PI		—	0.528	0.816	0.835
PMM			—	0.756	0.350
PP				—	0.640
TR					—

TABLE 3: HTMT Values for Discriminant Validity

HTMT = Heterotrait-Monotrait ratio; PC = Privacy Concerns; PI = Purchase Intention; PMM = Personalized Marketing Messages; PP = Perceived Personalization; TR = Trust.

Source: Authors' own calculations

Structural model

After establishing the reliability and validity of the measurement model, the structural model was evaluated to assess the hypothesized relationships among the constructs. Path coefficients and their significance levels were used to assess the strength and direction of these relationships ([Hair et al., 2017](#)), as presented in Figure 3.

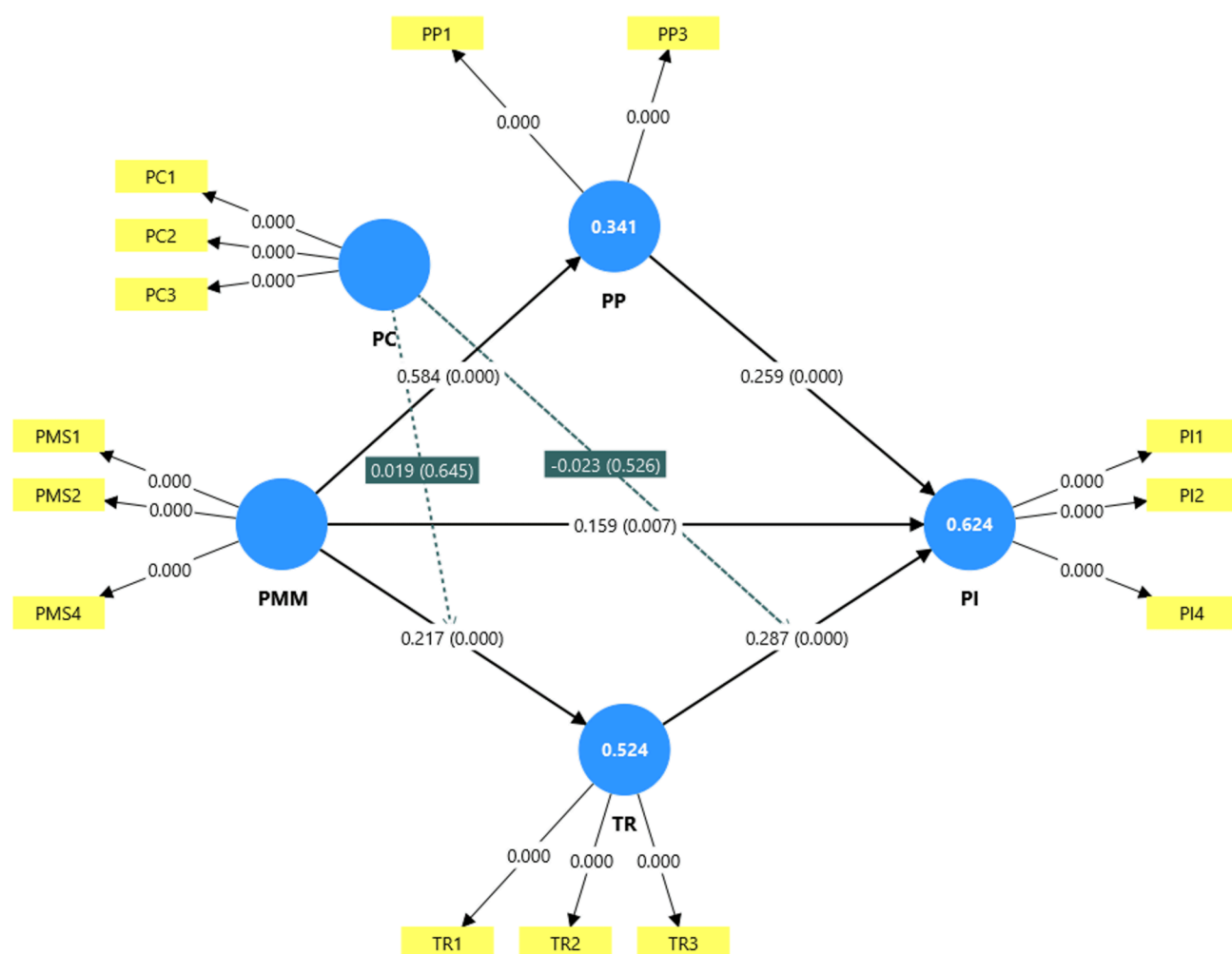


FIGURE 3: Structural Model with Standardized Path Coefficients (β), p-values, and R² Values

Note: Values on structural paths represent standardized path coefficients (β) and p-values (in parentheses), while values inside circles represent R² values.

Source: Authors' own creation using SmartPLS 4

Personalized marketing messages have a significant positive effect on perceived personalization ($\beta = 0.584$, $p < 0.001$) and trust ($\beta = 0.217$, $p < 0.001$), indicating that tailored marketing communication enhances perceived relevance and consumer confidence. Perceived personalization also positively affects purchase intention ($\beta = 0.259$, $p < 0.001$), suggesting that consumers are more likely to purchase when marketing messages align with their preferences. Trust further has a significant positive impact on purchase intention ($\beta = 0.287$, $p < 0.001$), highlighting its role in reducing uncertainty in online shopping contexts.

In addition to these indirect effects, personalized marketing messages also have a direct effect on purchase intention ($\beta = 0.159$, $p = 0.007$), indicating both direct and mediated relationships.

Descriptive statistics and correlation analysis

Descriptive statistics were examined to understand the distributional characteristics of the main constructs included in the study. Reporting descriptive statistics is considered an important preliminary step in SEM-based research because it provides insight into respondents' overall perceptions and the variability of the study variables before structural relationships are assessed (Hair et al., 2019). The results indicate that respondents generally reported moderate to

relatively positive perceptions toward personalized marketing messages, perceived personalization, and purchase intention. In contrast, trust and privacy concerns showed comparatively moderate mean scores, reflecting differences in consumer attitudes toward online platforms and the use of personal information in personalized marketing environments. The descriptive statistics of all constructs are presented in Table 4.

Construct	Mean	SD	Min	Max
PMM	3.786	0.805	1.25	5.00
PP	3.283	0.697	1.00	5.00
TR	2.903	0.845	1.00	5.00
PC	2.788	0.788	1.00	5.00
PI	3.219	0.863	1.00	5.00

TABLE 4: Descriptive Statistics of Main Constructs

Note: Values represent construct-level descriptive statistics. SD = Standard Deviation; Min = Minimum; Max = Maximum; PC = Privacy Concerns; PI = Purchase Intention; PMM = Personalized Marketing Messages; PP = Perceived Personalization; TR = Trust.
Source: Authors’ own calculations

Correlation analysis was also conducted to examine the relationships among the study variables prior to hypothesis testing. Correlation analysis helps in understanding the direction and strength of associations among constructs and provides preliminary support for the proposed conceptual relationships. The results reveal positive associations among most constructs, particularly between personalized marketing messages and perceived personalization, and between trust and purchase intention. These findings are consistent with the proposed Stimulus-Organism-Response (S-O-R) framework and provide initial support for the hypothesized relationships. The correlation matrix of the main constructs is presented in Table 5.

Construct	1	2	3	4	5
1. PMM	—				
2. PP	0.560	—			
3. TR	0.281	0.403	—		
4. PC	0.218	0.300	0.599	—	
5. PI	0.360	0.450	0.584	0.519	—

TABLE 5: Correlation Matrix of Main Constructs

PC = Privacy Concerns; PI = Purchase Intention; PMM = Personalized Marketing Messages; PP = Perceived Personalization; TR = Trust.

Source: Authors' own calculations

Hypothesis testing

The results indicate that most proposed relationships are statistically significant, with five out of seven hypotheses supported. The structural model was evaluated using the bootstrapping procedure in SmartPLS 4, which generated standardized path coefficients (β), t-values, p-values, and 95% confidence intervals (CIs) for all relationships. Path coefficients indicate the strength and direction of the relationships, while p-values confirm their statistical significance.

PMM have a strong positive effect on PP ($\beta = 0.584$, $t = 11.506$, $p < 0.001$), supporting H1 and indicating that personalized communication plays a central role in shaping how consumers evaluate the relevance of marketing messages. A positive relationship is also observed between personalized marketing messages and TR ($\beta = 0.217$, $t = 4.177$, $p < 0.001$), supporting H2 and suggesting that personalization contributes to the development of trust in online platforms. Perceived personalization has a significant positive effect on PI ($\beta = 0.259$, $t = 4.088$, $p < 0.001$), supporting H3 and indicating that consumers are more likely to consider purchasing when marketing messages are perceived as relevant and tailored. Trust also shows a positive relationship with purchase intention ($\beta = 0.287$, $t = 3.886$, $p < 0.001$), supporting H4 and highlighting its role in reducing uncertainty in online transactions.

Alongside these indirect effects, personalized marketing messages also have a direct effect on purchase intention ($\beta = 0.159$, $t = 2.676$, $p = 0.007$), supporting H5 and indicating that personalization influences decision-making both directly and through mediating variables. The moderating effects of privacy concerns are not supported. The interaction between privacy concerns and personalized marketing messages on trust is not significant ($\beta = 0.019$, $t = 0.460$, $p = 0.645$), leading to the rejection of H6. The interaction between privacy concerns and trust on purchase intention is also not significant ($\beta = -0.023$, $t = 0.634$, $p = 0.526$), leading to the rejection of H7. In addition, the confidence intervals for both moderating effects include zero, further confirming the absence of significant moderation effects. These findings suggest that privacy concerns did not significantly alter the relationships in the present sample, indicating that consumers responded to personalized marketing in a relatively consistent manner across different levels of privacy concern. The detailed bootstrapping results are presented in Table 6.

Hypothesis	Relationship	β	Sample Mean (M)	Std. Dev.	t-value	p-value	95% CI LL	95% CI UL	Decision
H1	PMM → PP	0.584	0.588	0.051	11.506	0	0.479	0.679	Supported
H2	PMM → TR	0.217	0.218	0.052	4.177	0	0.113	0.32	Supported
H3	PP → PI	0.259	0.26	0.063	4.088	0	0.138	0.385	Supported
H4	TR → PI	0.287	0.285	0.074	3.886	0	0.137	0.426	Supported
H5	PMM → PI	0.159	0.161	0.059	2.676	0.007	0.043	0.276	Supported
H6	PC × PMM → TR	0.019	0.018	0.041	0.46	0.645	−0.064	0.096	Not Supported
H7	PC × TR → PI	−0.023	−0.024	0.036	0.634	0.526	−0.095	0.047	Not Supported

TABLE 6: Results of Hypothesis Testing and Bootstrapping Analysis

Note: β = Standardized path coefficient; M = Sample mean; Std. Dev. = Standard deviation; CI = Confidence Interval; LL = Lower Limit; UL = Upper Limit; PC = Privacy Concerns; PI = Purchase Intention; PMM = Personalized Marketing Messages; PP = Perceived Personalization; TR = Trust.

Source: Authors' own calculations

Explanatory power and predictive relevance

The model's explanatory power was assessed using the coefficient of determination (R^2) and adjusted R^2 , which indicate the proportion of variance in the endogenous constructs explained by their predictors. Adjusted R^2 provides a more conservative estimate by accounting for model complexity. The model explains 34.1% of the variance in perceived personalization, 52.4% in trust, and 62.4% in purchase intention (as shown in Table 7). The corresponding adjusted R^2 values are close to the R^2 values, indicating that the model's explanatory power is stable.

Construct	R ²	Adjusted R ²	Q ²
PP	0.341	0.338	0.327
TR	0.524	0.517	0.506
PI	0.624	0.614	0.511

TABLE 7: Coefficient of Determination (R²), Adjusted R², and Predictive Relevance (Q²)

PI = Purchase Intention; PP = Perceived Personalization; TR = Trust

Source: Authors' own calculations

The variance explained in purchase intention is the highest among all endogenous constructs, indicating that the model captures key determinants of consumer decision-making. The explanatory power for trust is also substantial, suggesting that personalization-related factors contribute to consumer confidence. The variance explained in perceived personalization is comparatively lower, though still within an acceptable range, indicating that additional factors may influence how consumers evaluate personalization.

Predictive relevance was assessed using the Stone-Geisser Q² value from the blindfolding procedure. Q² values for perceived personalization (0.327), trust (0.506), and purchase intention (0.511) are all greater than zero, indicating that the model has predictive relevance. The magnitudes of these values suggest moderate predictive relevance for perceived personalization and strong predictive relevance for trust and purchase intention.

Discussion

This study examined how personalized marketing messages influence consumers' purchase intentions in online shopping environments using the S-O-R framework. The findings provide empirical support for the proposed model and offer insights into the psychological mechanisms through which personalization shapes consumer behavior. The results indicate that personalized marketing messages influence purchase intention through both indirect pathways involving internal evaluations and a direct pathway reflecting an immediate behavioral response. The strong positive effect of personalized marketing messages on perceived personalization indicates that consumers actively evaluate the relevance of marketing content. When communication aligns with prior behavior and individual preferences, it is perceived as personally meaningful rather than generic, consistent with prior research (Tam and Ho, 2006) (Pappas et al., 2014). The magnitude of this relationship highlights the importance of personalization quality in shaping consumers' evaluations of digital marketing stimuli. Personalized marketing messages also show a significant positive effect on trust, suggesting that personalization functions as a relational signal in uncertain digital environments. When communication appears tailored and appropriate, consumers may infer competence and responsiveness from the firm, which aligns with existing research emphasizing the role of trust in online transactions (Gefen et al., 2003) (Pappas et al., 2017). The positive effects of perceived personalization and trust on purchase intention further confirm their role as key internal mechanisms within the S-O-R framework, supporting earlier findings that relevance and trust reduce perceived risk and cognitive effort, thereby encouraging purchase behavior (Pappas et al., 2014) (Chandra et al., 2022).

The presence of a statistically significant but relatively modest direct effect of personalized marketing messages on purchase intention indicates partial mediation, suggesting that personalization operates through dual pathways. In one pathway, consumers engage in deliberate evaluation through perceived personalization and trust, while in another, highly relevant stimuli may trigger more immediate behavioral responses. This pattern aligns with dual-process perspectives in consumer decision-making, in which both reflective and intuitive processes influence behavior (Evans,

2008). The model has substantial explanatory power, with 62.4% of the variance in purchase intention explained by the proposed predictors, indicating that integrating personalization, perceived personalization, and trust provides a strong framework for understanding consumer decision-making in digital environments. The moderating role of privacy concerns is not supported, as the interaction effects are statistically insignificant. This finding contrasts with prior research on the personalization-privacy paradox, which suggests that privacy concerns weaken the effectiveness of personalization (Awad and Krishnan, 2006). Instead, the results indicate that personalization continues to influence consumer responses even when privacy concerns are present. This pattern can be interpreted through Privacy Calculus Theory, which explains how consumers evaluate the trade-off between perceived benefits and potential privacy risks (Xu et al., 2011). The perceived benefits of relevance and convenience may outweigh concerns related to data usage, consistent with recent findings (Nobile and Cantoni, 2023).

Theoretically, this study extends the S-O-R framework by showing that personalized marketing operates through both mediated and direct pathways. While prior research has largely focused on internal psychological mechanisms, the present findings show that personalized stimuli can also produce direct behavioral effects. By integrating cognitive (perceived personalization) and relational (trust) mechanisms within a single model, the study offers a more comprehensive explanation of how personalization influences consumer decision-making in digital environments. The findings also support the relevance of combining the S-O-R framework with dual-process perspectives, offering a more nuanced understanding of consumer responses to personalization.

Implications

The findings of this study have both theoretical and practical implications for research on personalized marketing in digital environments. The study strengthens the application of the S-O-R framework by showing how personalized marketing messages influence consumer behavior through both internal evaluations and direct behavioral responses (Mehrabian and Russell, 1974) (Pappas et al., 2017). The results highlight perceived personalization and trust as key mechanisms linking marketing stimuli to purchase intention. The presence of both direct and indirect effects also underscores the relevance of dual-process perspectives for explaining consumer decision-making. The findings also contribute to the literature on the personalization-privacy relationship. The absence of significant moderation effects suggests that privacy concerns do not consistently undermine personalization outcomes. Instead, consumers appear to evaluate personalization by weighing perceived benefits against potential risks, consistent with the logic of Privacy Calculus Theory (Awad and Krishnan, 2006). This suggests that privacy concerns may operate in a more context-dependent manner rather than acting as a uniform barrier.

From a practical perspective, the results underscore the importance of delivering meaningful, relevant personalization. The strong link between personalized marketing messages and perceived personalization suggests that firms should prioritize improving the quality and contextual relevance of communication rather than increasing the volume of targeted content. The positive effect of personalization on trust indicates that well-executed personalization can strengthen consumer confidence in digital platforms (Gefen et al., 2003). This, in turn, requires transparency in how personalization is implemented, including clear communication about data usage and recommendation processes. The presence of both direct and indirect effects suggests that personalized marketing can influence consumer decisions at multiple stages of the decision process. Timely, relevant personalized stimuli may prompt quicker decisions in routine contexts, whereas more complex decisions may rely more on perceived personalization and trust. For policymakers, the findings underscore the need to balance personalization with consumer protection through transparent data practices, informed consent, and accountability mechanisms.

Limitations and future research

Despite providing important insights into consumer responses toward personalized marketing, the present study has certain limitations that should be acknowledged. First, the study adopted a cross-sectional research design, which captures consumer perceptions at a single point in time. Consumer attitudes toward personalization and privacy may evolve with technological advancements and changing digital experiences. Future studies may therefore adopt longitudinal approaches to examine how responses toward personalized marketing change over time. Second, the study

was conducted in the Indian online shopping context using purposive sampling. Although this context is relevant due to the rapid growth of digital commerce and AI-driven personalization, the findings may not be fully generalizable across different countries, cultures, or consumer groups. Future research may conduct cross-country comparative studies or apply probability-based sampling approaches to improve generalizability.

The study also relied on self-reported questionnaire responses, which may be influenced by response bias or socially desirable answers. Future studies may combine survey-based methods with behavioral or experimental data to better examine actual consumer responses to personalized marketing practices. The study applied a prediction-oriented PLS-SEM approach to examine mediation and moderation relationships within the proposed framework. Although this method is appropriate for exploratory and prediction-focused research, future studies may compare the findings using covariance-based structural equation modeling approaches to assess the stability of the observed relationships across different analytical techniques. The non-significant moderating effects of privacy concerns suggest that additional contextual variables may influence consumer responses toward personalized marketing. Future research may therefore examine variables such as perceived transparency, personalization intrusiveness, digital literacy, algorithmic awareness, or platform trust to develop a deeper understanding of how consumers interpret AI-driven personalization practices in digital commerce environments.

Conclusions

This study examined the effect of personalized marketing messages on consumers' purchase intentions in online shopping environments using the S-O-R framework. The findings show that personalized marketing influences consumer behavior through both indirect and direct pathways. Perceived personalization and trust serve as key mechanisms through which consumers interpret and respond to personalized communication, while the presence of a direct effect indicates that behavioral responses may also occur without extensive cognitive processing. The results underscore the importance of relevance and trust in shaping consumer decisions in digital contexts. Consumers are more likely to make purchases when marketing messages align with their preferences and when they perceive the platform as reliable. The model demonstrates substantial explanatory and predictive power, indicating that integrating personalization, perceived personalization, and trust provides a strong framework for understanding consumer behavior in online shopping environments. The findings further indicate that privacy concerns do not significantly moderate the relationships examined in the model. This suggests that consumers may continue to respond positively to personalized marketing despite awareness of potential privacy risks, particularly when the perceived benefits of personalization outweigh these concerns. The study contributes to the literature on personalized marketing by providing empirical evidence on the mechanisms through which personalization influences consumer decision-making. It offers a structured framework that integrates cognitive evaluation, trust formation, and behavioral response into a single model. Future research can build on this work by examining additional contextual factors, such as product categories, cultural settings, or levels of consumer involvement. Longitudinal approaches may also offer deeper insights into how consumers' responses to personalization evolve over time.

Appendices

The detailed measurement items used to operationalize each construct in this study are presented in Table 8. All constructs were measured using multi-item scales adapted from prior literature and modified to suit the context of online shopping and personalized marketing. Responses were recorded using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The demographic characteristics of the respondents are summarized in Table 9.

Construct	Statements (Items)	Adapted Source(s)
Personalized Marketing Messages (PMM)	1. The online ads I see are usually aligned with my interests. 2. I often receive product suggestions based on my past browsing or purchases. 3. Marketing messages I receive are tailored to my preferences. 4. The content I see from online brands feels personalized to me.	(Tam and Ho, 2006); (Xu et al., 2008); (Pappas et al., 2017)
Perceived Personalization (PP)	1. I feel that online retailers personalize their messages specifically for me. 2. Personalized messages make me feel recognized by the brand. 3. I believe the marketing content is tailored based on my behavior and preferences. 4. I notice a difference when a marketing message is personalized versus generic.	(Tam and Ho, 2006); (Pappas et al., 2017)
Trust (TR)	1. I trust online retailers that send me personalized marketing messages. 2. I believe these retailers will not misuse my personal information. 3. I feel confident buying from brands that send me personalized content. 4. I think personalized content shows the brand cares about my preferences.	(Gefen et al., 2003); (Pappas et al., 2014)
Privacy Concerns (PC)	1. I worry that my online shopping data is being tracked without my consent. 2. I feel uncomfortable with how much companies know about me. 3. I am concerned about the privacy of the personal data I share online. 4. I hesitate to engage with personalized messages due to privacy issues.	(Xu et al., 2011); (Awad and Krishnan, 2006)
Purchase Intention (PI)	1. Personalized marketing messages increase my likelihood to purchase online. 2. I often click and explore products shown in personalized ads. 3. I am more likely to buy a product when I receive a tailored message. 4. Personalized marketing encourages me to complete online purchases.	(Pappas et al., 2014); (Pappas et al., 2017)

TABLE 8: Measurement Items and Adapted Scale Sources

Note: The measurement items were adapted and contextually modified based on concepts and scales reported in the cited studies to fit the online shopping and personalized marketing context.
Source: Authors

Variable	Categories
Age	18–24; 25–34; 35–44; 45–54; 55 and above
Gender	Male; Female; Prefer not to say
Educational Qualification	12th; Undergraduate; Postgraduate; Doctorate
Employment Status	Student; Private Sector; Government/Public Sector Undertaking; Others
Monthly Income	<₹25,000; ₹25,000–₹50,000; ₹50,000–₹1,00,000; ₹1,00,000–₹2,00,000; >₹2,00,000
Area of Residence	Urban; Semi-Urban; Rural
Online Shopping Frequency	Rarely; Occasionally; Frequently; Very Frequently

TABLE 9: Demographic Profile Variables and Response Categories

Source: Authors

Additional Information

Disclosures

Human subjects: Consent was obtained or waived by all participants in this study. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Data Availability Statements

The datasets (and/or code) supporting this study are available from the corresponding author upon reasonable request.

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