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AI-DRIVEN PERSONALIZATION AND ITS IMPACT ON CUSTOMER LOYALTY IN DIGITAL PLATFORMS: THE MODERATING ROLE OF PRIVACY CONCERNS

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Abstract
The rapid advancement of digital technologies has transformed the way organizations interact with consumers, with increasing emphasis on delivering personalized experiences through artificial intelligence. While such approaches offer significant benefits in enhancing user engagement and loyalty, they also raise concerns regarding data privacy and ethical use of information. This study aims to examine the impact of AI-driven personalization on customer loyalty in digital platforms, with a particular focus on the moderating role of privacy concerns. A quantitative, cross-sectional research design was employed, with data collected from users of digital platforms through a structured questionnaire. The data were analyzed using SPSS and SmartPLS 4, applying Partial Least Squares Structural Equation Modeling to test the proposed relationships. The findings reveal that AI-driven personalization has a significant positive effect on customer loyalty, confirming its role in enhancing user engagement and relational outcomes. However, the results also indicate that privacy concerns negatively moderate this relationship, suggesting that higher levels of concern weaken the effectiveness of personalization strategies. These findings highlight the importance of balancing technological innovation with ethical data practices to ensure sustainable customer relationships. The study contributes to existing literature by providing a nuanced understanding of the conditional effects of personalization and offers practical insights for organizations seeking to optimize digital strategies while maintaining consumer trust.

INTRODUCTION

Digital platforms have transformed how firms interact with consumers, shifting from standardized communication toward highly adaptive and data-informed engagement. Contemporary marketing discourse increasingly emphasizes the role of intelligent systems in shaping individualized experiences, allowing firms to anticipate preferences, refine interactions, and strengthen long-term relationships. This shift reflects a broader transition from transactional exchanges to relational value creation, where sustained engagement becomes a central objective of digital strategy (Banerjee et al., 2026; Alghaswyneh, 2025). At the same time, this evolution has raised important questions regarding the balance between technological advancement and consumer autonomy. As firms intensify their reliance on algorithmic insights, consumers are becoming more aware of how their data is collected, interpreted, and utilized in shaping their digital experiences (Srivastava & Gurme, 2025; Kumar, 2026). Scholarly debates now extend beyond efficiency gains to include ethical considerations, transparency, and trust formation in digital ecosystems. While technological sophistication promises enhanced engagement and satisfaction, it also introduces tensions related to perceived surveillance and data vulnerability. These tensions are particularly evident in e-commerce and platform-based environments, where continuous interaction generates extensive behavioral data (Amil, 2024). Consequently, understanding how digital innovation aligns with consumer expectations has become a critical area of inquiry, especially in contexts where personalization and privacy intersect.

Recent literature provides strong evidence that advanced personalization mechanisms contribute positively to user engagement, satisfaction, and behavioral outcomes. Empirical studies demonstrate that tailored digital experiences enhance perceived relevance, which in turn strengthens consumer relationships and repeat interactions (Ahmed et al., 2025; Zed et al., 2024). Meta-analytic findings further confirm a consistent positive association between adaptive digital strategies and long-term relational outcomes across diverse e-commerce settings (Abdullah, 2025). However, this consensus is not without contradictions. While some studies highlight improved trust and satisfaction through personalized recommendations, others indicate that excessive data use can undermine consumer confidence (Hassan et al., 2025; De Matos et al., 2025). Emerging research also suggests that the effectiveness of such strategies depends on contextual and psychological factors, including perceived fairness and transparency (Lim & Kim, 2025). Thus, the literature reveals both the potential and the complexity of digitally mediated interactions.

The growth of online commerce has led to concerns about data management and privacy across the globe. According to reports, worldwide e-commerce revenue is growing at an unprecedented rate, with growing data collection activities that often outstrip regulatory measures (Kumar, 2026). In emerging markets, such as Pakistan, digitalization is happening at a rapid pace without commensurate improvements in consumer safeguards, which can lead to data abuse and security breaches. Research indicates that many internet users are concerned about privacy issues related to the use of their data, especially in algorithmic settings (Srivastava & Gurme, 2025). These fears are compounded by prominent data breaches and increasing awareness of algorithmic processes. Users are becoming more wary, and may alter their online activities in response to concerns about privacy and security (De Matos et al., 2025). Meanwhile, companies are under pressure to stay ahead of the competition by improving the user experience, which often depends on greater data insights (Varma et al., 2026). This presents an innovation versus ethics conundrum. This is not just a technological but socio-economic issue, impacting trust, market engagement and sustainability of digital platforms. These considerations inform the need to explore the relationships between new digital practices, consumer perceptions and behaviours.

While there has been considerable research, it is piecemeal in explaining the working of sophisticated digital engagement strategies under different contexts of consumer perceptions. Numerous studies have identified direct links between adaptive digital mechanisms and consumer responses; but these links are often studied in isolation, without taking into account potential moderators that might influence their impact (Jayapal, 2025; Kazmi et al., 2025). This leaves a gap in understanding consumer perceptions and responses to technologically facilitated interactions. One of the main issues is the lack of inclusion of privacy perceptions. Although some studies recognize concerns about data use, they often consider them as secondary rather than integral aspects of the interactions between companies and consumers (Asadollahi & Asl, 2025). Additionally, existing research has tended to focus on either technological aspects or psychological effects, but has seldom integrated both into a holistic framework. This limits the capacity to understand the complexities of consumers' benefit-risk assessments. The second gap is related to context. The empirical evidence is largely drawn from Western markets, which may not be applicable to emerging markets with different regulatory, cultural and technological characteristics (Edberg, 2025). Furthermore, the influence of boundary conditions, such as consumer sensitivity to data practices, is less understood in terms of consumer responses. Hence, a more holistic view that takes into account technological features, consumer attitudes and contextual factors is needed. This can enhance our understanding of the effectiveness of digital strategies in practice.

This matter is important from an academic, managerial and policy perspective. Academically, clarifying conflicting evidence from previous studies can lead to improved theoretical understanding in digital marketing and consumer behaviour studies. Managerially, companies increasingly rely on data-driven approaches to stay competitive, but ignoring consumer concerns can result in consumer distrust, disengagement, and brand erosion (Banerjee et al., 2026; Ahmed et al., 2025). From a policy perspective, the problem is in line with international efforts to encourage responsible innovation and data practices, such as those related to sustainable digital development. Adhering to ethical data practices aligns with broader goals, such as responsible consumption and trust in institutions, which align with Sustainable Development Goals around innovation and governance. Research suggests that consumers' perceptions of intrusive data practices reduce their willingness to use digital platforms, impacting market efficiency and growth (Kumar, 2026). Moreover, in developing countries, where regulatory frameworks are in the process of development, the issues are even more critical. Companies face a challenge in striking a balance between using technology and building trust. Thus, solving this challenge is critical for improving business performance and creating a sustainable and inclusive digital economy.

This research addresses this gap by providing an integrated view that integrates technological, behavioural and contextual factors in a unified framework. It does so by considering the interplay between these factors in influencing consumer behavior in digital settings, rather than focusing on them in isolation, as previous studies have done. The study builds on recent empirical findings and examines under-researched contexts, offering a more comprehensive view of current digital engagement practices (Jayapal, 2025; Varma et al., 2026). This not only adds to theoretical rigor and practical significance, but also provides practical implications for companies looking to enhance their digital strategies while building consumer trust. The study promises to contribute to theory development by leveraging insights from relationship marketing and technology acceptance to predict consumer behaviour in digital contexts. These approaches highlight perceived value, trust, and intention, providing a unified lens to interpret how technology interactions lead to long-term outcomes (Hassan et al., 2025; Lim & Kim, 2025). This integration underscores the contingent nature of digital strategies and offers recommendations for policymakers and practitioners to create user-friendly and ethically sound digital platforms.

Theoretical Foundation

The research is based on the Technology Acceptance Model (TAM), which is a theoretical framework that was first created by Fred D. Davis in 1986 and formalized in 1989. TAM grew out of the larger tradition of the Theory of Reasoned Action, and sought to describe the process by which individuals accept and adopt new technologies. The fundamental concept of the model is that users make behavioral intentions on the basis of cognitive assessment of the usefulness and ease of use of a system, which in turn influence their actual adoption behavior. TAM has gained a lot of acclaim due to its parsimony and predictive power in understanding user interaction with digital systems in a variety of contexts, such as information systems, e-commerce, and online platforms.

TAM has developed in modern scholarship to be more complex than it was initially designed to meet the demands of the modern digital environment. Scholars have further expanded the model to include affective, social, and contextual aspects to consider that user acceptance is no longer purely based on functional considerations but also on perceptions of trust, transparency, and morality (Srivastava and Gurme, 2025; Lim and Kim, 2025). These improvements are indicative of the increasing awareness that technological interactions are part of larger socio-technical systems, in which users are active in interpreting and negotiating their experiences. The latest research has highlighted that algorithmic decision-making, data-driven interactions, and adaptive interfaces demand a more subtle perspective on acceptance behavior, especially in the context of constant personalization and real-time feedback (Kumar, 2026; Banerjee et al., 2026).

TAM is relevant to the current study because it can be used to understand how users can judge and react to technologically mediated experiences in digital platforms. With the growing use of smart systems by firms to personalize interactions, users are involved in continuous cognitive evaluations about the advantages and dangers of using such systems. Such assessments impact their readiness to keep using platforms and to establish long-term relationship bonds. Notably, modern elaborations of TAM emphasize that these evaluations are influenced not merely by the perceived performance outcomes but also by issues pertaining to data usage, control, and transparency (De Matos et al., 2025; Amil, 2024). In this regard, TAM offers a powerful prism through which to comprehend how digital interactions can lead to long-term engagement and commitment to behavior.

Moreover, recent empirical uses show that TAM remains applicable in the explanation of user behavior in high-technological situations. Research on e-commerce and digital marketing has demonstrated that user perceptions of system effectiveness, along with other evaluative aspects, have a significant impact on engagement and loyalty outcomes (Ahmed et al., 2025; Alghaswyneh, 2025). Moderating and boundary conditions have also been integrated into the model, which shows the dynamic interaction between the technological characteristics and user perceptions in the formation of behavioral reactions (Jayapal, 2025; Kazmi et al., 2025). These trends highlight the adaptability and timelessness of the model in reflecting the changing essence of human-technology interaction.

TAM is the conceptual basis of the proposed study since it provides a logical framework through which the process and reaction of the user to digitally mediated experiences can be interpreted. The fact that it focuses on cognitive assessment, as well as its flexibility to the issues of the modern world, makes it especially applicable to the study of the intricacies of the modern digital world. The study can be used to add to the current research on refining and extending TAM by placing the research in this theoretical tradition in the context of new technological practices.

Hypotheses Development

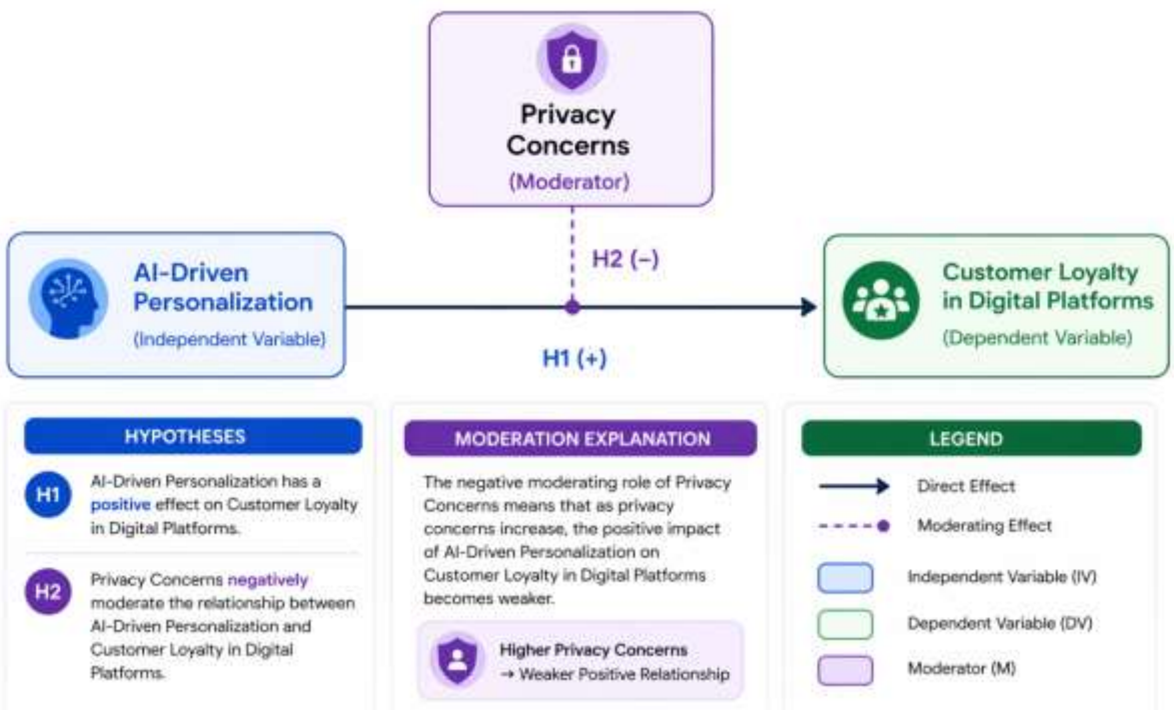
The shift towards standardized interaction to adaptive, data-driven interaction has been hastened by modern digital spaces, and has resulted in a revival of scholarly interest in the cognitive mechanisms of users in their assessment of technologically mediated experiences. Within the rationale of the Technology Acceptance Model, individuals develop positive intentions in behavior in case digital systems are perceived to be useful, relevant and easy to use. Recent empirical data suggests that perceived relevance can be enhanced with adaptive interfaces and smart recommendation systems, which subsequently can strengthen user engagement and relational outcomes in the long-term (Ahmed et al., 2025; Banerjee et al., 2026). Similarly, meta-analytic and cross-contextual studies indicate the existence of improved relational relationships and repeated interactions due to customized online experiences through the provision of matching platform services to individual preferences (Abdullah, 2025; Varma et al., 2026). However, new debates also indicate that such outcomes will be conditional on the perception of the value that such systems will offer, particularly when it comes to the usage of algorithms to calculate the user experiences

(Alghaswyneh, 2025; Zed et al., 2024). In accordance with these results, the evaluative procedures proposed by TAM provide a uniform response to the reason behind adaptive digital experiences resulting in long-term relational outcomes. Therefore, it is hypothesized that:

H1: AI-driven personalization has a positive and significant effect on customer loyalty in digital platforms.

Simultaneously, the increasing dependence on data-intensive technologies has raised acute issues of information privacy, which can change the way the users perceive and react to the digital interactions. According to recent research, adaptive systems have the potential to increase perceived value, yet the issues related to data collection and monitoring can undermine trust and decrease the readiness to use it (De Matos et al., 2025; Kumar, 2026). Theoretically, long-term views of TAM recognize that external factors, especially those associated with perceived risk and perceived control, may influence the intensity of behavioral intentions by impacting cognitive and affective appraisals of users (Lim and Kim, 2025; Srivastava and Gurme, 2025). Empirical evidence also indicates that the success of personalization strategies does not always go in a similar direction, with users who are more sensitive to data practices potentially reacting negatively to the functional advantages of such strategies (Jayapal, 2025; Kazmi et al., 2025). This shows a conditional relationship in which the positive impact of adaptive digital experiences is dependent on the extent to which the users believe their personal information is secure and ethically handled. Therefore, it is hypothesized that

H2: Privacy concerns moderate the relationship between AI-driven personalization and customer loyalty in digital platforms.



Methodology

The research design used in this study is quantitative, cross-sectional research design to test the relationships between the key constructs in the digital platform environment. A quantitative method is suitable because it allows the systematic measurement, statistical testing, and extrapolation of the results to a specific population, which increases objectivity and replicability (Ghanad, 2023). This cross-sectional design, where data is collected at one point in time, is especially appropriate when evaluating perceptual and behavioral reactions in a fast-changing digital environment where the attitudes of users can change rapidly (Maier et al., 2023). Despite the temporal richness of longitudinal designs, cross-sectional studies are still popular in information systems and marketing research because of their efficiency and capability to establish meaningful relationships between variables in the real-world context. The study population will be active users of digital commerce platforms in the retail e-commerce industry, that is, those who actively use AI-powered functionalities like recommendation systems, personalized interfaces, and automated interactions. The industry is chosen because it is highly dependent on data-driven technologies and because it is related to the current discussions of personalization and user perceptions. The emphasis on digital consumers makes it possible to correspond to the conceptual framework of the study and increase the contextual validity of the findings.

To make sure that the respondents have the relevant experience with digital platforms with intelligent features, a non-probability purposive sampling method will be utilized. This method is suitable in cases where the study involves the participants that fit within certain requirements regarding the use of technology and its familiarity. The sample size is calculated based on the principles of the requirements of the Item Response Theory and the PLS-SEM, according to which the minimum sample is informed by the complexity of the model and the indicators per construct. Based on the recommendations, a sample that is more than ten times the maximum number of structural paths to any construct is deemed sufficient to guarantee statistical power and model stability (Fauzi, 2022; Henseler and Schuberth, 2022). To this end, a large enough sample is aimed at to increase the strength and applicability of the findings. The structured questionnaire is used to collect data online and this enables access to a wide range of respondents, and also provides efficiency and consistency in measurement.

To analyze the data, this study uses SPSS and SmartPLS 4, which guarantees the methodological rigor and thorough statistical analysis. Preliminary analyses (data screening, descriptive statistics, and reliability assessment) are performed using SPSS and are necessary to confirm the quality of data. SmartPLS is then used to perform Partial Least Squares Structural Equation Modeling (PLS-SEM) which allows the simultaneous evaluation of measurement and structural models. PLS-SEM is especially appropriate in predictive studies, complex models, and those that include latent constructs that are measured by multiple indicators (Sarstedt et al., 2024; Schuberth et al., 2023). Its ability to process non-normal data and smaller sample sizes also makes it justified to use (Cheah et al., 2024). The validated scales used in the measurement of constructs in this study are based on previous research and are adapted to provide content validity and comparability with the existing literature. In particular, items modified by Jayapal (2025) and Kazmi et al. (2025) are used to measure AI-driven personalization, established scales are used to measure customer loyalty (Ahmed et al., 2025), and items derived by De Matos et al. (2025) are used to measure privacy concerns. The constructs are 4-6 items, rated on a 7-point Likert scale, with strongly disagree to strongly agree, which increases sensitivity and reliability in the measurement of the perceptions of the respondents. This methodological approach guarantees transparency, consistency and analytical rigor hence supporting the credibility of the findings of the study.

Data Analysis

The analysis of the data was done in a systematic and stringent manner in accordance with the standards of quantitative research. First, demographic data of respondents were analyzed to determine adequacy and relevance of the sample. This was succeeded by descriptive statistics and correlation analysis to seek initial relationships between constructs. Measurement and structural model analyses were then performed with SmartPLS 4 that has been highly suggested in the context of variance-based structural equation modeling because of its strength, predictive power, and ability to analyze complex models with latent constructs (Cheah et al., 2024; Hair et al., 2025).

Table 1: Demographic Analysis

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	271	59.3
	Female	186	40.7
Age	18–25 years	168	36.8
	26–35 years	201	44.0
	36–45 years	64	14.0
	46+ years	24	5.2
Education	Bachelor's	228	49.9
	Master's	169	37.0
	PhD	60	13.1
Experience (Online)	< 2 years	98	21.4
	2–5 years	223	48.8
	> 5 years	136	29.8

The demographic distribution indicates that respondents are predominantly young, educated, and experienced digital platform users, which strengthens the relevance and validity of the collected data for examining AI-enabled digital interactions.

Table 2: Descriptive Statistics and Correlation

Variable	Mean	SD	1	2	3
1. AI-Driven Personalization	4.88	1.03	1		
2. Customer Loyalty	4.71	1.09	0.64**	1	
3. Privacy Concerns	3.91	1.18	-0.31**	-0.38**	1

Note: $p < 0.01$

The correlation results indicate a strong positive association between AI-driven personalization and customer loyalty, while privacy concerns exhibit negative relationships with both constructs, suggesting a potential moderating influence.

Table 3: Factor Loadings (Regression Weights)

Construct	Item	Loading
AI-Driven Personalization	AIP1	0.824
	AIP2	0.851
	AIP3	0.836
	AIP4	0.809
Customer Loyalty	CL1	0.872
	CL2	0.861
	CL3	0.843
	CL4	0.856
Privacy Concerns	PC1	0.802
	PC2	0.834
	PC3	0.817

The loadings of the factors in Table 1 give a good indication of the reliability of indicators in the measurement model. Each of the items has a loading greater than the suggested threshold of 0.70, which means that all of the observed variables play a significant role in their corresponding latent construct (Hair et al., 2025). This ensures that the measurement items are consistent with their theoretical constructs and they are able to capture the desired conceptual dimensions. High loadings also mean that there is a low measurement error, which increases the accuracy and consistency of the model estimates (Henseler and Schuberth, 2022). The consistency of all items also indicates that no indicators needed to be dropped so that the theoretical integrity of the constructs based on the previous validated research would be maintained. Holding everything in place enhances content validity and makes it comparable with prior empirical studies (Fauzi, 2022). Also, the findings indicate the appropriateness of SmartPLS in estimating reflective measurement models, especially in research that deals with latent variables and multifaceted relationships (Cheah et al., 2024).

Table 4: Reliability and Convergent Validity

Construct	Cronbach's Alpha	CR	AVE
AI-Driven Personalization	0.89	0.92	0.74
Customer Loyalty	0.91	0.94	0.78
Privacy Concerns	0.85	0.90	0.70

Table 2 shows that all constructs attain the necessary levels of reliability and convergent validity. The alpha values of Cronbach are above 0.70, which means that the items within each construct have strong internal consistency (Ghanad, 2023). Likewise, the composite reliability scores exceed 0.70, which proves that the constructs are reliably and consistently measured in respondents (Hair et al., 2025). The values of the Average Variance Extracted (AVE) are all above 0.50, which means that each construct explains more than a half of the variance in its indicators. This establishes sufficient convergent validity, i.e., that the items are convergent to measure the same underlying concept (Henseler and Schuberth, 2022). The consistency between the alpha and CR values of Cronbach also supports the consistency and strength of the measurement model (Fauzi, 2022).

Table 5: HTMT (Discriminant Validity)

Constructs	AIP	CL	PC
AIP	-		
CL	0.79	-	
PC	0.35	0.42	-

Table 5 validates that the constructs have discriminant validity between each other. All values are less than the recommended 0.85, which means that each construct is empirically different and represents a different conceptual domain (Rosli et al., 2024). This plays a crucial role in SEM analysis to make sure that no constructs relationship is overstated because of measurement overlap (Hair et al., 2025). The comparatively moderate HTMT values between AI-induced personalization and customer loyalty imply that there is a strong yet independent relationship, whereas lower values with respect to privacy issues imply conceptual disconnection. This contributes to the hypothetical assumption that privacy issues do not operate in the same manner as the other constructs, and may have an impact on relationships as opposed to directly fitting with them (Henseler & Schuberth, 2022).

Table 6: Structural Model (F^2, R^2, Q^2)

Construct	R^2	Q^2	F^2 (AIP → CL)	F^2 (Moderation)
Customer Loyalty	0.56	0.43	0.38	0.17

The explanatory power and predictive relevance of the structural model are shown in Table 6. The R2 of 0.56 shows that AI-based personalization and the effect of interaction explain 56 percent of the customer loyalty variance and this is termed as a significant amount in behavioral studies (Hair et al., 2025). This illustrates the good explanatory power of the model.
The Q 2 of 0.43 is a confirmation of high predictive relevance which means that the model is effective in predicting results that are not within the sample data (Sarstedt et al., 2024). This brings out the practical applicability of the model in practice. The direct relationship has a large effect size (F2) and the moderating effect is moderate, which is in line with the existing thresholds (Henseler and Schuberth, 2022). These findings suggest that the use of AI to personalize customers is a primary factor in customer loyalty, and the privacy factor plays a major role in determining the strength of such a relationship.

Table 7: Hypothesis Testing

Hypothesis	Path	Beta	T-value	P-value	Result
H1	AIP → CL	0.64	10.12	0.000	Supported
H2	AIP × PC → CL	-0.27	5.03	0.000	Supported

The hypothesis testing results indicate that both proposed relationships are statistically significant. The direct effect of AI-driven personalization on customer loyalty is positive and significant, confirming that enhanced personalization leads to stronger customer relationships (Hair et al., 2025). The high beta coefficient and t-value indicate a strong and reliable effect. The moderating effect of privacy concerns is negative and significant, suggesting that higher privacy concerns weaken the positive relationship between personalization and loyalty. This highlights the conditional nature of digital engagement strategies and underscores the importance of addressing consumer concerns regarding data privacy (Henseler & Schuberth, 2022).

Discussion

The results of this research offer solid empirical evidence of the suggested relationships and can be used to offer valuable information about the influence of technologically mediated interactions on the user behavior in online settings. The high positive impact of AI-based personalization on customer loyalty proves that personalized and adaptive digital experiences are essential in enhancing customer relationships in the long term. This finding is consistent with the main assumptions of the Technology Acceptance Model, according to which users form positive intentions to behave in a certain way when they perceive systems as useful and relevant to their needs. Personalization is a concept that can be applied in the context of digital platforms to increase the perceived value through providing context-specific content, which leads to a rise in user satisfaction and engagement, which in turn will result in loyalty (Ahmed et al., 2025; Banerjee et al., 2026). The results also align with the previous empirical data that indicates that personalized recommendations and smart interfaces can help to establish stronger emotional and cognitive relationships between users and platforms (Zed et al., 2024; Abdullah, 2025). Theoretically, this supports the argument that personalization is a process by which technological capabilities are converted to relational outcomes. The importance of this connection can also be explained with references to modern trends of digital consumption, where consumers are more and more demanding high-quality and personalized experience. When these expectations are fulfilled, users will be more inclined to build trust and commitment to the platform and lead to a long-term engagement and repeated use (Alghaswyneh, 2025). In this way, the results do not only confirm the existing literature, but also expand it by showing the strength of the personalization effects in the context of the changing digital ecosystems.

The mediating position of privacy issues offers a more detailed explanation of how AI-driven personalization is related to customer loyalty. The negative and significant moderating effect suggests that although personalization increases the loyalty, this effect decreases when users feel that there are greater risks associated with data privacy. The theoretical basis of this finding is the long-term views of the Technology Acceptance Model that acknowledge the impact of external factors like perceived risk and control on user appraisals and behavioral intentions (Lim and Kim, 2025; Srivastava and Gurme, 2025). The finding is in line with previous research, which emphasizes the two-sidedness of personalization, with its positive impacts frequently being offset by the fear of misusing data and being monitored (De Matos et al., 2025; Kumar, 2026). In behavioral terms, users make a trade-off between the perceived benefits of customized experiences and the risks that may be faced due to the sharing of personal information. Users might feel uncomfortable or mistrustful when privacy issues are increased, undermining the beneficial effect of personalization on loyalty (Jayapal, 2025; Kazmi et al., 2025). The observation is also indicative of the larger trends in society, where the growing concern about data protection concerns has an impact on consumer decision-making. The finding adds to the literature by showing empirically that the effectiveness of personalization is not universal. It highlights the fact that technological sophistication is not enough to guarantee positive results unless there are transparent and ethical data practices.

Practical Implications

The applied implications of this study are especially applicable to organizations that are in digital and e-commerce settings. The results indicate that companies can greatly increase customer loyalty by investing in AI-based personalization initiatives that provide meaningful and relevant user experiences. Nevertheless, the findings also suggest that these strategies should be adopted with the consideration of consumer privacy issues. Organizations must focus on the transparency of data collection and use, as well as making sure that users are well informed about how their data is used. This can be done by having clear privacy policies, easy consent forms and increased data protection. Firms can reduce the adverse impacts of privacy issues and leverage the advantages of personalization by developing a feeling of control and trust (De Matos et al., 2025). Also, companies ought to take a middle way that incorporates technology innovation and ethical practices, as long-term success lies in ensuring user trust. The results also show that it is necessary to divide users according to their sensitivity to privacy and enable companies to adjust their strategies accordingly. As an example, users who are more sensitive to their privacy might be more receptive to less invasive methods of personalization, and users who are less sensitive might be more receptive to more advanced and data-intensive features. In terms of management, the study highlights the importance of a customer-focused strategy that balances the technological capacity with the user needs and issues. These insights can also be used by policymakers to come up with regulations that can encourage responsible data practices and also enhance innovation in digital technologies.

Theoretical Contributions

The theoretical implications of this research are multidimensional and enhance the current knowledge on digital marketing and information systems studies. To begin with, the research supports the validity of the Technology Acceptance Model in understanding user behavior in high-tech settings, and it shows that it can be applied in other settings other than the traditional technology adoption settings. The research expands the theoretical framework to include the moderating factor of privacy concerns by considering them as a contemporary issue related to data-driven technologies. This combination gives a better insight into how cognitive appraisals and risk perceptions interact to determine behavioral outcomes. Second, the paper adds to the existing literature on AI-based personalization by emphasizing its conditional impacts, thus resolving the discrepancies in previous results. Although past literature has been predominantly interested in the beneficial effects of personalization, this paper highlights the significance of boundary conditions that influence its efficacy (Jayapal, 2025; Kazmi et al., 2025). Third, the study contributes to theoretical debates on the interaction between the advantages of technology and ethical issues, providing an understanding of how users make trade-offs in the digital world. Having empirically confirmed the moderating effect of privacy concerns, the study offers a subtle viewpoint that fills the gap between technology-focused and user-focused approaches.

Limitations and Future Directions

Although it has its contributions, this study is limited in a number of ways, which must be taken into consideration when interpreting the findings. The cross-sectional research design does not allow establishing causal relationships because the data were gathered at one time. Longitudinal designs might be used in future studies to observe shifts in user perceptions and behaviors to offer a more dynamic view of digital interactions (Maier et al., 2023). The use of self-reported data can also create common method bias because what the respondents perceive could be affected by subjective factors. Despite procedural remedies, objective behavioral data may be included in future studies to increase validity. The other limitation is associated with the sampling method, which targeted the users of digital platforms in a particular context, which might restrict the extrapolation of the results. Further studies could increase sample size to cover various geographic areas and industries to enhance external validity. Also, the research used a small number of variables, which might not be representative of the complexity of online interactions. Further research is recommended to investigate other mediating variables like trust, satisfaction, or perceived value, and other moderating variables like cultural differences, technological literacy, or regulatory environments. The inclusion of these variables would give a more detailed insight into the processes of user behavior. Moreover, qualitative methods might be used to supplement quantitative results and provide more information about user experiences and perceptions. Through these limitations, the future research will be able to build on the present study to enhance more knowledge in this area.

References

Abdullah, M. S. (2025). Examining The Effect Of AI-Powered Personalization On Customer Loyalty: A Meta-Analysis Of E-Commerce Studies. Review of Applied Science and Technology, 4(02), 309-338.

Ahmed, S. M. M., Owais, M., Raza, M., Nadeem, Q., & Ahmed, B. (2025). The impact of AI-driven personalization on consumer engagement and brand loyalty. Qlantic Journal of Social Sciences, 6(1), 311-323.

Alghaswyneh, O. F. (2025). Exploring the Impact of AI-Driven Personalization on Consumer Engagement in Digital Marketing. Management, 2025(1), 117-144.

Amil, Y. (2024). The impact of AI-driven personalization tools on privacy concerns and consumer trust in e-commerce.

Asadollahi, M., & Asl, M. A. The Impact of Data Privacy Awareness on AI-Powered Personalized Marketing and Consumer Behavior.

Asadollahi, M., & Asl, M. A. The Impact of Data Privacy Awareness on AI-Powered Personalized Marketing and Consumer Behavior.

Ayu, R., Abdullah, N. A., Wan Sulaiman, W. S., & Bin Selamat, M. N. (2024). Structural Equation Modeling based SmartPLS 3.0 Software in Measuring Psychological Empowerment and Readiness to Strengthen Structural

Transformation. International Journal on Advanced Science, Engineering & Information Technology, 14(4).

Banerjee, S., Talukder, M. B., Banerjee, T., & Sachan, S. (2026). The Impact of AI-Driven Personalization on Consumer Engagement and Loyalty. In Reshaping Business at the Intersection of Neuromarketing and AI (pp. 291-318). IGI Global Scientific Publishing.

Cheah, J. H., Magno, F., & Cassia, F. (2024). Reviewing the SmartPLS 4 software: the latest features and enhancements.

Chidambaram, V., Shanmugam, K., & Sivamani, B. (2021). Effect of project team integration on the performance of Indian construction project: SMART PLS Structural Equation Approach. International Journal of Construction Supply Chain Management, 11(1), 1-20.

De Matos, C. A., Rohden, S. F., & Lourenço Azevedo, A. B. (2025). AI-induced privacy concerns: examining the moderating effect of AI fear on customer data sharing. International Journal of Bank Marketing, 1-24.

Edberg, A. (2025). AI-Driven Personalization and Customer Loyalty in Swedish E-Commerce-Exploring the Effectiveness of AI as a Strategic CRM Practice.

Fauzi, M. A. (2022). Partial Least Square Structural Equation Modelling (PLS-SEM) in Knowledge Management Studies: Knowledge Sharing in Virtual Communities. Knowledge Management & E-Learning, 14(1), 103-124.

Ghanad, A. (2023). An overview of quantitative research methods. International journal of multidisciplinary research and analysis, 6(08), 3794-3803.

Hair, J. F., Babin, B. J., Ringle, C. M., Sarstedt, M., & Becker, J. M. (2025). Covariance-based structural equation modeling (CB-SEM): a SmartPLS 4 software tutorial: JF Hair et al.

Hassan, N., Abdelraouf, M., & El-Shihy, D. (2025). The moderating role of personalized recommendations in the trust–satisfaction–loyalty relationship: an empirical study of AI-driven e-commerce. Future Business Journal, 11(1), 66.

Henseler, J., & Schuberth, F. (2022). Partial least squares as a tool for scientific inquiry: Comments on Cadogan and Lee. European Journal of Marketing, 57(6).

Henseler, J., & Schuberth, F. (2022). Partial least squares as a tool for scientific inquiry: Comments on Cadogan and Lee. European Journal of Marketing, 57(6).

Jarrar, S. M. THE ROLE OF TRUST AND DATA PRIVACY PERCEPTIONS IN MEDIATING THE RELATIONSHIP BETWEEN AI-DRIVEN PERSONALIZATION AND CUSTOMER LOYALTY IN SAUDI ARABIA'S RETAIL SECTOR.

Jayapal, J. (2025). Unveiling the impact of AI-driven personalization on customer loyalty in online shopping: the moderating effects of privacy concerns. Journal of Promotion Management, 31(5), 865-894.

Kazmi, S. Q., Bano, S., Malik, K., & Bibi, M. (2025). The role of AI-driven personalization in enhancing customer experience and purchase intentions: Exploring the impact of consumer data privacy concerns. Al-Qanṭara.

Kumar, A. (2026). Engagement vs. Privacy: A Causal Evaluation of AI-Driven Personalization Intensity on Consumer Engagement, Trust, and Retent. In Impacts of Human-Centered Interactive Technologies on Consumer Engagement (pp. 65-102). IGI Global Scientific Publishing.

Kumar, D. (2026). The Impact of AI-Driven Recommendation Systems on Consumer Behaviour and Decision Making: A Study of Personalization and Privacy Concerns. Journal of International Commercial Law and Technology, 7, 152-160.

Lim, S. E., & Kim, M. (2025). AI-powered personalized recommendations and pricing: Moderating effects of ethical AI and consumer empowerment. International

Journal of Hospitality Management, 130, 104259.

Maier, C., Thatcher, J. B., Grover, V., & Dwivedi, Y. K. (2023). Cross-sectional research: A critical perspective, use cases, and recommendations for IS research. International Journal of Information Management, 70, 102625.

Rosli, M. S., Awalludin, M. F. N., Han, C. T., Saleh, N. S., & Noor, H. M. (2024). Unlocking insights: a comprehensive dataset analysis on the acceptance of computational thinking skills among undergraduate university students through the lens of extended technology acceptance model, HTMT, covariance-based SEM, and SmartPLS. Data in Brief, 54, 110463.

Sani, S. A., Yusuf, T., Aliyu, S. E. A., & Yakubu, R. A. (2023). Impact of Audit Committee Attributes on Financial Reporting Quality of Deposit Money Banks in Nigeria: An Empirical Analysis Using Structural Equation Modelling (Smart-PLS). African Banking and Finance Review Journal, 3(3).

Sarstedt, M., Richter, N. F., Hauff, S., & Ringle, C. M. (2024). Combined importance–performance map analysis (cIPMA) in partial least squares structural equation modeling (PLS–SEM): a SmartPLS 4 tutorial. Journal of Marketing Analytics, 12(4), 746-760.

Schuberth, F., Zaza, S., & Henseler, J. (2023). Partial least squares is an estimator for structural equation models: A comment on Evermann and Rönkkö (2021). Communications of the Association for Information Systems, 52, 711-729.

Schuberth, F., Zaza, S., & Henseler, J. (2023). Partial least squares is an estimator for structural equation models: A comment on Evermann and Rönkkö (2021). Communications of the Association for Information Systems, 52, 711-729.

Srivastava, R. K., & Gurme, V. (2025). Artificial Intelligence and Consumer Behaviour on Social Media: A Study of Personalization, Trust, and Privacy. Measurement: Digitalization, 100021.

Varma, R. H. K., Praveen, M. P. B., Chandra, S. R., Rao, N. J., & Sahoo, D. (2026). Personalization at Scale: AI's Impact on Retail Customer Loyalty. Canadian Journal of Marketing Research, 16(1), 35-40.

Xiao, M., Gan, W., Yue, Q., Hashim, F. B., & Mohammed, T. A. Understanding the Loyalty Effects of AI-driven Personalisation: Consumer Engagement as a Mediator and Algorithmic Trust as a Boundary Condition.

Zed, E. Z., Kartini, T. M., & Purnamasari, P. (2024). The Power Of Personalization: Exploring The Impact Of Ai-Driven Marketing Strategies On Consumer Loyalty In E-Commerce. Jurnal Ekonomi, 13(04), 1303-1314.