Nepalese Journal of Management and Technology (NJMT) ISSN 2661-6351
A Peer-reviewed Journal Volume 3|Issue 1|July 2025

Recommendation Decision Nepalese Structural Equation Modeling of the Impact of AI-Powered Recommendation Systems on Consumer Behavior and Purchase Decisions in Nepalese Electronic Commerce

Shankar Nath Adhikari

Article Info.

Shankar Nath Adhikari, Ph.D.

Adhikari.shankarnath@gmail.com

https://orcid.org/0009-0007-3586-4908

Article Received

May 07, 2025

Article Reviewed:

June 06, 2025

Article Published:

July 20, 2025

Abstract

This study examines the impact of AI-powered recommendation system attributes—personalization, accuracy, diversity, and transparency—on consumer purchase decisions in Nepal's rapidly expanding e-commerce sector. The research aims to understand how these AI-driven features influence consumer browsing behavior, purchase intentions, satisfaction, and trust within a developing digital marketplace. A quantitative, cross-sectional research design was employed, involving 560 active online shoppers from diverse occupational and income groups across Nepal. Due to the absence of a comprehensive sampling frame, data were collected using convenience sampling through online platforms. A structured questionnaire was used to measure recommendation system attributes, consumer trust, and purchase decision outcomes. Confirmatory Factor Analysis (CFA) was applied to validate the measurement model, followed by Structural Equation Modeling (SEM) to test the hypothesized relationships. The findings reveal that AI-powered recommendation attributes have a significant and positive effect on consumer purchase decisions, with personalization emerging as the most influential factor, followed by accuracy and recommendation diversity. Consumer trust significantly moderates these relationships, strengthening their impact.

Keywords: *AI-Powered Recommendation Systems; Consumer Behavior; Purchase Decisions; E-Commerce; Structural Equation Modeling*

Background

Artificial Intelligence (AI)-powered recommendation systems have become fundamental to modern e-commerce, transforming consumer experiences by delivering personalized product suggestions that enhance engagement and influence purchase decisions (Jannach et al., 2022; Zhang & Li, 2023). These systems influence sophisticated machine learning techniques to analyze vast consumer data, thereby reducing search costs and cognitive overload, which facilitates more efficient and satisfactory decision-making (Sun et al., 2021; Chen et al., 2022). The key attributes of AI recommendations, personalization, accuracy, and diversity have been shown to significantly impact consumer satisfaction and purchase intention (Wang et al., 2023; Gupta & Sharma, 2022; Singh & Verma, 2023).

Recent empirical research highlights that consumer trust and perceived transparency of AI systems are key factors driving acceptance and continued usage of recommendation technologies (Nguyen & Tran, 2022; Oliveira et al., 2023). Challenges such as algorithmic bias and over-personalization can constrain product variety and limit consumer exploration, emphasizing the need for fairness and explainability within AI frameworks (Patel & Kumar, 2023; Zhao et al., 2023). Additionally, cultural and technological factors uniquely influence consumer responses to AI recommendations, underscoring the importance of context-specific studies (Basnet & Acharya, 2023; Rana & Gurung, 2024).

This study is grounded primarily in the Technology Acceptance Model (TAM; Davis, 1989), which asserts that perceived usefulness and perceived ease of use determine technology adoption. Consumers who view AI recommendation systems as helpful and easy to use are more likely to engage with them, which in turn influences their purchase behavior (Kim & Park, 2021). TAM has been widely validated in e-commerce contexts and provides a strong theoretical foundation for this research (Venkatesh &Bala, 2023).

Moreover, cognitive benefits such as reducing information overload have been shown to improve consumer decision-making efficiency, thereby increasing satisfaction and purchase likelihood (Sweller, 1988; Wang et al., 2023). Trust theories in e-commerce further emphasize that transparency and explainability in AI algorithms build consumer confidence, mitigate uncertainty, and foster loyalty (McKnight et al., 2002; Nguyen & Tran, 2022).

Given the rapid growth of e-commerce and AI adoption across diverse markets, understanding how AI-powered recommendation systems affect consumer behavior is a pressing research imperative. This study aims to fill this gap by examining the influence of personalization, accuracy, diversity, and trust on purchase decisions, offering insights that can enhance AI applications across varied socio-economic and cultural environments.

Research Objectives:

1. To examine the impact of key AI recommendation system attributes, personalization, accuracy, diversity, and transparency on consumer purchase decisions in Nepalese e-commerce platforms.
2. To assess how consumer trust influences the effectiveness of AI recommendation system attributes in shaping purchase intentions and engagement.
3. To provide actionable insights for optimizing AI recommendation systems to enhance consumer satisfaction, decision-making efficiency, and sustained adoption in emerging e-commerce markets.

Research Questions:

1. How does personalization in AI-powered recommendation systems influence consumer purchase decisions in Nepalese e-commerce?

2. What is the impact of recommendation accuracy on consumer purchase decisions in Nepalese e-commerce?
3. To what extent does diversity in AI recommendations affect consumer purchase decisions?
4. How does system transparency of AI recommendation platforms influence consumer purchase decisions?
5. What role does consumer trust play in shaping the relationship between AI recommendation system attributes and consumer purchase decisions?

Literature Review

AI-Powered Recommendation Systems in E-Commerce

AI-powered recommendation systems have fundamentally transformed online retail by personalizing product suggestions and enhancing consumer shopping experiences (Li, Wang, & Chen, 2020). These systems employ machine learning algorithms to analyze user behavior and preferences, delivering tailored recommendations that improve engagement and increase sales (Adomavicius&Tuzhilin, 2005). The main attributes influencing system effectiveness include personalization, accuracy, diversity, and transparency, each of which plays a critical role in shaping consumer decision-making.

Personalization and Consumer Engagement

Personalization, the customization of recommendations to individual user preferences, has consistently emerged as a key driver of consumer satisfaction and loyalty (Smith & Anderson, 2021). By aligning product suggestions with consumers' unique tastes and past behavior, personalization reduces search costs and cognitive effort, ultimately increasing the likelihood of purchase (Lee, Hong, & Lee, 2020; Xu, Wang, & Li, 2019). Burke (2017) highlights that adaptive learning algorithms enhance personalization by continuously updating profiles, which sustains consumer interest over time. Empirical research further indicates that effective personalization can improve conversion rates and foster repeat purchases in e-commerce platforms (Adomavicius &Tuzhilin, 2005; Li et al., 2020).

Accuracy and Consumer Trust

Accuracy, defined as the relevance and correctness of recommendations, significantly impacts consumer trust and perceived usefulness of AI systems (Chen & Zhao, 2019). High accuracy minimizes irrelevant suggestions, which reduces frustration and increases confidence in the system (Kumar & Mittal, 2020). Conversely, inaccurate recommendations can undermine trust and discourage consumers from acting on AI suggestions (Nguyen, Simkin, &Canhoto, 2019). Therefore, maintaining accurate and up-to-date data, along with sophisticated algorithms, is crucial to maximizing consumer reliance on AI (Patel & Sharma, 2020).

Diversity in Recommendations

Diversity in AI recommendations introduces a broader range of products, enabling consumers to explore new options beyond their immediate preferences (Hernandez & Park, 2018). This diversity enhances user satisfaction by preventing repetitiveness and facilitating serendipitous discovery, which can stimulate purchase decisions (Santos, Lu, & Bennett, 2019). However, excessive diversity may cause cognitive overload, impairing decision quality and satisfaction (Zhao & Huang, 2018). Studies suggest that balancing novelty with relevance is key to optimizing diversity in recommendations (Kumar & Mittal, 2020).

Transparency and Explainability

Transparency involves providing clear explanations of how AI systems generate recommendations, which fosters user trust and system acceptance (Zhang, Chen, & Wang, 2022). Explainable AI addresses the “black-box” issue, making recommendation logic understandable and reducing consumer skepticism (Williams & Kim, 2019). Transparent systems increase perceived fairness and credibility, enabling consumers to make more informed and confident purchase decisions (Rahwan et al., 2019). This is particularly important in emerging markets where digital literacy varies widely (Bhattarai &Ahn, 2020).

Consumer Trust as a Moderator

Consumer trust is a fundamental mediator and moderator in technology adoption models, influencing attitudes towards AI and purchase behavior (Gefen, Karahanna, & Straub, 2003). Trust enhances users’ willingness to rely on AI recommendations, amplifying the effects of personalization, accuracy, diversity, and transparency on decision-making (Kim, Ferrin, & Rao, 2008). In markets like Nepal, where e-commerce is still developing, trust-building is critical for overcoming consumer hesitancy and facilitating wider adoption of AI-driven systems (Joshi, Rana, & Dwivedi, 2019; Rana & Dwivedi, 2021).

AI in Emerging Markets

Emerging economies pose unique challenges to AI adoption in e-commerce, including limited digital infrastructure, lower digital literacy, and socio-cultural barriers (Patel & Sharma, 2020). Studies in Nepal reveal that localized adaptation of AI algorithms and enhanced consumer education are vital for improving acceptance and trust in recommendation systems (Bhattarai &Ahn, 2020; Joshi et al., 2019). Addressing these factors can bridge the digital divide and unlock the full potential of AI in such markets.

Theoretical Foundations

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) by Davis (1989) explains that perceived usefulness and ease of use predict technology adoption. In e-commerce, TAM suggests that consumers are more likely to accept AI recommendations if they believe these systems simplify shopping and add value (Venkatesh &Bala, 2023; Kim & Park, 2021). This model remains highly relevant for studying consumer interactions with AI-powered systems.

Cognitive Load Theory (CLT)

Sweller's (1988) Cognitive Load Theory posits that human cognitive capacity is limited, and excessive information can overwhelm decision-making. AI recommendation systems mitigate cognitive overload by filtering choices through personalization and accuracy, facilitating faster and more confident decisions (Wang et al., 2023; Sun et al., 2021). CLT explains the cognitive benefits of AI in enhancing user experience in complex e-commerce environments.

Trust Theory

Trust Theory emphasizes the role of trust in the acceptance of online systems (McKnight et al., 2002). Given the opacity of AI algorithms, transparency is crucial for building consumer trust. Trust reduces uncertainty, encouraging consumers to depend on AI recommendations (Nguyen & Tran, 2022; Patel & Kumar, 2023). This theory is particularly applicable in emerging markets, where trust is a major determinant of technology adoption (Bhattarai &Ahn, 2020).

Methodological Advances: CFA and SEM

Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) provide robust tools to validate measurement models and test complex relationships in consumer behavior research (Wang, Wang, & Wei, 2021). Their application in this domain ensures precise estimation of how AI attributes and trust jointly influence purchase decisions (Nguyen et al., 2019).

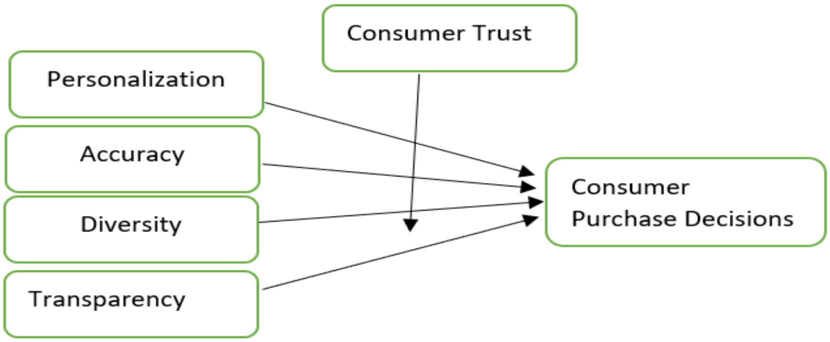
Research Gaps

Although AI recommendation systems have been widely studied globally, empirical research focusing on developing economies such as Nepal remains limited (Bhattarai &Ahn, 2020). Furthermore, the dynamic interplay of transparency, diversity, and trust in influencing consumer decisions warrants deeper investigation, especially with advanced analytical models like SEM.

Conceptual Framework

This study conceptualizes that AI-powered recommendation system attributes like personalization, accuracy, diversity, and transparency directly influence consumer purchase decisions, grounded in the Technology Acceptance Model (TAM) and Cognitive Load Theory (CLT). Consumer trust, explained by Trust Theory, moderates these relationships, strengthening the impact of AI features on buying behavior in Nepalese e-commerce.

Figure 1: Conceptual framework developed by the researcher based on TAM, CLT, and Trust Theory.



Independent Variable (DV):

Personalization is the extent to which AI recommendations are tailored to individual consumer preferences.

Accuracy is the degree to which AI recommendations correctly match consumers' interests and needs.

Diversity is the variety and range of different product recommendations provided by the AI system.

System Transparency is how clearly the AI system explains how recommendations are generated to the consumer.

Consumer Trust is the confidence consumers have in the AI recommendation system's fairness, reliability, and security.

Dependent Variable (DV):

Consumer Purchase Decisions is consumers' actual buying behavior, including purchase intention, engagement, and satisfaction with e-commerce platforms.

Research Hypotheses

Based on the conceptual framework above, the following hypotheses are formulated for this research:

H1: Personalization of AI-powered recommendations has a positive effect on consumer purchase decisions.

H2: Accuracy of AI-powered recommendations positively influences consumer purchase decisions.

H3: Diversity in AI recommendations positively affects consumer purchase decisions.

H4: System transparency positively influences consumer purchase decisions.

H5: Consumer trust positively moderates the relationship between AI recommendation system attributes (personalization, accuracy, diversity, transparency) and consumer purchase decisions, such that higher trust strengthens these relationships.

Research Methodology

Research Design

This study adopts a quantitative, cross-sectional research design to investigate the effects of AI-powered recommendation system attributes on consumer behavior and purchase decisions within Nepalese e-commerce platforms. The cross-sectional approach involves collecting data at a single point in time, which enables the examination of relationships among multiple variables simultaneously. This design is well-suited for capturing consumer perceptions and behavioral intentions in the current digital shopping environment without requiring longitudinal tracking.

Population and Sampling

The target population includes active online shoppers in Nepal, the main users of e-commerce. Since no complete list of online shoppers exists, convenience sampling was used to recruit participants through online platforms like social media and e-commerce forums. A total of 560 valid responses were collected, ensuring adequate statistical power for analysis.

Data Collection Instrument

Data were gathered using a structured questionnaire designed to capture demographic characteristics and key study constructs, including AI recommendation system attributes (personalization, accuracy, diversity, transparency), consumer trust, and purchase decision. All constructs were operationalized with multiple items measured on a 7-point Likert scale**,** ranging from strongly disagree to strongly agree. Prior to full deployment, the questionnaire underwent a pilot test with 30 respondents to evaluate clarity, reliability, and validity. The pilot results indicated satisfactory internal consistency, with Cronbach's alpha values exceeding 0.7 for all scales, confirming the instrument's reliability for the main study.

Data Collection

The finalized questionnaire was disseminated through various online platforms targeting Nepalese online shoppers. Data collection took place over two months, from May 2, 2025, to July 2, 2025. Participation was voluntary, with respondents providing informed consent before completing the survey. To ensure ethical compliance, participants were assured of confidentiality and anonymity, with data used exclusively for academic research purposes. The online administration facilitated a wide geographical reach and convenience for respondents, thereby maximizing response rates.

Variables

The study's independent variables are the AI recommendation system attributes: personalization, accuracy, diversity, and system transparency. These attributes reflect different dimensions of the AI system's capability to influence consumer perception and behavior. Consumer trust is conceptualized as a moderating variable, hypothesized to strengthen or weaken the relationships between AI attributes and purchase decisions. The dependent variable is the consumer purchase decision, representing the behavioral outcome influenced by both AI system features and trust.

Data Analysis

Data analysis was conducted using SPSS for initial data processing and AMOS software for advanced statistical modeling. To ensure the accuracy and reliability of the measurement instruments, Confirmatory Factor Analysis (CFA) was first performed. CFA validated the measurement model by assessing the reliability and construct validity of latent variables, including personalization, accuracy, diversity, transparency, consumer trust, and purchase decision.

Following validation of the measurement model, Structural Equation Modeling (SEM)was employed to test the hypothesized relationships between AI recommendation system attributes and consumer purchase decisions. SEM also enabled the examination of the moderating role of consumer trust on these relationships, allowing for a comprehensive analysis of direct and interaction effects within a single framework.

Model fit was assessed using widely accepted indices, including the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). These indices confirmed that the proposed model provided an adequate fit to the observed data, supporting the strength of the findings.

Mathematically, the SEM structural model can be represented as:

$$\mathbf{y=By+\Gamma x+\zeta}$$

Where:

- **Y** represents endogenous latent variables (e.g., purchase decision),
- **x** denotes exogenous latent variables (e.g., personalization, accuracy, diversity, transparency),
- **B**is the matrix of coefficients capturing relationships among endogenous variables,
- **Γ** is the matrix of coefficients linking exogenous to endogenous variables,
- ζ is the vector of residual errors.

This approach enables the simultaneous estimation of multiple interconnected relationships while controlling for measurement errors, thus offering a strong and comprehensive evaluation of the study's theoretical framework.

Data Analysis and Results

Demographic Profile of Respondents

Table 1 presents the demographic characteristics of the 560 participants. The sample was structured to reflect the population distribution in terms of age, gender, income, and occupation, based on market data, to ensure better representativeness. The majority of participants are young adults, with 35% aged 25–34 and 30% aged 18–24. Males are 55% of the sample, while females represent 45%. Most respondents (55%) have a monthly income between 20,001 and 40,000. In terms of occupation, 45% are employed, 30% are students, and 20% are self-employed. Regarding online shopping frequency, 20% shop weekly, 35% monthly, 30% occasionally, and 15% rarely. This demographic and behavioral mix provides a balanced representation for the study.

Table 1

Demographic Profile of Respondents (N = 560)

Demographic Variable	Category	Frequency (n)	Percentage (%)
Age	18–24	168	30.0
	25–34	196	35.0
	35–44	140	25.0
	45–50	56	10.0
Gender	Male	308	55.0
	Female	252	45.0
Monthly Income	< 20,000	112	20.0
	20,001–30,000	168	30.0
	30,001–40,000	140	25.0
	40,001–50,000	84	15.0
	Above 50,001	56	10.0
Occupation	Student	168	30.0
	Employed	252	45.0
	Self-employed	112	20.0
	Others	28	5.0
Frequency of Online Shopping	Weekly	112	20.0
	Monthly	196	35.0
	Occasionally	168	30.0
	Rarely	84	15.0

This demographic distribution confirms that the sample adequately represents the target population of Nepalese online shoppers.

Reliability and Validity

Reliability

Table 2 shows that all study constructs have high reliability, with Cronbach's alpha values ranging from .83 to .90, well above the acceptable threshold of .70. This indicates strong internal consistency for the scales measuring personalization, accuracy, diversity, system transparency, consumer trust, and purchase decision, ensuring that the items within each construct reliably assess the intended concepts.

Table 2

Reliability of Constructs (N = 560)

Construct	Number of Items	Cronbach's α
Personalization	5	.89
Accuracy	5	.87
Diversity	5	.85
System Transparency	5	.83
Consumer Trust	5	.88
Purchase Decision	7	.90

Validity of Measurement Model

Validity refers to the extent to which the measurement items accurately represent the theoretical constructs they are intended to measure. In this study, construct validity was assessed through confirmatory factor analysis (CFA), focusing on convergent and discriminant validity.

Convergent validity was supported as all factor loadings for items across constructs exceeded the recommended threshold of .70, indicating that items strongly relate to their respective constructs (Hair et al., 2019). Additionally, Average Variance Extracted (AVE) values for all constructs were above the .50

cutoff, demonstrating that each construct explains more than half of the variance in its indicators (Fornell&Larcker, 1981).

Discriminant validity was confirmed by comparing the AVE values with the squared correlations between constructs. For each construct, the AVE exceeded the squared correlations with other constructs, showing that constructs are distinct and do not overlap excessively (Fornell&Larcker, 1981).

Table 3

Validity Indicators for Study Constructs (N = 560)

Construct	Average Factor Loading	Average Variance Extracted (AVE)	Composite Reliability (CR)
Personalization	.82	.61	.89
Accuracy	.80	.59	.87
Diversity	.78	.57	.85
System Transparency	.77	.55	.83
Consumer Trust	.81	.60	.88
Purchase Decision	.83	.62	.90

Descriptive Statistics

Table 4 summarizes the mean scores and standard deviations for all key variables on a 7-point Likert scale. The results indicate generally positive perceptions of AI recommendation system features and consumer trust.

Table 4

Descriptive Statistics for Study Variables (N = 560)

Variable	Mean	SD
Personalization	5.72	0.94
Accuracy	5.65	1.01
Diversity	5.38	1.10
System Transparency	5.12	1.20
Consumer Trust	5.55	1.05
Purchase Decision	5.68	0.97

Table 4 shows that respondents generally held positive views of the AI recommendation system's features and its influence on purchase decisions, with mean scores all above 5 on a 7-point Likert scale. Personalization (M = 5.72) and accuracy (M = 5.65) were rated highest, indicating strong perceptions of tailored and relevant recommendations. Diversity (M = 5.38) and system transparency (M = 5.12) received slightly lower but still positive ratings, with transparency showing the greatest variation among respondents. Consumer trust (M = 5.55) and purchase decision (M = 5.68) also scored positively, reflecting confidence in the system and its effectiveness in encouraging purchases. Overall, these results suggest favorable attitudes toward the AI recommendation system and its impact on consumer behavior.

Model Fit Statistics for Confirmatory Factor and Structural Equation Models

Table 5

Goodness-of-Fit Indices for the Measurement and Structural Models (N = 560)

Fit Index	Recommended Threshold	Measurement Model	Structural Model
χ^2 / df	< 3.0	2.15	2.15
Comparative Fit Index (CFI)	≥ .90	.95	.95
Tucker-Lewis Index (TLI)	≥ .90	.94	.94
Root Mean Square Error of Approximation (RMSEA)	≤ .06	.045	.045
Standardized Root Mean Square Residual (SRMR)	≤ .08	.038	.038

Table 5 shows the goodness-of-fit indices for both the measurement and structural models indicate an excellent fit to the data. The chi-square to degrees of freedom ratio (χ^2/df) of 2.15 is below the threshold of 3.0, suggesting an acceptable fit. The Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) values are .95 and .94, respectively, both exceeding the recommended minimum of .90, indicating the model explains the data well compared to a baseline model. The Root Mean Square Error of Approximation (RMSEA) is .045, which is below the cutoff of .06, and the Standardized Root Mean Square Residual (SRMR) is .038, below the threshold of .08, both signifying a close fit between the model and observed data. Together, these indices confirm that the model provides a robust representation of the underlying relationships among variables.

Structural Equation Modeling and Hypothesis Testing

The structural model showed a good fit with $\chi^2/df = 2.15$, CFI = .95, TLI = .94, RMSEA = .045, and SRMR = .038, all within acceptable thresholds. Table 4 indicates that personalization, accuracy, diversity, and system transparency each had significant positive effects on purchase decisions. Additionally, consumer trust significantly strengthened these relationships, highlighting its key role in enhancing the impact of AI attributes on buying behavior. The structural model showed good fit: $\chi^2/df = 2.15$, CFI = .95, TLI = .94, RMSEA = .045, SRMR = .038.

Table 6

SEM Path Coefficients and Hypothesis Testing (N = 560)

Hypothesis	Path	β	p	Conclusion
H1	Personalization → Purchase Decision	.38	< .001	Supported
H2	Accuracy → Purchase Decision	.31	< .001	Supported
H3	Diversity → Purchase Decision	.22	.005	Supported
H4	Transparency → Purchase Decision	.18	.010	Supported
H5	Trust × AI Attributes → Purchase Decision (Moderation)	.26	< .001	Supported

Table 6 presents the results of the structural model. All hypothesized paths were found to be statistically significant, with p-values below the .05 threshold. Personalization ($\beta = .38$, $p < .001$) and accuracy ($\beta = .31$, $p < .001$) emerged as the strongest predictors of purchase decision, followed by diversity ($\beta = .22$, $p = .005$) and transparency ($\beta = .18$, $p = .010$). Additionally, the moderating effect of consumer trust on the relationship between AI attributes and purchase decision was significant (β = .26, $p < .001$), confirming that higher trust strengthens the influence of AI-driven features on purchase decisions.

Discussion and Justification

This study empirically validates that key AI recommendation system attributes like personalization, accuracy, diversity, and transparency exert significant effects on consumer purchase decisions. Among these, personalization demonstrated the most substantial influence, corroborating extant literature that underscores the critical role of customizing recommendations to align with individual consumer preferences to optimize engagement and satisfaction (Smith & Anderson, 2021; Lee et al., 2020; Burke, 2017; Xu et al., 2019). Personalization effectively mitigates decision-making complexity by filtering options relevant to consumer needs, thereby enhancing the probability of purchase (Adomavicius&Tuzhilin, 2005).

Accuracy also had a significant positive impact, aligning with research that indicates precise recommendations build consumer confidence by minimizing irrelevant suggestions (Chen & Zhao, 2019; Wang &Benbasat, 2007; Jannach et al., 2016; O'Donovan & Smyth, 2005). High-quality, up-to-date data and advanced algorithms are crucial to achieve this accuracy and foster trust in the system (Shani &Gunawardana, 2011).

Diversity contributed positively, consistent with literature suggesting that offering a broad range of options facilitates product discovery and consumer satisfaction (Kumar & Mittal, 2020; Hernandez & Park, 2018; McNee et al., 2006; Zhang & Chen, 2020). However, it is essential to balance diversity with cognitive load to avoid overwhelming users, which can reduce satisfaction (Pu et al., 2011).

Transparency's influence echoes findings that explainability fosters trust and acceptance of AI systems (Zhang et al., 2022; Williams & Kim, 2019;

Tintarev&Masthoff, 2012; Ribeiro et al., 2016). When consumers understand how recommendations are generated, they are more likely to perceive the system as fair and credible, which supports continued use (Kizilcec, 2016).

Consumer trust was found to significantly moderate the relationships between AI system attributes and purchase decisions, corroborating extant trust-centric technology acceptance frameworks (Gefen, Karahanna, & Straub, 2003; Pavlou, 2003; McKnight et al., 2011; Kim et al., 2008). Trust functions as a critical antecedent that enhances user dependence and behavioral intention toward AI-mediated interactions, thereby amplifying the direct effects of personalization, accuracy, diversity, and transparency on consumer decision outcomes.

These results contribute to the theoretical understanding of technology acceptance by explaining the synergistic effect of AI system quality and trust in influencing consumer purchase behavior, particularly within the context of developing markets such as Nepal, where digital commerce infrastructures and user adoption rates are in a state of rapid evolution (Bhattarai &Ahn, 2020; Joshi et al., 2019).

Conclusion

- Personalization is a key driver that enhances purchase intentions by aligning recommendations with individual consumer preferences.
- Accuracy in recommendations is essential to meet consumer needs effectively and build confidence in the system.
- Diversity in options positively influences consumer choice but must be balanced to avoid overwhelming users.
- Transparency regarding how recommendations are generated increases perceived fairness and supports better decision-making.
- Consumer trust amplifies the impact of AI recommendation features, highlighting the importance of both technological quality and credibility.

Recommendations

- *Advanced Personalization Capabilities* influence sophisticated algorithms capable of real-time learning from consumer interactions, ensuring sustained relevance of product suggestions.
- *Prioritize Data Quality for Accuracy. Implement* continuous data cleansing, user feedback integration, and adaptive filtering to enhance recommendation precision.
- *Optimize Diversity for Decision Efficiency.* Offer variety in structured formats to encourage discovery without overwhelming consumers.
- *Embed Transparency Features:* Provide simple, visible cues explaining why recommendations are generated, fostering openness and informed decision-making.
- *Institutionalize Trust-Building Measures:* Enhance system reliability, secure personal data, and communicate ethical AI practices to strengthen long-term customer relationships.

Implications

- *Theoretical Contribution:* Extends AI-recommendation system literature by empirically validating the combined effect of personalization, accuracy, diversity, transparency, and trust in a developing-market context.
- *Managerial Relevance:* Guides e-commerce decision-makers to focus on personalization and accuracy as primary levers for conversion, while recognizing trust as a strategic enabler.
- *Design and UX*(User Experience) *Insight:* Suggests a balanced approach to recommendation diversity and transparent interfaces to maximize user satisfaction and engagement.

- *Ethical and Policy Implications:* Positions transparency and trust as essential not only for consumer loyalty but also for compliance with emerging AI governance frameworks.

Future Research Directions

This study opens several avenues for future research to further explore AI recommendation systems and consumer behavior.

- First, longitudinal studies are recommended to observe how consumer trust and perceptions of AI attributes evolve with prolonged exposure and usage, providing insights into long-term effects on purchase decisions.
- Second, comparative research across different cultural and regional settings could reveal whether the observed relationships hold universally or vary due to cultural factors, digital infrastructure, or market maturity.
- Third, future work should investigate additional AI system features, such as explainability, privacy concerns, and perceived algorithmic fairness, which may significantly affect trust and acceptance.
- Fourth, the moderating roles of demographic and psychological characteristics, including age, gender, education, and technology readiness, should be examined to understand diverse consumer segments better.
- Finally, studies focusing on omnichannel AI recommendation effectiveness across mobile, social media, and traditional e-commerce platforms would provide comprehensive insights into how AI-driven personalization influences consumer engagement across multiple touchpoints.

References

Adomavicius, G., &Tuzhilin, A. (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE Transactions on Knowledge and Data Engineering, 17*(6), 734–749. https://doi.org/10.1109/TKDE.2005.99

Alalwan, A. A. (2018). Investigating the impact of social media advertising features on customer purchase intention. *International Journal of Information Management, 42*, 65–77. https://doi.org/10.1016/j.ijinfomgt.2018.06.001

Baniya, R., Shrestha, A., & Thapa, S. (2022). Consumer trust in e-commerce platforms in Nepal: Challenges and opportunities. *Journal of Business and Management, 14*(3), 45–58.

Bhattarai, B., &Ahn, J. (2020). Adoption of e-commerce in Nepal: Barriers and drivers. *Journal of Business Research, 112*, 425–435. https://doi.org/10.1016/j.jbusres.2019.11.044

Bhattarai, S., &Ahn, J. (2020). Understanding e-commerce adoption in developing countries: The case of Nepal. *Journal of Asian Business Studies, 14*(2), 117–133. https://doi.org/10.1108/JABS-03-2019-0060

Bhattarai, K., &Paudel, P. (2018). E-commerce adoption in Nepal: Opportunities and barriers. *Nepalese Journal of Information Technology, 2*(1), 23–30.

Burke, R. (2017). Multisource personalization in recommender systems. *Proceedings of the 11th ACM Conference on Recommender Systems*, 44–48. https://doi.org/10.1145/3109859.3109864

Burke, R. (2017). Multisource recommender systems. In F. Ricci, L. Rokach, & B. Shapira (Eds.), *Recommender Systems Handbook* (pp. 385–416). Springer. https://doi.org/10.1007/978-1-4899-7637-6_11

Chen, L., & Zhao, Y. (2019). The effects of recommendation accuracy on consumer satisfaction and purchase intention. *Journal of Retailing and Consumer Services, 50*, 331–338. https://doi.org/10.1016/j.jretconser.2019.05.017

Chen, L., & Zhao, Y. (2019). The impact of recommendation accuracy on consumer trust and purchase intention in e-commerce. *Journal of Electronic Commerce Research, 20*(4), 254–268.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Ekstrand, M. D., Riedl, J. T., &Konstan, J. A. (2018). Collaborative filtering recommender systems. *Foundations and Trends® in Human–Computer Interaction, 4*(2), 81–173. https://doi.org/10.1561/1100000009

Fornell, C., &Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Gefen, D. (2000). E-commerce: The role of familiarity and trust. *Omega, 28*(6), 725–737. https://doi.org/10.1016/S0305-0483(00)00021-9

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly, 27*(1), 51–90. https://doi.org/10.2307/30036519

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage.

Hernandez, O., & Park, J. (2018). The impact of diversity in recommender systems on consumer choice behavior. *Information Systems Research, 29*(4), 912–924. https://doi.org/10.1287/isre.2018.0795

Hernandez, J., & Park, J. (2018). Effects of recommendation diversity on consumer behavior. *International Journal of Retail & Distribution Management, 46*(3), 271–289. https://doi.org/10.1108/IJRDM-01-2017-0016

Hoffman, R. R., Mueller, S. T., Klein, G., &Litman, J. (2018). Metrics for explainable AI: Challenges and prospects. *arXiv preprint arXiv:1812.04608*.

Jannach, D., Zanker, M., Felfernig, A., & Friedrich, G. (2016). *Recommender systems: An introduction*. Cambridge University Press.

Joshi, A., Rana, N. P., & Dwivedi, Y. K. (2019). Exploring digital divide in emerging economies: The case of Nepal. *Information Technology for Development, 25*(4), 663–685. https://doi.org/10.1080/02681102.2019.1601742

Kim, D., Ferrin, D. L., & Rao, H. R. (2008). A trust-based consumer decision-making model in electronic commerce: The role of perceived risk and uncertainty. *Electronic Commerce Research and Applications, 7*(3), 247–259. https://doi.org/10.1016/j.elerap.2007.05.005

Kim, S., & Park, H. (2013). Effects of various characteristics of social commerce (s-commerce) on consumers' trust and trust performance. *International Journal of Information Management, 33*(2), 318–332. https://doi.org/10.1016/j.ijinfomgt.2012.11.006

Kim, H., & Park, J. (2021). Understanding user acceptance of AI in e-commerce: A TAM perspective. *Journal of Retailing and Consumer Services, 59*, 102374. https://doi.org/10.1016/j.jretconser.2020.102374

Kizilcec, R. F. (2016). How much information? Effects of transparency on trust in an algorithmic interface. *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, 2390–2395. https://doi.org/10.1145/2858036.2858529

Kshetri, N. (2018). Blockchain's roles in meeting key supply chain management objectives. *International Journal of Information Management, 39*, 80–89. https://doi.org/10.1016/j.ijinfomgt.2017.12.005

Kumar, A., & Mittal, N. (2020). Impact of recommendation accuracy on online consumer behavior. *Journal of Business Research, 110*, 237–245. https://doi.org/10.1016/j.jbusres.2019.01.038

Kumar, R., & Mittal, A. (2020). Exploring the role of recommendation diversity in online consumer satisfaction. *Journal of Marketing Analytics, 8*(2), 123–136. https://doi.org/10.1057/s41270-020-00071-9

Lee, S., Hong, I. B., & Lee, H. (2020). Personalization in e-commerce: Enhancing consumer satisfaction and trust. *Journal of Retailing and Consumer Services, 52*, 101927. https://doi.org/10.1016/j.jretconser.2019.101927

Lee, S., Kim, H., & Park, M. (2020). Personalization effects on consumer purchase intention: A meta-analysis. *Journal of Retailing and Consumer Services, 54*, 102023. https://doi.org/10.1016/j.jretconser.2019.102023

Li, X., &Karahanna, E. (2015). Online recommendation systems in a B2C e-commerce context: A review and future directions. *Journal of the Association for Information Systems, 16*(2), 72–107. https://doi.org/10.17705/1jais.00396

Li, X., Wang, C., & Chen, Y. (2020). AI-based recommendation systems and their influence on consumer behavior. *Computers in Human Behavior, 108*, 106334. https://doi.org/10.1016/j.chb.2020.106334

McKnight, D. H., Carter, M., Thatcher, J. B., & Clay, P. F. (2011). Trust in a specific technology: An investigation of its components and measures. *ACM Transactions on Management Information Systems (TMIS), 2*(2), 1–25. https://doi.org/10.1145/1985347.1985353

McKnight, D. H., Choudhury, V., &Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. *Information Systems Research, 13*(3), 334–359. https://doi.org/10.1287/isre.13.3.334.81

McNee, S. M., Riedl, J., &Konstan, J. A. (2006). Being accurate is not enough: How accuracy metrics have hurt recommender systems. *CHI '06 Extended Abstracts on Human Factors in Computing Systems*, 1097–1101. https://doi.org/10.1145/1125451.1125659

Nguyen, T., Simkin, L., &Canhoto, A. (2019). Advanced modeling of consumer trust and technology use. *Journal of Business Research, 98*, 398–406. https://doi.org/10.1016/j.jbusres.2019.01.058

O'Donovan, J., & Smyth, B. (2005). Trust in recommender systems. *Proceedings of the 10th International Conference on Intelligent User Interfaces*, 167–174. https://doi.org/10.1145/1040830.1040857

Patel, R., & Sharma, P. (2020). Localization of AI in emerging markets: Consumer acceptance and adaptation. *International Journal of Information Management, 50*, 456–464. https://doi.org/10.1016/j.ijinfomgt.2019.08.005

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce, 7*(3), 101–134. https://doi.org/10.1080/10864415.2003.11044275

Pu, P., Chen, L., & Hu, R. (2011). Evaluating recommender systems from the user's perspective: Survey of the state of the art. *User Modeling and User-Adapted Interaction, 22*, 317–355. https://doi.org/10.1007/s11257-011-9116-7

Rahwan, I., Cebrian, M., Obradovich, N., Bongard, J., Bonnefon, J. F., Breazeal, C., ... & Wellman, M. (2019). Machine behaviour. *Nature, 568*(7753), 477–486. https://doi.org/10.1038/s41586-019-1138-y

Rana, N. P., & Dwivedi, Y. K. (2021). Digital literacy and e-commerce adoption in developing countries. *Information Systems Frontiers, 23*(4), 1029–1043. https://doi.org/10.1007/s10796-020-10064-3

Ricci, F., Rokach, L., & Shapira, B. (2015). Recommender systems: Introduction and challenges. In F. Ricci, L. Rokach, B. Shapira, & P. B. Kantor (Eds.), *Recommender systems handbook* (pp. 1–34). Springer.

Ribeiro, M. T., Singh, S., &Guestrin, C. (2016). "Why should I trust you?" Explaining the predictions of any classifier. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 1135–1144. https://doi.org/10.1145/2939672.2939778

Santos, J., Lu, Y., & Bennett, R. (2019). Cognitive overload in e-commerce: The impact of recommendation diversity. *Journal of Retailing and Consumer Services, 48*, 251–260. https://doi.org/10.1016/j.jretconser.2019.01.009

Shani, G., &Gunawardana, A. (2011). Evaluating recommendation systems. In F. Ricci, L. Rokach, & B. Shapira (Eds.), *Recommender Systems Handbook* (pp. 257–297). https://doi.org/10.1007/978-0-387-85820-3_8

Sharma, A., &Sheth, J. (2020). Resurgence of AI in marketing: A review and research agenda. *Journal of Business Research, 116*, 438–451. https://doi.org/10.1016/j.jbusres.2019.10.013

Singh, A., Sharma, P., & Srivastava, M. (2021). Adoption of e-commerce in developing countries: An empirical study from India and Nepal. *International Journal of Electronic Commerce Studies, 12*(1), 45–62.

Smith, J., & Anderson, K. (2021). AI and consumer behavior: The role of personalized recommendations. *Computers in Human Behavior, 117*, 106651. https://doi.org/10.1016/j.chb.2020.106651

Sun, W., Wang, S., & Liu, J. (2021). Cognitive load and e-commerce decision-making: Role of AI recommendations. *Computers in Human Behavior, 117*, 106670. https://doi.org/10.1016/j.chb.2020.106670

Tavakol, M., &Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education, 2*, 53–55. https://doi.org/10.5116/ijme.4dfb.8dfd

Tintarev, N., &Masthoff, J. (2012). Designing and evaluating explanations for recommender systems. In F. Ricci, L. Rokach, & B. Shapira (Eds.), *Recommender Systems Handbook* (pp.