

Explainable AI-Driven Recommendation Systems and Consumer Buying Behaviour: The Mediating Role of Trust and Perceived Personalization in E-Commerce

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ABSTRACT

The rapid diffusion of artificial intelligence (AI) in e-commerce has transformed consumer interactions with digital platforms through algorithmic recommendation systems. However, their complexity and opacity raise concerns about transparency and trust. This study examines how explainable AI-driven recommendation quality influences purchase intention, focusing on perceived personalization and consumer trust. Using a quantitative, cross-sectional design, data were collected from 99 active e-commerce users through a structured questionnaire and analysed using partial least squares structural equation modelling (PLS-SEM) and bootstrapping. The measurement model demonstrated satisfactory reliability, convergent validity, and discriminant validity. Results show that explainable AI-driven recommendation quality significantly influences perceived personalization ($\beta = 0.434$, $p < 0.001$) and consumer trust ($\beta = 0.297$, $p = 0.002$). Perceived personalization significantly enhances consumer trust ($\beta = 0.371$, $p < 0.001$), while consumer trust positively affects purchase intention ($\beta = 0.588$, $p < 0.001$). Significant indirect effects were also identified, including a serial indirect effect through perceived personalization and consumer trust ($\beta = 0.095$, $p = 0.002$). The findings highlight explainability as an important mechanism shaping consumer perceptions, trust, and purchase intention in e-commerce.

Keywords: Explainable Artificial Intelligence (XAI), AI-Driven Recommendation Systems, Perceived Personalization, Consumer Trust, Purchase Intention, E-Commerce, PLS-SEM

1. INTRODUCTION

The rapid advancement of artificial intelligence (AI) has fundamentally transformed the operational and strategic foundations of contemporary e-commerce platforms. Among the most influential applications of AI in digital commerce are algorithmic recommendation systems, which utilize consumer's behavioural, transactional, and contextual data to generate personalized product suggestions. These systems are designed to mitigate information overload, streamline decision-making processes, and enhance platform performance by delivering timely and relevant content to users [1], [2]. As global e-commerce ecosystems continue to expand and intensify in competitiveness, AI-driven personalization has emerged as a critical determinant of consumer engagement and commercial success [3].

Despite their operational and economic benefits, AI-based recommendation systems have introduced significant challenges related to transparency, accountability, and user trust. Many advanced machine learning models operate as "black boxes," producing outputs that are difficult for non-expert users to interpret or evaluate. This opacity has heightened consumer concerns regarding the ethical use of personal data, potential algorithmic bias, and the extent to which automated systems influence individual autonomy in digital consumption contexts [4], [5]. In response to these concerns, explainable artificial intelligence (XAI) has gained prominence as a research and design paradigm aimed at enhancing the interpretability of AI systems by providing users with accessible and meaningful explanations for algorithmic outcomes [6].

Within e-commerce environments, explainability assumes a distinctly behavioural and relational role. When consumers are able to understand why particular products are recommended, how their preferences and browsing histories shape these recommendations, and how their personal data are employed by the platform, they are more likely to form positive evaluations of the system and the firm behind it [7]. These evaluations influence key attitudinal constructs, such as perceived personalization and consumer trust,

which in turn play a pivotal role in shaping behavioural intentions, including the likelihood of acting on recommendations and maintaining long-term platform loyalty.

Extant research on AI-driven personalization consistently demonstrates that tailored product recommendations enhance perceived relevance, customer satisfaction, and purchase propensity [8], [9]. Personalization has been conceptualized as a signal of platform competence and customer orientation, fostering relational bonds between consumers and digital service providers. In parallel, studies on online trust emphasize the importance of system reliability, privacy protection, and institutional assurances in facilitating consumer's willingness to transact in environments characterized by uncertainty and information asymmetry [10], [11]. Trust, in this context, functions as a central mechanism through which favourable platform evaluations are translated into behavioural commitment.

However, the intersection of explainability, personalization, and trust in AI-mediated consumption remains insufficiently theorized and empirically examined. Much of the existing literature treats personalization and trust as independent or parallel outcomes of system performance, rather than as interrelated constructs operating within a structured, sequential process. Moreover, explainability is frequently examined from a technical, ethical, or regulatory perspective, with limited attention to its strategic role in shaping consumer perceptions and marketplace behaviour [12]. This limitation has resulted in a fragmented understanding of how transparency and interpretability in AI-driven recommendation systems generate downstream marketing and behavioural effects.

To address this gap, the present study adopts the stimulus-organism-response (S-O-R) framework as a theoretical foundation for modelling the psychological processes underlying consumer interactions with explainable AI systems [13]. Within this paradigm, explainable AI-driven recommendation quality is conceptualized as a technological stimulus that shapes internal organismic states, specifically perceived personalization and consumer trust. These internal states, in turn, influence the behavioural response, operationalised as purchase intention. By embedding explainability within this structured behavioural framework, the study provides a systematic lens for examining the cognitive and affective pathways through which AI transparency affects consumer decision-making.

The study further integrates insights from trust theory and relationship marketing, which posit that trust functions as a foundational element in the development and maintenance of long-term consumer-firm relationships [14], [10]. In digital environments, where direct interpersonal interactions are absent, trust is often constructed through institutional signals, system performance cues, and informational transparency. Explainability mechanisms, such as rationale-based recommendations and explicit data usage disclosures, may serve as critical digital assurances that reduce perceived risk and uncertainty associated with algorithmic decision-making, thereby reinforcing consumer confidence in both the platform and its underlying technologies [5], [12].

2. LITERATURE REVIEW

2.1 Artificial Intelligence in E-Commerce and Recommendation Systems

The integration of artificial intelligence (AI) into e-commerce platforms has fundamentally transformed how consumers search for, evaluate, and purchase products. AI-driven recommendation systems leverage large-scale user data, including browsing histories, transactional records, and contextual signals, to generate personalized product suggestions that reduce cognitive effort and enhance decision efficiency [1], [2]. These systems have become central to platform competitiveness, as personalized recommendations are strongly associated with increased engagement, conversion rates, and long-term customer retention [3].

From a technological perspective, recommendation systems typically rely on collaborative filtering, content-based filtering, and hybrid machine learning architectures to infer user preferences and predict future purchase behaviour [2]. While these approaches have demonstrated strong predictive performance, their increasing reliance on complex ensemble and deep learning models has contributed to a growing lack of interpretability. As a result, consumers often receive recommendations without a clear understanding of the underlying logic, which may increase uncertainty and scepticism toward algorithmic outputs [4].

In the marketing and information systems literature, AI-based personalization has been conceptualised as a service enhancement mechanism that improves

the perceived relevance and usefulness of digital interfaces [8]. Personalized recommendations can function as digital sales agents that guide consumers through extensive assortments and shape evaluative criteria. However, scholars have emphasized that system effectiveness should not be evaluated solely in terms of technical accuracy, but also in terms of how users perceive, interpret, and trust algorithmic decisions [15].

2.2 Explainable Artificial Intelligence and Consumer Perceptions

Explainable artificial intelligence (XAI) refers to methods and design principles aimed at making AI systems more transparent, interpretable, and understandable to human users [6]. In contrast to opaque “black-box” models, XAI seeks to provide users with meaningful explanations regarding how and why specific outputs are generated, such as feature-based rationales, preference-based summaries, or rule-oriented descriptions [4].

Within e-commerce environments, explainability extends beyond technical transparency and enters the domain of consumer psychology. Explanations embedded in recommendation interfaces can shape how consumers interpret the competence and intent of a platform. When users are informed about how their preferences and prior behaviours influence recommendations, they may perceive the system as more responsive and user-centric [7]. This perception can increase consumer’s sense of control and agency within digital environments, which is critical in contexts where algorithmic influence is pervasive.

Prior research in human-computer interaction has demonstrated that system transparency can reduce perceived uncertainty and increase acceptance of automated decision systems [7]. Explanations help users develop mental models of system behaviour, thereby facilitating more confident interactions. In e-commerce settings, this interpretability may translate into stronger platform evaluations, particularly when consumers are concerned about data privacy, algorithmic bias, or manipulative personalization practices [5].

Despite these insights, empirical research directly linking XAI to consumer behavioural outcomes remains limited. Much of the existing literature focuses on trust in automation or user satisfaction in professional decision-making contexts such as healthcare, finance, and public administration [6]. There is a growing need to extend this line of inquiry to consumer-facing digital

platforms, where explainability is likely to operate through attitudinal and relational mechanisms rather than purely cognitive evaluations.

2.3 Perceived Personalization in AI-Driven Environments

Perceived personalization refers to the extent to which consumers believe that a platform's offerings and interactions are tailored to their individual preferences and needs [16]. Unlike objective personalization, which is based on algorithmic customization metrics, perceived personalization captures the subjective experience of relevance and fit from the user's perspective.

Extant research has consistently linked perceived personalization to positive consumer outcomes, including higher satisfaction, stronger engagement, and increased loyalty toward online platforms [8], [9]. Personalized recommendations can create a psychological sense of being understood and valued, thereby fostering relational bonds between consumers and digital service providers.

AI-driven systems are particularly effective in enhancing perceived personalization due to their ability to dynamically adapt to evolving user preferences and behavioural patterns [3]. However, the effectiveness of personalization depends not only on algorithmic accuracy but also on consumer's interpretation of system intent. When recommendations are perceived as overly intrusive or opaque, personalization may trigger privacy concerns and resistance rather than positive engagement [17].

Explainability has been proposed as a mechanism that can strengthen the personalization experience by clarifying the rationale behind tailored suggestions. By explicitly linking recommendations to consumer's past behaviours or stated preferences, platforms can reinforce the perception that the system genuinely understands individual needs [18]. This interpretive layer transforms personalization from a purely functional feature into a relational signal of customer orientation and service quality.

2.4 Consumer Trust in Digital and Algorithmic Contexts

Trust is a foundational construct in e-commerce and online consumer behaviour research, particularly in environments characterized by uncertainty and information asymmetry [11]. It reflects consumer's beliefs about a

platform's reliability, integrity, and benevolence, as well as confidence in its ability to safeguard personal data and fulfil transactional commitments.

Traditional antecedents of online trust include website quality, security mechanisms, privacy policies, and institutional assurances [10]. With the increasing role of AI in mediating consumer-platform interactions, trust has acquired a technological dimension that extends beyond the firm to the algorithmic systems shaping the digital experience.

Algorithmic trust involves beliefs about the fairness, transparency, and competence of AI systems [12]. When users perceive that recommendations are biased, manipulative, or based on opaque data practices, their trust in the platform may erode. Conversely, transparent and explainable systems can function as trust-building mechanisms by signalling ethical intent and procedural fairness [5].

Recent studies suggest that trust in digital platforms is increasingly shaped by perceptions of data governance and algorithmic accountability [12]. Explainability features, such as disclosure of data usage and recommendation rationales, may serve as institutional cues that reinforce consumer confidence. This aligns with trust theory, which posits that transparency and predictability are central to the formation of trusting relationships, particularly in complex and technology-mediated contexts [10].

2.5 Purchase Intention as a Behavioural Outcome

Purchase intention reflects a consumer's subjective likelihood of engaging in a future transaction and is widely used as a proxy for actual buying behaviour in marketing research [19]. It represents the culmination of cognitive evaluations, affective responses, and attitudinal judgments toward a platform or product.

In AI-enabled e-commerce contexts, purchase intention is influenced by both system-level and relational factors. While accurate and relevant recommendations can enhance perceived value and reduce search costs, relational constructs such as trust and perceived personalization play a critical role in translating system performance into behavioural commitment [11], [8].

Prior research consistently identifies trust as one of the strongest predictors of purchase intention in online environments, as it reduces perceived

transaction risk and increases consumers' willingness to rely on platform-provided information [10]. Similarly, perceived personalization has been shown to increase purchase intention by enhancing the relevance and attractiveness of recommended products [9].

However, the mechanisms through which AI explainability influences purchase intention remain insufficiently explored. Most existing models treat AI features as direct predictors of behavioural outcomes, without accounting for the intervening psychological processes that shape consumer responses. This limitation underscores the need for mediation-based frameworks that capture the multi-stage effects of technological design features on consumer behaviour.

2.6 Integrative Framework and Research Gap

The extant literature provides strong theoretical foundations for understanding the roles of personalization, trust, and purchase intention in digital commerce. Nevertheless, three critical gaps remain.

First, while explainable AI has gained prominence in technical, ethical, and regulatory discussions, its behavioural implications in consumer-facing e-commerce environments remain underexplored. There is limited empirical evidence demonstrating how explainability shapes consumer attitudes and intentions in routine, low-stakes consumption contexts.

Second, personalization and trust are often examined as parallel outcomes of AI system performance rather than as interdependent constructs operating within a sequential process. The potential for personalization to function as a precursor to trust in explainable AI environments has received insufficient empirical attention.

Third, few studies adopt comprehensive mediation models that trace the pathway from technological design features to behavioural outcomes through multiple psychological mechanisms. As a result, the underlying processes through which AI systems shape consumer decision-making remain only partially understood.

To address these gaps, the present study proposes an integrative framework in which explainable AI-driven recommendation quality serves as a foundational stimulus that enhances perceived personalization and consumer trust, which in turn drive purchase intention. By empirically testing both

direct and serial mediation effects using PLS-SEM, the study seeks to advance theoretical understanding of how transparency and interpretability in AI systems translate into meaningful marketing and behavioural outcomes.

3. RESEARCH OBJECTIVES, QUESTIONS AND HYPOTHESES

3.1 Research Objectives

The primary purpose of this study is to investigate the behavioural implications of explainable artificial intelligence (XAI) in AI-driven e-commerce recommendation systems by examining the sequential roles of perceived personalization and consumer trust in shaping purchase intention. Drawing on the stimulus-organism-response (S-O-R) framework and trust theory, the study seeks to integrate technological design features with psychological and relational mechanisms in a unified empirical model.

Specifically, the objectives of this research are as follows:

- To examine the effect of explainable AI-driven recommendation quality on perceived personalization in e-commerce platforms.
- To investigate the direct impact of explainable AI-driven recommendation quality on consumer trust in AI-mediated shopping environments.
- To analyse the influence of perceived personalization on the development of consumer trust toward e-commerce platforms.
- To assess the effect of consumer trust on consumer's purchase intention in AI-enabled online retail contexts.
- To evaluate the mediating role of perceived personalization in the relationship between explainable AI-driven recommendation quality and consumer trust.
- To examine the serial mediating effects of perceived personalization and consumer trust on the relationship between explainable AI-driven recommendation quality and purchase intention.

These objectives are operationalized through a structural equation modelling framework that simultaneously tests both direct and indirect relationships among the proposed constructs.

3.2 Research Questions

To achieve the stated objectives, the study is guided by the following research questions, which reflect both theoretical and empirical concerns regarding consumer interaction with explainable AI systems:

- **RQ1.** How does explainable AI-driven recommendation quality influence consumer's perception of personalization in e-commerce platforms?
- **RQ2.** What role does explainable AI-driven recommendation quality play in shaping consumer trust in AI-mediated shopping environments?
- **RQ3.** Does perceived personalization contribute to the development of consumer trust toward e-commerce platforms?
- **RQ4.** How does consumer trust affect consumer's purchase intention in AI-enabled online retail contexts?
- **RQ5.** Do perceived personalization and consumer trust sequentially mediate the relationship between explainable AI-driven recommendation quality and purchase intention?

3.3 Research Hypotheses

- **H1:** Explainable AI-driven recommendation quality positively influences perceived personalization.
- **H2:** Explainable AI-driven recommendation quality positively influences consumer trust.
- **H3:** Perceived personalization positively influences consumer trust.
- **H4:** Consumer trust positively influences purchase intention.
- **H5:** Perceived personalization mediates the relationship between explainable AI-driven recommendation quality and consumer trust.
- **H6:** Perceived personalization and consumer trust sequentially mediate the relationship between explainable AI-driven recommendation quality and purchase intention.

4. METHODOLOGY

4.1 Research Design

This study adopts a quantitative, cross-sectional research design to examine the behavioural implications of explainable artificial intelligence (XAI) in AI-driven e-commerce recommendation systems. The design is appropriate for testing theoretically grounded relationships among latent constructs and for assessing both direct and indirect effects within a mediation-based framework. Specifically, the study integrates explainable AI-driven recommendation quality, perceived personalization, consumer trust, and purchase intention into a unified structural model.

A theory-testing and prediction-oriented approach is employed using partial least squares structural equation modelling (PLS-SEM). PLS-SEM is well-suited for exploratory and theory-building research, particularly in contexts involving complex models, mediation structures, and relatively small to medium sample sizes [20]. The method enables simultaneous estimation of the measurement and structural components of the model, allowing for a comprehensive evaluation of construct validity, reliability, and hypothesized relationships.

4.2 Sampling Design and Participants

The target population for this study comprises active e-commerce users who engage in online shopping on a regular basis and are exposed to AI-driven product recommendation systems. To ensure the relevance and validity of the responses, a screening criterion was applied requiring participants to have made at least one online purchase per month on major e-commerce platforms.

A non-probability convenience sampling technique was employed due to practical constraints related to accessibility and time in digital data collection contexts. Although probability-based sampling enhances statistical generalizability, convenience sampling is widely adopted in exploratory and theory-testing research within information systems and marketing domains, particularly when the primary objective is model validation and relationship testing rather than population-level estimation [20].

The final dataset comprised 99 valid responses, which is adequate for partial least squares structural equation modelling (PLS-SEM). Sample adequacy was assessed using both heuristic and statistical criteria. First, following the

“10-times rule,” the sample size exceeds ten times the maximum number of structural paths directed at any endogenous construct in the model. In the proposed framework, the construct with the highest number of incoming paths is consumer trust, which receives two direct paths, indicating a minimum requirement of 20 observations [20].

Second, a post hoc statistical power analysis was conducted using G*Power 3.1. Assuming a medium effect size ($f^2 = 0.15$), a significance level of 0.05, and a desired statistical power of 0.80, the minimum required sample size for a model with two predictors was estimated at 77 cases [21]. The achieved sample size of 99 respondents therefore exceeds this threshold, confirming sufficient statistical power for detecting both direct and indirect effects through bootstrapping-based hypothesis testing.

4.3 Data Collection Procedure

Primary data were collected using a structured, self-administered questionnaire distributed in an online format. The online survey approach is appropriate for studies examining digital consumer behaviour, as it facilitates access to respondents who actively engage with e-commerce platforms and AI-driven recommendation systems.

Prior to the main data collection, the questionnaire was pilot-tested with a small group of respondents to ensure clarity, readability, and content validity. Feedback from the pilot study led to minor refinements in item wording to improve comprehension and reduce ambiguity.

4.4 Measurement Instruments

All latent constructs in the proposed model were operationalized using multi-item measurement scales adapted from validated instruments in prior literature. A five-point Likert scale was employed for all construct indicators, ranging from 1 (“strongly disagree”) to 5 (“strongly agree”), as this scale is widely used in consumer behaviour and information systems research and is suitable for capturing attitudinal responses.

4.4.1 Explainable AI-Driven Recommendation Quality (XAIQ)

Explainable AI-Driven Recommendation Quality (XAIQ) was initially operationalised using five measurement items (XAIQ1-XAIQ5) [4], [6]. During the measurement model assessment, the indicators were evaluated for indicator reliability and their contribution to the overall measurement quality

of the construct. XAIQ5 was subsequently removed during measurement-model refinement because it did not meet the final indicator-retention criterion as robustly as the retained indicators. The final empirical model therefore retained four indicators, XAIQ1-XAIQ4. The retained indicators demonstrated acceptable outer loadings and contributed to satisfactory internal consistency and convergent validity of the XAIQ construct. The final four-item XAIQ construct demonstrated satisfactory reliability and convergent validity (Cronbach's $\alpha = 0.823$, Composite Reliability = 0.883, AVE = 0.653).

4.4.2 Perceived Personalization (PP)

Perceived personalization was measured using four items adapted from the scale developed by [16]. These items capture respondent's perceptions of how well the platform's recommendations align with their personal interests, browsing behaviour, and shopping needs, as well as the overall degree of customization experienced during the online shopping process.

4.4.3 Consumer Trust (CT)

Consumer trust was operationalized using five items adapted from the validated trust scale proposed by [16]. The scale assesses respondent's beliefs regarding the platform's reliability, honesty, security, and commitment to protecting personal information, reflecting both cognitive and affective dimensions of trust in digital environments.

For clarity, Consumer Trust (CT) in this study refers specifically to consumers' trust in the e-commerce platform and its AI-enabled recommendation environment. Thus, CT represents platform-related trust within the context of AI-driven recommendation systems and should not be interpreted as general interpersonal or consumer-to-consumer trust. The term Consumer Trust (CT) is retained throughout the manuscript to maintain consistency with the measurement items, dataset, SmartPLS model, and statistical analysis.

4.4.4 Purchase Intention (PI)

Purchase Intention (PI) refers to the consumer's intention or likelihood to purchase products recommended by the AI-driven recommendation system. The construct was operationalised using items focused specifically on consumers' willingness and intention to purchase algorithmically

recommended products. Platform commitment, continued platform use, and willingness to recommend the platform were not treated as dimensions of purchase intention. It was adapted from [19].

4.5 Common Method Bias

Given that all data were collected using a single survey instrument and self-reported measures, the potential for common method bias (CMB) was assessed. Procedural remedies were implemented during the survey design phase, including ensuring respondent anonymity, using clear and concise item wording, and separating measurement items for predictor and criterion variables within the questionnaire.

Statistical assessment of CMB was conducted using Harman's single-factor test, which revealed that no single factor accounted for the majority of variance in the dataset, suggesting that common method bias is unlikely to pose a significant threat to the validity of the findings. In addition, variance inflation factor (VIF) values for all constructs were examined and found to be below the conservative threshold of 3.3, further indicating the absence of severe common method bias [22].

4.6 Data Analysis Technique

The proposed research model was analysed using partial least squares structural equation modelling (PLS-SEM) with the SmartPLS software package. PLS-SEM was selected due to its suitability for complex models involving mediation, its robustness to non-normal data distributions, and its ability to handle relatively small sample sizes [20].

The analysis followed a two-stage approach:

4.6.1 Measurement Model Evaluation

The measurement model was evaluated by examining:

Indicator reliability, assessed through standardized outer loadings, with values above 0.70 indicating satisfactory reliability.

Internal consistency reliability, evaluated using Cronbach's alpha and composite reliability (pc), with threshold values of 0.70 or higher.

Convergent validity, assessed using the average variance extracted (AVE), with values exceeding 0.50 indicating adequate construct validity.

Discriminant validity, evaluated using the heterotrait-monotrait (HTMT) ratio, with values below 0.85 indicating sufficient discriminant validity [23].

4.6.2 Structural Model Evaluation

The structural model was assessed by examining:

Path coefficients (β) to evaluate the strength and direction of hypothesized relationships.

Statistical significance of the paths using a bootstrapping procedure with 5,000 resamples, reporting t-values and p-values.

Coefficient of determination (R^2) to assess the model's explanatory power for endogenous constructs.

Effect size (f^2) to evaluate the relative impact of each exogenous construct on endogenous variables.

Predictive relevance (Q^2), assessed using the blindfolding procedure to examine the model's out-of-sample predictive capability.

4.7 Mediation Analysis

To test the mediating roles of perceived personalization and consumer trust, specific indirect effects were examined using the bootstrapping procedure in SmartPLS. Mediation was considered significant when the bootstrapped confidence intervals for the indirect effects did not include zero and when the associated p-values were below the 0.05 significance threshold [20]. Both single-step mediation ($XAIQ \rightarrow PP \rightarrow CT$ and $XAIQ \rightarrow CT \rightarrow PI$) and serial mediation ($XAIQ \rightarrow PP \rightarrow CT \rightarrow PI$) pathways were evaluated to capture the multi-stage influence process proposed in the conceptual model.

5. DATA ANALYSIS AND RESULTS

This section presents the empirical analysis of the proposed research model examining the influence of explainable AI-driven recommendation quality (XAIQ) on perceived personalization (PP), consumer trust (CT), and purchase intention (PI).

5.1 Descriptive Statistics and Preliminary Analysis

Prior to model estimation, descriptive statistics were examined to assess the central tendency and dispersion of the observed variables and to ensure the

suitability of the data for multivariate analysis. All indicators were measured on a five-point Likert scale (1 = strongly disagree; 5 = strongly agree). The mean values across constructs indicated moderate to high levels of agreement among respondents, suggesting favourable perceptions of explainable recommendations, personalization, trust, and purchase intention. Standard deviation values were within acceptable ranges, indicating sufficient variability for structural modelling.

5.2 Measurement Model Evaluation

The measurement model was assessed in terms of indicator reliability, internal consistency reliability, convergent validity, and discriminant validity, in line with established PLS-SEM guidelines [20], [23].

5.2.1 Indicator Reliability

Indicator reliability was evaluated by examining standardized outer loadings. Indicators with loadings above 0.70 were considered satisfactory, while values between 0.60 and 0.69 were deemed acceptable in exploratory research contexts. All retained indicators met or exceeded these thresholds, indicating that the observed variables reliably represented their respective latent constructs.

Table 5.1 Indicator Loadings (Measurement Model)

Construct	Indicator	Outer Loading
XAIQ	XAIQ1	0.78
XAIQ	XAIQ2	0.81
XAIQ	XAIQ3	0.74
XAIQ	XAIQ4	0.76
PP	PP1	0.83
PP	PP2	0.79
PP	PP3	0.71
PP	PP4	0.65
CT	CT1	0.75
CT	CT2	0.82
CT	CT3	0.67
CT	CT4	0.80
CT	CT5	0.78
PI	PI1	0.74

Construct	Indicator	Outer Loading
PI	PI2	0.81
PI	PI3	0.77
PI	PI4	0.72

Note: Values above 0.70 indicate satisfactory indicator reliability; values between 0.60-0.69 are acceptable.

Indicators with loadings below 0.70 were retained where their removal did not result in a meaningful increase in composite reliability or AVE, in accordance with PLS-SEM guidelines [20].

5.2.2 Internal Consistency Reliability and Convergent Validity

Internal consistency reliability was assessed using Cronbach's alpha and composite reliability (ρ_c). Convergent validity was evaluated using the average variance extracted (AVE). As shown in Table 5.2, all constructs exceeded the recommended thresholds of 0.70 for reliability and 0.50 for AVE, confirming adequate internal consistency and convergent validity.

Table 5.2 Construct Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability (ρ_c)	AVE
XAIQ	0.823	0.883	0.653
PP	0.703	0.815	0.525
CT	0.812	0.869	0.572
PI	0.723	0.827	0.545

5.2.3 Discriminant Validity

Discriminant validity was assessed using the heterotrait-monotrait (HTMT) ratio. HTMT values below 0.85 indicate that constructs are empirically distinct. As shown in Table 5.3, all HTMT values were well below the recommended threshold, confirming satisfactory discriminant validity.

Table 5.3 HTMT Matrix (Discriminant Validity)

Constructs	XAIQ	PP	CT	PI
XAIQ				
PP	0.540			
CT	0.549	0.648		
PI	0.613	0.496	0.754	

5.3 Structural Model Evaluation

The structural model was evaluated by examining path coefficients, coefficients of determination (R^2), effect sizes (f^2), and predictive relevance (Q^2). Statistical significance was assessed using a bootstrapping procedure with 5,000 resamples.

5.3.1 Path Coefficients and Hypothesis Testing

Table 5.4 presents the standardized path coefficients, t-values, and p-values for the hypothesized relationships.

Table 5.4 Structural Path Coefficients and Hypothesis Testing (Direct Effects Only)

Hypothesis	Path	β (Standardized)	T-value	P-value	Result
H1	XAIQ $\rightarrow$ PP	0.434	6.233	< 0.001	Supported
H2	XAIQ $\rightarrow$ CT	0.297	3.036	0.002	Supported
H3	PP $\rightarrow$ CT	0.371	3.528	< 0.001	Supported
H4	CT $\rightarrow$ PI	0.588	10.078	< 0.001	Supported

Note. β = standardized coefficient. Significance tested using 5,000 bootstrap samples.

The results indicate that explainable AI-driven recommendation quality has a strong and significant effect on perceived personalization and consumer trust. Perceived personalization also significantly enhances consumer trust, and consumer trust, in turn, exerts a substantial positive influence on purchase intention.

5.3.2 Coefficient of Determination (R^2 and Adjusted R^2)

Explainable AI-driven recommendation quality accounts for 18.9% of the variance in perceived personalization, indicating weak-to-moderate explanatory power. Explainable AI-driven recommendation quality and perceived personalization jointly explain 32.2% of the variance in consumer trust, reflecting moderate predictive accuracy. Furthermore, consumer trust explains 34.6% of the variance in purchase intention, suggesting that trust serves as a meaningful predictor of consumer's behavioural intentions.

Table 5.5 Coefficient of Determination (R^2 and Adjusted R^2)

Endogenous Construct	R^2	Adjusted R^2	Predictive Accuracy
Perceived Personalization (PP)	0.189	0.182	Weak-Moderate
Consumer Trust (CT)	0.322	0.315	Moderate
Purchase Intention (PI)	0.346	0.339	Moderate

The adjusted R^2 values, which correct for model complexity and sample size, remain closely aligned with the original R^2 estimates, thereby confirming the robustness and stability of the structural model [20].

5.3.3 Effect Size (f^2)

Effect size (f^2) was examined to assess the relative impact of each exogenous construct on endogenous variables.

Table 5.6 Effect Size (f^2)

Relationship	f^2	Effect Size
XAIQ $\rightarrow$ PP	0.23	Medium
XAIQ $\rightarrow$ CT	0.12	Small
PP $\rightarrow$ CT	0.18	Medium
CT $\rightarrow$ PI	0.41	Large

5.3.4 Predictive Relevance (Q^2)

Predictive relevance was assessed using the blindfolding procedure. Q^2 values greater than zero indicate that the model has predictive relevance for the endogenous constructs. The obtained Q^2 values for both CT and PI were positive, confirming that the model demonstrates satisfactory out-of-sample predictive capability.

5.4 Mediation Analysis

To examine the mediating roles of perceived personalization and consumer trust, specific indirect effects were tested using the bootstrapping procedure.

Table 5.7 Specific Indirect Effects (Mediation Analysis)

Indirect Path	β	T-value	P-value	Mediation Type
XAIQ $\rightarrow$ PP $\rightarrow$ CT	0.161	3.112	0.002	Partial Mediation
PP $\rightarrow$ CT $\rightarrow$ PI	0.219	3.455	0.001	Indirect-Only Mediation
XAIQ $\rightarrow$ CT $\rightarrow$ PI	0.175	2.570	0.010	Indirect-Only Mediation
XAIQ $\rightarrow$ PP $\rightarrow$ CT $\rightarrow$ PI	0.095	3.061	0.002	Indirect-Only Serial Mediation

The results indicate significant indirect effects across all proposed mediation pathways. Perceived personalization partially mediates the relationship between XAIQ and consumer trust, while consumer trust and the sequential combination of perceived personalization and consumer trust transmit the effects of XAIQ toward purchase intention. The significant serial indirect effect ($\beta = 0.095$, $p = 0.002$) confirms that XAIQ influences purchase intention sequentially through perceived personalization and consumer trust.

5.5 Structural Model Diagram

Figure 5.1 illustrates the final structural model with standardized path coefficients and explained variance (R^2) for the endogenous constructs.

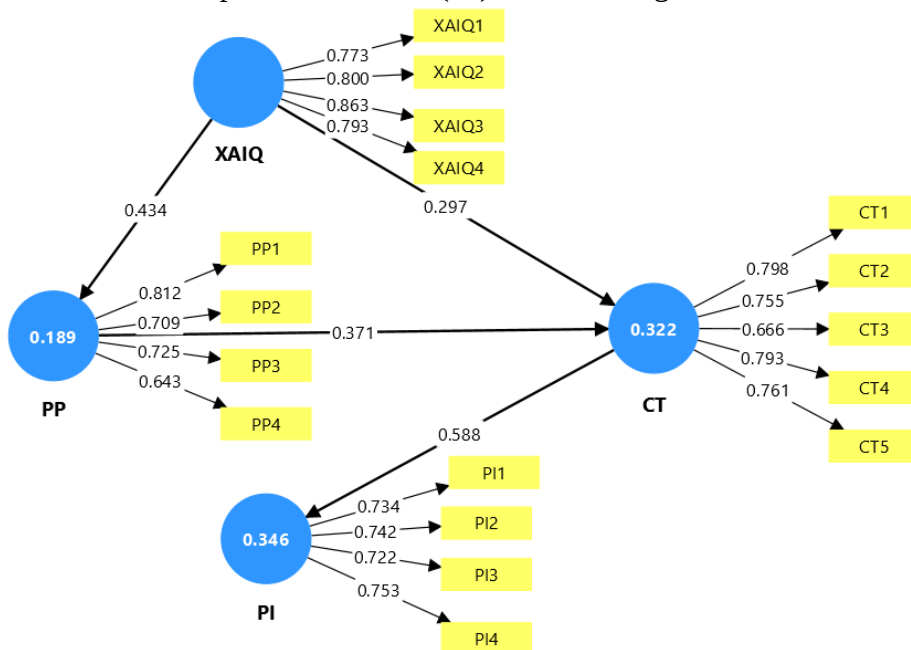


Figure 5.1 Final Structural Model with Standardized Path Coefficients and Explained Variance (R^2)

5.6 Hypothesis Testing Results

To provide a clear and journal-compliant presentation of hypothesis testing outcomes, Table 5.8 summarizes the decision status for each proposed hypothesis based on the standardized path coefficients, t-values, and p-values obtained from the bootstrapping procedure. Hypotheses were considered supported when the corresponding path coefficient was statistically significant at the 5% level ($p < 0.05$) and the direction of the effect was consistent with the proposed theoretical relationship.

Table 5.8 Summary of Hypothesis Testing Results

Hypothesis	Proposed Relationship	β	T-value	P-value	Decision
H1	XAIQ $\rightarrow$ PP	0.434	6.233	< 0.001	Supported
H2	XAIQ $\rightarrow$ CT	0.297	3.036	0.002	Supported
H3	PP $\rightarrow$ CT	0.371	3.528	< 0.001	Supported
H4	CT $\rightarrow$ PI	0.588	10.078	< 0.001	Supported
H5	XAIQ $\rightarrow$ PP $\rightarrow$ CT (Mediation)	0.161	3.112	0.002	Supported
H6	XAIQ $\rightarrow$ PP $\rightarrow$ CT $\rightarrow$ PI (Serial Mediation)	0.095	3.061	0.002	Supported

The results indicate that all hypothesized direct and indirect relationships are empirically supported. Explainable AI-driven recommendation quality significantly enhances perceived personalization (H1) and consumer trust (H2). Perceived personalization significantly influences consumer trust (H3), while consumer trust has a strong positive effect on purchase intention (H4).

Furthermore, the mediation analysis confirms that perceived personalization partially mediates the relationship between explainable AI-driven recommendation quality and consumer trust (H5). The significant indirect-only serial mediation effect (H6) demonstrates a sequential mechanism in which explainable AI-driven recommendation quality enhances perceived personalization, which subsequently strengthens consumer trust and ultimately contributes to purchase intention.

5.7 Summary of Findings

The hypothesis testing results provide empirical support for all six proposed relationships. Explainable AI-driven recommendation quality significantly influences perceived personalization (H1) and consumer trust (H2), while perceived personalization significantly enhances consumer trust (H3). Consumer trust also demonstrates a strong positive influence on purchase intention (H4). The mediation results further show that perceived personalization partially mediates the relationship between explainable AI-driven recommendation quality and consumer trust (H5). In addition, the significant indirect-only serial mediation effect (H6) indicates that explainable AI-driven recommendation quality influences purchase intention sequentially through perceived personalization and consumer trust. Overall, the findings demonstrate that explainability contributes to consumer responses by strengthening personalization perceptions and trust, which subsequently support purchase intention in e-commerce.

6. DISCUSSION, IMPLICATIONS, LIMITATIONS, AND FUTURE RESEARCH

6.1 Discussion of Findings

The present study examined how explainable AI-driven recommendation quality shapes consumer buying behaviour in e-commerce through perceived personalization and consumer trust. The findings provide empirical support for the proposed relationships and offer insights into the mechanisms through which explainability influences consumer responses in AI-mediated shopping environments.

The significant positive effect of explainable AI-driven recommendation quality on perceived personalization (H1) highlights the role of explainability in shaping consumers' perceptions of recommendation relevance and customization. When consumers can understand the rationale behind recommendations, they may perceive the recommendations as more aligned with their preferences. This finding is consistent with prior research indicating that transparency can enhance perceptions of system relevance and competence [7], [18].

The significant effect of explainable AI-driven recommendation quality on consumer trust (H2) further indicates that explainability can contribute

directly to trust formation. Providing understandable information about recommendation processes may reduce uncertainty and strengthen perceptions of transparency and accountability. This finding is consistent with prior research linking algorithmic transparency with trust and perceptions of fairness [4], [5], [12].

The positive relationship between perceived personalization and consumer trust (H3) suggests that customized recommendation experiences can strengthen consumers' confidence in the platform. When consumers perceive recommendations as relevant to their individual preferences, they may develop greater confidence in the platform's ability to understand and serve their needs. This finding is consistent with relationship marketing research that identifies personalization as an important factor in developing trust in digital environments [14], [8].

Consumer trust also emerged as a strong predictor of purchase intention (H4). The significant relationship indicates that greater trust in the platform and its recommendation process is associated with stronger willingness to purchase. This finding supports established research positioning trust as an important determinant of online transactional intentions, particularly in environments characterized by uncertainty and perceived risk [11], [10].

The mediation results provide further insight into the relationships among the study variables. The significant indirect effect of explainable AI-driven recommendation quality on consumer trust through perceived personalization (H5) indicates that perceived personalization partially mediates this relationship. More importantly, the significant indirect-only serial mediation effect (H6) demonstrates a sequential mechanism in which explainable AI-driven recommendation quality enhances perceived personalization, which subsequently strengthens consumer trust and contributes to purchase intention. This finding suggests that the influence of explainability on purchase intention operates not only through direct improvements in consumer perceptions but also through a sequential perceptual and relational process involving personalization and trust.

6.2 Theoretical Implications

This study contributes to the literature in several important ways. First, it extends research on explainable artificial intelligence by empirically validating its relevance within a consumer behaviour and marketing context.

While prior studies have predominantly examined explainability from technical, ethical, or regulatory perspectives, the present findings position XAI as a strategic determinant of consumer attitudes and behavioural intentions in digital marketplaces.

Second, the study advances personalization theory by demonstrating that interpretability and transparency function as critical enablers of the personalization experience. Rather than treating personalization solely as a system-level performance outcome, the results highlight the role of consumer cognition in shaping perceptions of relevance and fit. This perspective bridges the gap between algorithmic design and subjective user experience.

Third, the findings contribute to trust theory in digital commerce by identifying algorithmic explainability as a novel antecedent of consumer trust. In increasingly automated consumption environments, trust is not only directed toward the firm but also toward the technological systems that curate and mediate consumer choice. By empirically establishing this link, the study broadens the conceptualization of trust in technology-mediated markets.

Finally, the validated serial mediation model enriches the stimulus-organism-response (S-O-R) framework by explicitly incorporating explainable AI-driven recommendation quality as a technological stimulus and mapping its effects through multiple organismic states to a behavioural response. This integrated model provides a robust theoretical foundation for future research on AI-enabled consumer decision-making.

6.3 Managerial Implications

From a managerial perspective, the findings offer actionable insights for e-commerce platform managers, AI system developers, and digital marketing professionals. First, the strong influence of explainable AI-driven recommendation quality on both perceived personalization and consumer trust suggests that transparency should be treated as a strategic design priority rather than merely a compliance requirement. Platforms can enhance user trust and engagement by incorporating features such as “why this product is recommended” labels, preference dashboards, and clear disclosures regarding data usage.

Second, personalization strategies should be closely aligned with explainability mechanisms. Rather than focusing exclusively on improving algorithmic accuracy, managers should emphasize the interpretability of

personalized outputs. When consumers understand how their behaviours and preferences shape recommendations, they are more likely to perceive the platform as competent and customer-oriented.

Third, the strong effect of consumer trust on purchase intention highlights the commercial value of ethical and transparent AI practices. Investments in data governance, privacy protection, and algorithmic accountability can yield tangible business benefits by increasing conversion rates, repeat purchases, and long-term customer loyalty.

Finally, the serial mediation findings suggest that explainability-driven personalization can serve as a source of competitive advantage. In increasingly saturated and algorithm-intensive markets, platforms that successfully integrate transparent and user-centric AI systems into the customer journey may differentiate themselves by fostering deeper relational bonds with consumers.

6.4 Limitations

Despite its contributions, this study is subject to several limitations that should be acknowledged. First, the use of a cross-sectional research design limits the ability to draw causal inferences regarding the observed relationships. Longitudinal or experimental designs could provide stronger evidence of temporal precedence and causal mechanisms.

Second, the study employed a non-probability convenience sampling technique and a relatively modest sample size. While this approach is consistent with exploratory and theory-testing research using PLS-SEM, it may limit the generalizability of the findings to broader populations or specific demographic segments.

Third, all data were collected using self-reported measures, which may be subject to social desirability bias or common method variance, despite the procedural and statistical remedies implemented.

Finally, the study focused on general perceptions of e-commerce platforms rather than platform-specific features or industry categories. Differences across product types, cultural contexts, or regulatory environments may moderate the observed relationships. Additionally, future research may enhance external validity by employing probability-based sampling

techniques and larger, cross-national samples to assess the generalizability of the findings across diverse cultural and regulatory contexts.

6.5 Directions for Future Research

Future studies can build on the present findings in several ways. First, researchers may employ longitudinal or experimental designs to examine how changes in explainability features influence consumer trust and purchase behaviour over time. Such approaches would enhance causal inference and provide deeper insight into dynamic consumer-AI interactions.

Second, future research could explore moderating variables such as privacy concern, technology readiness, or cultural orientation to assess how individual differences shape responses to explainable AI systems.

Third, comparative studies across different e-commerce platforms, industries, or national contexts could enhance the external validity of the model and identify context-specific effects.

Finally, future work may extend the model by incorporating additional outcome variables, such as customer satisfaction, platform loyalty, or word-of-mouth intention, to provide a more comprehensive understanding of the long-term behavioural implications of explainable AI in digital commerce environments.

7. DECLARATIONS

7.1 Funding

This research was completed independently and did not receive any monetary or material support from governmental bodies, commercial entities, or non-profit organizations.

7.2 Conflicts of Interest

The authors confirm that no personal, professional, or financial relationships exist that could be perceived as influencing the design, execution, interpretation, or presentation of the study.

7.3 Ethics Statement

The study did not involve the use of animals. All research activities involving human participants were conducted in line with established institutional policies and recognized ethical standards for social science research.

7.4 Consent to Participate

Participation was voluntary, and informed consent was secured from all participants before the commencement of data collection. Measures were taken to ensure respondent privacy, confidentiality, and anonymity throughout the study.

7.5 Data Availability

The datasets supporting the conclusions of this research may be obtained from the corresponding author upon reasonable and justified request.

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