

**Artificial Intelligence–Driven Cross-Platform Data
Integration and Its Impact on Consumer
Purchase Intention: The Mediating Role of
Personalization effectiveness and Consumer
Trust in AI**

Artificial Intelligence–Driven Cross-Platform Data Integration and Its Impact on Consumer Purchase Intention: The Mediating Role of Personalization effectiveness and Consumer Trust in AI

Submitted to:

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Date of submission: July 22, 2026

LETTER OF TRANSMITTAL

July 22, 2026

Mr. Ahmed Imran Kabir
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Subject: Submission of Project Report

Dear Sir,

Please accept this project report, prepared to fulfill the requirements of my BBA program (Major in Business Analytics) at the School of Business and Economics, United International University, titled "Artificial Intelligence–Driven Cross-Platform Data Integration and Its Impact on Consumer Purchase Intention: The Mediating Role of Personalization Effectiveness and Consumer Trust in AI."

The paper seeks to uncover the effects on consumer buying intentions of key AI capabilities on various platforms, as well as to understand how personalization and consumer buying decisions, with particular attention to the mediating roles that personalization and trust in AI play in that process. The above report is prepared by theory Stimulus-Organism-Response (S-O-R) framework and Trust Theory and empirical analysis with survey data collected from 229 digitally active consumers of Bangladesh. This effort is an attempt to make the report complete, well researched and within the scope of the course requirements.

I would like to show gratitude for all of your guidance and supervision over the course of this project; much that has been helpful in developing this work.

Sincerely,

Afsana Reza
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Major: Business Analytics
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DECLARATION OF THE STUDENT

I confirm that this project report "Artificial Intelligence–Driven Cross-Platform Data Integration and its Effect on Consumer Purchase Intention: The Mediating Role of Personalization Effectiveness and Consumer Trust in AI" as an original work under the guidance of Mr. Ahmed Imran Kabir, Assistant Professor, School of Business & Economics, United International University.

The work reflects independent research, analysis, and interpretation carried out in good faith. Every finding, data point, and conclusion presented is genuine — none has been fabricated, altered, or manipulated.

Any work used or referenced by other researchers, authors or sources has been used and referenced properly according to APA (6th Edition) referencing style.

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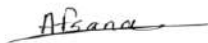
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ACKNOWLEDGEMENT

I would like to express my gratitude towards the Almighty Allah for giving me the strength, patience, clearness of thought and the ability to successfully complete this project report.

I'm thankful and grateful towards Mr. Ahmed Imran Kabir, Assistant Professor, School of Business & Economics, United International University for his significant guidance, constructive comments and constant encouragement throughout the course of this study. His feedback and deep knowledge of research methodology and structural equation modelling were central to getting this work done well.

I'm also thankful to the faculty of the School of Business and Economics for equipping me with the theoretical grounding needed for a study of this scope, and to the 229 respondents whose time and honesty made the empirical portion of this research possible.

Finally, to my family and friends — thank you for your patience and encouragement, which kept me motivated to see this through.

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ABSTRACT

Despite its prominent role in digital commerce, the impact of AI on actual purchasing behavior is under-theorized and understudied. There is a theoretical and empirical gap in understanding the impact of artificial intelligence on the actual purchase by consumers. This study constructs and tests an integrated model based on Stimulus-Organism-Response (S-O-R) and Trust Theory to illustrate the relationships among four AI capabilities (data integration, algorithmic recommendation quality, transparency, and perceived intelligence), purchase intention, mediated by personalization effectiveness and trust in AI, in the context of cross-platform e-commerce.

229 Bangladeshi consumers were digitally active and these were analyzed with the help of PLS-SEM (SmartPLS 3.2.8). Measurement model had good reliability (composite reliability 0.867-0.938; Cronbach's α 0.796-0.912) and validity (AVE 0.620-0.791; HTMT<0.85). In contrast to the hypothesized models, the four types of AI did not directly predict purchase intention. On the other hand, three indirect paths were found: recommendation quality influenced purchase intention via personalization effectiveness ($\beta = 0.144$, $p = 0.031$); while transparency influenced purchase intention via trust in AI ($\beta = 0.151$, $p < 0.001$) and perceived intelligence influenced purchase intention via trust in AI ($\beta = 0.186$, $p < 0.001$). The model explained 55.6% of the variance in purchase intention, 46.3% in personalisation effectiveness and 32.9% in trust in AI.

Combined, these findings indicate that instead of being valuable in itself, the value of AI skills is more likely to stem from the consumer's reception and mental evaluation of the technology. The study offers insight for both AI-consumer behavior research and for e-commerce firms aiming to get better returns on AI investment by prioritizing personalization and trust.

Keywords: Artificial intelligence; e-commerce; intention; personalization effectiveness; consumer trust in AI; AI transparency; PLS-SEM; Stimulus-Organism-Response theory; digital commerce; AI-driven personalization

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LIST OF ACRONYMS & ABBREVIATIONS

Acronym	Full Form
AI	Artificial Intelligence
AIDIC	AI-based Data Integration Capability
ARQ	Algorithmic Recommendation Quality
AIT	AI Transparency
PAI	Perceived AI Intelligence
PE	Personalization Effectiveness
CT	Consumer Trust in AI
PI	Purchase Intention
S-O-R	Stimulus-Organism-Response (Theory)
PLS-SEM	Partial Least Squares Structural Equation Modeling
SEM	Structural Equation Modeling
SmartPLS	Smart Partial Least Squares (software)
AVE	Average Variance Extracted
CR	Composite Reliability
HTMT	Heterotrait-Monotrait Ratio
VIF	Variance Inflation Factor
SRMR	Standardized Root Mean Square Residual
Q²	Stone-Geisser Predictive Relevance
f²	Cohen's Effect Size
TAM	Technology Acceptance Model

CHAPTER I: INTRODUCTION

1.1 Background of the Study

As technology continues to evolve, the internet replaced the way people do business and conduct online transactions, and Artificial Intelligence (AI) is a key player in driving innovation and engagement across the internet. AI tools, such as smart recommendations, chatbots, predictive analysis, and automated decisioning are now standard features of e-commerce platforms, are increasingly an integral part of contemporary e-commerce platforms, helping them better understand customer preferences and enhance the shopping experience. These technologies will help businesses improve their service offerings and gain better competition in the digital landscape.

Over the years, e-commerce has gone beyond the one-channel internet and moved through online marketplaces, thus increasing the difficulty of businesses to ensure a regular customer experiences across all their platforms. To enable seamless personalisation, companies need to incorporate customer data gathered from multiple digital interactions. With AI-driven data integration, businesses can integrate and analyze these various data sources, enabling them to build a comprehensive customer profile for more accurate recommendations and personalized marketing approaches (Afzal et al. 2025). The personalization is based on AI and uses large-scale behavioral and transactional data to provide users with personalized product recommendations and marketing messages, which increase engagement, satisfaction, and purchase intention(Mei et al. 2025).Empirical research demonstrates that AI-based personalization can result in a high rate of conversion, trust and loyalty when properly and ethically applied. However, there are cross-platform data integration problems with this environment. Consumer data are typically disjointed within channels and systems, and in heterogeneous formats with different quality, which prevents the creation of unified customer profiles and restrict the accuracy of personalization.

In this context, there are a number of fundamental constructs that have been used to explain consumer responses. AI-Based Data Integration Capability is a feature that allows platforms to integrate and analyze data across various digital touchpoints with the help of AI to create consistent consumer profiles (Dai and Liu 2024). The quality of recommendation by AI-generated products and content is perceived as Algorithmic Recommendation Quality and it is one of the most important aspects to consider because of the direct impact on the satisfaction, and buying behavior. AI Transparency indicates how platforms are transparent about the way AI systems utilize information and produce outputs, which creates privacy perceptions and trust. Perceived AI Intelligence refers to the thinking of the of consumers regarding the skillfulness, flexibility, and problem-solving capacity of AI systems that influences their desire to use AI-based recommendations. (Malik et al. 2025)

Two critical psychological factors that are expected to shape consumers' purchasing decisions are the effectiveness of the AI personalization and consumer trust in AI. Personalisation is effective when the AI system delivers suggestions and material that aligns with the user's tastes and interests, but not in a way that feels intrusive or overbearing, thus improving the user experience and engagement (Raji et al., 2024). Similarly, users' trust in AI grows when they think that AI systems are dependable, transparent, and ethical in the way it manages their data. Studies that have tested AI capabilities have found that while they can help to increase purchase intent, the effect is typically indirect and can be moderated by consumers' view of the quality of personalization and their trust in the AI system. Thus, this paper now aims to explore the effect of AI-Based Data Integration Capability, Algorithmic Recommendation Quality, AI Transparency, and Perceived AI Intelligence on personalization effectiveness and consumer trust in AI, which will affect the consumer's purchase intention in AI-powered cross-platform e-commerce surroundings.

1.2 Statement of the Problem

The abundance of information online puts online consumers in a situation of information overload, where they constantly face a flood of products, advertisements, and content on a variety of digital platforms, which complicates their decision-making and can lead to

cognitive fatigue. Simultaneously, consumer data are still distributed across platforms, and are held in different systems with different standards, which limit the capability of firms to create unified customer perceptions and provide consistent cross-channel experiences. This disintegration causes a challenge in providing personalization. Although AI-based recommendation systems can generate meaningful recommendations in the context of individual platforms, the lack of the data integration across platforms can affect the effectiveness of personalization and lead to irrelevant or repeated suggestions. Furthermore, AI systems are limited to integration environments (Kumar et al. 2025; Mohsin 2024; Sipos 2025). They demand big amounts of quality, harmonized data, and problems like data silos, interoperability deficiencies, and inconsistent governance lower the accuracy of AI-based insights and decision support (Becan 2025). These constraints hamper the implementation of entirely intelligent, cross platform personalization plans.

This research is aimed at bridging the gaps by creating and empirically a model to test where AI-based cross-platform data integration and AI capability perceptions affect consumer purchase intention mediated by the personalization effectiveness and consumer trust in AI. It is aimed at explaining how particular AI functionalities can be coordinated to create an effective and reliable personalization that assists consumers in making a purchase in multi-platform retail contexts. (Khoso et al. 2025)

1.3 Research Questions

The research questions that will be answered are central to the problem statement and problem objectives and include the following:

1. In a cross-platform ecommerce context, how do the capabilities and qualities of AI-based data integration, algorithmic recommendations, perceived AI intelligence, and AI transparency impact personalization effectiveness and consumer trust in AI?
2. How much does the effectiveness of personalization and consumer trust towards AI influence consumer purchase intention on AI-powered digital platforms?
3. What is the relationship between AI capabilities (AI-based data integration capability, algorithmic recommendation quality, perceived AI intelligence and AI transparency) and consumer purchase intention mediated by personalization effectiveness and consumer trust in AI?

1.4 Objective of the Study

The study aimed to examine the influence of the AI-enabled cross-platform data integration and the AI related capabilities on consumers' purchase intention, mediated by the personalization effectiveness and AI trust in AI-enabled e-commerce platforms.

Specific Objectives

- To understand the impact of AI-Based Data Integration Capability on the effectiveness of personalization.
- To measure the effect of Algorithmic Recommendation Quality (ARQ) on the effectiveness of personalization.
- To measure the effect of PAI on personalized effectiveness.
- To assess the impact of AI Transparency on consumer trust of AI.
- To know how Perceived AI Intelligence affects consumer trust in AI.
- To learn about the effect of Personalization Effectiveness on the consumer's intention to purchase.
- To measure the effect of Consumer Trust in AI on Consumer Purchase Intent.
- To examine the mediating between AI capabilities and purchase intention and the mediation process is Personalization Effectiveness.
- To test the mediator of Consumer Trust in AI between AI capabilities and purchase intention.

1.5 Significance of the Study

Conceptually, this research is a part of an emerging stream of research in AI and consumer behavior in digital commerce, as it presents one of the first cross-platform structural models that integrates AI capabilities, personalization effectiveness, consumer trust in AI, and purchase intention which has been validated empirically. From a managerial view, the study provides empirical evidence-based insights for e-commerce practitioners and platform developers to direct their investments toward the areas where AI has the most impact at the consumer level.

The study's design additionally brings a couple of fascinating and nuanced details regarding when direct and indirect impacts of the AI features can be detected, and how

this learning can contribute to the current literature. By facilitating practitioners' awareness of areas that are most impactful at the consumer level, such as relevance of recommendations, transparency of data governance, and an understanding of the adaptiveness and learning of AI, the study serves as a guide. The study guides practitioners by helping them focus on areas where it can have the highest consumer level impact, including relevance of recommendations, transparency of data governance, and the visibility of the adaptiveness and learning of AI. (Alghaswyneh 2025)

1.6 Scope and Limitations

The paper pays attention to the response of consumers to AI-driven e-commerce places in Bangladesh, while the sample consists mainly of young adult consumers involved with digital commerce. It utilizes a cross-sectional quantitative research design to investigate if the hypothesized relationships between seven constructs, which is tested through PLS-SEM method. It is optimized for the context of cross-platform e-commerce and excludes the use of AI in physical retail, finance and more. The use of an easier sample of students and young professionals is a limitation in generalization of the study's conclusions, as may be the level of e-commerce maturity in markets that are not the same.

1.7 Definition of Key Terms

Artificial Intelligence (AI): It allows computers to carry out tasks that would like require human intelligence, such as processing natural language, identifying patterns, making predictions and learning from data, to assist with business decisions and digital services.

AI-Based Data Integration Capability: The ability of AI tools to collect and integrate data from various digital channels, standardize and structure it, and generate customer profiles with meaningful content.

Quality of Algorithms Recommendation: How well consumers find that AI suggestions are accurate, relevant, useful and suitable for their personal tastes and buying habits.

AI Transparency: The extent to which organizations are clear about how AI systems gather, handle, and use consumer data; and explain the rationale for the AI's suggestions to the consumer.

Perceived AI Intelligence: The consumers' sense of what an AI system can learn, adapt, solve problems, and understand their individual preferences before making suitable suggestions.

Personalization Effectiveness: How well does AI-driven personalization provide relevant products, services or content that meets the needs of the individual without causing a sense of intrusion.

Consumer Trust in AI: The consumer's trust in the reliability, fairness, ethical and responsible use, and safeguarding personal data and providing reliable recommendations by AI systems.

Consumer Purchase Intention: Probability or willingness of consumers in purchasing products or services following an interaction with an AI based digital platform.

1.8 Structure of the Remaining Chapters

In the end of the paper, it is structured to give a thorough investigation of AI-powered cross-platform data integration and its impact on consumer paying actions. Chapter 1 gives just background information on the study, problem statement, purpose of its study, scope and definition, and the terms used in the study. Chapter II is a literature review that discusses relevant studies, identifies the gaps in the literature, and relies on the framework to propose hypotheses. The research method used is detailed in Chapter III and includes the design, target population, sampling process, measurement instruments and data collection. The data analysis results will be provided by characteristics of the sample, descriptive statistics, and findings for data validation. The result of the analysis of the data found will be presented in Chapter IV in following items: Sample Demography, Descriptive Statistics, Data Validation Results in case of reliability and validity, and Structural validation results. The results of the research will be analyzed in Chapter V to discuss the theoretical and managerial implications, highlighting the limitations of the research and proposing further research opportunities in the field of AI-driven consumer behaviors and Responsible personalisation.

CHAPTER II: REVIEW OF THE LITERATURE

2.1 Relevant Theory

This study is grounded primarily in S-O-R theory and Trust Theory, though it also draws on the Technology Acceptance Model (TAM), Personalization Theory, media richness theory, and heuristic-systematic models. Within AI-based e-commerce, perceived usefulness typically drives how effective consumers judge AI-based recommendations, personalization, and decision support to be — shaping how efficiently they shop, how confident they feel in decisions, and how convenient the process feels overall (Chowdhury et al. 2024). Perceived ease of use, meanwhile, reflects how effortless consumers find AI-driven interfaces and recommendation tools. (Chowdhury et al. 2024). Perceived ease of use describes the ease with which consumers can use AI-driven interfaces and recommendation systems.

Recent studies in AI and e commerce build upon the TAM addition of constructs of perceived intelligence, trust and risk, and demonstrate that online buying intention is significantly predictable by the acceptance of AI personalization and recommendations(Avinash et al. 2025; Gupta 2025; Shoib and Agus Hermawan 2025). Perceived usefulness is increased when the AI-based data integration helps create a more accurate and seamless personalization, whereas ease of use is improved with consumer-friendly recommendation interfaces. Both of these perceptions lead to more positive attitudes toward AI, thus raising the level of trust and purchase intention. TAM therefore offers a basis of connecting (Abdullah et al. 2024; Afzal et al. 2025; Alsaffarini and Awwad 2026; Bhatnagar and Sharma 2024; Deo 2025; Jameel et al. n.d.; Lopes, Silva, and Massano-Cardoso 2024; Pathange et al. 2024; Wen and Li 2025)

Trust Theory considers trust to be a major predictor of cooperative acts in the face of uncertainty, particularly in technology-mediated contexts where users are not able to monitor fully processes or outcomes. The AI-based e commerce consumers have to make a decision on whether to trust the recommendations and data processing of the AI algorithms despite having little understanding of AI functionality(Abdullah et al. 2024; Arora 2024; Jameel et al. n.d.; Raji et al. 2024; Tang et al. 2024). Trust is usually

conceptualized in terms of competence, benevolence and integrity and it is affected by clearness, reliability and ethically practice data. The Stimulus-Organism-Response theory (S-O-R) is a theory that describes the way environmental stimuli affect internal psychological conditions that in turn cause behavioral reactions.

Personalization Theory is an extension of it by stating that personalized content, offers, and experiences (according to preferences and behaviors of users) are more perceived to be relevant, enjoyable and valuable than their generic counterparts(Raji et al. 2024).The successful personalization is achieved when the systems are effective to provide the content to the needs of the users, at the right time and context, and not to be intrusive. The success of personalization in AI-enabled e commerce requires effective data integration, smart algorithms, and open communication, all of which influence the cognitive and affective reactions of consumers (e.g., perceived relevance, satisfaction, trust) as well as their behavioral reactions (purchase intention, loyalty).

2.2 Literature Survey

2.2.1 AI-Based Data Integration

AI-based data integration is a process that involves collecting, cleaning, matching, and combining heterogeneous consumer data of various sources (websites, apps, social media, third-party platforms) using AI and machine learning methods to create unified actionable consumer profiles(Khandelwal et al. 2024; Torthienchai and Chuaikaew 2025). This involves real time processing, entity resolving and predictive enrichment to aid analytics and personalization.

Role in the omnichannel systems. Integrated data are crucial in omnichannel and cross-platform ecosystems and the provision of a seamless experience. The integration based on AI allows platforms to have complete insight into the customer journey, monitor cross-channel behavior, and organize marketing, recommendations, and service interactions. (Marwan Effendi, Alfi Fuadah, and Mar'atush Sholihah 2025). Studies point to the fact that integrated customer data enhance the accuracy of personalization, campaign performance, and strategic decisions, as well as facilitate dynamic pricing and inventory control.

2.2.2 Algorithmic Recommendation Quality

The quality of AI-generated recommendations really matters to consumers. They want relevant and useful suggestions that help them find what they need. Good recommendations should be timely. Assist in finding useful alternatives that might have gone unnoticed. Research shows that when recommendations are accurate and relevant consumers are satisfied, perceive higher value and engage more. This in turn builds trust. Encourages purchases. For instance, when search results match what users are looking for, they put in effort and feel more confident in their decisions. On the hand irrelevant or unhelpful recommendations can be annoying make consumers distrustful and even make them feel like they're being watched. This can harm the effectiveness of personalization and trust(K 2025; Yin and Qiu 2021).

2.2.3 AI Transparency

AI transparency is about being clear and open about how AI systems work gather data and produce outputs. It involves explaining why certain items are recommended what data sources are used and how users can manage their data and personalization options. Transparency helps build trust and perceived fairness, in AI systems. It decreases the perceived power asymmetry and opacity. In e-commerce transparency can be achieved through messages explaining why a recommendation was made, explicit consent messages and easily accessible privacy policies. (Michael et al. n.d.). However, transparency must be effective and easy to understand. Technical or ambiguous explanations can confuse users and even increase uncertainty.

2.2.4 Perceived AI Intelligence

Perceived AI intelligence is a dimension that indicates what consumers believe the smartness, adaptiveness and human-like decisions of AI systems are. It includes the capability of AI to learn about user preferences, learn during interactions, make suitable assumptions, and react dynamically to new situations (İNaI and BiL 2023; Martina and Kurdaningsih 2025). The research shows that in case consumers perceive AI in terms of intelligence and competence, they will be more inclined to follow its advice, consider it a valuable decision-making tool, and have positive attitude towards the AI-based services.

The perceived usefulness could be elevated and the effort in information processing could be minimized by high perceived intelligence, which leads to an increase in adoption and purchase intention. However, highly anthropomorphic or excessively independent AI can also cause discomfort or loss of control, indicating a subtle interaction between the perceived intelligibility, trust and acceptance.

2.2.5 Personalization Effectiveness

Personalization effectiveness which the consumers view AI-driven personalization as relevant, accurate, and helpful. Good personalization is presented with personalized content, offers, and recommendations with consideration of their needs and preferences without seeming intrusive or manipulative. Literature has constantly discovered that selecting effective personalization enhances engagement, satisfaction, perceived value and loyalty, and is a powerful indicator of their buying intention in e commerce. Conversion rates and retention can be greatly enhanced with help of AI-powered personalization utilizing the rich data and advanced algorithms, though ethical and privacy issues need to be considered; But when perceived as creepy or too invasive, it may backfire, causing loss of trust and avoidance (Iqbal et al. 2025)

2.2.6 Consumer Trust in AI

Consumer believe in Artificial intelligence denotes to the readiness to use AI systems and accept their output, on that believe that they are mostly reliable, secure, fair and consistent with the interests of the users (Patil n.d.; Sipos 2025). A Trust in AI is a set of beliefs in the technical performance of AI (e.g., accuracy, robustness) and ethical behavior of organizations (e.g., privacy protection, non-manipulative use of data).

Empirical studies demonstrate that important in AI-powered personalization and advertising: when perceived as useful and respectful, personalization is likely to lead to higher trust, although this effect can be undone by privacy concerns. In various studies, trust has been identified to mediate the relationships between personalization and satisfaction, loyalty, and purchase intention(Sipos 2025). In turn, a lack of trust results in resistance, decreased adoption, and decreased responsiveness to AI recommendations (Hasan, Shams, and Rahman 2020).

2.2.7 Purchase Intention

Purchase intentions is the behavioral outcome that indicates the individual probability or willingness to likely to purchase of a product or service in the near term(Ameen et al. 2020; Raji et al. 2024; Tang et al. 2024). Perceived usefulness of AI, personalization effectiveness, trust, satisfaction, perceived value, and affective responses are some of the factors that affect purchase intention in AI-enabled e commerce (G. Agila 2025; Raji et al. 2024). The study of Artificial intelligence marketing, digital ad and e commerce has been consistent for one thing – AI-personalization can have much greater impact on the purchase intention when considered relevant and trustworthy. The mediation analyses match the findings of many studies on this topic where it is found that the effect of personalization and the quality of recommendations on purchase intention are largely mediated through satisfaction, perceived value and trust (Avinash et al. 2025; Dang and Erorita 2025; Mohammed and Sundararajan 2025).

2.3 Hypothesis Development

AI-Based Data Integration Capability and Purchase Intention

The capability of AI systems to collect, combine, and process data across channels and platforms to form a single, consistent view of the consumer and to enable consistent interactions across touchpoints can be considered AI based data integration capability. Personalized recommender systems, predictive analytics, and virtual assistance, which are dependent on large, heterogeneous streams of data, are built upon such integration in e retailing (Bawack et al. 2022; Jain, Wadhwani, and Eastman 2023). Thus, once consumers believe that AI systems can combine data across platforms to provide coherent interactions, they will develop confidence in the system and use its outputs to make purchases. Thus, leads to the following hypothesis:

H1: *AI-based data integration capability positively and significantly influences consumer purchase intention in cross-platform contexts.*

Algorithmic Recommendation Quality and Purchase Intention

The quality of algorithmic recommendations is explained as the perceived relevance, accuracy and usefulness of the AI-generated product or content recommendations that are perceived by consumers to be relevant, useful and accurate over time and across platforms. The empirical investigation of the AI based recommendation systems in e commerce always emphasizes that high quality recommendations, that is, the one that is most aligned with consumer interests and context, increase perceived value, satisfaction, and intention to purchase by making the choice easier and less information-saturated and High quality recommendations in AI enabled cross platform e commerce enable SMEs and online retailers to continue relating to the relevant suggestions as customers cross websites, apps and social platforms, thereby supporting the engagement and nudging purchase decisions at various touchpoints(Ahire 2025; Vemula 2025). As such, when consumers observe the AI driven recommendations to be true, platform contextually relevant and useful, they tend to respond to such suggestions by developing stronger purchase intentions. In this regard, one can argue that increased perceived quality of the algorithmic recommendations will be associated with increased purchase intention in cross platform settings. So, the hypothesis is as follows:

H2: *Algorithmic recommendation quality positively and significantly influences consumer purchase intention in cross-platform contexts.*

AI Transparency and Purchase Intention

AI transparency is the way to which AI systems explicitly tell how recommendations are made, what data are used, and on what basis decisions or suggestions are made, which is frequently referred to as explainable AI (XAI) and ethical, interpretable models(Marwan Effendi et al. 2025).Past research highlights that explainable and transparent AI systems positively influence perceived value, trust, and ethical acceptability by mitigating the characteristics of a black box of the algorithmic process, which alleviates fears of manipulation and injustice. An example is AI-inspired recommendations in the purchase of functional foods, where transparency in the source of data, as well as reasoning, do not necessarily directly drive purchase intention but have extreme positive effect on perceived value and are an additional significant trust building mechanism (Yin and Qiu

2021). Thus, once consumers feel that AI systems are transparent in their functions and suggestions on the platforms, they will tend to regard the system as credible, equitable, and in their interests, which will in turn, raise their intention to buy. Thus, from on the above communication the hypothesis is being proposed:

H3: *AI transparency positively and significantly influences consumer purchase intention in cross-platform contexts.*

Perceived AI Intelligence → Purchase Intention

Theoretically, based on the media richness theory and technology acceptance theory, perceived intelligence can be used to predict functional performance, as well as social presence; when consumers assume that an AI system can be intelligent, they assume that the system can give high quality assistance and recommendations, therefore, enhancing perceived usefulness, enjoyment, and finally purchase intention (Mallika 2025). Intelligent AI capable of monitoring channel-based behavior, predicting needs, and offering adaptive support can also be useful in the sense of cross platform e commerce and SMEs, where previous research indicates that it improves engagement, loyalty, and conversion. Thus, consumers who view AI as incredibly smart in knowing and acting upon their needs in a cross-platform manner tend to be more willing to use these systems and turn favorable judgments into intentions to make purchases (Dai and Liu 2024). Based on this, it is arguable that the higher the perceived AI intelligence, the high will be consumer purchase intention in cross platform situations. Theoretically, the hypothesis can be formulated:

H4: *Perceived AI intelligence positively and significantly influences consumer purchase intention in cross-platform contexts.*

Personalization Effectiveness as Mediator (Data Integration → Purchase Intention)

In theory, in the S- O -R model, the stimulus is integrated data and AI capabilities and the response is purchase intention; the effectiveness of personalization is the mediator that changes technical integration into psychologically significant experiences (relevance, convenience, and perceived fit) into the personal organism (internal evaluative state) (Yin and Qiu 2021). Integrated AI systems that convert multi source data into coherent and

personalized experiences are especially prone to impact purchase decisions in the case of cross platform SME and e commerce, where consumers always have to switch between platforms and devices (Jain et al. 2023; Menaka and Selvam 2025). Hence, in case AI-based data integration can increase the effectiveness of the personalization, consumers will feel more satisfied and their view value, that will strengthen the buying intention, instead of integration having its influence only in a direct way. Here, we can therefore hypothesized that:

H5: *Personalization effectiveness mediates the relationship between AI-based data integration capability and consumer purchase intention in cross-platform contexts.*

Personalization Effectiveness as Mediator (Recommendation Quality → Purchase Intention)

Theoretically, recommendations quality is a technological stimulus, personalization effectiveness is an internal cognitive and affective evaluation (e.g., perceived fit, relevance, and enjoyment), and purchase intention is a response behavior, so the effect of the quality of recommendations on buying should work through the perception of the consumer that the AI is successfully personalizing their experience. High quality algorithmic suggestions they think as personally relevant are mainly to enhance personalization strength in cross platform e commerce and SME environments, where consumers are more into the recommendations via mix channels, which in turn motivates consumers to pursue those recommendations and make purchases. Thus, high perceived quality of algorithmic recommendations will make consumers perceive AI personalization to be more effective and this perception will mediate the influence of suggestions quality on buying like hood across platforms. To the end, it may be argued that the effectiveness of personalization can be seen as a major mediating variable in between the quality of algorithmic recommendations and the consumer purchase intention in cross platform settings. Thus, the hypothesis is now proposed below:

H6: *Personalization effectiveness mediates the relationship between algorithmic recommendation quality and consumer purchase intention in cross-platform contexts.*

Consumer Trust in AI as Mediator (AI Transparency → Purchase Intention)

Consumers believe in AI is feeling that AI functions are trustworthy, altruistic, powerful, and will act upon in the interest of the consumer, when processing data and making recommendations or decisions. An increasing literature recognizes trust as a decisive factor of the behavioral pattern of its intention of consumers for AI technologies in online shopping, with higher levels of trust resulting in stronger adoption and purchase intentions, and perceived risk and skepticism being the barriers to adoption (Bharathi and Elakkiyan 2026). Previous research highlights that the antecedent to trust is AI transparency and explainable practices: transparent recommendations and clear explanations of how data are utilized and how decisions are made mitigates uncertainty and perceived self-threat, thus leading to trust in AI technology. Transparency is particularly topical in cross platform e commerce, where data are exchanged between different apps and websites, and explainable and ethical AI should be employed by both SMEs and large platforms to establish trust in the whole ecosystem (Bawack et al. 2022; Vemula 2025). Thus, the effect of AI transparency on buying intention should manifest itself on a large scale by improving consumer trust in AI instead of a straight effect. Following the previous results, we can propose that:

H7: *Consumer trust in AI mediates the relationship between AI transparency and consumer purchase intention in cross-platform contexts.*

Consumer Trust in AI as Mediator (Perceived AI Intelligence → Purchase Intention)

As mentioned above, perceived AI intelligence encompasses the perception of consumers that AI functions are more able to perceive, learn and react to their needs in a way reminiscent of human like cognitive abilities. According to previous studies, these types of perceptions of intelligence can lead to both functional and social psychological reactions, such as their believe and readiness to use AI in the their process (Wulansari Wulansari et al. 2025). In retail AI studies, having consumer perceptions of AI agents as capable and smart has been found to insure consumer trust, either moderates or mediates the relationship between the two and purchase intention(My &, 2025; Sipos, 2025). Therefore, it can be presumed that the influence of perceived AI intelligence on paying intention is mediated by consumer believe in AI: the smarter perceived to be the

greater the trust, the better the purchase intention. In this sense, it could be claimed that in cross-platform scenarios, consumer trust in AI affects the link between the perception of AI intelligence and purchase intent. The above discussion indicates the following hypothesis:

H8: *Consumer trust in AI Moderates the relationship between Perceived Artificial Intelligence (PAII) and Consumer Purchase Intention (CPI) in Cross-platform Contexts.*

2.4 Conceptual Framework and Hypotheses Summary

This paper thoroughly checks the impact of various AI functions on consumer purchasing intention in cross-platform settings. In particular, the framework hypothesizes that four fundamental AI-related variables, such as the capability of integrating AI-based data, the quality of algorithmic recommendations, AI transparency, and perceived AI intelligence are the main determinants of consumer behavior.

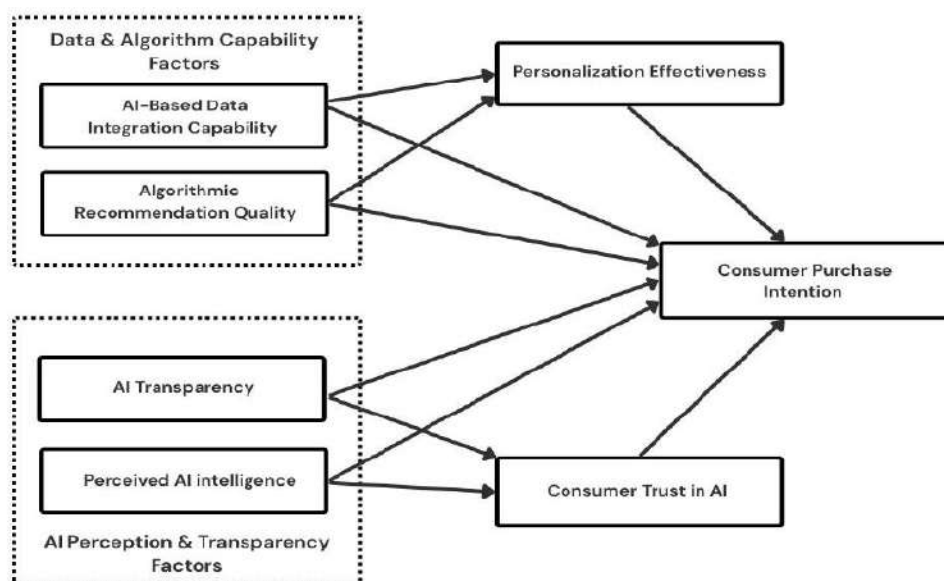


Figure 1. Conceptual Framework

The model hypothesizes that these AI functions do not have direct influence on the buying intention itself, but rather their impact is partially mediated by two crucial mediating variables, namely personalization effectiveness and consumer trust in AI. Personalization effectiveness describes the degree to which AI systems can provide personalized recommendations and experiences to users and consumer trust measures the trust that

users place in the comfortable and fairness of AI functions. The quality of algorithmic recommendations and its capability of AI-based data integration are to increase the buying perceptions because the effectiveness of personalization. Concurrently, AI transparency, and perceived AI intelligence are suggested to develop consumer trust, which subsequently boosts purchase intention. Generally, the framework points out that AI-induced attributes affect consumer purchase intention directly and indirectly by increasing personalization and trust in AI systems.

Hypotheses Summary

According to the suggested conceptual framework, this research paper tests a series of eight hypotheses that jointly describe the effect of cross-platform capabilities powered by AI on consumer buying thinking due to the effectiveness of personalization and consumer believes in AI. The AI-based data integration functionality, quality of algorithmic recommendations, AI transparency, and perceived AI intelligence are also placed at the status of key antecedent variables of both technological functionality and consumer perception of AI functions in digital marketplaces. The effectiveness of personalization, as well as consumer trust in AI, are modelled as mediator mechanisms that translate these AI-related antecedents into purchase intention, in accordance with S-O-R and trust-based views of AI-powered personalization and decision support.

CHAPTER III: METHODOLOGY

3.1 Research Design

In this paper I have used the quantitative research to explore and learn relationships between AI-based Data Integration Capability, Algorithmic Recommendation Quality, AI Transparency, Perceived AI Intelligence, Personalization Effectiveness, Consumer Trust in AI and Consumer Purchase Intention. A cross-sectional survey design was used since the data were gathered from respondents at one time only, and it was suitable for the study of the proposed theoretical relationships between AI-enabled cross-platform e-commerce.

This research simply tried the deductive method in which hypotheses were generated from the theories and empirical data and then tested by using reliable statistical analysis. To gather primary data, a structured questionnaire with validated measurement items from past studies was used to accumulate important primary data from consumers who actively use AI-driven online platforms in Bangladesh.

Partial Least Squares Structural Equation Modeling (PLS-SEM) is commonly done for the evaluation of the conceptual framework proposed. This method of analysis was critically selected due to its suitability for prediction-oriented research with multiple latent variables, mediation effects, and complex structural relationships. Additionally, PLS-SEM works well with relatively small samples and but cannot assume normal data distribution, thus it is better for this study. In the second part, the collected data were analyzed based on the approach of Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 3.2.8 ver. To achieve high-quality and reliable data, the data was screened prior to structural analysis for incomplete responses, inconsistencies and potential outliers.

3.2 Population and Sampling

This paper main target is to investigate the target audience of those users actively using online shopping platforms that are available on digital platforms, and what percentage of them are equipped with AI technology. The respondents consisted of people who have experience with AI-powered recommendation functions, personalized digital interactions,

intelligent product suggestions, and AI-powered online shopping experiences. The method of data collection followed by a non-probability sampling method - convenience sampling. Digital active consumers who have previously interacted with the AI commerce systems were the focus of the study and probabilistic sampling would not have been feasible.

The questionnaire was sent via several online and social networking outlets to target respondents who use digital commerce technologies on a regular basis. There was a total of 300 responses originally. The data were subjected to screening process and 229 valid responses were selected for final analysis. The sample size was precise to be sufficient for PLS-SEM analysis. (Hair et al. 2021) state that the sample size can be more than 200 if there are multiple constructs and mediation effects are included, as well as if the analysis is predictive.

3.3 Data Collection Procedure

The main data was gathered by using an organized self-administered questionnaire that was adapted from the previous studies that have been conducted in the related part of artificial intelligence, recommendation systems, personalization, consumer trust and purchase behavior. It was decided that the questionnaire would have two main parts:

1. Demographic of respondents such as gender, age, occupation and frequency of digital platform use.
2. Study constructs related measurement items.

Here used a Likert scale with five point was used for all survey items ranging from: 1 to 5

In psychology and other behavioral and social sciences, the most widely used approach to measuring attitudes, perceptions, and behavioral intentions is the Likert scale. The online survey design approach is suitable for rapidly collecting data from digitally engaged consumers with the possibility of studying internet and consumer behavior and AI-assisted commerce environments. The constructs were measured by slightly modified and adapted items from previous studies, based on the context of cross-platform digital commerce with AI.

3.4 Measurement of Constructs

The study used seven major constructs of the proposed conceptual framework:

- AI Transparency (AIT)
- AI Based Data Integration Capability (AIDIC)
- Algorithmic Recommendation Quality (ARQ)
- Consumer Trust in AI (CT)
- Perceived AI Intelligence (PAI)
- Personalization Effectiveness (PE)
- Consumer Purchase Intention (PI)

A variety of reflective measures were used for each construct, and they were taken from previously validated scales in the literature. Measurement items were adapted contextually with modifications to reflect the environment of "AI-enable digital commerce" with conceptual consistency.

3.5 Data Analysis Technique

In this paper all the analysis was done by two approaches. In the beginning step was to test the measurement model, which included testing the reliability and validity of the constructs. Internal consistency reliability was calculated using Cronbach's Alpha and Composite Reliability (CR) while convergent validity was done using Average Variance Extracted (AVE) and indicator loadings. To ensure that each construct was empirically different, discriminant validity was established by three methods

To determine if there was no multicollinearity, the Variance Inflation Factor (VIF) used to assess collinearity of the predictor variables. The Coefficient of Determination (R^2) helped to check the explanatory power of the model, and Stone-Geiser's Predictive Relevance (Q^2) and Cohen's Effect Size (f^2) were calculated to assess predictive capability, as well as to obtain the magnitude of all the predictor's part.

Last, the importance of both direct and indirect relationships was tested by resampling 5,000 times using the bootstrapping approach.

CHAPTER IV: FINDINGS AND ANALYSIS

4.1 Demographic Profile of Respondents

In regards to the gender distribution of respondents, the data indicated that the distribution among those who responded was (n=126) Female (55.1%) and (n=102) Male (44.9%) reflecting the gender distribution of the active Digital commerce Users in Bangladesh. The age respondents showed that maximum number of respondents were aged between 18 to 25 years (44.1%), 26 to 35 years (27.1%), reflecting a fairly young adult population representative of frequent online users. Respondents aged 36 to 45 accounted for 15.7%, those under 18 for 9.2%, and those above 45 for 3.5%. As far as occupation is concerned, 51.1% of the respondents were students, 24.9% were working in private sector, 16.6% were professionals/businessman, 6.6% were house wife and 0.4% belonged to other occupational groups. The profile suggests a technologically engaged, digitally literate sample, who frequently interacts with AI-powered online marketplaces.

Table 1. Demographic Profile of Respondents

Characteristic	Category	Frequency	Percentage (%)
Gender	Female	126	55.1%
	Male	102	44.9%
Age	Under 18	21	9.2%
	18–25 years	101	44.1%
	26–35 years	62	27.1%
	36–45 years	36	15.7%
	46 and above	8	3.5%
Occupation	Student	117	51.1%
	Employed	57	24.9%
	Businessman	38	16.6%
	Housewife	15	6.6%
	Other	1	0.4%

4.2 Measurement Model Assessment

4.2.1 Indicator Reliability and Internal Consistency

Indicator reliability and internal consistency are assessed in accordance with the following:

Table 2. Measurement Model Assessment: Reliability and Validity

Constructs	Items	Loading	AVE	CR	Alpha	R ²	NFI	SRMR
AI-based data integration capability (AIDIC)	AIDIC1	0.732	0.620	0.867	0.796		0.737	0.07
	AIDIC2	0.854						
	AIDIC3	0.801						
	AIDIC4	0.759						
AI Transparency (AIT)	AIT1	0.884	0.752	0.924	0.890			
	AIT2	0.860						
	AIT3	0.874						
	AIT4	0.851						
Algorithmic Recommendation Quality (ARQ)	ARQ1	0.855	0.698	0.902	0.856			
	ARQ2	0.838						
	ARQ3	0.839						
	ARQ4	0.809						
Consumer Trust in AI (CT)	CT1	0.875	0.750	0.923	0.889	0.329		
	CT2	0.879						
	CT3	0.856						
	CT4	0.853						
Perceived AI Intelligence (PAI)	PAI1	0.767	0.642	0.877	0.814			
	PAI2	0.839						
	PAI3	0.819						
	PAI4	0.778						
Personalization Effectiveness (PE)	PE1	0.860	0.737	0.918	0.881	0.463		
	PE2	0.856						
	PE3	0.878						
	PE4	0.839						
Consumer Purchase Intention (PI)	PI1	0.886	0.791	0.938	0.912	0.556		
	PI2	0.898						
	PI3	0.885						
	PI4	0.888						

The reliability of the indicators was assessed through outer loadings ranging between 0.732 (for the indicator AIDIC1) and 0.898 (for the indicator PI2), with all the indicators being above the 0.70 threshold, meaning that each indicator possesses a high percentage of the variance of the associated latent construct. The inner consistency was measured by calculating Cronbach's alpha and composite reliability (CR). Cronbach's alpha coefficient for inner consistency reliability of all the items of the instrument ranged between 0.796 for the instrument measure of AI-based data integration capability and 0.912 for the instrument measure of consumer purchase intention. The internal consistency of each reflective construct was also good (0.867–0.938). The average variance extracted (AVE) values were greater than 0.50, for AI-based data integration capability (AVE = 0.620), AI transparency (AVE = 0.752), algorithmic recommendation quality (AVE = 0.698), consumer trust in AI (AVE = 0.750), perceived AI intelligence (AVE = 0.642), personalization effectiveness (AVE = 0.737), and consumer purchase intention

(AVE = 0.791). The results as a whole support the conclusion that the constructs reflect a greater amount of variance in their indicators than in the error terms.

Overall, the model had good fit according to PLS-SEM with NFI equal to 0.737, and SRMR equal to 0.07. The R^2 values of the tests are found to be significant and the R^2 values for the key endogenous variables of the consumer purchase intention, personalization effectiveness and consumer trust in AI are found to be of significant variance explained.

Table 3. Stone-Geisser Predictive Relevance (Q^2) and Cohen's Effect Size (f^2)

Variables	Q^2	Consumer Purchase Intention (f^2)	Consumer Trust in AI (f^2)	Personalization Effectiveness (f^2)
AI Transparency		0.016	0.115	
AI-based Data Integration Capability		0.000		0.060
Algorithmic Recommendation Quality		0.036		0.415
Consumer Purchase Intention	0.405			
Consumer Trust in AI	0.226	0.304		
Perceived AI Intelligence		0.002	0.176	
Personalization Effectiveness	0.314	0.060		

Note: Large effect > 0.35; Medium effect > 0.15; Small effect > 0.02 (Cohen, 1988).

Table 3 gives the Stone-Geisser Q^2 values and Cohen's f^2 effect sizes for the structural relationships, which reflect the predictive similarity and practical importance of these relationships, respectively. All the three endogenous constructs have a relatively high Q^2 (consumer purchase intention: 0.405; personalization effectiveness: 0.314; and consumer trust in AI: 0.226) proves that the model has some predictive relevance for all three. On a Cohen's f^2 scale, the quality of algorithmic recommendations has a large influence on the effectiveness of personalization ($f^2 = 0.415$), and consumer trust in AI has a moderate to large influence on purchase intention ($f^2 = 0.304$). Perceived AI intelligence results in a small-to-medium-sized effect on consumer trust in AI ($f^2 = 0.176$), as does AI transparency ($f^2 = 0.115$). The effect sizes are theoretically plausible and are consistent with the overall mediation-based structure of the model.

4.3 Discriminant Validity

4.3.1 Fornell-Larcker Criterion Analysis

To check discriminant validity, the criterion by Fornell & Larcker (1981) was applied which entails comparison of the square root of AVE of all the variables with all other in this model. Table 4 showed the results on the diagonal values of AVE ranging from 0.788 to 0.889 that each diagonal value was higher than off-diagonal value in the same row and column.

Table 4. Fornell-Larcker Criterion Matrix (Diagonal = $\sqrt{\text{AVE}}$)

Variable	AIT	AIDIC	ARQ	PI	CT	PAI	PE
AI Transparency (AIT)	0.867						
AI-based Data Integration Capability (AIDIC)	0.429	0.788					
Algorithmic Recommendation Quality (ARQ)	0.446	0.512	0.836				
Consumer Purchase Intention (PI)	0.314	0.374	0.549	0.889			
Consumer Trust in AI (CT)	0.459	0.421	0.526	0.690	0.866		
Perceived AI Intelligence (PAI)	0.409	0.445	0.560	0.440	0.501	0.801	
Personalization Effectiveness (PE)	0.461	0.490	0.657	0.620	0.625	0.648	0.858

Note: Diagonal values (bold) represent the square root of the AVE; off-diagonal values represent inter-construct correlations.

AI Transparency (AIT) in particular achieved a square root of AVE of 0.867, better than the highest score they had achieved with any other construct, which was with Personalization Effectiveness (PE) with a score of 0.461. Likewise, AI-based Data Integration Capability (AIDIC) had a square root of AVE of 0.788, above the highest off-diagonal correlation with Algorithmic Recommendation Quality (ARQ), which was 0.512. The Algorithmic Recommendation Quality (ARQ) construct got a square root of AVE of 0.836, which is higher than the highest correlation of 0.657 with the Personalization Effectiveness (PE) construct. Notably, the diagonal value for Consumer Purchase Intention (PI) in the matrix is 0.889, surpassing the highest inter-construct correlation it shares with Consumer Trust in AI (CT) (0.690). Consumer Trust in AI (CT) exhibited a square root of AVE exceeding its diagonal maximum value of 0.690, with PI recorded at

0.866. The diagonal value for Perceived AI Intelligence (PAI) was 0.801, exceeding all other diagonal values, including the highest one, which was the Personalization Effectiveness (PE) at 0.648. Finally, Personalization Effectiveness (PE), having a square root of AVE of 0.858, exceeded the highest off-diagonal correlation for ARQ, recorded at 0.657. Strong empirical evidence for discriminant validity within the measurement model is observed across all 7 constructs, with each diagonal correlation's magnitude exceeding that of all other inter-construct correlations.

4.3.2 Heterotrait-Monotrait (HTMT) Analysis

It has assessed with the Fornell-Larcker test with the additional requirement of a Heterotrait-Monotrait (HTMT) ratio of correlations or the purpose of supplementing the Fornell-Larcker test.

Table 5. Heterotrait-Monotrait (HTMT) Ratio for Discriminant Validity

Variable	AIT	AIDIC	ARQ	PI	CT	PAI	PE
AI Transparency (AIT)							
AI-based Data Integration Capability (AIDIC)	0.517						
Algorithmic Recommendation Quality (ARQ)	0.509	0.625					
Consumer Purchase Intention (PI)	0.345	0.430	0.623				
Consumer Trust in AI (CT)	0.512	0.498	0.602	0.762			
Perceived AI Intelligence (PAI)	0.480	0.551	0.674	0.510	0.579		
Personalization Effectiveness (PE)	0.518	0.581	0.756	0.691	0.704	0.768	

Note: It is supported when $HTMT < 0.85$ (Henseler et al., 2015); all values are below this threshold.

The values of the HTMT given in Table 5 indicate that all 21 unique construct pairs had HTMT ratios well below the conservative limit of 0.85. The highest here HTMT value was 0.768 between Personalization Effectiveness (PE) and Perceived AI Intelligence (PAI). While this pair was the closest to the threshold, the score is still significantly lower than 0.85, suggesting that they are empirically separate despite being conceptually adjacent in the field of AI personalization. The second highest HTMT ratio was found between PE

and ARQ which was 0.756; between CT and PI, which was 0.762; and between PE and CT, which was 0.704.

Three pairs of constructs showed particularly low values of HTMT, which also further confirmed their empirical independence. The correlation between Consumer Purchase Intention (PI) and AI Transparency (AIT) was 0.345; and the correlation between PI and AIDIC was 0.430, both of which suggested that the shared variance was very small between these two constructs that are theoretically far removed. Similarly, the HTMT of AIT and ARQ was 0.509 and that of AIT and CT was 0.512 indicating good discrimination between the AIT related antecedent constructs.

4.3.3 Cross-Loading Analysis

As an additional check of discriminant validity, cross-loadings were examined across all 28 indicators and seven constructs.

Table 6. Cross-Loading Values of Individual Items

Items	AIT	AIDIC	ARQ	PI	CT	PAI	PE
AIT1	0.338	0.732	0.406	0.252	0.361	0.437	0.371
AIT2	0.269	0.854	0.387	0.387	0.369	0.412	0.445
AIT3	0.381	0.801	0.411	0.265	0.293	0.272	0.383
AIT4	0.395	0.759	0.425	0.249	0.301	0.264	0.332
AIDIC1	0.884	0.334	0.384	0.320	0.405	0.322	0.383
AIDIC2	0.860	0.337	0.302	0.250	0.377	0.298	0.337
AIDIC3	0.874	0.463	0.463	0.289	0.448	0.442	0.482
AIDIC4	0.851	0.342	0.387	0.218	0.349	0.348	0.385
ARQ1	0.261	0.417	0.855	0.470	0.396	0.452	0.554
ARQ2	0.364	0.397	0.838	0.478	0.484	0.492	0.519
ARQ3	0.397	0.496	0.839	0.449	0.417	0.531	0.586
ARQ4	0.474	0.398	0.809	0.439	0.466	0.393	0.534
PI1	0.375	0.342	0.451	0.621	0.875	0.471	0.554
PI2	0.405	0.428	0.517	0.644	0.879	0.491	0.572
PI3	0.407	0.356	0.410	0.539	0.856	0.367	0.461
PI4	0.405	0.328	0.437	0.576	0.853	0.395	0.569
CT1	0.321	0.394	0.431	0.335	0.328	0.767	0.530
CT2	0.327	0.326	0.403	0.360	0.486	0.839	0.488
CT3	0.189	0.342	0.401	0.378	0.381	0.819	0.503
CT4	0.481	0.376	0.571	0.337	0.396	0.778	0.565
PAI1	0.305	0.398	0.577	0.558	0.515	0.603	0.860
PAI2	0.408	0.408	0.536	0.548	0.580	0.538	0.856
PAI3	0.458	0.425	0.575	0.514	0.531	0.586	0.878
PAI4	0.416	0.453	0.565	0.509	0.520	0.496	0.839
PE1	0.180	0.249	0.458	0.886	0.627	0.348	0.507
PE2	0.284	0.319	0.445	0.898	0.645	0.429	0.599
PE3	0.368	0.397	0.536	0.885	0.590	0.419	0.558
PE4	0.287	0.368	0.519	0.888	0.590	0.370	0.541

Note: Bold values indicate each item's highest loading on its intended construct.

The findings from the present study (Table 6) substantiated this finding, as all the indicators loaded most strongly on the construct they were intended to measure, with no significant discrepancies in cross-loading. All of the AI Transparency (AIT) items loaded on their own construct with the greatest coefficient of cross-loading being 0.395 for PE, which is a significant difference. The same held true for the AIDIC indicators (0.334–0.463 on own construct) compared to all other cross-loadings for the other constructs. Own-construct loadings were between 0.809 and 0.855, with the maximum cross-loading being 0.586 for ARQ3 on PE. The loadings of the Consumer Purchase Intention (PI) items were

the highest in the matrix (0.886–0.898), and there was a cross-loading of 0.875 between the CT and the PI1 item; this was the closest proximity observed across the entire matrix, which aligns with the theoretical overlap between purchase intention and consumer trust in AI contexts. The own loading of Consumer Trust in AI (CT) items ranged from 0.767 to 0.839, while the maximum cross-loading of these items was 0.565. The same was true of the Perceived AI Intelligence (PAI) and Personalization Effectiveness (PE) indicators, which had higher own-construct loadings than all of their cross-loadings, with the highest cross-loading in the case of PE2 (0.898) on PI, consistent with the close conceptual connection between the two constructs in AI personalization research.

4.4 Structural Model Assessment

The structural model estimated with PLS-SEM utilized 5,000 bootstrap resamples to obtain t-statistics and the confidence intervals for the path coefficients. The bootstrapping method does not require any assumptions about data normality and is resilient for making inferences. The hypothesized relationships, both direct and indirect (mediated), were examined at the 95% confidence level, with $t \geq 1.96$ and $p \leq 0.05$.

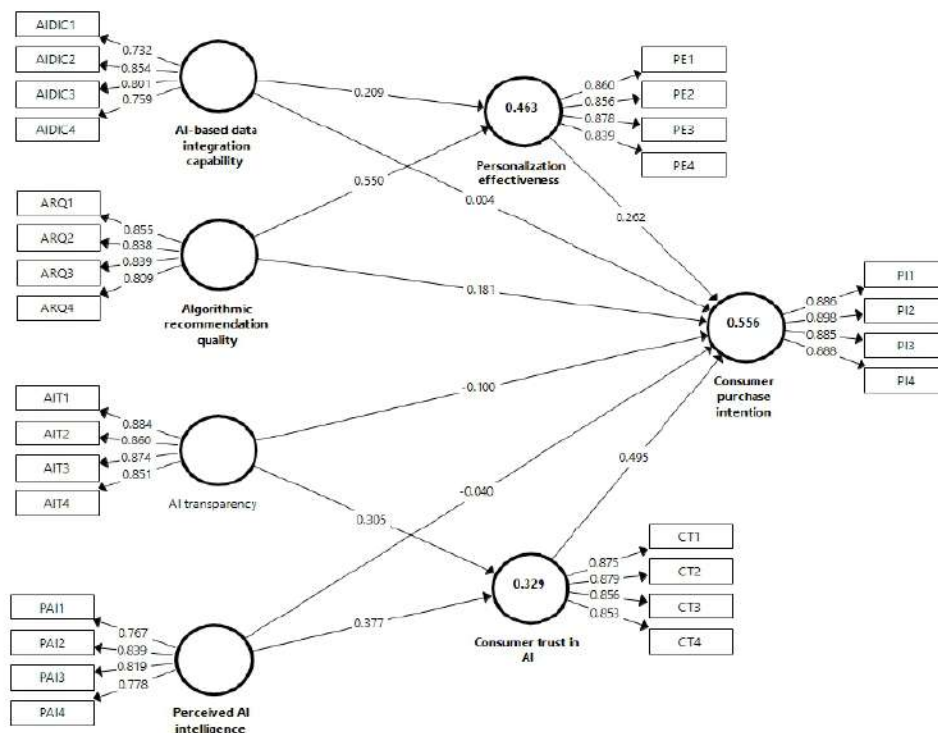


Figure 2. Standardized Results of SEM Calculations

4.5 Hypotheses Testing: Direct and Indirect Effects

Table 7 displays standardized path coefficients, standard errors, t-values, level of significance (p-values) and decisions for all eight hypotheses.

Table 7. Hypotheses Testing Results: Direct and Indirect Effects (5,000 Bootstrap Resamples)

Hypotheses	Relationship	β	SE	t-value	p-value	Decision
H1	AI-based data integration capability → Consumer purchase intention	0.004	0.077	0.058	0.954	Not Supported
H2	Algorithmic recommendation quality → Consumer purchase intention	0.181	0.101	1.800	0.072	Not Supported
H3	AI transparency → Consumer purchase intention	-0.100	0.061	1.642	0.101	Not Supported
H4	Perceived AI intelligence → Consumer purchase intention	-0.040	0.084	0.480	0.631	Not Supported
H5	AI-based data integration capability → Personalization effectiveness → Consumer purchase intention	0.055	0.035	1.580	0.114	Not Supported
H6	Algorithmic recommendation quality → Personalization effectiveness → Consumer purchase intention	0.144	0.067	2.160	0.031	Supported
H7	AI transparency → Consumer trust in AI → Consumer purchase intention	0.151	0.037	4.055	<0.001	Supported
H8	Perceived AI intelligence → Consumer trust in AI → Consumer purchase intention	0.186	0.045	4.154	<0.001	Supported

4.5.1 Direct Effects (H1–H4)

H1 (AI-based data integration capability → purchase intention) was not supported ($\beta = 0.004$, $t = 0.058$, $p = 0.954$). Consumers' estimates of this platform's capability to connect the data they use across channels, in isolation, do not lead to a measurable direct propensity to purchase, based on the near zero beta coefficient.

H2 (Algorithmic recommendation quality → purchase intention) was not significant either ($\beta = 0.181$, $t = 1.800$, $p = 0.072$) but the direction of the relationship was positive, and the t-value was close to the conventional value. While this is a marginal finding, it implies that there is a suggestion of purchase intention being influenced by the quality of the recommendation, which is not standalone evidence of the influence but is only mediated by personalization. The third hypothesis, AI transparency and purchase intention was not

supported and had a negative coefficient ($\beta = -0.100$, $t = 1.642$, $p = 0.101$). Additionally, the negative direction requires theory development: a higher perceived transparency does not immediately boost purchase intention, and in some cases can even lead to cognitive awareness of data collection practices, which can cause hesitation, the so-called "privacy paradox". H4 (Perceived AI intelligence $\rightarrow$ purchase intention) was also not supported by (β is -0.040 , t is 0.480 , p is 0.631), suggesting that there is essentially no direct relationship.

4.5.2 Mediated Indirect Effects (H5–H8)

Here the AI-based data integration capability (H5) didn't support (β value is 0.055 , t value is 1.580 , p value is 0.114). The indirect pathway through personalization effectiveness, as suggested, is in the positive direction but it is not significant. This learning from the discovery highlights that there is more to relevance and fit than data integration can provide to consumers' front-end view of relevance and fit, as they do not always see or feel the benefits of back-end data consolidation.

Hypothesis: H6 (Algorithmic recommendation quality $\rightarrow$ personalization effectiveness $\rightarrow$ purchase intention) was supported (β is 0.144 , t value 2.160 , p is 0.031). The findings indicate that the experiential journey of personalization effectiveness has a positive indirect impact on buying intention by the quality of AI recommendations. The large f^2 effect of the algorithmic recommendation's quality on the personalization effectiveness ($f^2 = 0.415$) express that the quality of the algorithmic suggestions is a key driver of consumers' impression of the effectiveness of AI personalization, which also significantly increases purchase intention.

H7 (AI transparency $\rightarrow$ consumer trust in AI $\rightarrow$ purchase intention) strongly supported the ($\beta = 0.151$, t is 4.055 , p came < 0.001). This is one of the best outcomes of the research. Consumer trust is high when the communication of AI is transparent, such as making disclosures about the data collection, processing, and use, thereby greatly improving the purchase intention from a customer perspective. Here, its effect of transparency on consumer trust is small but significant ($f^2 = 0.115$), while the impact of consumer trust on intention to buy is medium to large ($f^2 = 0.304$), indicating that consumer trust is an

important intermediate variable to study when examining the effect of transparency of their behavior.

The indirect effect estimates that were statistically significant were for H8 (Perceived AI intelligence → consumer trust in AI → purchase intention) with a β of 0.186 ($t = 4.154$, $p < 0.001$). Consumers feel more at ease with AI systems that appear intelligent, adaptable, and contextually aware, which greatly enhances their willingness to buy. The perceived AI intelligence and consumer trust in AI subscale ($f^2 = 0.176$) is in the small to moderate range as indicated by the literature.

The perceived AI intelligence and consumer trust in AI subscale ($f^2 = 0.176$) is in the small to medium range of the literature on anthropomorphic AI and technology cleared. By marching H7 and H8 make the psychological link between transparency and intelligence perceptions and commercial behavior. They also set up the consumer trust in AI as the psychological lever.

CHAPTER V: DISCUSSION

5.1 Overview of Key Findings

In discussion part it will explain the effect of four AI capabilities (AI-Based Data Integration Capability, Algorithmic Recommendation Quality, AI Transparency and Perceived AI Intelligence) on purchase intention of consumers. Here it also examined if these relationships mediate through Personalization Effectiveness and Consumer Trust in AI. The data, obtained from 229 valid respondents, were analyzed using PLS-SEM, showing interesting patterns. All of the AI capability constructs showed no significant impact on consumer purchase intention. Their effects, however, showed up in indirect ways, through consumers' psychological and experiential assessments. The results show that consumers do not change their buying habits until they feel that AI technologies offer them value and they trust an AI system. Hence, it contributes to the existing literature by emphasizing the role of consumer perception on behavioral intentions, not only based on the technical capabilities.

5.2 Why Direct Effects Were Absent: A Theoretical Reinterpretation

Interestingly, the outcome from this paper found that none of the four constructs of AI had significant impacts on consumer purchase intention. Despite the lack of support for hypotheses H1, H2, H3, and H4, these findings should not be interpreted as the opposite that the capability with AI is not important. Instead, they indicate that technological features should be more to encourage consumers to buy products unless they feel they are benefited by personalization and trust.

The insignificant direct effect of AI Based Data Integration Capability on purchase intention (H1: β is 0.004, p is 0.954) can be explained as follows: Data integration runs in the background. As a result, they are not directly assessed on these technical capabilities when deciding on purchases. The impact of data integration, on the other hand, is only truly significant if it improves the quality of personalized experiences. This interpretation also accounts for the indirect relationship between Personalization Effectiveness (H5) and the indirect effect here not statistically important, as it might be related to the results of data integration, not to the technology per se.

Algorithmic Recommendation Quality had a positive but statistically insignificant direct link with purchase intention ($\beta = 0.181$, $t = 1.800$, $p = 0.072$) in the same way. The impact was close to the established significance level but results showed that recommendation quality has a significant effect on purchasing decision through improving the perception of personalization rather than purchasing behavior itself. People seem to only be interested in recommendations if they feel that they are relevant, helpful, and in line with their own tastes. More surprisingly, the correlation between AI Transparency and the purchase intention was also unexpected. Overall, transparency was seen as a positive indicator; however, the direct effect was slightly negative and not statistically significant ($\beta = -0.100$, $p = 0.101$). A potential reason is that the more information is given on how the data is collected and how AI is used for decision-making the more consumers might become aware of privacy concerns. This means that transparency can lead to uncertainty rather than instant sales. The results indicate that transparency is not enough to impact consumer choices if they don't trust AI systems first.

Similarly, there was a non-significant direct effect of Perceived AI Intelligence on purchase intention (H4: $\beta = -0.040$, $p = 0.631$). Consumers might perceive AI systems as intelligent or high tech, but this doesn't directly translate to buying behavior. In contrast, a sense of competence towards AI seems to only drive purchase intention when they gain confidence in the recommendations of the AI system. This explanation aligns with Malhotra and Ramalingam (2023), who proposed that competence beliefs need psychological interpretation and to affect behaviour. The significant result for H8 ($\beta = 0.186$, $t = 4.154$, $p < 0.001$) further supports the hypothesis that consumer trust in the AI technology is the strongest link between AI perceived intelligence and purchase intention.

In general, these results support the theoretical approach of Stimulus – Organism – Response (S-O-R). AI is an external stimulus, and how it affects buying decisions will rely on the thoughts and feelings of consumers. Thus, AI alone does not motivate customers to buy, unless it successfully delivers custom experiences and builds trust.

5.3 The Mediating Role of Personalization Effectiveness

The effectiveness of personalization was confirmed, its effect between the algorithmic recommendation quality and purchase intention was obtained (H6: $\beta = 0.144$, $t = 2.160$,

$p = 0.031$). It is also consistent with the Personalization Theory of (Raji et al. 2024); (Wang, Chen, and Kuang 2025), which asserts that positive effect of external stimuli like quality of recommendations generated by AI on the behavior of consumers is through the evaluative process of the cognitive and affective mechanisms of consumers. Unlike technical indicators, the recommendation quality does not directly influence purchasing decisions, but rather relies on the consumer's perception of the AI-powered shopping experience, such as its relevance, personalization, and non-intrusiveness. It is noteworthy that in this case the size of the effect for the relationship between the quality of the recommendation and effectiveness of the personalization is large ($f^2 = 0.415$). It establishes a standard that the AI's recommendations must be relevant and accurate so as to be felt by the individual to set the value for personalization; this has implications as far as how value for personalization is created and felt by the individual are concerned. This is in line with

(Avinash et al. 2025), and (Yin and Qiu 2021), who both concluded that the relevance of the recommendations to the consumer as well as their difficulty level, did not matter, but instead the perceived personalization value was found to be dependent on the quality of the recommendations. Recommendations always correspond with individual preferences, which means that consumers will cognitively evaluate in terms of understanding them, and thus will be willing to purchase.

Due to the limitations of this nonsensitive indirect pathway via data integration capability, it is not immediately interpretable as a nonsignificant effect on personalization effectiveness (H5; $f^2 = 0.060$). The effect size is not large, so if there is a relationship between the two variables then it may not be measurable at this time in this sample or it may be dependent on the boundary conditions of the relationship, which cannot be described in this context.

(Gadjah Mada University et al. 2025; Mohammed and Sundararajan 2025). Future studies conducted on a larger number of samples and/or in contextually different platform needs to be addressed this ambiguity.

5.4 The Pivotal Role of Consumer Trust in AI

In the structural model, the valuable is trust in AI, in addition to being statistically the most precise ($t = 4.055$ and $t = 4.154$, respectively, $p < 0.001$), and the most powerful in terms of effect on the outcome variable ($f^2 = 0.304$). The findings support the consumer trust as the core psychological mechanism by which the characteristics of AI systems are translated into consumer behavioral intention in cross-platform e-commerce, which goes beyond previous research in which trust was considered a peripheral or control variable.

Research on the relationship between AI transparency and consumer trust toward AI systems has been expanded with support for the H7 (AI transparency – consumer trust – purchase intention) relationship, which supports the idea that consumers can cope with the inherent uncertainty of data sharing through AI by feeling more in control of information (Dai and Liu 2024; Wang et al. 2025). Transparency is a trust signal that does not directly influence purchase intention, but rather works as a trust signal in a cross-platform e-commerce context where consumer data flows through various touch points and third-party systems. (Abdullah et al. 2024) and (Sipos 2025) found similar mediated relationships in different retail settings, further indicating that the mechanism of mediated relationships is generalizable across different cultures.

The support for H8 (perceived AI intelligence → consumer trust → purchase intention; $\beta = 0.186$, $t = 4.154$) indicates a complementary, competence-based process of forming consumer trust. From the multidimensional view of trust, the competence dimension of trust is operationalized in perceived AI intelligence: When consumers perceive the AI system as intelligent, they then become more confident of its ability to generate recommendations that are accurate and relevant in the context, and purchase intention is activated through the competence dimension of trust as opposed to the perception that the AI system is intelligent. It supports the interpretation of perceived AI intelligence as a critical antecedent of trust in various e-commerce settings (Suleman et al. 2025).

H7 and H8 form a dual-pathway trust mechanism in cross-platform AI commerce, with the first pathway through perceptions of transparency to trust, and the second pathway through intelligence attributions to trust, with a trust cross-over that culminates in purchase intention. The dual-pathway structure has not been tested and confirmed at the

same time across different platforms in previous cross-platform e-commerce studies and represents a theoretical innovation over single-antecedent trust models that are very common in the literature.

5.5 Theoretical Contributions

This study contributes to the theory on consumer behavior in relation to AI in four aspects.

First, it offers one of the first empirically-supported models that integrates AI capability constructs (data integration, recommendation quality, transparency, perceived intelligence), an experiential mediator (personalization effectiveness), a psychological mediator (consumer trust), and behavioral intention within a holistic cross-platform framework. Previous studies have mainly explored these relationships in dyadic or triadic settings (e.g., the relationship between recommendation quality and satisfaction, or transparency and trust), missing the complexity of interdependencies between constructs and overemphasizing direct effects as they are, as shown in this study, mostly mediated (Damberg et al. 2024) and (Wen and Li 2025). Second, the study adds empirical support to the AI marketing field by applying S-O-R theory that suggests AI capabilities act as stimuli with the effects on behavior completely or partially mediated by cognitive-experiential and psychological organismic processes. The systematic absence of the four AI capability constructs, coupled with the positive indirect effects that mediated between the AI stimuli and the response, demonstrates that AI features do not have a strong direct persuasive effect, and that the interpretation and evaluation of the AI by the consumer is an essential intermediary between the AI and the response.

Third, the study addresses a longstanding confusion in the literature on AI transparency about its directionality and conditionality, whether it is the direction of causality or the circumstances under which transparency has a behavioral impact. The results confirm that the behavioral effect of transparency is not direct, but is mediated by its positive indirect effect via consumer trust; privacy salience and reduced purchase motivation are the two possible negative effects of transparency that were found to be significantly stronger and more direct when it failed to positively influence purchase, and they are not mediated by consumer trust. This conditional framing offers a more nuanced theory than previous research that posited a uniform positive outcome for transparency (Wasilewski,

Chawla, and Prałat 2025). Fourth, the finding that perceived AI intelligence was the greatest predictor of mediated purchase intention (H8: $\beta = 0.186$), supports the theoretical arguments that the perceptions of anthropomorphic, user-centric, and realistic traits of AI were the strongest predictors of mediated purchase intention. The result indicates that perceived AI intelligence is a construct that is theoretically unique and practically relevant, calling for further investigation in AI-consumer behavior research.

5.6 Limitations and Future Research Directions

The sample is largely made up of students and young adults in Bangladesh who are using digital platforms, but may not be representative of all digital platform users by age, gender, culture and socioeconomic factors. Future researcher can try to extend this model using more wider, multi-country samples to test for cross cultural generalizability of the pathways to trust and personalization explored in this study.

Second, it only provides a small glimpse of consumer AI capability thinking at a single time point, that's the reason it does not want the identification of causal relationships per se, and reduces the ability to draw conclusions about the development of AI capability perceptions over the course of the platforms' lifespan.

Third, the non-significant relationship between data integration capability and personalization effectiveness to purchase intention could be explained, in part, by a measurement constraint: consumers might not be able to directly tie the impact of their personalization experience in one platform with data integration processes in another platform. Future research needs to create more sophisticated and detailed perceptions of perceived data integration quality that reflect consumers' experiential awareness of the consistency and seamlessness of the data across platforms.

Last, the constructs examined here should be expanded more for upcoming findings to include the effects of consumer reactions toward AI agents, chatbots, and virtual advisors as elements of conversational transparency, perceptions of agent intelligence, and interactional personalization for believing in it and purchase pattern in novel AI-mediated environments.

5.7 Conclusion

In this paper, it investigated the structural connection of the AI related capabilities, personalization effectiveness, consumer trust in AI, and purchase intention in AI supported cross-platform e-commerce environment. Based on the findings, AI capabilities do not directly affect the intention to buy, but have a mediating effect through the experiential path (through the effectiveness of personalization) and the psychological path (through consumer trust in AI), through PLS-SEM analysis and 229 respondents. Overall, algorithmic recommendation quality and AI transparency and perceived AI intelligence were the most critical antecedents of consumer trust, which was the most predictive of purchase intention in the model, followed by the perceived personalization effectiveness. Importantly, the lack of significance of the direct effects is not a sign of the unimportance of capabilities of AI. Rather, they reveal the nature of consumer experience of and interpretation of AI features always mediate the nature of AI. Consumers are not only consumers of AI technology but also consumers of what AI technology does (and doesn't) for them, and about AI technology, through their perception of the quality of the personalization provided by AI, and their trust in AI systems. Companies that are good suited to grab any of the commercial opportunities or positive side of the AI in the increasingly complex, cross-platform digital marketplace will be platforms and practitioners that are able to apply AI investment approaches to these mediating mechanisms in the consumer-centric environment.

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APPENDIX-A

How do different AI capabilities influence customers' intention to purchase through personalization and trust?

Independent Variables (IVs)

These variables represent AI's technical capability to process data and generate recommendations.

SECTION 4: AI-Based Data Integration Capability

- AIDIC1: The platform integrates data from multiple sources effectively
- AIDIC2: The platform uses my past behavior to improve recommendations
- AIDIC3: The system combines my data across different platforms seamlessly
- AIDIC4: The platform creates a unified view of my preferences

SECTION 5: Algorithmic Recommendation Quality

- ARQ1: AI recommendations match my interests
- ARQ2: Suggested products are relevant to my needs
- ARQ3: AI recommendations help me discover useful products
- ARQ4: The system provides accurate recommendations

These variables represent how consumers perceive and understand the AI system.

SECTION 6: AI Transparency

- AIT1: The platform explains why certain products are recommended
- AIT2: I understand how my data is used for recommendations
- AIT3: The platform is open about its data practices
- AIT4: I am informed about how AI decisions affect me

SECTION 7: Perceived AI Intelligence

- PAII1: The AI system appears intelligent
- PAII2: The AI adapts to my preferences effectively
- PAII3: The system learns from my behavior over time
- PAII4: The AI provides smart and relevant suggestions

Moderating Variable (MV)

SECTION 8: Personalization Effectiveness

- PE1: The platform provides personalized recommendations
- PE2: The content shown to me fits my personal needs
- PE3: The personalization improves my shopping experience
- PE4: The personalization feels appropriate and not intrusive

SECTION 9: Consumer Trust in AI

- CTAI1: I do believe in AI recommendations on this platform
- CTAI2: The AI system is reliable
- CTAI3: I believe my data is handled responsibly
- CTAI4: I feel confident relying on AI recommendations

Dependable Variable (DV)

SECTION 10: Purchase Intention

- PI2: I might like to buy the products suggested by my AI
- PI3: I may like to purchase products recommended by the system.
- PI3: I plan to be buying in the future via this platform.
- PI4: I am willing to trust the recommendations made by AI before buying decision.