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The Role of Perceived Relevance and Consumer Trust in the Relationship Between AI Recommendations and Purchase Intention

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Abstract. *The development of artificial intelligence (AI) has transformed how consumers search for, evaluate, and select products in digital environments. One adopted application is AI recommendation, which provides product suggestions based on consumers' preferences, behaviors, and interactions. Although recommendation technology can improve product-search efficiency, its effectiveness in stimulating purchase intention depends not only on algorithmic sophistication but also on perceived relevance and consumer trust. This study aims to examine the effect of AI Recommendation on Purchase Intention and investigate the roles of Perceived Relevance and Consumer Trust as mechanisms explaining this relationship. A quantitative approach was employed through a survey of 160 respondents using digital or e-commerce platforms with AI-based recommendation features. Data were analyzed using Partial Least Squares–Structural Equation Modeling (PLS-SEM) with SmartPLS. The results show that AI Recommendation positively and significantly affects Perceived Relevance and Consumer Trust. Perceived Relevance and Consumer Trust positively and significantly influence Purchase Intention. AI Recommendation has a significant direct effect on Purchase Intention. Mediation analysis indicates that Perceived Relevance and Consumer Trust significantly mediate the relationship between AI Recommendation and Purchase Intention, demonstrating partial mediation. These findings indicate that consumers evaluate whether recommendations are relevant to their needs and whether the system is trustworthy. Theoretically, this study reinforces the Stimulus–Organism–Response (S-O-R) perspective in explaining consumer behavior in AI-enabled environments. Managerially, businesses should develop accurate, personalized, transparent, and trustworthy recommendation systems to enhance purchase intention.*

Keywords: *AI Recommendation; Consumer Trust; Perceived Relevance; Purchase Intention; S-O-R.*

1. INTRODUCTION

The rapid development of artificial intelligence (AI) has fundamentally transformed how firms understand, serve, and influence consumers in digital environments. AI is no longer limited to a conventional analytical tool for processing historical data; it has evolved into a technology capable of predicting preferences, identifying behavioral patterns, generating recommendations, and interacting adaptively with consumers. This transformation is particularly visible in e-commerce, where consumers are increasingly exposed to extensive numbers of products, information, reviews, promotional messages, and alternative choices. Under such conditions, AI has become an important technological mechanism for reducing search complexity and helping consumers identify products that are expected to match their needs and preferences (Hermann & Puntoni, 2024; Vaid et al., 2023). Recent systematic research confirms that the AI–consumer behavior literature has expanded rapidly, with major research themes including trust, decision-making, consumer–AI interaction, personalization, engagement, and technology adoption (Jain, 2024; Zulaikha et al., 2026).

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One of the most important applications of AI in digital marketing is the artificial intelligence-based recommendation system. Recommendation systems are designed to filter information and present products or services that are expected to match users' characteristics, previous behaviors, preferences, and contextual conditions. Advances in machine learning have enabled recommendation systems to become increasingly adaptive because they can process large volumes of consumer data and continuously update predictions based on new interactions (Adomavicius & Tuzhilin, 2005; Ricci et al., 2022). In e-commerce, this capability has strategic importance because recommendation systems can simultaneously reduce information overload for consumers and improve the relevance of firms' offerings. Existing research suggests that recommendation systems do not merely facilitate information search; they can also shape consumers' consideration sets, product evaluations, attitudes, trust, and purchase decisions (Liu et al., 2021; Yun & Chun, 2024).

Nevertheless, the presence of AI-generated recommendations does not automatically guarantee positive consumer responses. Consumers do not merely evaluate whether a product has been recommended; they also assess whether the recommendation is genuinely relevant to their needs, preferences, goals, and situational circumstances. This issue is closely related to perceived relevance, referring to the extent to which consumers perceive the information or recommendation provided by a system as appropriate and useful for their decision-making needs. Relevance is particularly important because consumers tend to allocate greater attention to information that is perceived to be directly related to their search objectives. In information-rich digital environments, relevant recommendations can reduce search effort and simplify the evaluation of alternatives (Tam & Ho, 2006; Adomavicius & Tuzhilin, 2005). Therefore, the effectiveness of an AI recommendation should not be evaluated exclusively through the technical accuracy of the algorithm but also through consumers' subjective perceptions of whether the recommendation fits their needs.

Perceived relevance becomes particularly important because personalization can produce both positive and negative consequences. On the positive side, increasingly personalized recommendations may improve convenience, perceived value, and the probability that consumers discover products that fit their preferences. On the negative side, excessive personalization may create perceptions of intrusiveness, manipulation, or excessive surveillance regarding consumers' personal information. The personalization paradox literature demonstrates that consumers may simultaneously appreciate the benefits of personalization while experiencing discomfort regarding the collection and use of personal data required to provide such personalization (Aguirre et al., 2015; Bleier & Eisenbeiss, 2015).

Recent research further suggests that personalized recommendations can generate psychological resistance when consumers perceive that recommendation systems attempt to manipulate their choices or reduce their sense of autonomy (Wang et al., 2025). Thus, relevance should not be conceptualized merely as a technical property of recommendation algorithms but as a consumer-level evaluation of the fit between the recommendation and the consumer's needs.

In addition to relevance, consumer trust represents another important mechanism for understanding consumers' responses to AI-based recommendation systems. Online purchasing involves uncertainty because consumers cannot always physically inspect products, may not fully understand how recommendations are generated, and must rely on information provided by digital platforms. Under these conditions, trust can function as a mechanism for reducing perceived uncertainty and increasing consumers' willingness to rely on information provided by the system. Research on recommender systems indicates that trust is associated with perceptions of system capability, intelligence, transparency, learning ability, and information quality (Wang & Benbasat, 2016; Dong et al., 2022). Empirical evidence further indicates that perceived system ability to learn and intelligence cues can shape consumers' perceptions of the trustworthiness of information generated by recommendation systems (Chen et al., 2022).

Consumer trust becomes more complex when recommendations are generated by AI because consumers must evaluate not only the product information but also the algorithmic mechanism underlying the recommendation. Consumers may question whether the system genuinely recommends products according to their interests or whether recommendations are primarily driven by the commercial interests of the platform. Consequently, transparency, explainability, privacy, and perceived competence become important dimensions that may shape trust. Research on explainable recommendation systems demonstrates that explanations can contribute to trust calibration, although poorly designed explanations may also encourage consumers to place disproportionate trust in AI recommendations (Naiseh et al., 2021). Similarly, research on e-commerce recommendation transparency demonstrates that transparency can influence consumer trust through perceived effectiveness and discomfort (Wang et al., 2024). Consumer trust in AI recommendation systems should therefore be understood as an evaluation of whether the system possesses sufficient capability, reliability, and credibility to generate recommendations that consumers are willing to use.

The relationship between AI recommendation and purchase intention is consequently important because the ultimate marketing objective of personalization is not merely to generate recommendations but to influence consumer behavior. Purchase intention reflects consumers'

willingness or behavioral inclination to purchase a product after evaluating available information and alternatives. Existing research indicates that recommendation quality, personalization, trust, perceived value, and consumer experience can contribute to purchase intention. Yun and Chun (2024), for example, conceptualize personalized recommendation as a mechanism that can influence purchase intention through consumers' experiences and perceived trust. Recent evidence from fashion e-commerce further indicates that personalized recommendation system quality can increase perceived value and purchase intention, while post-purchase outcomes depend on whether recommendation-induced expectations correspond to actual product experiences (Jasim et al., 2026). Research comparing ChatGPT recommendations and conventional AI recommender systems also demonstrates that trust in the recommender can play an important role in the formation of consumers' consideration sets (Aoki & Matsui, 2025; Kim et al., 2023).

Despite these developments, several gaps remain in the literature. First, a substantial body of research emphasizes technical characteristics of recommendation systems, including accuracy, transparency, diversity, novelty, and system quality, whereas consumers' subjective evaluation of recommendation relevance has not always been positioned as a central mechanism explaining purchase intention. Second, studies examining trust frequently treat it as either an outcome or a direct predictor of behavioral intention, but fewer studies simultaneously integrate trust and perceived relevance as distinct psychological mechanisms through which AI recommendations affect purchase intention. Third, AI and consumer behavior research has developed across several relatively fragmented streams, including recommender systems, personalization, human–AI interaction, trust, consumer decision-making, and generative AI (Jain, 2024; Hermann & Puntoni, 2024). This fragmentation indicates the need for an integrated model that explains how AI recommendation characteristics are transformed into consumers' cognitive and psychological evaluations before ultimately affecting purchase intention.

This research gap becomes increasingly important as AI recommendation evolves beyond conventional product-ranking systems toward AI agents, conversational recommendation, and generative AI. Consumers can now obtain recommendations not only through automatically generated product lists but also through interactive conversations with AI systems. This development changes the role of AI from a technological filter of information into an active agent that participates in consumer decision-making. Research on AI agents demonstrates that characteristics such as anthropomorphism and gender-related cues can influence perceptions of competence, warmth, and the persuasiveness of AI recommendations

(Ahn et al., 2022). Recent research further indicates that AI-powered personalization may increase purchase intention through psychological mechanisms while simultaneously generating perceived intrusiveness when consumers feel overly influenced by the system (Jasim et al., 2026).

Against this background, the present study proposes that the effect of AI recommendation on purchase intention should not be conceptualized as a simple direct relationship. Instead, AI recommendation is expected to operate through two central psychological pathways. The first pathway is cognitive, whereby consumers evaluate the extent to which the recommendation is relevant to their needs and preferences. The second pathway is relational and evaluative, whereby consumers assess whether the AI system can be trusted to provide reliable recommendations. By positioning perceived relevance and consumer trust as mediating mechanisms, this study seeks to explain more comprehensively how AI recommendations are translated into purchase intention. This perspective is consistent with the growing AI and consumer behavior literature emphasizing trust, personalization, consumer experience, and decision-making as central dimensions of technology-mediated consumption (Vaid et al., 2023; Jain, 2024).

Accordingly, this study aims to examine the effect of AI recommendation on purchase intention and to investigate the mediating roles of perceived relevance and consumer trust. Theoretically, this study seeks to extend AI and consumer behavior research by demonstrating that the effectiveness of recommendation systems is not determined solely by their technological capability to generate recommendations but also by consumers' perceptions of recommendation relevance and system credibility. Practically, the findings are expected to provide guidance for e-commerce firms in designing recommendation systems that are not only personalized but also relevant, trustworthy, transparent, and consumer-oriented. Such an approach is increasingly important because the rapid development of AI requires firms to balance commercial objectives with consumer experience, trust, privacy, and responsible data practices (Das et al., 2026; Aliberti et al., 2026).

2. LITERATURE REVIEW

Stimulus–Organism–Response (S-O-R) theory provides a comprehensive framework for explaining how external environmental stimuli influence individuals' internal psychological states and subsequently generate behavioral responses. Rooted in the environmental psychology perspective of Mehrabian and Russell (1974), the S-O-R framework has been widely adopted in consumer behavior and digital commerce research. Within this

framework, the stimulus represents external environmental characteristics encountered by individuals, the organism represents internal cognitive and psychological processes, and the response represents the resulting behavioral outcome.

In the present study, S-O-R provides an appropriate theoretical foundation for explaining how AI recommendation influences purchase intention through consumers' internal evaluations. AI recommendation is conceptualized as the stimulus because consumers are exposed to product recommendations generated through artificial intelligence based on behavioral data, preferences, and interaction contexts. These recommendations are subsequently evaluated internally by consumers in terms of their relevance to personal needs and the trustworthiness of the recommendation system. Therefore, perceived relevance and consumer trust are conceptualized as organismic states, whereas purchase intention represents the behavioral response.

The application of S-O-R is particularly relevant to AI-enabled e-commerce because consumers do not respond to technology mechanically. When receiving an AI-generated recommendation, consumers evaluate whether the recommendation is useful, relevant, credible, and trustworthy before incorporating it into their decision-making process. Recent research on AI-powered chatbots in e-commerce has applied S-O-R to explain how AI service quality influences purchase intention through internal psychological mechanisms, including trust, consumer experience, and engagement. Similarly, recent research on AI-generated review summaries applies S-O-R to explain purchase intention through perceived diagnosticity and algorithm trust.

Accordingly, S-O-R provides a coherent structure for the proposed research model. AI recommendation represents the external stimulus, perceived relevance captures consumers' cognitive evaluation of recommendation fit, consumer trust reflects their psychological confidence in the AI system, and purchase intention represents the behavioral response. This theoretical structure implies that technological stimuli may affect consumer behavior indirectly through internal psychological evaluations rather than exclusively through direct effects.

A recommendation system is a technological mechanism designed to assist users in selecting products, services, or information that are likely to match their preferences and needs. Traditional recommendation systems have evolved from collaborative filtering and content-based filtering toward increasingly sophisticated approaches based on machine learning, deep learning, natural language processing, and contextual recommendation. The Recommender Systems Handbook identifies collaborative filtering, semantic-based recommendation, implicit

feedback, neural networks, and context-aware methods as major approaches within the recommender-system field (Ricci et al., 2022).

The development of artificial intelligence has transformed recommendation systems from relatively static information-filtering mechanisms into increasingly adaptive and predictive technologies. AI enables recommendation systems to process large volumes of consumer data, identify behavioral patterns, infer preferences, and dynamically generate product suggestions. In digital commerce, this capability enables firms to personalize consumer experiences while reducing the information overload associated with extensive product alternatives. In this study, AI recommendation refers to the perceived capability of an artificial intelligence-based system to generate personalized product recommendations based on consumer information and interaction contexts. The construct therefore goes beyond the mere presence of recommendations and incorporates consumers' perceptions of the system's ability to understand their preferences, provide accurate suggestions, personalize recommendations, and offer useful alternatives. Importantly, technological sophistication does not necessarily guarantee positive consumer responses. An algorithm may perform well according to technical metrics while consumers may still perceive its recommendations as irrelevant or untrustworthy. This distinction highlights the importance of examining consumer-level evaluations rather than focusing exclusively on algorithmic performance. Yun and Chun (2024) demonstrate that personalized recommendation can influence purchase intention through multiple dimensions of recommendation and consumer psychological processes, including perceived trust. Therefore, research on AI recommendation should account for the psychological mechanisms through which consumers interpret and evaluate AI-generated recommendations.

Perceived relevance refers to the extent to which consumers perceive information, recommendations, or messages as appropriate and consistent with their needs, preferences, goals, and situational circumstances. Relevance is fundamental to information processing because consumers are more likely to attend to information that is perceived as directly connected to their decision objectives. In information-intensive digital environments, relevance helps consumers filter information and reduce cognitive effort. Tam and Ho (2006) demonstrate that web personalization can influence users' information-processing activities and decision outcomes. Conceptually, when digital systems provide information that corresponds closely to users' needs, search and evaluation processes can become more efficient. Within recommendation systems, this implies that recommendations perceived as relevant are more likely to attract attention, be considered, and be incorporated into consumer decision-making. Perceived relevance should also be distinguished from algorithmic

recommendation accuracy. Accuracy represents a technical evaluation of system performance, whereas perceived relevance represents consumers' subjective judgments regarding whether the recommendation actually fits their personal needs. A system may therefore generate technically accurate recommendations that consumers nevertheless perceive as irrelevant because they do not correspond to the consumer's current context or objective. Within AI-enabled environments, perceived relevance is closely associated with personalization. When AI systems successfully infer consumers' preferences and provide appropriate recommendations, consumers may perceive greater value from the recommendation process. However, personalization can also produce negative outcomes. Aguirre et al. (2015) and Bleier and Eisenbeiss (2015) describe a personalization paradox in which consumers appreciate the benefits of personalization while simultaneously experiencing concerns about the collection and use of personal data. Perceived relevance can therefore be conceptualized as a cognitive mechanism connecting AI recommendation to consumer response. When consumers perceive recommendations as relevant, they have stronger reasons to use those recommendations during product evaluation. Relevance may also enhance perceived usefulness because appropriately matched recommendations reduce search effort and facilitate the comparison of alternatives.

Trust is a fundamental construct in digital consumer research. It can generally be defined as a belief that a trusted party possesses the capability, integrity, and benevolence necessary to act in a reliable manner. Mayer et al. (1995) conceptualize trust around ability, benevolence, and integrity. In technology-mediated environments, these dimensions provide a useful foundation for understanding consumers' evaluations of AI systems. In the present research, consumer trust refers to consumers' confidence that the AI recommendation system is capable of providing reliable, appropriate, and non-misleading recommendations. This conceptualization distinguishes trust in the AI recommendation system from trust in a brand, seller, or e-commerce platform. The focus is specifically on the credibility and reliability of the AI mechanism responsible for generating recommendations. Trust is particularly important because AI recommendation involves algorithmic uncertainty. Consumers may not understand how the system processes their data, why particular products are recommended, or whether recommendations reflect consumer interests or platform commercial objectives. Dong et al. (2022) identify trust as an important challenge in recommender systems, particularly when recommendations are inaccurate or insufficiently explained. Explainability is also relevant to trust formation. Naiseh et al. (2021) demonstrate that explanations can contribute to trust calibration by helping users develop a more appropriate understanding of recommendation processes. However, poorly designed explanations may also lead users to place excessive

confidence in algorithmic outputs. Research on AI-powered retail platforms further indicates that perceived trust represents an important factor in shaping consumers' purchase intentions toward AI-enabled shopping environments. Thus, consumer trust can be conceptualized as a psychological mechanism that reduces uncertainty and increases consumers' willingness to rely on AI-generated recommendations.

Purchase intention represents consumers' willingness or behavioral tendency to purchase a product after evaluating available information and alternatives. In consumer behavior research, purchase intention is frequently used as a proximal indicator of potential purchasing behavior. The Theory of Planned Behavior suggests that behavioral intention represents an important proximal determinant of actual behavior (Ajzen, 1991). Within the present research context, purchase intention represents the consumer response after exposure to and evaluation of AI-generated recommendations. Consumers who perceive recommendations as relevant and the recommendation system as trustworthy are expected to demonstrate stronger purchase intentions toward recommended products. In e-commerce, purchase intention is influenced by multiple factors, including perceived usefulness, perceived value, trust, perceived risk, recommendation quality, and personalization. Yun and Chun (2024) demonstrate a relationship between personalized recommendation and purchase intention in big-data environments. Research on personalized e-commerce experiences similarly indicates that trust can connect personalization with consumers' purchase-related responses. Accordingly, purchase intention is conceptualized as the response component of the S-O-R framework. This positioning emphasizes that purchase intention is not merely a technological consequence of AI recommendation but the outcome of consumers' cognitive and psychological evaluations.

AI recommendation is theoretically expected to have a positive relationship with perceived relevance. As recommendation systems become more capable of identifying consumer characteristics, preferences, behaviors, and contextual conditions, recommendations are more likely to be perceived as appropriate to individual needs. Modern recommendation systems are specifically designed to incorporate user information and contextual signals to improve personalization (Ricci et al., 2022). From an information-processing perspective, relevant recommendations help consumers filter information and reduce cognitive effort. AI recommendation therefore creates value when consumers perceive that the system assists them in locating products that genuinely match their needs. This relationship provides a theoretical basis for positioning perceived relevance as an important psychological consequence of AI recommendation.

AI recommendation is also expected to influence consumer trust. When recommendations are consistent, accurate, explainable, and appropriate, consumers may develop stronger confidence in the system. Conversely, inaccurate or opaque recommendations can undermine trust. Dong et al. (2022) identify trust as a major issue in recommender systems because users may reject recommendations when systems are perceived as inaccurate or insufficiently transparent. Recent research further demonstrates that transparency in AI-generated information and algorithm trust can represent important mechanisms connecting AI systems with purchase intention. Thus, consumers' experiences with AI recommendation can serve as a basis for trust formation. Repeated exposure to recommendations that are perceived as accurate and useful may strengthen consumers' beliefs that the system possesses sufficient competence to provide reliable recommendations.

Perceived relevance is expected to positively influence purchase intention because relevant information is more likely to attract attention, receive cognitive processing, and be incorporated into product evaluation. When recommendations fit consumers' needs, consumers may require less effort to search for and compare alternative products. Relevance can also increase the diagnostic value of product information. Information perceived as relevant is more capable of helping consumers assess whether a product fits their requirements. Recent research on AI-generated review summaries demonstrates that perceived diagnosticity can represent an important mechanism linking AI-mediated information to purchase intention. Consequently, perceived relevance represents more than a judgment regarding information quality; it functions as a cognitive mechanism that can increase the likelihood that consumers will use AI recommendations in their purchase decisions.

Consumer trust is theoretically expected to positively influence purchase intention because trust reduces uncertainty and perceived risk in digital transactions. When consumers trust an AI recommendation system, they become more willing to use its information as a basis for evaluating products. Trust becomes particularly important in AI-mediated environments because consumers cannot directly observe how algorithms generate recommendations. Confidence in the system's capability, reliability, and integrity therefore becomes an important basis for accepting algorithmic recommendations. Yun and Chun (2024) identify perceived trust as an important mechanism associated with personalized recommendation and purchase intention. Research on AI-powered retail platforms similarly emphasizes perceived trust as an important factor shaping purchase intention toward AI-enabled shopping services.

Perceived relevance is conceptualized as a mediator because AI recommendation does not automatically generate purchase intention. Recommendations must first be processed and evaluated by consumers. When recommendations are perceived as consistent with consumer needs, consumers are more likely to pay attention to them, reduce search effort, evaluate recommended products positively, and develop stronger purchase intentions. This mediating position extends prior research that has often examined direct relationships between recommendation quality or personalization and behavioral intention. Incorporating perceived relevance enables the study to explain the cognitive mechanism underlying the effect of AI recommendation on purchase intention. Within the S-O-R framework, AI recommendation functions as the stimulus, perceived relevance represents the consumer's internal cognitive state, and purchase intention represents the behavioral response. Therefore, the proposed mediation relationship is theoretically consistent with the S-O-R framework.

Consumer trust is also conceptualized as a mediator because AI recommendation may influence purchase intention through the formation of confidence in the recommendation system. Consumers who consistently receive recommendations that appear reliable, appropriate, and useful may become more willing to rely on those recommendations during product evaluation. This mechanism is particularly important in digital transactions because purchase decisions require not only product information but also confidence in the credibility of the information source. Research on recommender systems identifies trust as a central issue in the acceptance and effectiveness of AI-based recommendations. Positioning consumer trust as a mediator allows the study to determine whether AI recommendation affects purchase intention because consumers perceive the recommendation system as trustworthy. This provides a stronger theoretical explanation than merely testing a direct relationship between AI recommendation and purchase intention.

Based on the preceding theoretical discussion, this study conceptualizes AI recommendation as the stimulus, perceived relevance and consumer trust as two distinct organismic mechanisms, and purchase intention as the behavioral response. The model assumes that consumers do not immediately translate exposure to AI recommendations into purchase intentions. Instead, they first assess whether the recommendation is relevant to their needs and whether the AI system can be trusted.

The proposed model therefore contains two psychological pathways. The first is a cognitive pathway, represented by AI recommendation → perceived relevance → purchase intention. The second is a trust pathway, represented by AI recommendation → consumer trust

→ purchase intention. These two pathways allow the study to capture both cognitive and relational dimensions of consumer responses to AI-generated recommendations.

This positioning is consistent with recent developments in AI and consumer behavior research, which increasingly emphasize trust, personalization, transparency, consumer experience, and behavioral responses rather than technological capability alone. Recent research on AI-generated review summaries further demonstrates the value of integrating S-O-R with signaling theory to explain purchase intention through algorithm trust and perceived diagnosticity.

The theoretical contribution of the present study therefore lies in integrating two distinct psychological mechanisms perceived relevance and consumer trust to explain how AI recommendation is translated into purchase intention. This integration provides a more comprehensive account of consumer decision-making in increasingly AI-mediated e-commerce environments.

3. RESEARCH METHOD

This study employs a quantitative explanatory research design to examine the effect of AI Recommendation on Purchase Intention and to investigate the mediating roles of Perceived Relevance and Consumer Trust. A quantitative approach is appropriate because the study aims to empirically test relationships among latent constructs using numerical data collected from consumers. The conceptual model is grounded in the Stimulus–Organism–Response (S-O-R) framework, which proposes that external stimuli influence individuals' internal psychological states and subsequently generate behavioral responses (Mehrabian & Russell, 1974).

In the proposed model, AI Recommendation represents the stimulus because consumers receive product recommendations generated through artificial intelligence based on their information, preferences, behavioral patterns, or previous interactions. Perceived Relevance and Consumer Trust represent the organism, reflecting consumers' cognitive and psychological evaluations of AI-generated recommendations. Purchase Intention represents the response, reflecting consumers' willingness or tendency to purchase recommended products.

A cross-sectional design is employed, whereby data are collected during a single research period. Primary data are obtained through an online questionnaire using a five-point Likert scale. The relationships among the latent constructs are examined using Partial Least Squares Structural Equation Modeling (PLS-SEM). PLS-SEM is appropriate because the research model consists of multiple latent constructs measured by several indicators and includes mediation relationships that need to be simultaneously estimated (Hair et al., 2022).

The population consists of consumers who have used e-commerce or digital platforms providing artificial intelligence-based product recommendations. This population was selected because respondents need to have actual experience with personalized product recommendations in order to evaluate recommendation relevance and trust in AI-based recommendation systems. The study employs purposive sampling because not all e-commerce users have sufficient experience with AI recommendations. Respondents are required to meet specific eligibility criteria before participating in the study. The inclusion criteria are: (1) respondents must be at least 18 years old; (2) have experience using e-commerce or digital shopping platforms; (3) have received or viewed AI-generated or AI-personalized product recommendations; and (4) have considered products based on recommendations provided by digital platforms. A total of 160 respondents who fulfilled all eligibility criteria were included in the study. The sample was used to estimate the proposed research model using PLS-SEM. Sample adequacy in PLS-SEM depends not only on the number of observations but also on model complexity, the number of indicators, structural relationships, and statistical power (Hair et al., 2022).

Primary data were collected through a structured online questionnaire. The questionnaire was developed based on measurement indicators established in previous studies and adapted to the context of AI recommendation in e-commerce. Prior to the main survey, the questionnaire was reviewed to ensure the clarity of wording and the appropriateness of the measurement items. Screening questions were included at the beginning of the questionnaire to ensure that respondents had relevant experience with e-commerce and AI-based product recommendations. Respondents were informed about the purpose of the research and the use of their responses. Participation was voluntary, and respondents were not required to provide personally identifying information that was unnecessary for the research.

Table 1. Variable Operationalization.

Variable	Operational Definition	Indicators	Code	Scale
AI Recommendation (X)	Consumers' perception of the ability of an AI system to provide product recommendations that match their preferences and needs.	The recommendations match my preferences	AR1	Likert 1–5
		AI recommendations are personalized according to my needs	AR2	Likert 1–5
		The AI recommendations are accurate	AR3	Likert 1–5
		AI recommendations help me find suitable products	AR4	Likert 1–5
		AI recommendations provide useful product alternatives	AR5	Likert 1–5

Perceived Relevance (M1)	Consumers' perception of the extent to which AI recommendations are relevant to their needs, preferences, and shopping circumstances.	The recommendations are relevant to my needs	PR1	Likert 1–5
		The recommended products match my preferences	PR2	Likert 1–5
		The recommendations are relevant to my interests	PR3	Likert 1–5
		The recommendations are relevant to my search objectives	PR4	Likert 1–5
		The recommendations help me find products I need	PR5	Likert 1–5
Consumer Trust (M2)	Consumers' confidence that the AI recommendation system is reliable, credible, and capable of providing trustworthy recommendations.	I trust the recommendations provided by the AI system	CT1	Likert 1–5
		The AI system is reliable in providing recommendations	CT2	Likert 1–5
		I believe the AI recommendations can be trusted	CT3	Likert 1–5
		The AI system is capable of providing good recommendations	CT4	Likert 1–5
		I feel safe relying on recommendations from the AI system	CT5	Likert 1–5
Purchase Intention (Y)	Consumers' willingness or tendency to consider and purchase products recommended by an AI system.	I intend to purchase products recommended by AI	PI1	Likert 1–5
		I will consider products recommended by AI	PI2	Likert 1–5
		The likelihood that I will purchase an AI-recommended product is high	PI3	Likert 1–5
		I am willing to choose products based on AI recommendations	PI4	Likert 1–5
		I will use AI recommendations in my purchase decisions	PI5	Likert 1–5

AI Recommendation. AI Recommendation refers to the ability of an artificial intelligence-based system to analyze consumer information and generate personalized product recommendations. The construct focuses on consumers' perceptions of recommendation accuracy, personalization, appropriateness, and usefulness. Perceived Relevance. Perceived Relevance refers to the extent to which consumers perceive AI-generated recommendations as directly related to their needs, preferences, interests, and search objectives. The construct emphasizes consumers' subjective assessment rather than the technical accuracy of the algorithm. Consumer Trust. Consumer Trust refers to consumers' confidence that an AI recommendation system is capable of providing reliable and trustworthy recommendations. The construct specifically concerns trust in the AI recommendation system rather than trust in

the brand or seller. Purchase Intention. Purchase Intention refers to consumers' willingness, likelihood, and behavioral tendency to consider or purchase products after receiving recommendations from an AI-based system.

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS. The analysis consists of three main stages: measurement model assessment, structural model assessment, and mediation analysis.

The measurement model is evaluated to determine whether the indicators adequately measure their respective constructs. The assessment includes *outer loadings*, Cronbach's alpha, composite reliability, Average Variance Extracted (AVE), and discriminant validity. Outer loadings are examined to determine the contribution of each indicator to its corresponding construct. Indicator loadings of ≥0.70 are generally considered satisfactory. Indicators with loadings between 0.40 and 0.70 may be retained when their removal does not substantively improve the measurement model. Internal consistency reliability is assessed using Cronbach's alpha and Composite Reliability. Values of approximately 0.70 or higher indicate acceptable reliability. Convergent validity is assessed using Average Variance Extracted (AVE). An AVE value of ≥0.50 indicates that the construct explains at least 50% of the variance in its indicators. Discriminant validity is assessed using the Heterotrait–Monotrait Ratio (HTMT) to establish that AI Recommendation, Perceived Relevance, Consumer Trust, and Purchase Intention represent empirically distinct constructs.

After establishing adequate measurement reliability and validity, the structural model is assessed. The evaluation includes collinearity diagnostics, path coefficients, coefficient of determination (R^2), effect size (f^2), and predictive capability. R^2 is used to determine the proportion of variance in endogenous constructs explained by the predictors. Particular attention is given to the ability of AI Recommendation, Perceived Relevance, and Consumer Trust to explain Purchase Intention. Path coefficients are examined to determine the direction and magnitude of the relationships among constructs. Statistical significance is assessed using the bootstrapping procedure. Results are reported using β coefficients, t-statistics, p-values, and confidence intervals.

Based on the proposed conceptual model, the following hypotheses are tested:

H1: AI Recommendation has a positive effect on Perceived Relevance.

H2: AI Recommendation has a positive effect on Consumer Trust.

H3: Perceived Relevance has a positive effect on Purchase Intention.

H4: Consumer Trust has a positive effect on Purchase Intention.

H5: AI Recommendation has a positive effect on Purchase Intention.

In addition to the direct relationships, two mediation hypotheses are examined:

H6: Perceived Relevance mediates the relationship between AI Recommendation and Purchase Intention.

H7: Consumer Trust mediates the relationship between AI Recommendation and Purchase Intention.

Hypotheses are supported when the estimated path coefficient has the expected direction and the confidence interval for the tested effect does not include zero.

Mediation analysis is a central component of the study because the research seeks not only to determine whether AI Recommendation influences Purchase Intention but also to explain how this influence occurs.

The first mediation pathway is specified as:

AI Recommendation → Perceived Relevance → Purchase Intention

The second mediation pathway is specified as:

AI Recommendation → Consumer Trust → Purchase Intention

Indirect effects are evaluated using bootstrapping. A mediation effect is considered statistically significant when its confidence interval does not include zero. The direct effect of AI Recommendation on Purchase Intention is also assessed to determine the nature of the mediation.

This procedure allows the study to determine whether the influence of AI Recommendation on Purchase Intention operates primarily through a cognitive mechanism represented by perceived relevance, a trust mechanism represented by consumer trust, or through both mechanisms simultaneously. Potential common method bias is considered because the independent, mediating, and dependent constructs are measured from the same respondents using the same questionnaire. Procedural remedies include clear questionnaire wording, neutral questions, respondent anonymity, and conceptual separation among the constructs. In addition to procedural remedies, common method bias may be statistically assessed using an appropriate PLS-SEM procedure. This assessment is conducted to ensure that the observed relationships among constructs are not primarily attributable to the measurement method.

The study follows established research ethics principles. Participation is voluntary, and respondents are informed about the purpose of the study and the use of their responses. Respondents have the right to discontinue participation at any stage. Respondent information is treated confidentially and is used solely for academic purposes. Personal identifying

information that is not necessary for the study is not collected. The research findings are reported in aggregate form to protect the identity and privacy of individual respondents.

4. FINDINGS AND DUSCUSSION

The study analyzed data from 160 respondents to examine the relationships among AI Recommendation, Perceived Relevance, Consumer Trust, and Purchase Intention.

Table 2. Reliability and Convergent Validity.

Construct	Cronbach's Alpha	Composite Reliability	AVE	Decision
AI Recommendation	0.912	0.935	0.741	Valid & Reliable
Perceived Relevance	0.901	0.927	0.718	Valid & Reliable
Consumer Trust	0.918	0.939	0.753	Valid & Reliable
Purchase Intention	0.925	0.944	0.771	Valid & Reliable

The results demonstrate satisfactory internal consistency and convergent validity. All constructs exhibit Cronbach's alpha and composite reliability values above acceptable levels, while AVE values exceed the recommended threshold.

Table 3. Coefficient of Determination.

Endogenous Construct	R^2	Adjusted R^2	Interpretation
Perceived Relevance	0.492	0.489	Moderate
Consumer Trust	0.438	0.434	Moderate
Purchase Intention	0.641	0.634	Moderate–Strong

The R^2 value of 0.641 indicates that AI Recommendation, Perceived Relevance, and Consumer Trust collectively explain 64.1% of the variance in Purchase Intention.

Table 4. Hypothesis Testing Results.

Hypothesis	Relationship	Path Coefficient (β)	t-value	p-value	Decision
H1	AI Recommendation → Perceived Relevance	0.701	14.286	0.000	Supported
H2	AI Recommendation → Consumer Trust	0.662	11.847	0.000	Supported
H3	Perceived Relevance → Purchase Intention	0.397	4.892	0.000	Supported
H4	Consumer Trust → Purchase Intention	0.361	4.317	0.000	Supported
H5	AI Recommendation → Purchase Intention	0.214	2.683	0.008	Supported

All five direct hypotheses are supported because the t-values exceed 1.96 and the p-values are below 0.05.

The strongest relationship is observed between AI Recommendation and Perceived Relevance ($\beta = 0.701$), followed by AI Recommendation and Consumer Trust ($\beta = 0.662$). This indicates that the primary contribution of AI recommendation occurs through consumers' cognitive evaluation of relevance and their confidence in the recommendation system.

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Table 5. Mediation Testing Results.

Hypothesis	Indirect Relationship	Indirect Effect (β)	t-value	p-value	Decision
H6	AI Recommendation → Perceived Relevance → Purchase Intention	0.278	4.631	0.000	Supported
H7	AI Recommendation → Consumer Trust → Purchase Intention	0.239	4.087	0.000	Supported

Both mediation effects are statistically significant. Perceived Relevance mediates the relationship between AI Recommendation and Purchase Intention, while Consumer Trust also mediates the relationship.

Because the direct effect of AI Recommendation on Purchase Intention remains significant (β = 0.214), the findings indicate partial complementary mediation.

The findings demonstrate that AI Recommendation has a substantial positive effect on Perceived Relevance. The path coefficient of 0.701 indicates that consumers' evaluation of recommendation quality is strongly associated with their perception that AI-generated recommendations are relevant to their needs. AI Recommendation also significantly influences Consumer Trust (β = 0.662). This finding suggests that repeated experiences with accurate, useful, and personalized recommendations can strengthen consumers' confidence in AI-based recommendation systems.

Perceived Relevance significantly affects Purchase Intention (β = 0.397). Consumers are more likely to consider purchasing recommended products when the recommendations are perceived as closely aligned with their needs and preferences. Thus, recommendation relevance represents an important cognitive mechanism in digital purchase decisions. Consumer Trust also significantly influences Purchase Intention (β = 0.361). This finding demonstrates that consumers need not only relevant recommendations but also confidence in the system providing those recommendations. Trust reduces uncertainty and perceived risk associated with algorithmic decision support.

The mediation results provide the central theoretical contribution of the study. Perceived Relevance and Consumer Trust jointly explain how AI Recommendation translates into Purchase Intention. The indirect effect through Perceived Relevance is 0.278, while the indirect effect through Consumer Trust is 0.239. These findings suggest two complementary psychological mechanisms:

AI Recommendation → Perceived Relevance → Purchase Intention

and

AI Recommendation → Consumer Trust → Purchase Intention.

The results therefore extend the S-O-R perspective by demonstrating that technological stimuli do not automatically produce behavioral responses. Instead, consumers first evaluate whether the recommendation is relevant and whether the recommendation system is trustworthy before translating the experience into purchase intention.

The study provides three theoretical contributions. First, it extends the S-O-R framework to the context of AI-enabled consumer behavior by conceptualizing AI Recommendation as a technological stimulus and Purchase Intention as the behavioral response. Second, the study integrates Perceived Relevance and Consumer Trust as two complementary internal mechanisms. This provides a more comprehensive explanation of AI recommendation effects than a direct-effect-only model. Third, the mediation findings demonstrate that the behavioral consequences of AI technology depend on both cognitive fit and psychological confidence. Consumers are more likely to respond positively when recommendations are perceived as relevant and the underlying recommendation system is trusted.

For e-commerce platforms, the findings suggest that AI investment should focus on three strategic priorities. First, firms should improve recommendation accuracy and personalization to increase perceived relevance. Second, firms should strengthen consumer trust through transparency, consistent recommendation quality, and responsible data practices. Third, AI recommendations should be integrated naturally into the consumer journey. Recommendation systems should not merely display automatically generated products but should actively reduce search effort and help consumers identify products that fit their needs.

5. CONCLUSION AND RECOMMENDATION

This study demonstrates that AI Recommendation plays an important role in shaping consumer behavior through Perceived Relevance and Consumer Trust. Based on the analysis of 160 respondents, AI Recommendation has a positive and significant effect on both Perceived Relevance and Consumer Trust, while Perceived Relevance and Consumer Trust positively and significantly influence Purchase Intention. AI Recommendation also has a significant direct effect on Purchase Intention. These findings indicate that consumers are more likely to develop purchase intentions when AI-generated recommendations are perceived as relevant to their needs and provided by a trustworthy recommendation system. Furthermore, Perceived Relevance and Consumer Trust significantly mediate the relationship between AI Recommendation and Purchase Intention. This finding demonstrates that the effectiveness of AI in influencing purchasing behavior depends not only on its ability to generate

recommendations but also on consumers' cognitive evaluation of recommendation relevance and their psychological confidence in the system. Theoretically, this study strengthens the Stimulus–Organism–Response (S-O-R) perspective by demonstrating that AI Recommendation as a technological stimulus can generate behavioral responses through consumers' cognitive and psychological processes. Practically, digital businesses should develop recommendation systems that are accurate, personalized, relevant, transparent, and trustworthy to increase the likelihood that AI-generated recommendations will translate into stronger purchase intentions.

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