AI-Driven Personalization and E-Commerce Loyalty: An Empirical Study from Emerging Markets

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ABSTRACT

Purpose – Artificial intelligence (AI)-driven personalization has become a cornerstone of modern e-commerce, yet its role in fostering long-term customer loyalty remains underexplored, particularly in emerging market contexts. This study investigates the relationship between perceived AI-driven personalization and e-commerce loyalty and examines how shopping frequency and platform type moderate this relationship.

Design/methodology/approach – Drawing on service-dominant (S-D) logic and the technology acceptance model (TAM), the study employs a quantitative, cross-sectional design. Survey data were collected from 413 e-commerce users across Saudi Arabia, India and neighboring economies. Hierarchical regression and moderation analyses were conducted to test the hypothesized relationships.

Findings – The results reveal that perceived AI-driven personalization is strongly and positively associated with e-commerce loyalty ($\beta = 0.58$, $p < 0.001$). *While the study focuses on direct effects and moderators, we acknowledge that customer satisfaction may play a mediating role – a key avenue for future research.* Furthermore, shopping frequency ($\beta = 0.17$, $p < 0.01$) and platform type ($\beta = 0.14$, $p < 0.01$) significantly moderate this relationship, with stronger effects observed for frequent shoppers and global platforms.

Originality/value – This study extends personalization research beyond developed markets by providing empirical evidence from rapidly evolving emerging economies. It advances theoretical understanding by integrating relational (S-D logic) and technological (TAM) perspectives and highlights the contingent nature of personalization effectiveness.

Keywords : AI-driven personalization, e-commerce loyalty, emerging markets, shopping frequency, platform type, service-dominant logic, technology acceptance model

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1. INTRODUCTION

Online retail has grown dramatically over the past decade, changing the fundamental ways businesses operate and interact with their customers. Within this evolving landscape, artificial intelligence has become essential for implementing customer-focused approaches, with personalization standing out as particularly influential. E-commerce platforms now leverage AI to process extensive user data, enabling them to offer customized product suggestions, adaptive user interfaces, and responsive interactions that reflect individual preferences and behaviors in real time (Huang & Rust, 2021; Grewal et al., 2021). As competition intensifies and product differentiation becomes increasingly difficult to sustain, personalization is widely regarded as a key mechanism for enhancing customer experience and fostering long-term loyalty.

For online retailers, securing lasting customer commitment presents ongoing difficulties given how easily shoppers can move between competing websites. Digital marketplaces differ fundamentally from physical stores by providing nearly unlimited product selections, clear pricing comparisons, and virtually no costs associated with changing platforms. These conditions create substantial obstacles for companies trying to build enduring connections with their customers (Lemon & Verhoef, 2016). Within digital retail environments, customer allegiance involves not only repeat transactions but also psychological components including confidence in the seller, emotional attachment, and active advocacy toward others (Zeithaml et al., 1996). Personalization is often positioned as a strategic response to these challenges, enhancing perceived relevance, reducing information overload and improving decision-making efficiency (Bleier & Eisenbeiss, 2015; Wedel & Kannan, 2016).

Although many companies have embraced AI-based personalization, questions persist about whether this technology actually produces lasting customer allegiance. Personalization may boost immediate interaction and short-term purchasing behaviors, but whether it meaningfully improves deeper relationship metrics remains uncertain (Kumar et al., 2019). Consumers may perceive personalized recommendations as helpful and convenient when aligned with their preferences, but they may also view them as intrusive or manipulative when concerns about privacy, transparency or data usage arise (Aguirre et al., 2015; Martin & Murphy, 2017). These mixed responses suggest that personalization effectiveness depends not only on technological capabilities but also on how consumers interpret and evaluate personalized interactions (Aguirre et al., 2015; Martin & Murphy, 2017; Huang & Rust, 2021).

From a theoretical perspective, understanding the role of AI-driven personalization requires integrating both relational and perceptual frameworks. Service-dominant (S-D) logic provides a useful lens by conceptualizing value as co-created through interactions between firms and consumers, rather than embedded in products or services (Vargo & Lusch, 2004, 2008). Within online retail contexts, customized features create fluid and responsive exchanges that support joint value creation by matching platform outputs with specific user requirements (Ramaswamy & Ozcan, 2018). At the same time, the technology acceptance model (TAM) explains how consumers evaluate and adopt technology-enabled services based on perceived usefulness and ease of use (Davis, 1989; Dwivedi et al., 2019). Integrating these perspectives allows for a more comprehensive understanding of how personalization influences both experiential value and behavioural intentions in digital contexts (Wang et al., 2023).

The relevance of this integration becomes even more pronounced in emerging markets, where e-commerce adoption has accelerated rapidly in recent years. Regions such as the Middle East and South Asia have experienced substantial growth in digital retail, driven by increased internet penetration, mobile device usage and supportive government initiatives (Grewal et al., 2021). In Saudi Arabia, national programmes such as Vision 2030 have facilitated the expansion of digital infrastructure and online retail ecosystems. Similarly, India has witnessed significant e-commerce growth due to rising digital literacy and expanding middle-class consumption. However, consumer responses to AI-driven personalization in these contexts may differ from those observed in developed markets due to variations in trust, digital experience and cultural expectations (Ameen et al., 2022; Dwivedi et al., 2021).

Existing research on personalization and loyalty has largely focused on developed economies and often relies on single-theory perspectives, limiting its applicability to diverse market conditions. Moreover, much of the literature emphasizes direct relationships between personalization and behavioural outcomes, with less attention given to contextual factors that may influence these relationships. In particular, user engagement and platform characteristics are likely to play an important role in shaping personalization effectiveness. Consumers who interact more frequently with e-commerce platforms generate richer behavioural data, enabling more accurate personalization and potentially stronger relational outcomes (Kumar et al., 2019; Moodley & Sookhdeo, 2025). Similarly, differences between global and local platforms in terms of technological capabilities, data resources and brand trust may influence how personalization is perceived and how it translates into loyalty (Verhoef et al., 2015).

To address these gaps, the present study examines the relationship between perceived AI-driven personalization and e-commerce loyalty in emerging markets by integrating S-D logic and TAM. In addition to testing the direct association between personalization and loyalty, the study investigates the moderating roles of shopping frequency and platform type. Using survey data collected from 413 e-commerce users across Saudi Arabia, India and neighbouring economies, this study makes three key contributions. First, it extends personalization research beyond developed markets by providing empirical evidence from rapidly evolving emerging economies. Second, it advances theoretical understanding by integrating relational and technological perspectives to explain personalization–loyalty relationships. Third, it highlights the importance of contextual factors in shaping personalization outcomes, offering insights into how engagement intensity and platform characteristics influence consumer responses.

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 AI-DRIVEN PERSONALIZATION IN E-COMMERCE

AI-driven personalization has become a defining capability in contemporary e-commerce, enabling firms to tailor customer experiences based on individual preferences, behaviours and contextual data. Advances in machine learning, predictive analytics and real-time data processing have allowed platforms to move beyond static segmentation toward dynamic, individualized interactions (Huang & Rust, 2021; Wedel & Kannan, 2016). In digital retail environments characterized by extensive product assortments and information overload, personalization plays a critical role in simplifying decision-making and improving customer experience.

Personalization in e-commerce typically manifests through recommendation systems, customized search results, targeted promotions and adaptive interfaces (Grewal et al., 2021; Kumar et al., 2019). These mechanisms are designed to reduce search effort, increase relevance and enhance efficiency, thereby improving the perceived usefulness of the platform. Empirical research consistently shows that personalization positively influences engagement, purchase intentions and customer satisfaction when executed effectively (Bleier & Eisenbeiss, 2015; Wang et al., 2023; Moodley & Sookhdeo, 2025).

However, personalization outcomes are not universally positive. A growing body of literature highlights the “personalization paradox,” whereby consumers appreciate personalized services but simultaneously express concerns about privacy, data usage and algorithmic control (Aguirre et al., 2015; Martin & Murphy, 2017; Wedel & Kannan, 2016; Kumar et al., 2019). When personalization is perceived as intrusive or inaccurate, it may undermine trust and reduce its effectiveness (Aguirre et al., 2015; Martin & Murphy, 2017). These findings suggest that the impact of personalization depends not only on technological performance but also on how consumers perceive and interpret personalized interactions.

2.2 PERSONALIZATION, PRIVACY AND TRUST

The relationship between personalization and consumer response is often shaped by the balance between perceived benefits and perceived risks. According to privacy calculus theory, shoppers assess personalized services by comparing the benefits of tailored content and time savings against potential drawbacks such as data harvesting and perceived monitoring (Li et al., 2010). In AI-driven environments, these concerns may be amplified due to the opacity of algorithmic decision-making and limited transparency in how recommendations are generated (Martin & Murphy, 2017).

Trust emerges as a critical factor in mitigating these concerns. When consumers trust a platform, they are more likely to accept personalization and perceive it as beneficial rather than intrusive (Ameen et al., 2022). Research indicates that trust is influenced by factors such as transparency, perceived fairness and prior experience with digital platforms (Canhoto et al., 2024). In the absence of trust, even technically accurate personalization may fail to generate positive outcomes (Aguirre et al., 2015; Ameen et al., 2022). Personalization has been shown to significantly enhance AI trust, which in turn positively influences willingness to buy, particularly when platforms effectively address performance risk concerns (Alam, 2026).

In emerging markets, where digital literacy and institutional trust levels may vary, these dynamics become particularly important. Consumers may be more cautious in sharing data or engaging with AI-driven features, making trust-building strategies essential for effective personalization (Dwivedi et al., 2021). This highlights the need to examine personalization not only as a technological capability but also as a relational mechanism shaped by consumer perceptions and contextual factors.

2.3 SERVICE-DOMINANT LOGIC AND VALUE CO-CREATION

To understand how personalization creates value, the service-dominant logic framework offers valuable insights. This perspective holds that value emerges from collaborative exchanges between companies and their customers rather than being pre-packaged within goods or services (Vargo & Lusch, 2004, 2008). When applied to e-commerce, this means personalization serves as a mechanism through which platforms and users jointly construct meaningful shopping experiences. Within online retail settings, customization allows digital stores to modify product presentations in response to user behavior, supporting ongoing and fluid exchanges between both parties. Viewed through this theoretical lens, AI-enabled personalization functions as an active resource that converts raw information into responsive service encounters. Shoppers participate by leaving digital traces through their browsing history, purchase records, and interaction patterns. In turn, platforms analyze this information to sharpen their recommendation algorithms and enhance overall service quality (Ramaswamy & Ozcan, 2018). This reciprocal interaction strengthens the co-creation process and enhances perceived value. Recent research applying S-D logic to digital platforms has demonstrated how platform design facilitates resource integration and personalized service experiences (Katsifaraki & Theodosiou, 2024; Rodriguez-Ardura et al., 2025).

Research in engagement marketing further emphasizes the role of AI in enabling scalable and personalized interactions across the customer journey (Kumar et al., 2019). By tailoring experiences at multiple touchpoints, personalization enhances involvement, perceived responsiveness and emotional connection with the platform. These relational outcomes are central to the development of customer loyalty in digital environments.

However, S-D logic also acknowledges that co-creation is contingent on alignment between firm actions and consumer expectations. When personalization fails to meet consumer needs or violates expectations, the co-creation process may break down, leading to dissatisfaction and reduced loyalty. This reinforces the importance of examining contextual factors that influence personalization effectiveness.

2.4 TECHNOLOGY ACCEPTANCE MODEL AND PERSONALIZATION

Whereas S-D logic emphasizes relationship dynamics, the technology acceptance model explains the cognitive processes underlying consumer adoption of personalized systems. TAM proposes two primary factors that shape whether people embrace new technologies: how beneficial they believe the technology will be and how simple they find it to operate (Davis, 1989). For personalized AI applications in retail settings, perceived usefulness captures whether shoppers feel the system helps them find products faster and make better choices. Perceived ease of use reflects how naturally and effortlessly customers can engage with recommendation features without frustration or confusion.

Empirical studies consistently find that perceived usefulness is a strong predictor of positive attitudes toward personalization, while ease of use reduces cognitive effort and enhances user experience (Dwivedi et al., 2019). In AI-enabled environments, these factors are complemented by considerations of trust, perceived risk and transparency, which influence both adoption and post-adoption behaviour (Dwivedi et al., 2021). Research examining AI acceptance in e-commerce has confirmed that perceived usefulness and perceived ease of use positively impact attitudes toward use and intention to use AI technology (Wang et al., 2023).

Integrating TAM with S-D logic provides a more comprehensive understanding of personalization outcomes. While TAM explains how consumers cognitively evaluate personalization features, S-D logic captures the relational processes through which these evaluations translate into value and loyalty. This combined perspective is particularly relevant in e-commerce, where technological functionality and relational experience are closely intertwined.

2.5 E-COMMERCE LOYALTY

Customer loyalty in e-commerce is a multidimensional construct encompassing both behavioural and attitudinal components. Behavioural loyalty refers to repeat purchasing behaviour, while attitudinal loyalty includes trust, commitment and positive word-of-mouth (Zeithaml et al., 1996). In digital environments, loyalty is influenced by the overall quality of the customer experience, including factors such as convenience, reliability and perceived value.

Personalization has been identified as a key driver of loyalty in online retail. By enhancing relevance and reducing effort, personalization improves customer satisfaction and strengthens the relationship between consumers and platforms (Bleier & Eisenbeiss, 2015). However, the relationship between personalization and loyalty is not always direct. Instead, it is often mediated by intermediate factors such as satisfaction, trust and perceived value (Kumar et al., 2019). Research has shown that trust has a significant positive influence on both satisfaction and loyalty, with personalization further strengthening these relationships. Recent evidence also confirms that AI-driven personalization enhances customer loyalty through improved perceived value and reduced search effort (Kumar et al., 2019; Bleier & Eisenbeiss, 2015).

The challenge of maintaining loyalty is particularly pronounced in e-commerce due to low switching costs and intense competition. Consumers can easily compare alternatives and switch platforms, making it essential for firms to deliver consistently positive experiences. In this context, personalization serves as a strategic tool for differentiating the platform and reinforcing customer relationships.

A growing body of research suggests that the relationship between AI-driven personalization and e-commerce loyalty is not purely direct but is likely mediated by customer satisfaction. When personalization successfully reduces search effort and presents highly relevant options, it enhances perceived convenience and enjoyment, which in turn fosters satisfaction (Bleier & Eisenbeiss, 2015; Kumar et al., 2019). This satisfaction, rather than the mere awareness of AI, is what drives repeat purchases and positive word-of-mouth. Consequently, scholars have called for greater attention to the mediating role of experiential outcomes in personalization research (Wang et al., 2023). While the present study focuses on the direct effect of personalization on loyalty and its moderators (shopping frequency, platform type), we recognise that satisfaction may serve as an important intervening mechanism – a possibility that we address in the limitations section.

2.6 CONTEXTUAL MODERATORS IN EMERGING MARKETS

The effectiveness of personalization is influenced by contextual factors that shape consumer perceptions and behaviour. Two such factors are shopping frequency and platform type, both of which are particularly relevant in emerging market contexts.

Shopping frequency reflects the level of consumer engagement with e-commerce platforms. Frequent shoppers interact with platforms more regularly, generating richer data and gaining greater familiarity with personalization features (Kumar et al., 2019). This increased engagement enhances the accuracy of recommendations and strengthens perceived usefulness, leading to stronger loyalty outcomes. In contrast, infrequent users may have limited exposure to personalization and may be less responsive to its benefits. Research on customer loyalty-aware recommender systems has demonstrated that incorporating loyalty indicators such as purchase frequency significantly enhances recommendation accuracy.

Platform type also plays a significant role in shaping personalization effectiveness. Global platforms typically have access to larger datasets and more advanced AI capabilities, enabling more accurate and scalable personalization (Verhoef et al., 2015). Local platforms, while potentially offering greater cultural relevance, may have more limited technological resources. These differences influence how consumers perceive personalization and its contribution to value and loyalty. Studies in emerging markets have shown that AI-driven personalization has a statistically significant positive effect on customer outcomes (Alam, 2026).

In emerging markets, where digital ecosystems are still evolving, these contextual factors are particularly important. Variations in digital literacy, trust and platform maturity can influence how personalization is experienced and evaluated (Ameen et al., 2022). This highlights the need to adopt a context-sensitive approach when examining personalization outcomes.

2.7 RESEARCH GAP AND THEORETICAL INTEGRATION

Despite extensive research on personalization and e-commerce loyalty, several gaps remain. First, much of the existing literature is concentrated in developed markets, limiting its applicability to emerging economies with different consumer behaviours and digital environments. Second, prior studies often rely on single-theory perspectives, focusing either on technological adoption or relational processes, without integrating both dimensions.

Third, limited attention has been given to contextual moderators that influence personalization effectiveness. Factors such as shopping frequency and platform type are likely to play a critical role in shaping how personalization is perceived and how it translates into loyalty outcomes. Addressing these gaps requires an integrated framework that captures both relational and perceptual mechanisms while accounting for contextual variability.

Accordingly, this study adopts a combined S-D logic and TAM framework to examine the relationship between AI-driven personalization and e-commerce loyalty in emerging markets, while explicitly incorporating shopping frequency and platform type as moderating variables.

The conceptual framework developed in this study is presented in Figure 1.

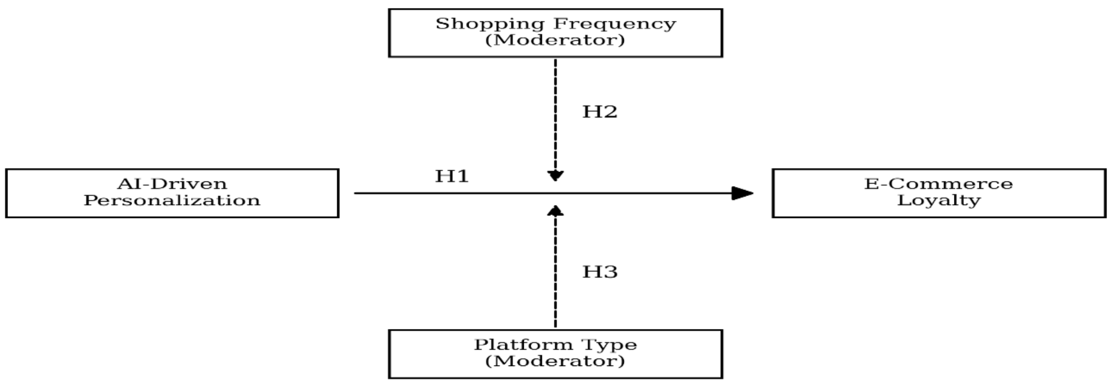

FIGURE 1. CONCEPTUAL FRAMEWORK ILLUSTRATING THE EFFECT OF AI-DRIVEN PERSONALIZATION ON E-COMMERCE LOYALTY, WITH SHOPPING FREQUENCY AND PLATFORM TYPE AS MODERATING VARIABLES.

The conceptual framework posits that AI-driven personalization positively influences e-commerce loyalty, with shopping frequency and platform type moderating the strength of this relationship.

3. HYPOTHESES DEVELOPMENT

3.1 AI-DRIVEN PERSONALIZATION AND E-COMMERCE LOYALTY

AI-driven personalization has become a central mechanism through which e-commerce platforms enhance customer experience and strengthen relational outcomes. Drawing on S-D logic, personalization can be conceptualized as an operant resource that facilitates value co-creation through adaptive interactions between firms and consumers (Vargo & Lusch, 2004, 2008). By aligning product recommendations, content and interfaces with individual preferences, personalization enhances perceived relevance and responsiveness, thereby improving the overall service experience.

Through repeated interactions, personalized experiences contribute to relational outcomes such as trust, satisfaction and emotional engagement, which are critical for loyalty formation in digital environments. Consumers who perceive that a platform consistently understands and responds to their needs are more likely to develop positive attitudes and maintain long-term relationships with that platform (Ramaswamy & Ozcan, 2018; Kumar et al., 2019).

From the perspective of TAM, personalization enhances perceived usefulness by improving decision efficiency and reducing search effort (Davis, 1989; Dwivedi et al., 2019). When personalized features are perceived as beneficial and easy to use, consumers are more likely to adopt and continue using the platform. This sustained engagement reinforces loyalty-related behaviours such as repeat purchases and positive word-of-mouth.

Personalization has a net positive effect on customer outcomes (Aguirre et al., 2015; Ameen et al., 2022; Kumar et al., 2019). In emerging market contexts, where uncertainty and variability in platform quality are more pronounced, personalization may play an even more important role in reducing perceived risk and enhancing confidence in the platform (Moodley & Sookhdeo, 2025).

Based on these theoretical and empirical insights, the following hypothesis is proposed:

H1. AI-driven personalization is positively associated with e-commerce loyalty.

3.2 MODERATING ROLE OF SHOPPING FREQUENCY

Shopping frequency reflects the extent of consumers' engagement with e-commerce platforms and their familiarity with platform features. From an S-D logic perspective, frequent interactions enable deeper resource integration between consumers and platforms, facilitating more effective value co-creation (Vargo & Lusch, 2008). As consumers interact with platforms more regularly, they generate richer behavioural data, allowing personalization algorithms to produce more accurate and relevant recommendations.

This increased accuracy enhances the perceived value of personalization and strengthens its impact on relational outcomes such as loyalty. Frequent shoppers are also more likely to develop habitual engagement patterns, reinforcing the effects of personalization over time (Kumar et al., 2019). In contrast, infrequent users may have limited exposure to personalization features and may not fully recognize or trust their benefits.

From a TAM perspective, repeated interaction with personalized systems increases familiarity and reduces uncertainty, thereby enhancing perceived ease of use (Dwivedi et al., 2019). As consumers become more accustomed to personalization features, they are more likely to perceive them as useful and integrate them into their decision-making processes. This increased acceptance strengthens the relationship between personalization and loyalty.

Empirical studies support the view that user engagement intensity influences the effectiveness of personalization, with stronger effects observed among more active users. In emerging markets, where levels of digital experience vary widely, shopping frequency is likely to play a particularly important role in shaping personalization outcomes.

Accordingly, the following hypothesis is proposed:

H2. Shopping frequency positively moderates the relationship between AI-driven personalization and e-commerce loyalty, such that the relationship is stronger for more frequent shoppers.

3.3 MODERATING ROLE OF PLATFORM TYPE

Platform type represents a structural characteristic that may influence how personalization is implemented and perceived. Global e-commerce platforms typically possess advanced technological infrastructures, extensive datasets and sophisticated AI capabilities, enabling highly accurate and scalable personalization (Verhoef et al., 2015). In contrast, local platforms may offer greater contextual relevance and cultural alignment but may have more limited technological resources.

From an S-D logic perspective, both global and local platforms engage in value co-creation, but the nature of these interactions may differ. Global platforms may emphasize efficiency, breadth of offerings and algorithmic optimization, while local platforms may rely more on contextual understanding and relational cues. These differences can influence how consumers perceive personalization and its contribution to value-in-use.

TAM further suggests that platform characteristics shape perceived usefulness and ease of use. Consumers may perceive personalization on global platforms as more reliable and technologically advanced, enhancing their confidence in the system and increasing its perceived usefulness (Dwivedi et al., 2021). This perception can strengthen the impact of personalization on loyalty outcomes. Conversely, personalization on local platforms may be perceived as less technologically sophisticated, potentially moderating its effectiveness.

Prior research indicates that platform characteristics influence consumer trust, perceived quality and loyalty in digital environments, particularly in emerging markets where platform ecosystems are still evolving (Ameen et al., 2022). Research on AI acceptance in retail has shown that personalization and interactivity significantly enhance AI trust, which in turn positively influences behavioural outcomes, with cultural dimensions also playing a significant role (Alam, 2026). These findings suggest that the effectiveness of personalization may vary depending on the type of platform on which it is implemented.

Accordingly, the following hypothesis is proposed:

H3. Platform type moderates the relationship between AI-driven personalization and e-commerce loyalty, such that the relationship is stronger for global platforms than for local platforms.

4. METHODOLOGY

4.1 RESEARCH DESIGN

This study adopts a quantitative, cross-sectional research design to examine the relationship between AI-driven personalization and e-commerce loyalty in emerging market contexts. A survey-based approach was selected because it allows for the systematic collection of consumer perceptions, attitudes and behavioural intentions across diverse user groups. Such an approach is widely used in e-commerce and digital marketing research, particularly when the objective is to test theoretically grounded relationships involving perception-based constructs.

The research design is consistent with the integrated S-D logic and TAM framework adopted in this study. Specifically, it focuses on how consumers evaluate AI-enabled personalization features and how these evaluations translate into loyalty outcomes. Although cross-sectional data do not allow for causal inference, they are appropriate for examining associations and interaction effects within real-world digital environments.

4.2 SAMPLING AND DATA COLLECTION

The study gathered information from individuals who actively shop online across several developing economies. Most participants came from Saudi Arabia and India, with additional respondents drawn from nearby countries including the United Arab Emirates and Qatar. To ensure the relevance of the sample, respondents were required to meet two criteria: they had to be at least 18 years old and have made at least one online purchase within the previous 12 months. These criteria ensured that participants had sufficient exposure to e-commerce platforms and were familiar with personalization features.

Researchers used a mixed non-random approach that combined convenience sampling with snowball techniques. Online distribution channels included social media sites, professional networking platforms, academic email lists, and discussion groups focused on digital shopping. This approach is commonly used in digital commerce research where access to a comprehensive sampling frame is limited and where the target population consists of active internet users.

Data collection was conducted over a three-month period. A total of 635 responses were initially received. After data screening, which involved removing incomplete responses, patterned responses and entries with inconsistent demographic information, the final sample consisted of 413 valid responses. This sample size is considered adequate for regression-based analysis and moderation testing, providing sufficient statistical power for hypothesis testing. A post-hoc power analysis using G*Power indicated that the achieved sample size exceeded the minimum required to detect a small-to-medium effect ($f^2 = 0.10$) with $\alpha = 0.05$ and power = 0.80.

4.3 SAMPLE CHARACTERISTICS

The sample reflects a diverse group of e-commerce users across emerging markets. Respondents were predominantly male (58.6%), with the largest age group between 18 and 24 years (32.4%), followed by respondents aged 25–34 years (28.1%) and 35–44 years (21.3%). Most participants reported holding at least a bachelor's degree (67.8%), indicating relatively high levels of education. In terms of country distribution, 38.5% of respondents were from Saudi Arabia, 34.6% from India, 15.0% from the United Arab Emirates and 11.9% from Qatar.

In terms of platform usage, global e-commerce platforms—particularly Amazon—were most frequently identified as primary shopping platforms (64.2%). Local platforms such as Noon and Flipkart were also represented (35.8%). Shopping frequency varied across respondents, with 22.5% reporting daily purchases, 31.7% weekly, 28.3% monthly and 17.5% less than monthly. Most respondents (71.4%) had been using their primary platform for more than one year, suggesting familiarity with platform features, including AI-driven personalization.

4.4 MEASUREMENT INSTRUMENTS

All constructs were measured using multi-item scales adapted from established literature, with modifications to reflect the context of AI-driven personalization in e-commerce. The use of previously validated scales enhances the reliability and validity of the measurement instrument.

AI-driven personalization was measured using a five-item scale capturing the extent to which respondents perceived recommendations and content as tailored to their preferences. The items assessed relevance, adaptability and the platform's ability to learn from user behaviour over time. Sample items included "This platform recommends products that match my interests" and "The recommendations I receive become more accurate as I use the platform more". Responses were recorded on a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). The scale demonstrated good internal consistency (Cronbach's $\alpha = 0.85$).

E-commerce loyalty was measured using a ten-item scale reflecting both behavioural and attitudinal dimensions. The scale included items related to repurchase intention ("I intend to continue using this platform for my future purchases"), preference for the platform ("This is my preferred e-commerce platform") and willingness to recommend it to others ("I would recommend this platform to my friends and family"). This construct captures not only repeat usage but also the strength of the consumer–platform relationship. The reliability of this scale was high (Cronbach's $\alpha = 0.94$).

Moderating variables. Shopping frequency was measured as an ordinal variable indicating how often respondents made purchases on their primary platform (1 = less than monthly, 2 = monthly, 3 = weekly, 4 = daily). Platform type was operationalized as a binary variable, with global platforms (Amazon, AliExpress) coded as 1 and local platforms (Noon, Flipkart, regional platforms) coded as 0.

Control variables. Several demographic and usage-related variables were included as controls, including age (categorical: 18–24, 25–34, 35–44, 45–54, 55+), gender (male/female), education level (high school, bachelor's degree, postgraduate) and duration of platform usage (less than 6 months, 6–12 months, 1–3 years, more than 3 years). These variables have been shown in prior research to influence online shopping behaviour and loyalty.

4.5 RELIABILITY AND VALIDITY ASSESSMENT

Internal consistency reliability was assessed using Cronbach's alpha coefficients. All constructs exceeded the recommended threshold of 0.70, indicating acceptable reliability. In addition, composite reliability values were above 0.80, further supporting the consistency of the measurement scales.

Construct validity was evaluated using exploratory factor analysis (EFA). The Kaiser–Meyer–Olkin (KMO) measure exceeded 0.80 (KMO = 0.87), and Bartlett's test of sphericity was statistically significant ($\chi^2 = 2{,}847.6$, $p < 0.001$), indicating that the data were suitable for factor analysis. All items loaded strongly on their intended constructs, with factor loadings above 0.70, supporting convergent validity.

Discriminant validity was assessed using the Fornell–Larcker criterion. The average variance extracted (AVE) for each construct (personalization: AVE = 0.63; loyalty: AVE = 0.71) exceeded the squared inter-construct correlation ($r^2 = 0.37$), confirming that the constructs were empirically distinct. Additionally, heterotrait-monotrait (HTMT) ratios were below 0.85, further supporting discriminant validity.

To address potential common method bias, given that all variables were self-reported from the same survey, Harman's single-factor test was conducted. The unrotated factor solution revealed that a single factor accounted for 28.4% of the total variance, well below the 50% threshold, suggesting that common method bias is unlikely to be a significant concern in this study.

4.6 DATA ANALYSIS PROCEDURE

Data analysis was conducted in several stages. First, descriptive statistics were calculated to summarize sample characteristics and key variables. Second, correlation analysis was performed to examine bivariate relationships between constructs.

Hypotheses were tested using hierarchical multiple regression analysis. In the first step, control variables were entered into the model. In the second step, AI-driven personalization was included to test its direct effect on e-commerce loyalty. In the third step, shopping frequency and platform type were introduced along with their interaction terms to assess moderation effects.

To reduce potential multicollinearity, continuous variables were mean-centred prior to creating interaction terms. Diagnostic tests were conducted to verify model assumptions, including normality (Kolmogorov–Smirnov test, $p > 0.05$), linearity (visual inspection of residual plots) and homoscedasticity (Breusch–Pagan test, $p > 0.05$). Variance inflation factor (VIF) values were below 2.5, well below the acceptable threshold of 5, indicating no significant multicollinearity issues.

4.7 ETHICAL CONSIDERATIONS

Ethical standards were maintained throughout the research process. The study received approval from the institutional research ethics committee prior to data collection. Participation was voluntary, and informed consent was obtained from all respondents prior to data collection. Respondents were assured that their responses would remain anonymous and confidential. No personally identifiable information was collected, and the data were used solely for academic research purposes.

5. RESULTS

5.1 PRELIMINARY ANALYSIS

Prior to hypothesis testing, the dataset was examined for completeness and suitability for regression analysis. Missing values were minimal (less than 2% per variable) and handled through listwise deletion during the data cleaning stage. Diagnostic checks confirmed that the assumptions of multiple regression were reasonably satisfied. Variance inflation factor (VIF) values were below the recommended threshold of 5, indicating no significant multicollinearity concerns. Additionally, inspection of residual plots suggested no serious violations of linearity or homoscedasticity.

5.2 DESCRIPTIVE STATISTICS AND CORRELATIONS

Table 1 presents the means, standard deviations and correlations among the key variables included in the analysis.

TABLE 1. DESCRIPTIVE STATISTICS AND CORRELATION MATRIX

Variable	Mean	SD	1	2	3	4
1. AI-driven personalization	3.94	0.68	(0.85)			
2. E-commerce loyalty	3.88	0.72	0.61**	(0.94)		
3. Shopping frequency	2.73	1.02	0.29**	0.34**	—	
4. Platform type (global = 1)	0.64	0.48	0.21**	0.27**	0.18*	—

*Notes: n = 413. SD = standard deviation. Cronbach's alpha coefficients are presented in parentheses along the diagonal. *p < 0.05, *p < 0.01.

The bivariate analysis revealed a robust positive link between perceived algorithmic customization and platform allegiance ($r = 0.61$, $p < 0.01$), which preliminarily confirms our hypothesized connection. Shopping frequency ($r = 0.34$, $p < 0.01$) and platform type ($r = 0.27$, $p < 0.01$) also show moderate positive correlations with loyalty. All correlations among independent variables were below 0.70, suggesting that multicollinearity is not a significant concern.

5.3 HYPOTHESIS TESTING: DIRECT EFFECT

Hierarchical regression analysis was conducted to test the direct relationship between AI-driven personalization and e-commerce loyalty. Control variables (age, gender, education, platform usage duration) were entered in Model 1, followed by AI-driven personalization in Model 2.

TABLE 2. REGRESSION RESULTS FOR DIRECT EFFECT (H1)

Model	Variable	β	t-value	p-value
Model 1	Controls only	—	—	—
Model 2	AI-driven personalization	0.58	12.41	<0.001

Model statistics: $R^2 = 0.42$, $\Delta R^2 = 0.36$, $F(1, 405) = 98.32$, $p < 0.001$

AI-driven personalization has a strong and statistically significant positive effect on e-commerce loyalty ($\beta = 0.58$, $p < 0.001$). This result supports **H1**, indicating that consumers who perceive higher levels of personalization are more likely to exhibit loyalty toward e-commerce platforms. The increase in explained variance ($\Delta R^2 = 0.36$) suggests that personalization accounts for a substantial proportion of variation in loyalty, after controlling for demographic and usage-related factors.

5.4 MODERATION ANALYSIS: SHOPPING FREQUENCY

To examine the moderating role of shopping frequency (H2), an interaction term between AI-driven personalization (mean-centred) and shopping frequency was included in the regression model. The results are presented in Table 3.

TABLE 3. MODERATION RESULTS FOR SHOPPING FREQUENCY (H2)

Variable	β	t-value	p-value
AI-driven personalization	0.52	10.83	<0.001
Shopping frequency	0.21	4.12	<0.001
Personalization × Frequency	0.17	3.45	<0.01

Model statistics: $R^2 = 0.48$, $\Delta R^2 = 0.06$, $F(3, 403) = 76.54$, $p < 0.001$

The interaction term between AI-driven personalization and shopping frequency is positive and statistically significant ($\beta = 0.17$, $p < 0.01$), supporting **H2**. This indicates that the effect of personalization on loyalty becomes stronger as shopping frequency increases. The incremental variance explained by the interaction term ($\Delta R^2 = 0.06$) represents a small but meaningful moderation effect (Cohen's $f^2 = 0.12$).

Simple slope analysis was conducted to examine the conditional effect of personalization at different levels of shopping frequency. For frequent shoppers (one standard deviation above the mean, i.e., weekly or daily purchases), the relationship between personalization and loyalty was notably stronger ($\beta = 0.69$, $p < 0.001$) compared to less frequent shoppers (one standard deviation below the mean, i.e., monthly or less frequent purchases; $\beta = 0.35$,

$p < 0.001$). This suggests that users who engage more regularly with e-commerce platforms are better able to recognize and benefit from personalized features.

5.5 MODERATION ANALYSIS: PLATFORM TYPE

The moderating effect of platform type (H3) was tested by introducing an interaction term between AI-driven personalization (mean-centred) and platform type (0 = local, 1 = global). The results are presented in Table 4.

TABLE 4. MODERATION RESULTS FOR PLATFORM TYPE (H3)

Variable	β	t-value	p-value
AI-driven personalization	0.49	9.76	<0.001
Platform type (global = 1)	0.18	3.58	<0.001
Personalization × Platform Type	0.14	2.97	<0.01

Model statistics: $R^2 = 0.46$, $\Delta R^2 = 0.04$, $F(3, 403) = 69.21$, $p < 0.001$

The interaction between AI-driven personalization and platform type is positive and significant ($\beta = 0.14$, $p < 0.01$), supporting **H3**. The results indicate that the impact of personalization on loyalty is stronger for global platforms compared to local platforms. The moderation effect size ($f^2 = 0.07$) is modest but statistically meaningful.

To interpret the interaction effect, separate regression analyses were conducted for each platform type. For global platforms ($n = 265$), the effect of personalization on loyalty was $\beta = 0.63$ ($p < 0.001$). For local platforms ($n = 148$), the effect was $\beta = 0.43$ ($p < 0.001$). Although both effects are positive and significant, the magnitude is notably larger for global platforms. This suggests that consumers may perceive personalization efforts on global platforms as more effective, possibly due to greater technological sophistication and data capabilities.

5.6 SUMMARY OF HYPOTHESIS TESTING

TABLE 5. SUMMARY OF HYPOTHESIS TESTING RESULTS

Hypothesis	Statement	Result	Effect Size
H1	Personalization → Loyalty	Supported	$\beta = 0.58$, $R^2 = 0.42$
H2	Moderation by shopping frequency	Supported	$\beta = 0.17$, $\Delta R^2 = 0.06$
H3	Moderation by platform type	Supported	$\beta = 0.14$, $\Delta R^2 = 0.04$

6. DISCUSSION

The purpose of this study was to examine how AI-driven personalization influences e-commerce loyalty in emerging market contexts and to explore the moderating roles of shopping frequency and platform type. While the present study focused on direct effects and moderation, we acknowledge that customer satisfaction may play an important mediating role – a possibility that should be examined in future research . The findings provide consistent support for the proposed model and offer several insights into how personalization operates as both a technological and relational mechanism in digital retail environments.

6.1 THEORETICAL IMPLICATIONS

The analysis provides clear evidence that AI-enabled personalization correlates substantially with increased customer allegiance to online retailers. Earlier investigations have reported comparable patterns, finding that customized experiences boost shopper involvement and deepen relational bonds by making content more pertinent and simplifying choice processes (Bleier & Eisenbeiss, 2015; Kumar et al., 2019). However, the present study extends this understanding by demonstrating that personalization remains a significant predictor of loyalty in emerging markets, where consumer expectations and digital maturity vary across contexts (Ameen et al., 2022; Dwivedi et al., 2021).

Viewed through the service-dominant logic lens, our findings underscore how customized experiences function as a collaborative value-generating process. By adapting to individual preferences and behaviours, AI-driven systems enable platforms to participate more actively in the consumer decision-making process. This continuous interaction fosters a sense of responsiveness and relevance, which contributes to stronger relational ties between consumers and platforms (Vargo & Lusch, 2008; Ramaswamy & Ozcan, 2018). The findings suggest that personalization is not merely a functional tool but a core component of the value creation process in digital retail, consistent with recent S-D logic applications in online retailing (Katsifaraki & Theodosiou, 2024; Rodriguez-Ardura et al., 2025).

At the same time, the results are consistent with TAM, which emphasizes the importance of perceived usefulness in shaping user behaviour (Davis, 1989; Dwivedi et al., 2019). When customization elements boost shopping efficiency and reduce choice complexity, users tend to find them beneficial, which encourages ongoing platform engagement and allegiance. The strength of the observed relationship between personalization and loyalty indicates that consumers are not only aware of personalization features but also actively incorporate them into their shopping routines. This is consistent with recent findings that AI-driven personalization significantly improves consumer trust and satisfaction, with satisfaction acting as a key mediator for behavioural outcomes (Wang et al., 2023; Alam, 2026).

A key novel finding from this research concerns how often people shop, which emerged as an important condition affecting personalization's effectiveness. Specifically, the beneficial impact of customized recommendations on customer loyalty proved more pronounced among those who make purchases regularly compared to occasional buyers. This finding underscores the importance of user engagement in shaping personalization outcomes. Frequent users generate richer behavioural data, which allows personalization algorithms to perform more accurately and deliver more relevant recommendations. Over time, this creates a reinforcing cycle in which increased engagement leads to improved personalization, which in turn strengthens loyalty. This finding aligns with research demonstrating that incorporating loyalty indicators such as purchase frequency significantly enhances recommendation accuracy and platform engagement. (Kumar et al., 2019)

This result also provides insight into how consumers learn to interact with personalized systems. Frequent exposure to personalization features may increase familiarity and reduce uncertainty, making consumers more receptive to algorithmic recommendations. In contrast, less frequent users may not experience sufficient interaction to fully appreciate the benefits of personalization, which may weaken its impact. This highlights the need to consider user heterogeneity when evaluating personalization effectiveness.

The moderating role of platform type further illustrates the contextual nature of personalization. The findings indicate that the relationship between personalization and loyalty is stronger for global platforms than for local platforms. This difference may be attributed to variations in technological capabilities, data availability and perceived platform credibility. Global platforms typically operate at a larger scale and invest heavily in AI technologies, enabling more accurate and sophisticated personalization (Verhoef et al., 2015). As a result, consumers may perceive personalization on these platforms as more reliable and effective. This is consistent with research showing that personalization and interactivity significantly enhance AI trust, which in turn positively influences willingness to buy, particularly when platforms effectively address performance risk concerns (Alam, 2026).

However, this does not imply that local platforms are inherently disadvantaged. Instead, it suggests that the effectiveness of personalization depends on how well it aligns with consumer expectations. Local platforms may compensate for technological limitations by leveraging contextual knowledge and cultural relevance. Nevertheless, the findings indicate that, in the current stage of digital market development, technological sophistication remains a key driver of personalization effectiveness.

6.2 PRACTICAL IMPLICATIONS

The findings offer several practical implications for e-commerce firms seeking to leverage AI-driven personalization more effectively.

Companies should recognize that effective personalization requires strategic thinking rather than merely implementing technical solutions. Success depends on carefully matching customization approaches with actual customer expectations and behavioral patterns. This requires not only advanced algorithms but also a clear understanding of customer behaviour and expectations. Personalization that is perceived as relevant and useful is more likely to enhance loyalty, while poorly executed personalization may have limited impact or even generate negative responses due to privacy concerns (Canhoto et al., 2024; Jayapal, 2025).

Because shopping frequency moderates' personalization outcomes, businesses should develop distinct approaches for different customer groups. Those who shop often respond more strongly to customized content and may justify investment in advanced predictive recommendation systems and dynamic content optimization tools. For these users, firms can implement advanced personalization techniques such as predictive recommendations and dynamic content optimization. In contrast, less frequent users may require simpler and more transparent personalization features that build familiarity and trust over time. Segmenting users based on engagement levels can therefore improve the effectiveness of personalization initiatives. Research has shown that trust-building strategies and transparency features, such as explaining why certain products are recommended, can significantly enhance customer trust and acceptance of personalized AI systems. (Canhoto et al., 2024; Jayapal, 2025)

Third, the results highlight the importance of platform capabilities in shaping personalization outcomes. Global platforms tend to benefit from stronger personalization effects due to their technological infrastructure and access to large-scale data. For firms operating local or regional platforms, this suggests the need to invest in improving personalization capabilities or to differentiate through contextual relevance and localized content. Rather than attempting to replicate global platforms directly, local firms may achieve better outcomes by combining personalization with culturally relevant insights and customer-specific knowledge.

Fourth, the findings underscore the importance of balancing personalization with transparency and user control. Consumers are more likely to respond positively to personalization when they understand how it works and feel that they retain some control over their data and preferences (Aguirre et al., 2015). Providing clear explanations of personalization features and allowing users to customize their experience can enhance trust and improve long-term engagement. Organizations should invest in data privacy measures and transparent algorithms to maintain consumer confidence while leveraging AI to improve customer experience.

6.3 LIMITATIONS AND FUTURE RESEARCH

While this study provides valuable insights into AI-driven personalization and e-commerce loyalty, several limitations should be acknowledged.

First, the study relies on cross-sectional survey data, which limits the ability to draw causal inferences. Although the findings are consistent with the proposed theoretical framework, longitudinal or experimental designs would provide a stronger basis for establishing causality and examining how personalization effects evolve over time. Future research could employ longitudinal panel designs to track changes in personalization perceptions and loyalty outcomes across multiple time points.

Second, the study focuses on self-reported measures of personalization and loyalty. While such measures are widely used in marketing research, they may be subject to response bias or perceptual differences among respondents. Future research could complement survey data with behavioural data, such as actual purchase history or clickstream data, to provide a more comprehensive understanding of personalization effects. The growing availability of customer loyalty data from recommender systems offers promising opportunities for such behavioural investigations.

Third, the study is conducted within emerging market contexts, with a primary focus on Saudi Arabia and India. While this enhances the relevance of the findings for rapidly growing digital markets, it may limit generalizability to other regions with different levels of digital maturity and consumer behaviour. Future studies could extend this research by comparing personalization effects across developed and emerging markets to identify potential differences in consumer response. Cross-country comparative research would be particularly valuable for understanding how cultural factors shape personalization effectiveness (Alam, 2026).

Fourth, the study examines only two moderating variables—shopping frequency and platform type. While these factors provide important insights into contextual variability, other variables may also influence personalization effectiveness. For example, trust, perceived risk, privacy concerns and cultural values are likely to play a significant role in shaping how consumers respond to AI-driven personalization (Canhoto et al., 2024; Jayapal, 2025). The personalization–privacy paradox represents a particularly important area for future investigation, as consumers' concerns about data collection may substantially moderate the effects of personalization on loyalty outcomes.

Fifth, the study focuses on perceived personalization rather than objective measures of algorithmic performance. While perception is critical in shaping consumer behaviour, future research could explore the relationship between actual personalization accuracy and perceived value to better understand how technical performance translates into user experience. Additionally, as generative AI and agentic AI systems become more prevalent in retail environments, future research should examine how these emerging technologies reshape personalization effectiveness and consumer trust.

The study examined direct relationships between AI-driven personalization and loyalty, as well as moderating effects of shopping frequency and platform type. However, we did not include customer satisfaction as a mediator. Personalization likely enhances loyalty primarily through its impact on satisfaction – a mechanism that our cross-sectional design could not capture. Future research should therefore test a mediated model where satisfaction (or perceived experience quality) transmits the effect of personalization onto loyalty. Such a model would provide a more nuanced understanding of how personalized algorithms create relational value.

7. CONCLUSION

The primary objective of this research was investigating how artificial intelligence-enabled customization affects online retail loyalty specifically within developing economies. By merging service-dominant logic with technology acceptance theory, we examined not only whether personalization directly predicts loyalty but also how shopping regularity and platform origin influence this relationship. Using data collected from 413 e-commerce users across Saudi Arabia, India and neighboring economies, the findings provide consistent support for the proposed model.

The results demonstrate that perceived AI-driven personalization is a strong predictor of e-commerce loyalty. Consumers who perceive personalization as relevant, adaptive and useful are more likely to remain engaged with a platform and exhibit loyalty-related behaviours. In addition, the findings show that the effectiveness of personalization is not uniform but varies depending on user engagement and platform characteristics. Specifically, the relationship between personalization and loyalty is stronger among frequent shoppers and on global platforms, highlighting the importance of both behavioural and structural factors in shaping personalization outcomes.

Taken together, these findings confirm that customization occupies an essential position within modern digital retail approaches. Nevertheless, the strength of personalization's impact varies considerably based on user perceptions and the specific circumstances surrounding its deployment. As AI technologies advance and online shopping continues evolving, understanding these contextual conditions will remain crucial for both academic researchers and industry practitioners. By integrating relational and technological perspectives, the study provides a more comprehensive understanding of how AI-driven personalization contributes to long-term customer relationships. As e-commerce continues to evolve and AI technologies become increasingly sophisticated, understanding the nuanced conditions under which personalization drives loyalty will remain a critical priority for both researchers and practitioners.

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