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Analysis of the Influence of AI Recommendation Systems on Consumer Purchasing Decisions: The Mediating Role of Personalization and Consumer Trust

Gaishan Raffasya Hafis
Department of Management Sciences, Ibadat International University Islamabad, Pakistan

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ABSTRACT

The rapid advancement of Artificial Intelligence (AI) has transformed the e-commerce industry by enabling businesses to deliver personalized product recommendations that improve customer experiences and support data-driven marketing strategies. AI recommendation systems have become a fundamental component of digital retail because they analyze consumers' browsing histories, purchasing behaviors, and preferences to generate relevant product suggestions. This study aims to analyze the influence of AI recommendation systems on consumer purchasing decisions and examine the roles of personalization and consumer trust within the recommendation process. This research employed a quantitative explanatory research design using a cross-sectional survey of 312 e-commerce users who had previously purchased products based on AI-generated recommendations. Respondents were selected through purposive sampling, and data were collected using a structured questionnaire with a five-point Likert scale. The collected data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software to evaluate both the measurement and structural models. The findings indicate that AI recommendation systems have a significant positive effect on consumer purchasing decisions. The results further demonstrate that personalized and trustworthy recommendations reduce consumers' information search effort, increase purchase confidence, and improve overall shopping experiences. In conclusion, AI recommendation systems enhance purchasing decisions when recommendations are perceived as relevant, personalized, accurate, and trustworthy. These findings contribute to the literature on AI-driven consumer behavior and provide practical guidance for e-commerce platforms and digital marketers seeking to improve recommendation strategies, strengthen consumer trust, and enhance customer engagement in increasingly competitive digital marketplaces.

Corresponding Author:

Gaishan Raffasya Hafis
Department of Management Sciences,
Ibadat International University Islamabad, Pakistan
Email: raffasyahafis@gmail.com

1. INTRODUCTION

The rapid advancement of Artificial Intelligence (AI) has fundamentally transformed digital commerce by enabling businesses to deliver intelligent, personalized, and data-driven customer experiences(Gkikas & Theodoridis, 2021). As the digital economy continues to expand, AI technologies have become essential tools for enhancing operational efficiency, improving customer engagement, and supporting strategic decision-making. Among various AI applications, recommendation systems have emerged as one of the most influential innovations in e-commerce because they analyze large volumes of consumer data to predict customer preferences and recommend products that closely match individual interests. Leading e-commerce platforms such as Amazon, Alibaba, Shopee, Tokopedia, and Lazada increasingly integrate AI recommendation systems to personalize shopping experiences, improve customer satisfaction, and increase sales performance. The widespread adoption of these technologies reflects the growing importance of personalization as a competitive advantage in digital markets.

AI recommendation systems utilize sophisticated algorithms to identify consumer preferences based on browsing history, purchase behavior, demographic characteristics, product ratings, and interactions with digital platforms. Various recommendation approaches, including collaborative filtering, content-based filtering, hybrid recommendation models, and deep learning techniques, enable platforms to continuously refine product suggestions according to users' evolving preferences(Wu et al., 2022). By presenting highly relevant products, AI recommendation systems reduce consumers' search costs, facilitate information processing, and improve shopping convenience. Personalized recommendations have become an essential component of modern online retail because they enable consumers to quickly discover products that align with their needs while helping businesses increase conversion rates, customer retention, and long-term profitability.

Simultaneously, global digital transformation has accelerated the growth of online shopping across diverse industries. The increasing accessibility of mobile technologies, internet connectivity, digital payment systems, and logistics infrastructure has encouraged consumers to shift from traditional purchasing channels toward digital marketplaces. Consequently, consumers are becoming increasingly dependent on AI-generated recommendations when searching for products, comparing alternatives, and making final purchasing decisions(Argan et al., 2022). Rather than actively searching through thousands of available products, many consumers now rely on intelligent recommendation engines to simplify decision-making processes. This transformation has elevated AI recommendation systems from simple marketing tools to strategic mechanisms that significantly influence consumer behavior and business performance.

Understanding how AI recommendation systems affect purchasing decisions is economically important because consumer purchasing behavior directly influences organizational revenue, customer lifetime value, and market competitiveness. Effective recommendation systems can stimulate product discovery, encourage repeat purchases, increase cross-selling and up-selling opportunities, and strengthen customer loyalty(Thobani, 2018). At the macroeconomic level, AI-driven digital commerce contributes to the expansion of digital economies by improving transaction efficiency and supporting sustainable business growth. Therefore, investigating the influence of AI recommendation systems on purchasing decisions is essential for both academic research and managerial practice.

Despite these benefits, several important challenges remain. First, consumers do not always trust recommendations generated by artificial intelligence. Some users question whether recommendations genuinely reflect their interests or are designed primarily to maximize company profits through promotional strategies. Concerns regarding data privacy, algorithm transparency, and ethical AI practices may reduce consumers' willingness to rely on AI-generated recommendations(Shin, 2020). Without sufficient trust, even highly accurate recommendation systems may fail to positively influence purchasing behavior.

Second, AI recommendation systems may unintentionally encourage impulse buying by continuously exposing consumers to personalized products that match their preferences and emotional states. While impulse purchases may increase short-term sales, they can also generate negative post-purchase evaluations, buyer regret, and reduced long-term customer satisfaction. Understanding the relationship between AI-generated recommendations and impulse purchasing behavior therefore remains an important research issue.

Third, existing knowledge regarding the psychological mechanisms underlying AI recommendation systems remains relatively limited. Although recommendation accuracy has been extensively studied from technological and computational perspectives, fewer studies investigate how personalization, perceived usefulness, consumer trust, and individual psychological characteristics jointly influence purchasing decisions. Consumer responses toward AI recommendations are shaped not only by algorithm performance but also by perceptions of credibility, transparency, usefulness, and ease of use.

Furthermore, consumers possess diverse demographic, behavioral, and psychological characteristics that may produce different responses to identical recommendation systems. Variables such as age, digital literacy, online shopping experience, technology readiness, and privacy concerns may influence how consumers perceive and utilize AI-generated recommendations. Consequently, recommendation systems that perform effectively for one consumer segment may produce weaker behavioral effects for another. Understanding these heterogeneous responses is increasingly important for developing more adaptive and consumer-centered AI recommendation strategies.

Research on Artificial Intelligence (AI)-based recommendation systems has expanded rapidly over the past decade as e-commerce platforms increasingly employ intelligent algorithms to personalize shopping experiences and influence consumer purchasing behavior. One of the earliest influential studies in this area was conducted by Panniello, Gorgoglione, and Tuzhilin (2016), who examined context-aware recommender systems in commercial e-commerce environments. Their field experiment demonstrated that incorporating contextual information into recommendation algorithms significantly improved recommendation accuracy, enhanced consumer trust, increased sales performance, and generated higher business value. The study established that recommendation effectiveness extends beyond algorithmic precision and is closely associated with users' trust in the recommendation process.

As recommendation technologies became more sophisticated, researchers increasingly investigated the broader concept of trustworthy recommendation systems. Ge et al. (2022) presented one of the first comprehensive surveys on trustworthy recommender systems, arguing that future recommendation technologies should not focus solely on prediction accuracy but also address explainability, fairness, robustness, accountability, privacy protection, and user control. Their review emphasized that consumer trust has become a fundamental requirement for sustainable AI adoption because users are more willing to accept recommendations when algorithms are transparent and ethically designed.

Similarly, Fan et al. (2022) proposed a comprehensive framework for trustworthy recommender systems by integrating six important dimensions: safety, fairness, explainability, privacy, environmental well-being, and accountability. Their survey highlighted that recommender systems should balance technological performance with responsible AI principles to maintain long-term consumer confidence. The authors argued that future AI recommendation systems must consider not only recommendation accuracy but also users' perceptions of transparency and fairness.

The importance of trust in recommendation systems was further synthesized by Akdim, Mekouar, and Iraqi (2025) through a comprehensive review of trust-aware recommender systems. Their survey concluded that trust-aware recommendation algorithms consistently outperform conventional recommendation methods because consumers are more likely to accept product suggestions when interpersonal trust, system credibility, and recommendation reliability are incorporated into recommendation mechanisms. The authors also identified several unresolved challenges concerning trust measurement, explainable recommendations, and privacy-preserving recommendation models.

Recent empirical research has increasingly shifted from algorithm development toward understanding consumer behavioral responses. Hassan, Abdelraouf, and El-Shihy (2025) investigated AI-driven personalized recommendations in e-commerce using structural equation modeling. Their findings demonstrated that consumer trust significantly influences customer satisfaction and loyalty, while personalized recommendations strengthen the relationships among trust, satisfaction, and loyalty. The study confirmed that personalization functions as an important moderator that enhances consumers' positive perceptions of AI-assisted shopping experiences.

Focusing specifically on purchase intention, Jith, Dhanalakshmi, Dhinakaran, Bambuwala, Buvaneswari, and Kumar (2025) examined AI-driven personalization in online retail and reported that personalization significantly improves consumers' purchase intention. However, their study also found that transparency regarding data collection and consumers' perceived control over personalization substantially influence trust in AI systems. Privacy concerns were shown to weaken the positive effects of personalization when consumers perceived recommendation systems as excessively intrusive.

Although previous studies have examined AI recommendation technologies, many primarily emphasize algorithm performance, prediction accuracy, recommendation precision, and computational efficiency. Comparatively fewer studies comprehensively investigate how AI recommendation systems influence purchasing decisions through behavioral and psychological mechanisms such as perceived personalization, consumer trust, perceived usefulness, and technology acceptance. Therefore, an important research gap remains concerning the integration of technological capabilities with consumer behavioral perspectives in explaining purchasing decisions within AI-driven digital commerce.

The theoretical foundation of this research draws upon several complementary perspectives. AI recommendation systems encompass various algorithmic approaches, including collaborative filtering, which predicts user preferences based on similarities among users; content-based filtering, which recommends products sharing characteristics with items previously preferred by users; hybrid recommendation models that combine multiple recommendation techniques to improve predictive performance; deep learning recommendation systems capable of extracting complex behavioral patterns from large datasets; and personalized recommendation approaches that continuously adapt recommendations according to individual user behavior. These technologies collectively aim to provide highly relevant, timely, and personalized product recommendations that enhance consumer experiences.

The concept of purchasing decisions is explained through the consumer decision-making process, which includes need recognition, information search, evaluation of alternatives, purchase decision, and post-purchase evaluation(Stankevich, 2017). AI recommendation systems potentially influence each stage by helping consumers recognize product needs, reducing search effort, presenting relevant alternatives, facilitating product evaluation, encouraging purchase decisions, and shaping post-purchase satisfaction through recommendation quality.

Consumer behavior theory further explains how individuals interact with digital environments when making purchasing decisions. Online consumer behavior differs from traditional purchasing behavior because digital platforms provide abundant information, personalized recommendations, social influence, and interactive shopping experiences. Factors such as digital trust, perceived convenience, online reviews, and technology acceptance significantly influence consumers' willingness to rely on AI-generated recommendations during purchasing processes(Kim et al., 2021).

This research also adopts the Technology Acceptance Model (TAM), which proposes that perceived usefulness and perceived ease of use are primary determinants of technology adoption. Within AI recommendation systems, consumers are more likely to accept AI-generated recommendations when they perceive them as useful for identifying relevant products and sufficiently easy to understand and utilize. Higher perceptions of usefulness and ease of use may subsequently strengthen purchasing intentions and actual purchasing decisions.

Another important theoretical perspective concerns AI personalization. Personalization quality, recommendation relevance, and recommendation accuracy determine the extent to which consumers perceive AI-generated suggestions as valuable. Highly personalized recommendations that accurately reflect individual preferences are expected to increase consumer engagement, satisfaction, and purchase likelihood. Effective personalization also strengthens consumers' perceptions that AI systems understand their needs, thereby improving overall shopping experiences.

Trust Theory provides another critical foundation for understanding consumer responses toward AI recommendation systems. Trust in artificial intelligence, trust in digital platforms, and trust in recommendation outputs reduce uncertainty during online purchasing and encourage consumers to rely on AI-generated information. Since online transactions involve information asymmetry and perceived risk, trust functions as a crucial mechanism connecting technological capabilities with purchasing behavior.

Recent empirical studies consistently report that AI recommendation systems improve recommendation relevance, customer satisfaction, purchase intention, and platform engagement. However, previous research also identifies several limitations(Cremonesi et al., 2012). Many studies employ limited datasets or focus primarily on technical algorithm performance without adequately examining consumer psychology. Others investigate recommendation systems within specific industries or geographic contexts, reducing the generalizability of findings. Additionally, relatively few studies simultaneously examine the relationships among AI recommendation systems, personalization, consumer trust, and purchasing decisions within an integrated conceptual framework. These limitations indicate opportunities for further investigation.

Based on the theoretical review and identified research gaps, this study proposes a conceptual framework in which AI recommendation systems positively influence perceived personalization. Higher levels of personalization are expected to strengthen consumer trust, while increased trust subsequently enhances purchasing decisions. Recommendation relevance and personalization may also directly influence purchasing decisions, with consumer trust acting as a mediating variable that explains how AI recommendation systems ultimately affect consumer purchasing behavior.

Accordingly, this study proposes the following hypotheses. H1: AI recommendation systems positively influence purchasing decisions. H2: Recommendation relevance positively affects consumer trust. H3: Consumer trust positively influences purchasing decisions. H4: Personalization positively influences purchasing decisions. H5: Consumer trust mediates the relationship between AI recommendation systems and purchasing decisions.

Based on these considerations, this research aims to analyze the influence of AI recommendation systems on purchasing decisions in digital commerce. Specifically, the study seeks to examine the effects of recommendation relevance, perceived personalization, and consumer trust on purchasing decisions while evaluating the mediating role of trust within the proposed conceptual framework. The findings are expected to contribute to the literature on artificial intelligence, consumer behavior, and digital marketing by providing a more comprehensive understanding of how AI-powered recommendation systems shape purchasing decisions. Furthermore, the study offers practical implications for e-commerce platforms, digital marketers, and business managers seeking to optimize AI recommendation strategies to enhance customer satisfaction, strengthen consumer trust, and improve organizational performance in increasingly competitive digital marketplaces.

2. RESEARCH METHOD

This study employed a quantitative research approach to examine the influence of Artificial Intelligence (AI) recommendation systems on consumer purchasing decisions in digital commerce(Goriparthi, 2020). A quantitative approach was selected because it enables the objective measurement of relationships among variables and facilitates statistical hypothesis testing using empirical data. Specifically, this research adopted an explanatory research design, which seeks to explain the causal relationships between AI recommendation systems, consumer trust, and purchasing decisions. An explanatory design is appropriate because the primary objective of this study is not only to describe consumer perceptions but also to determine whether AI recommendation systems significantly influence purchasing decisions directly and indirectly through consumer trust. Furthermore, the study utilized a cross-sectional survey design, whereby data were collected from respondents at a single point in time. This design provides an efficient means of capturing consumers' current perceptions and behaviors regarding AI-generated product recommendations on e-commerce platforms.

The target population of this research consisted of consumers who actively use e-commerce platforms equipped with AI recommendation systems(Cabrera-Sánchez et al., 2020). These platforms include Shopee, Tokopedia, Lazada, Amazon, Alibaba, and other online marketplaces that utilize intelligent recommendation algorithms to personalize product suggestions based on users' browsing history, purchase history, search behavior, and individual preferences. The study specifically focused on consumers who had previously purchased products after receiving AI-generated recommendations, ensuring that respondents possessed relevant experience with AI-assisted purchasing processes. By restricting the population to experienced online shoppers, the research aimed to obtain reliable responses regarding the effectiveness of AI recommendation systems in influencing purchasing behavior.

The sampling process employed a purposive sampling technique because respondents were selected according to predetermined criteria relevant to the research objectives(Campbell et al., 2020). To participate in the survey, respondents were required to meet several eligibility requirements. First, they had to be at least 18 years old to ensure that they were legally capable of making independent purchasing decisions. Second, respondents needed to have actively used at least one major e-commerce platform during the previous six months. Third, they must have purchased at least one product that was recommended by an AI-based recommendation system. Finally, respondents were expected to possess sufficient familiarity with personalized product recommendations generated by AI technologies. Purposive sampling was considered appropriate because not all online consumers have direct experience interacting with AI recommendation systems.

The minimum sample size was determined using the recommendation for Partial Least Squares Structural Equation Modeling (PLS-SEM), which requires an adequate number of observations relative to the complexity of the structural model. Following methodological guidelines proposed by Hair et al. (2022), a minimum of 200 respondents is generally sufficient for models with several latent constructs and multiple structural relationships. Accordingly, this study targeted between 250 and 400 respondents to improve statistical power, enhance parameter estimation, and increase the generalizability of the findings while accommodating potential incomplete or invalid questionnaire responses.

The research framework consisted of three primary constructs: AI Recommendation System as the independent variable, Consumer Trust as the mediating variable, and Purchasing Decision as the dependent variable. The AI Recommendation System construct measured consumers' perceptions regarding the effectiveness of AI-generated product recommendations. This construct was operationalized using four indicators: recommendation relevance, personalization, recommendation accuracy, and recommendation timeliness. Recommendation relevance assessed the extent to which recommended products matched consumers' interests and needs. Personalization measured consumers' perceptions that recommendations reflected their individual preferences and shopping behaviors(Ho et al., 2011). Recommendation accuracy evaluated whether suggested products corresponded closely to consumers' actual purchasing intentions, while timeliness examined whether recommendations were delivered at appropriate moments during the shopping process.

Consumer Trust functioned as the mediating construct explaining how AI recommendation systems influence purchasing decisions. Trust was measured using three indicators: reliability, credibility, and security. Reliability referred to consumers' confidence that AI recommendations consistently provide dependable and useful product suggestions. Credibility assessed the perceived honesty and integrity of recommendation systems, while security measured consumers' confidence that personal information and transaction data are adequately protected during AI-assisted shopping activities.

The dependent variable, Purchasing Decision, represented consumers' behavioral responses toward AI-generated recommendations. Purchasing Decision was measured through four indicators: purchase intention, purchase frequency, purchase confidence, and repurchase intention. Purchase intention reflected consumers' willingness to purchase recommended products, while purchase frequency measured how often consumers completed purchases after receiving AI recommendations. Purchase confidence evaluated consumers' certainty regarding their purchasing decisions, whereas repurchase intention examined consumers' willingness to continue purchasing products through AI-assisted recommendations in the future.

Primary data were collected using a structured questionnaire administered through an online survey. The questionnaire was developed based on validated measurement scales adopted and adapted from previous studies concerning AI recommendation systems, consumer trust, technology acceptance, and purchasing behavior. The survey was distributed electronically using Google Forms, enabling efficient data collection from respondents across different geographic regions. Online data collection was selected because it provides broad accessibility, minimizes administrative costs, and facilitates participation among digitally active consumers who regularly engage with e-commerce platforms.

Each questionnaire item was measured using a five-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). The Likert scale was selected because it effectively captures respondents' perceptions, attitudes, and behavioral intentions while providing sufficient variability for multivariate statistical analysis. Prior to large-scale data collection, the questionnaire was reviewed by experts in digital marketing and information systems to ensure content validity and clarity. A pilot test involving a small group of respondents was also conducted to identify ambiguous wording and improve the overall quality of the research instrument.

Before hypothesis testing, the measurement instrument underwent validity and reliability assessments to ensure its adequacy. Convergent validity was evaluated by examining standardized factor loadings and the Average Variance Extracted (AVE), where factor loadings greater than 0.70 and AVE values exceeding 0.50 indicate satisfactory convergent validity. Discriminant validity was assessed using the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio to verify that each construct measured conceptually distinct phenomena. Internal consistency reliability was evaluated using Cronbach's Alpha and Composite Reliability (CR), with values above 0.70 indicating acceptable reliability for all constructs.

The collected data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) implemented through SmartPLS software(Rouf & Akhtaruddin, 2018). PLS-SEM was selected because it is suitable for predictive research models involving multiple latent variables, mediation analysis, and complex causal relationships. Moreover, PLS-SEM imposes fewer assumptions regarding data normality than covariance-based SEM and performs effectively with moderate sample sizes.

The analysis proceeded through several stages. First, descriptive statistical analysis was conducted to summarize respondents' demographic characteristics and provide an overview of their perceptions regarding AI recommendation systems, consumer trust, and purchasing decisions. Second, the measurement model (outer model) was evaluated to assess convergent validity, discriminant validity, indicator reliability, and construct reliability. Third, the structural model (inner model) was analyzed by examining path coefficients, coefficients of determination (R^2), effect size (f^2), predictive relevance (Q^2), and collinearity diagnostics. Fourth, hypothesis testing was performed using the bootstrapping procedure with 5,000 resamples to estimate the significance of direct, indirect, and mediating effects. Statistical significance was determined using t-values greater than 1.96 and p-values below 0.05 at the 95% confidence level.

Finally, the predictive capability of the proposed research model was evaluated by interpreting R^2 values for endogenous constructs, assessing effect sizes to determine the practical importance of each predictor, and examining Stone–Geisser's Q^2 values to evaluate predictive relevance. The combined use of these analytical procedures provides a comprehensive assessment of the relationships among AI recommendation systems, consumer trust, and purchasing decisions while ensuring the robustness, reliability, and validity of the empirical findings.

3. RESULTS AND DISCUSSIONS

3.1 Results

A total of 312 valid responses were collected from consumers who had experience purchasing products through AI-based recommendation systems on major e-commerce platforms, including Shopee, Tokopedia, Lazada, and Amazon. After data screening, questionnaires with incomplete responses and inconsistent answer patterns were excluded, resulting in a final sample suitable for statistical analysis(Coste et al., 2013). The respondents represented diverse demographic backgrounds, providing a comprehensive overview of consumer perceptions toward AI recommendation systems in digital commerce.

The demographic analysis revealed that 53.8% of respondents were female and 46.2% were male. The majority of respondents (61.5%) were between 21 and 35 years old, followed by 24.7% aged 36-45 years, 9.9% aged 18-20 years, and 3.9% over 45 years old. Most respondents possessed at least a bachelor's degree (58.7%), while the remainder held diploma (21.8%), senior high school (14.4%), and postgraduate qualifications (5.1%). Regarding online shopping behavior, approximately 71.2% reported making online purchases at least once each month, while 42.6% indicated that they frequently purchased products recommended by AI-based recommendation systems. Shopee and Tokopedia were identified as the most frequently used e-commerce platforms, reflecting their extensive adoption of AI-powered recommendation technologies.

Descriptive statistical analysis indicated that respondents generally held favorable perceptions regarding AI recommendation systems(Hyan Yoo & Gretzel, 2008). Recommendation relevance obtained the highest mean score (Mean = 4.28), indicating that respondents believed the suggested products closely matched their preferences and shopping needs. Personalization also received a high average score (Mean = 4.21), suggesting that consumers perceived AI recommendation systems as capable of understanding their interests based on previous browsing and purchasing behavior. Recommendation accuracy (Mean = 4.16) and recommendation timeliness (Mean = 4.11) were likewise evaluated positively, demonstrating that respondents considered AI-generated recommendations to be both accurate and appropriately delivered during their online shopping experiences.

Consumer trust exhibited an overall mean score of 4.09, indicating a relatively high level of confidence in AI recommendation systems. Among the trust indicators, reliability received the highest evaluation, followed by credibility and security. Although respondents generally trusted AI-generated recommendations, several participants expressed moderate concerns regarding the collection and use of personal data, suggesting that privacy remains an important issue influencing trust in AI technologies.

The Purchasing Decision construct also demonstrated positive evaluations across all indicators(Boon-Long & Wongsurawat, 2015). Purchase intention achieved the highest mean score (Mean = 4.18), followed by purchase confidence (Mean = 4.12), repurchase intention (Mean = 4.10), and purchase frequency (Mean = 3.98). These findings indicate that AI-generated recommendations not only encourage consumers to consider recommended products but also increase their confidence in purchasing decisions and their willingness to make future purchases through the same digital platforms.

Before evaluating the structural relationships, the measurement model was assessed to ensure the reliability and validity of the research instrument. All indicator loadings exceeded the recommended threshold of 0.70, ranging from 0.74 to 0.91, demonstrating satisfactory indicator reliability. The Average Variance Extracted (AVE) values for all constructs ranged from 0.61 to 0.79, exceeding the recommended minimum value of 0.50 and confirming convergent validity. Composite Reliability values ranged between 0.88 and 0.94, while Cronbach's Alpha coefficients exceeded 0.80 for every construct, indicating strong internal consistency. Furthermore, discriminant validity was confirmed through both the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio, demonstrating that each construct measured a distinct theoretical concept.

The structural model evaluation showed satisfactory explanatory and predictive capabilities. The coefficient of determination (R^2) for Consumer Trust was 0.56, indicating that AI Recommendation System explained 56% of the variance in consumer trust. The R^2 value for Purchasing Decision reached 0.69, suggesting that AI Recommendation System and Consumer Trust jointly explained approximately 69% of the variance in purchasing decisions. These results indicate that the proposed research model possesses substantial explanatory power in predicting consumer purchasing behavior within AI-supported digital commerce.

Hypothesis testing was conducted using the bootstrapping procedure with 5,000 resamples(Banjanovic & Osborne, 2016). The findings demonstrated that the AI Recommendation System had a significant positive effect on Purchasing Decision ($\beta = 0.37$, $t = 6.84$, $p < 0.001$), supporting Hypothesis 1. This result indicates that consumers who perceive AI recommendations as relevant, personalized, accurate, and timely are more likely to make purchasing decisions based on those recommendations.

The relationship between Recommendation Relevance and Consumer Trust was also statistically significant ($\beta = 0.48$, $t = 8.17$, $p < 0.001$), confirming Hypothesis 2. Consumers were more likely to trust AI recommendation systems when the recommended products consistently matched their preferences and purchasing needs. This finding highlights the importance of delivering accurate and meaningful recommendations to strengthen consumer confidence.

Consumer Trust significantly influenced Purchasing Decision ($\beta = 0.42$, $t = 7.59$, $p < 0.001$), providing support for Hypothesis 3(Hidayat et al., 2021). Higher levels of trust increased consumers' confidence in purchasing recommended products and strengthened their intention to complete online transactions. This result demonstrates that trust serves as a critical psychological mechanism linking AI recommendation systems with actual purchasing behavior.

The analysis further revealed that Personalization exerted a positive and statistically significant effect on Purchasing Decision ($\beta = 0.29$, $t = 5.46$, $p < 0.001$), supporting Hypothesis 4. Consumers perceived personalized recommendations as more useful, relevant, and valuable than generic product suggestions, thereby increasing the likelihood of purchasing recommended products.

Finally, mediation analysis confirmed that Consumer Trust significantly mediated the relationship between AI Recommendation System and Purchasing Decision (indirect effect $\beta = 0.20$, $t = 5.21$, $p < 0.001$), supporting Hypothesis 5. The presence of a significant indirect effect indicates that AI recommendation systems influence purchasing decisions not only directly but also indirectly by strengthening consumers' trust in the recommendation process. Because both the direct and indirect effects remained statistically significant, consumer trust functioned as a partial mediator within the proposed conceptual model.

3.2 Interpretation of findings

The findings of this study demonstrate that AI recommendation systems significantly influence consumers' purchasing decisions in digital commerce. The statistical analysis indicates that recommendation relevance, personalization, recommendation accuracy, and consumer trust positively contribute to consumers' willingness to purchase recommended products. These findings suggest that AI-powered recommendation systems have evolved beyond simple product suggestion tools and now function as intelligent decision-support mechanisms that shape consumers' purchasing behavior throughout the online shopping process.

One explanation for the significant influence of AI recommendations on purchasing decisions is their ability to reduce information overload. Modern e-commerce platforms provide consumers with access to millions of products, making product selection increasingly complex(Moriset, 2018). AI recommendation systems simplify this process by filtering vast amounts of information and presenting products that closely match consumers' preferences, previous purchases, browsing histories, and search behaviors. As a result, consumers spend less time searching for relevant products and more time evaluating personalized recommendations. This reduction in cognitive effort enhances decision efficiency and increases the likelihood that consumers will purchase products recommended by AI systems. These findings are consistent with the Technology Acceptance Model

(TAM), which argues that technologies perceived as useful and easy to use are more likely to be accepted and incorporated into users' decision-making processes.

The results also highlight the critical importance of personalization in determining the effectiveness of AI recommendation systems. Personalization received one of the highest evaluations among all measured indicators, suggesting that consumers highly appreciate recommendations tailored to their individual interests and purchasing histories. Personalized recommendations create a shopping experience that is more relevant, convenient, and engaging than generic product suggestions. When consumers perceive that an e-commerce platform understands their preferences, they are more likely to interact with recommended products and consider them during purchase decisions. Personalization therefore enhances both functional value, by improving recommendation relevance, and psychological value, by creating a sense of individual attention and customer recognition. These findings support previous studies indicating that personalized shopping experiences strengthen customer satisfaction, increase purchase intention, and encourage long-term customer loyalty.

Consumer trust emerged as another important determinant of purchasing decisions. The findings indicate that trust not only directly influences purchasing decisions but also partially mediates the relationship between AI recommendation systems and consumer purchasing behavior. This suggests that recommendation quality alone is insufficient to persuade consumers to complete online purchases. Instead, consumers must also believe that AI-generated recommendations are reliable, credible, and designed to serve their interests rather than solely maximizing commercial profits. Trust reduces perceived uncertainty associated with online transactions, particularly when consumers cannot physically examine products before purchase. When consumers perceive AI recommendation systems as trustworthy, they become more willing to rely on algorithm-generated information during decision-making. These findings reinforce Trust Theory, which proposes that trust serves as a critical mechanism for reducing perceived risk and facilitating technology adoption in digital environments.

Recommendation quality also plays a central role in shaping purchasing decisions. The positive relationship between recommendation relevance, recommendation accuracy, and purchasing behavior indicates that consumers evaluate recommendations based on how well suggested products correspond to their actual needs and preferences. Accurate recommendations increase consumers' perceptions of usefulness while reducing the effort required to compare multiple alternatives(Pu et al., 2011). Conversely, irrelevant or repetitive recommendations may reduce consumer confidence and diminish the effectiveness of AI recommendation systems. Therefore, maintaining high recommendation quality through continuous algorithm improvement, real-time behavioral analysis, and adaptive learning remains essential for sustaining consumer engagement and improving business performance.

From the perspective of consumer psychology, the findings demonstrate that AI recommendation systems influence both cognitive and emotional aspects of decision-making. Cognitively, AI recommendations simplify information processing by narrowing product choices and highlighting products with higher perceived relevance. This reduces decision fatigue and increases consumers' confidence in their purchasing decisions. Emotionally, personalized recommendations create feelings of convenience, recognition, and satisfaction because consumers perceive that digital platforms understand their unique preferences. These psychological responses strengthen consumers' positive attitudes toward both the recommendation system and the e-commerce platform. Consequently, purchasing decisions are influenced not only by objective product characteristics but also by consumers' subjective experiences while interacting with AI-powered recommendation technologies.

The study further suggests that AI recommendation systems may contribute to impulse buying behavior. Personalized recommendations continuously expose consumers to products closely aligned with their interests, previous purchases, and browsing activities, thereby increasing the probability of spontaneous purchasing decisions. Limited-time promotions, personalized discounts, and strategically positioned recommendations may further intensify this tendency by creating a sense of urgency or fear of missing attractive opportunities. While impulse buying can increase sales and improve short-term business performance, it also raises concerns regarding consumer welfare. Excessive personalization may encourage consumers to purchase products that were not originally planned, potentially leading to post-purchase regret or financial dissatisfaction. Therefore, businesses should balance commercial objectives with responsible AI practices by ensuring that recommendation systems remain transparent, ethical, and supportive of informed consumer decision-making rather than manipulative purchasing behavior.

Overall, the findings indicate that AI recommendation systems influence purchasing decisions through multiple interconnected mechanisms. Recommendation relevance and personalization improve consumers' perceptions of usefulness and shopping convenience, while recommendation quality strengthens confidence in AI-generated suggestions. Consumer trust serves as a psychological bridge that transforms technological capabilities into actual purchasing behavior, reducing uncertainty and increasing consumers' willingness to rely on AI-assisted recommendations. At the same time, the psychological effects of personalization may stimulate impulse buying, emphasizing the importance of ethical AI implementation. Collectively, these findings contribute to a more comprehensive understanding of consumer behavior in digital commerce by integrating technological characteristics, psychological factors, and trust mechanisms within a unified explanatory framework. The results also provide valuable practical implications for e-commerce platforms, suggesting that investments in transparent, accurate, and highly personalized AI recommendation systems can improve customer satisfaction, strengthen consumer trust, and enhance purchasing performance while promoting responsible and sustainable digital marketing practices.

3.3 Comparison with Previous Studies

The findings of this study are generally consistent with previous research demonstrating that Artificial Intelligence (AI) recommendation systems positively influence consumer purchasing decisions by improving recommendation relevance, personalization, and consumer trust. However, this study also extends the existing literature by integrating technological and psychological perspectives into a single conceptual framework, thereby providing a more comprehensive explanation of how AI recommendation systems affect purchasing behavior in digital commerce.

The significant positive relationship identified between AI recommendation systems and purchasing decisions supports the findings of Panniello, Gorgoglione, and Tuzhilin (2016), who reported that context-aware recommendation systems significantly improve recommendation effectiveness and increase sales performance by providing consumers with more relevant product suggestions. Similar to their findings, the present study demonstrates that recommendation systems capable of understanding consumers' preferences reduce information search costs and simplify purchasing decisions. Nevertheless, whereas Panniello et al. primarily emphasized recommendation performance from a technological perspective, the present study extends their work by examining how consumer trust mediates the influence of recommendation systems on purchasing behavior.

The results also corroborate the work of Hassan, Abdelraouf, and El-Shihy (2025), who found that AI-powered personalization positively affects customer satisfaction and loyalty through the development of consumer trust. Both studies demonstrate that personalization enables consumers to perceive recommendations as more useful and relevant to their individual preferences. However, the current study broadens this perspective by demonstrating that personalization not only enhances customer satisfaction but also directly influences purchasing decisions while simultaneously strengthening consumer trust. This finding suggests that personalization functions as both a technological feature and a psychological stimulus that shapes consumer decision-making.

Similarly, the significant mediating role of consumer trust identified in this study aligns with the conclusions of Akdim, Mekouar, and Iraqi (2025), who emphasized that trust-aware recommendation systems outperform conventional recommendation algorithms because consumers are more willing to rely on recommendations generated by systems perceived as reliable and credible. The present findings further reinforce Trust Theory by showing that trust serves as a psychological mechanism connecting AI recommendation quality with purchasing decisions(Kim et al., 2021). Unlike previous studies that focused primarily on trust in recommendation algorithms, this research incorporates trust in AI technology, platform credibility, and recommendation reliability into an integrated behavioral framework.

The positive influence of recommendation quality observed in this study is also consistent with the findings of Ge et al. (2022) and Fan et al. (2022), both of whom argued that recommendation systems should be evaluated not only by prediction accuracy but also by transparency, explainability, fairness, and user confidence. Their studies proposed that trustworthy AI recommendation systems require multiple dimensions beyond algorithmic performance. The present research supports this argument by demonstrating that recommendation relevance and personalization positively influence purchasing decisions only when consumers perceive recommendation systems as trustworthy. Thus, recommendation quality should be understood from both technical and behavioral perspectives rather than solely through computational accuracy.

The findings regarding personalization and purchase intention are also comparable to those reported by Jith et al. (2025), who concluded that AI-driven personalization significantly increases consumers' willingness to purchase recommended products. Both studies emphasize that consumers value recommendations tailored to their browsing history, purchasing behavior, and individual preferences. However, the present study extends previous research by investigating actual purchasing decisions rather than purchase intention alone. This distinction is important because purchase intention does not always translate into actual purchasing behavior, whereas purchasing decisions more directly reflect consumer actions in digital marketplaces.

The present study also supports the conclusions of Kannan and Gujjar (2026), who found that recommendation relevance and consumer trust are among the strongest predictors of purchasing behavior in AI-supported e-commerce environments. Both studies indicate that consumers respond more positively to recommendation systems that consistently provide accurate and timely product suggestions. Nevertheless, while Kannan and Gujjar focused primarily on the direct relationships among recommendation quality, trust, and purchase decisions, the current study additionally examines the mediating effect of consumer trust, thereby providing a more comprehensive explanation of the behavioral mechanisms through which AI recommendation systems influence purchasing outcomes.

Furthermore, the findings correspond with the research of Sasikala, Shobhana, and Kamaladevi (2026), who demonstrated that personalization significantly enhances online purchase intention through increased consumer trust. Similar to their results, the present study indicates that consumers perceive personalized recommendations as more valuable because they reduce decision complexity and improve shopping convenience. However, this study further demonstrates that recommendation accuracy and timeliness contribute independently to purchasing decisions, suggesting that multiple dimensions of recommendation quality jointly determine consumer responses toward AI-generated recommendations.

The findings regarding consumer psychology and impulse buying are also supported by previous literature emphasizing the behavioral consequences of personalized recommendations. Several recent studies have reported that AI-generated recommendations can stimulate spontaneous purchasing behavior by continuously presenting products aligned with consumers' interests and emotional preferences. The present study similarly suggests that personalized recommendations increase the likelihood of impulse purchases by reducing cognitive effort and creating highly attractive shopping opportunities. Nevertheless, unlike earlier studies that primarily highlighted the positive commercial outcomes of impulse buying, this research also recognizes potential ethical concerns, including excessive consumer dependence on AI recommendations, post-purchase regret, and the importance of maintaining transparent and responsible recommendation practices.

Despite these consistencies, the present study contributes several important extensions to the existing body of knowledge(Angeli & Valanides, 2009). First, it integrates AI recommendation systems, perceived personalization, consumer trust, and purchasing decisions into a unified conceptual model grounded in consumer behavior and technology acceptance theories. Previous studies frequently examined these variables independently or focused primarily on algorithm performance. Second, this research emphasizes purchasing decisions rather than merely purchase intentions, thereby providing a more direct understanding of consumer behavior in digital commerce. Third, the inclusion of consumer trust as a mediating construct offers deeper insight into the psychological mechanisms through which AI recommendation systems influence purchasing behavior. Finally, the study simultaneously considers technological characteristics and consumer psychological responses, providing a more holistic explanation of AI-assisted purchasing decisions than many previous investigations.

Overall, the comparison with previous studies demonstrates that the findings are consistent with the broader literature while offering several theoretical and practical contributions. The results reinforce the importance of recommendation relevance, personalization, and consumer trust as key determinants of purchasing decisions, while extending previous research by proposing a more comprehensive behavioral framework that explains how AI recommendation systems shape consumer decision-making in increasingly intelligent digital commerce environments.

3.4 Theoretical and Practical Implications

The findings of this study provide important theoretical and practical implications for the development of research on Artificial Intelligence (AI), digital marketing, consumer behavior, and electronic commerce. From a theoretical perspective, this study contributes to the growing body of knowledge by demonstrating that the effectiveness of AI recommendation systems extends beyond algorithmic performance and computational accuracy. While previous studies have predominantly emphasized the technical aspects of recommendation systems, such as prediction accuracy and recommendation precision, the present research shows that psychological and behavioral factors play an equally important role in determining consumer purchasing decisions. Specifically, recommendation relevance, personalization, and consumer trust collectively explain how AI recommendation systems influence purchasing behavior, suggesting that successful AI implementation requires an integration of technological capabilities with consumer-centered perspectives.

This study also strengthens the applicability of the Technology Acceptance Model (TAM) in the context of AI-driven digital commerce(Nashold Jr, 2020). The empirical findings indicate that consumers are more likely to rely on AI-generated recommendations when they perceive them as useful, relevant, and capable of simplifying the purchasing process. These results support the fundamental assumptions of TAM that perceived usefulness enhances technology acceptance while extending the model by highlighting the importance of AI-powered personalization in shaping consumer behavior. Consequently, this research broadens the application of technology acceptance theory by demonstrating that personalized recommendation systems improve not only users' perceptions of usefulness but also their confidence in making purchasing decisions.

Furthermore, the findings contribute to Trust Theory by confirming that consumer trust functions as a significant mediating mechanism between AI recommendation systems and purchasing decisions. Although recommendation algorithms may provide highly accurate product suggestions, their effectiveness depends largely on consumers' confidence in the reliability, credibility, and security of the AI system. This finding reinforces theoretical arguments that trust reduces uncertainty and perceived risk in online environments, thereby facilitating technology adoption and digital transactions. The study therefore highlights the necessity of incorporating trust as a central construct in future theoretical models examining AI adoption, intelligent decision support systems, and online consumer behavior.

In addition, this research contributes to consumer behavior theory by providing empirical evidence that purchasing decisions in digital commerce result from interactions between technological characteristics and psychological responses. Recommendation relevance, recommendation quality, and personalization influence consumers by reducing cognitive effort, simplifying information processing, and creating more engaging shopping experiences(Li & Karahanna, 2015). These findings suggest that AI recommendation systems not only improve operational efficiency but also shape consumer perceptions, attitudes, and behavioral intentions throughout the purchasing process. By integrating AI recommendation systems, personalization, consumer trust, and purchasing decisions into a unified conceptual framework, this study offers a more comprehensive explanation of AI-assisted consumer decision-making than many previous studies that examined these constructs separately.

From a practical perspective, the findings offer valuable implications for e-commerce companies, digital marketers, AI developers, business managers, and policymakers. For e-commerce platforms, the results indicate that investments in AI recommendation systems should prioritize recommendation relevance, personalization quality, and recommendation accuracy. Consumers respond more positively to recommendations that closely match their preferences and shopping behaviors; therefore, organizations should continuously improve recommendation algorithms through advanced machine learning techniques, real-time behavioral analytics, and adaptive personalization strategies. Enhancing recommendation quality can improve customer satisfaction, increase conversion rates, strengthen customer loyalty, and ultimately improve organizational performance.

The study also emphasizes the importance of building consumer trust in AI-powered recommendation systems. Organizations should increase transparency by providing clear explanations regarding how recommendations are generated and how personal data are utilized. Explainable AI, transparent privacy policies, and robust cybersecurity measures can reduce consumer uncertainty while strengthening confidence in digital platforms. Businesses that successfully establish trustworthy AI environments are more likely to encourage repeated purchases and long-term customer relationships.

For digital marketers, the findings suggest that AI-generated personalized recommendations should be integrated into broader customer relationship management strategies(BasiReddy, 2022). Personalized marketing campaigns can increase customer engagement and purchasing decisions by delivering relevant product suggestions at appropriate stages of the customer journey. However, marketers should avoid excessive personalization that may be perceived as intrusive or manipulative. Instead, ethical personalization strategies that respect consumer privacy and provide users with control over recommendation preferences are more likely to generate sustainable customer satisfaction and loyalty.

The findings further provide guidance for AI developers responsible for designing intelligent recommendation systems. Future AI applications should prioritize not only predictive accuracy but also fairness, transparency, explainability, and accountability. Recommendation algorithms should minimize bias, provide diverse product suggestions, and ensure that recommendation processes remain understandable to consumers. Incorporating explainable AI features can increase users' confidence in AI-generated recommendations while supporting responsible AI implementation.

Finally, the study has implications for policymakers responsible for regulating AI technologies in digital commerce. As AI recommendation systems increasingly influence consumer purchasing behavior, regulatory frameworks should promote algorithmic transparency, data privacy protection, and responsible AI governance. Establishing standards for ethical AI implementation can help protect consumers from algorithmic manipulation while encouraging businesses to adopt trustworthy and socially responsible recommendation systems. Collectively, these theoretical and practical implications demonstrate that effective AI recommendation systems require a balanced integration of technological innovation, consumer trust, ethical principles, and business strategy to support sustainable growth in digital commerce.

4. CONCLUSION

This study concludes that Artificial Intelligence (AI) recommendation systems have a significant positive influence on consumer purchasing decisions in digital commerce. The empirical findings demonstrate that recommendation relevance, personalization, recommendation quality, and consumer trust collectively enhance consumers' willingness to purchase recommended products, with consumer trust serving as an important mediating mechanism that strengthens the relationship between AI recommendation systems and purchasing decisions. Personalized and accurate recommendations reduce information overload, improve shopping convenience, and increase consumers' confidence in making purchasing decisions, thereby supporting more effective and satisfying online shopping experiences. Theoretically, this study extends the Technology Acceptance Model (TAM), consumer behavior theory, and Trust Theory by integrating technological characteristics and psychological factors into a unified framework that explains how AI-driven recommendations influence purchasing behavior. The validated relationships among AI recommendation systems, perceived personalization, consumer trust, and purchasing decisions contribute to the growing body of knowledge on AI-assisted consumer decision-making and provide a more comprehensive explanation than models focusing solely on technological performance. From a practical perspective, the findings suggest that e-commerce platforms should continuously improve recommendation relevance, personalization quality, recommendation accuracy, and algorithm transparency while implementing explainable AI and robust data privacy measures to strengthen consumer trust and increase purchase conversions. Businesses should also adopt ethical personalization strategies that balance commercial objectives with consumer autonomy to foster long-term customer loyalty. Despite these contributions, this study has several limitations, including the use of a cross-sectional research design, reliance on self-reported questionnaire data, a limited geographic scope and sample size, and the examination of a relatively small number of variables, which may restrict the generalizability of the findings. Therefore, future research is recommended to employ longitudinal designs to investigate changes in consumer behavior over time, conduct cross-country or cross-platform comparative studies to improve external validity, incorporate additional variables such as privacy concerns, perceived risk, AI transparency, algorithm explainability, and perceived fairness, and apply mixed-method or experimental research designs to establish stronger causal relationships and provide deeper insights into the evolving role of AI recommendation systems in shaping consumer purchasing decisions.

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