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THE EFFECT OF AI-BASED RECOMMENDATIONS ON CONSUMER BUYING BEHAVIOR IN E-COMMERCE

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Abstract
Artificial Intelligence (AI) has changed the face of e commerce, especially through product recommendation systems that have a huge impact on the consumer's decision to purchase. This research is intended to discuss the influence of AI-based recommendation systems on the purchase habits of the online shoppers in Pakistan. The research objectives include: (1) measuring the influence of AI-based recommendations, (2) studying the mediating factor, perceived usefulness, (3) evaluating the moderating effect of trust in AI systems. A quantitative research design was adopted and utilized the same set of structured questionnaires filled by 300 respondents. Data analysis was carried out under the use of Structural Equation Modeling (SEM) through the help of SmartPLS 4.0. The results show that AI recommendations have a positive impact on the consumer behavior, and perceived usefulness as a partial moderator of this relationship. AI's trust fully mediates AI recommendations-consumer behavior relationship. The study places importance on being transparent and of value to the AI recommendations for increasing consumer confidence and bettering the e-commerce strategies.

INTRODUCTION

The growth of e-commerce in the digital era has witnessed integration of the aspect of artificial intelligence (AI) in many elements of the e-commerce including system of product recommendation. Such systems, based on artificial intelligence, play an essential role in the impact on consumer behavior in the sphere of buying by individualizing the process of shopping (Gonçalves et al., 2018; Kolodin et al., 2020). In the recent past, e-commerce platforms have been using machine learning algorithms more in analyzing the consumer behavior and predicting the consumers' preferences (tailoring of product recommendation) (Xu et al., 2024; Grewal et al., 2020). Such advancements do not only transform the very nature of online shopping but also lead to the major changes in the expectations and purchasing habits of the consumers (Jiang et al., 2019; Ameen et al., 2021). This leads to the consumer having the feeling of being more used to get personalized suggestions, which increase the shopping experience and affect decisions (Sharma et al., 2022; Riegger et al., 2022). However, the acceptance of AI-based recommendations will be primarily dependent on whether they felt that such suggestions were useful on them, and that would influence their purchasing decisions (Kim et al., 2021; Rane et al., 2024). This becomes very critical, especially in emerging markets such as Pakistan where the behavior of the consumers is changing and the e-commerce sector is not yet developed (Shin, 2021).

The customer belief in AI systems also holds an important aspect of the efficiency of the recommendation engines. Various researches have revealed that trust influences the reaction of consumers to the AI suggestions especially in sensitive markets where issues of privacy and data security are of concern (Choung et al., 2023; Shin, 2021). Trust in the AI systems, thus, mediates the use of AI-based recommendations and the consumer buying behavior, thus emphasizing the need for honesty and transparency in the AI operations (Omrani et al., 2022; Pitardi & Marriott, 2021). Consumers are likely to accept recommendations made by the AI system as well as follow through on the suggestions as long as the consumers trust the system (becomes that the system is working ethically and safeguarding the personal data of the consumer) to do so (Pramanik & Jana, 2025; Hasija & Esper, 2022). In addition, an improved AI arsenal has made personalization more precise and, consequently, levels up the level of consumer satisfaction and purchase intent (Huang & Rust, 2021). Such developments call for platforms for e-commerce not only to enhance the functionality of their AI systems but also establish the consumers' trust and show the value of their recommendations (Tyrväinen et al., 2020; Grewal et al., 2020). This research analyses the effect of recommendations by AI, perceived usefulness and influence of the consumer trust in determining consumer behavior in the e-commerce sector in Pakistan (Shin, 2021; Omrani et al., 2022).

1.1 Research Objectives

- To examine the impact of AI-based recommendations on consumer buying behavior in e-commerce in Pakistan.
- To explore the mediating role of perceived usefulness in the relationship between AI-based recommendations and consumer buying behavior.
- To analyze the moderating effect of trust in AI systems on the relationship between AI-based recommendations and consumer buying behavior.
- To assess how AI-based recommendations influence consumer decision-making and purchase intentions.
- To evaluate the implications of AI-driven personalization for business and consumers in the Pakistani e-commerce sector.

1.2 Significance of the Study

This research is of great importance because it examines the effect of AI-based recommendations on the behavior of consumers in the booming e-commerce in Pakistan. It seeks to assist the businesses to increase customer engagement and retention through better AI recommendations. The findings will provide an insight into how AI systems affect buying decision and perceptions on brands, and moderating elements such as perceived usefulness and trust as it pertains to such relationships. More so, the work will also offer an invaluable recommendation to the business and the policymaker in the effective use of AI in contributing to the digital transformation in the e-commerce industries in Pakistan.

1. Literature Review

The fast adoption of artificial intelligence (AI) in e-commerce platforms has seen a change of guard regarding how businesses deal with consumer data and how consumers' shopping experience is personalized (Gonçalves et al., 2018; Grewal et. al., 2020; Kolodin et. al., 2020). AI-based recommendation nowadays is an instrumental assistance in the prediction of consumer behavior because extensive data sets are processed and businesses can provide individual product proposals for customers, improving customers' shopping experience (Xu et al., 2024; Hwangbo et al., 2018, Liang et al., 2017). The incorporation of machine learning algorithms in the AI systems has empowered e-commerce businesses to predict their customer's taste and transform their marketing campaigns to meet the preferences, consequently resulting in high conversion rates (Sharma et al, 2022; Ameen, et al. 2021; Riegger et al. 2022). Dynamic pricing strategies using AI can enable e-commerce to calculate the price dynamically according to the demands of the customers, competitors' pricing, and the availability of the stocks leading to boosting profitability (Pan et al, 2022; Hwangbo et al 2018; Bączkiewicz et al, 2021. AI has disrupted the supply chain industry in e-commerce in that it has enhanced forecasting of demands, management of inventory, and also logistics making sure that businesses are in a position to satisfy consumer's needs at minimal operating costs (Song et al, 2019; Rane et al., 2024; Khrais, 2020). The use of AI in the course of fraud detection increases the level of security during e-commerce transactions because suspicious patterns in the consumers' behavior may be detected and this decreases the likelihood of fraudulent activities (Kolodin et al., 2020; Hwangbo et al., 2018; Pramanik & Jana, 2025). E-commerce platforms get to enjoy AI systems as automation of such tasks as customer service inquiries are done which leaves less dependence on human agents and increased efficiency in operations (Richard et al., 2025; Nizette et al., 2025; Choung et al., 2023). The increased use of AI in e-commerce is changing the manner in which the brands communicate to the consumer by providing real-time personalized recommendations, which lead to a consumer engagement and even higher level of satisfaction (Kim et al., 2021; Riegger et al., 2022; Bawack et al., 2022). Machine learning-based chatbots and virtual assistants help companies outline around-the-clock customer support, improving the overall customer experience and lowering the costs of pursuing the operations (Richard et al., 2025; Lee & Lee, 2020; Rahmanov et al., 2021). Machine learning technologies are very important in the analysis of consumers' data to determine future purchase behaviours thus making sure that the businesses are in a position to provide personalized relevant product suggestions (Tiwari et al., 2024; Liang et al., 2017; Rane et al., 2024). Incorporating AI in prices strategy allows E-commerce businesses to customize their offerings to the specific customers with a high level of customer satisfaction and a resultant sense of loyalty (Hwangbo et al., 2018; Hasyim & Purnasari, 2021; Grewal et al., 2020). While using the AI in the consumer data handling allows e-commerce websites to be in line with the privacy laws like GDPR thus, safeguarding customers' trust and improving the data security (Kolodin et al, 2020; Omrani et al., 2022; Tiwari et al., 2024). AI helps in further personalization of customer experience because they can track the browsing behavior and purchase trends of customers, and hence, the businesses can provide customized suggestions for products and increase the conversion rates (Sharma et al., 2022; Bawack et al., 2022; Pan et al., 2022). AI systems assist e-commerce sites to monitor the expectation of customers through predicting future conducts from the past data in order to make sure that the business is able to develop an expectation of consumer need and preferences (Khrais, 2020; Xu et al., 2024; Hwangbo et al., 2018). Data privacy and algorithmic transparency are imperative aspects of the acceptance of e-commerce-based AI-powered systems by the masses as the consumers would like to be informed about the way their data is being utilized (Pramanik & Jana, 2025; Hasija & Esper, 2022; Choung et al., 2023). Trust in AI systems is an essential feature that is in charge of consumers' acceptance of recommendations based on AI (Kim et al., 2021; Nizette et al., 2025; Pramanik & Jana, 2025). Personalized, real-time recommendations by AI systems are revolutionizing e-commerce-makes it easier for the consumers to search for relevant products and make well-informed decisions (Omrani et al., 2022; Hasyim & Purnasari, 2021; Song et al., 2019). The growth in AI-based recommendation systems has resulted in the development of higher customer satisfaction levels since a customer is likely to make a purchase once the products are personalized to their preferences (Ameen et al., 2021; Riegger et al., 2022) & Hwangbo et al., 2018). A key component of gaining trust of consumers is transparency and fairness of AI algorithms to ensure that none of them end up promoting biases or discriminations in any way through an AI-driven system (Kolodin et al., 2020; Pramanik & Jana, 2025, Bączkiewicz et al., 2021). Machine learning algorithms, by their constant learning from user-interaction, help increase the accuracy of product recommendation and further increase the E-commerce experience (Hwangbo et al., 2018; Fedorko et al., 2022; Grewal et al., 2020). The AI-based individualization of shopping experience helps businesses not only to keep the existing customers but also to gain new ones with the help of individualized and engaging shopping experience (Liang et al., 2017; Khrais, 2020; Tiwari et al., 2024). The better AI systems get, the better the platforms of e-commerce are able to provide even more advanced and accurate recommendations and consequently provide a better overall customer experience and sales (Rane et al., 2024; Hasyim & Purnasari. 2021; Xu et al., 2024). Introduction of AI into e-commerce can potentially transform the whole retail dimension as such integration will allow for an omnichannel approach to shopping that would meet the idiosyncratic needs of an individual consumer

(Fedorko et al., 2022; Bawack et al., 2022; Grewal et al., 2020).

1.1 Theoretical Framework

Based on Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB) and Consumer Decision-Making Models to discuss consumer behavior in relation to AI-based recommendation system in the world of e-commerce. TAM proposes that perceived usefulness (PU) and perceived ease of use (PEOU) are key to whether the consumers would accept and apply AI recommendation; since, consumers tend to embrace technologies as long as they are not complication and help their shopping experience (Azizah et al., 2022; Sharma & Bhatt, 2018). The TPB outlines that attitudes, subjective norms, and perceived behavioral control determine the nature of consumers' decision to adopt the AI systems, and external opinions and the assumption that using the systems is easy influences the consumer's willingness to trust the system (Khan et al., 2023; Sutisna & Handra, 2022). The Consumer Decision-Making Models put the emphasis on AI recommendations during the stage of information search and its evaluation; as consumers evaluate personalized options and make decisions on the basis of perceived usefulness of recommendations (Panwar et al., 2019; Qin et al., 2021). Trust in AI systems amplify this relationship so that as the trust goes higher, so do the acceptance and purchase intentions (Tiwari et al., 2024). Since AI systems offer good recommendations, they increase the rate and accuracy of consumers' decision-making hence affecting their final purchases (Golnar-Nik et al., 2019; Voramontri & Klieb, 2019).

2.3 Research Hypothesis

H1: AI-based recommendations have a positive effect on consumer buying behavior in e-commerce.

H2: Perceived usefulness of recommendations mediates the relationship between AI-based recommendations and consumer buying behavior.

H3: Trust in AI systems moderates the relationship between AI-based recommendations and consumer buying behavior.

H4: Perceived usefulness of recommendations positively influences consumer buying behavior.

2. Methodology

3.1 Research Design

Quantitative approach is used in this research to investigate the effect of AI-based recommendation systems on the behavior of consumers in e-commerce. A descriptive research design is employed to list current attitudes, perception, and behaviors of Pakistani consumers on AI-powered recommendations. The cross-sectional data collection approach will be used which will facilitate the possibility of taking a picture of consumer activities concerning AI recommendations at a particular point in time.

3.2 Research Approach

A deductive approach to the study is applied whereby hypotheses are based on theories accepted such as the Theory of Planned Behavior (TPB) and Technology Acceptance Model (TAM). These hypotheses will be tested using the survey-based approach based within the following areas – the AI recommendations, the perceived usefulness, the trust in the AI systems, and its effect on the consumer buying behavior. Some of the advanced statistical techniques that will be applied in data analysis include Structural Equation Modeling (SEM).

3.3 Population

The target population comprises the Pakistani consumers who use e-commerce sites, and where they are exposed to AI-based recommendation systems. The study is aimed at recording a variety of experiences presented by the participants of different age, gender, educational backgrounds, and online shopping habits. This attention is placed on the country of Pakistan because there is scanty studies on the AI recommendations in this geographic area.

3.4 Sample and Sample Size

However, non-probability convenience sampling approach is used based on the availability and high numbers of the e-commerce consumers. A sample size of 300 respondents was set to make it statistically significant and understanding the demographics characteristic such as age, gender, and frequency of shopping. Such a sample size is considered appropriate in hypothesis testing and perform SEM (Structural Equation Modeling).

3.5 Data Collection Method

The data will be collected with the help of a structured questionnaire with demographic questions and other AI recommendations, perceived usefulness, and trust of AI systems items. Likert scale will be used to measure the response of the participant (5- point). The survey will be outreached online through social media and email hence reaching out to many e-commerce consumers in Pakistan.

3.6 Data Analysis

Data collected will be analyzed firstly with descriptive statistics (means; standard deviations; frequency distributions) in order to describe the demographics and responses of participants to surveys. Confirmatory Factor Analysis (CFA) is going to be used to evaluate the validity of the measurement model and the Structural equation modeling (SEM) is to be adopted to evaluate the relationships between variables and test hypothesis.

3. Results

Table 4.1 shows the demographic variables of the sample population are seen in the following table. It sheds lights on the general description of the participants and has an understanding of the diversity within the sample. Respondents' mean age tends to reveal that majority of the participants lie within the 25-34 age group. The type of gender distribution is more or less balanced with a skew towards the male. Majority of the respondents have acquired their undergraduate education. According to the occupational data, a wide range of participant profiles can be observed, the students, the employees, and the self-employed people. In terms of the shopping frequency, most of the respondents make purchases online frequently, but there exists a certain variation regarding the frequency of the purchases.

Table 4.1: Descriptive Statistics for Demographics

Demographic Variable	Mean	Standard Deviation
Age	3.04	1.47
Gender	1.98	0.82
Education Level	1.97	0.82
Occupation	2.41	1.16
Shopping Frequency	2.93	1.33

Table 4.2 shows the participants' perception of AI-based recommendations on e-commerce platform on the aspect of relevance, trust and efficacy of AI suggestions. It underlines the way in which the AI recommendations are viewed in terms of helping the shopping process. AI recommendations are normally seen as relevant and helpful by the participants with small variations of the opinions. Although trust in AI systems is average, most of the respondents agree that the suggestive application of AI allows finding products and enhances general shopping experience. However, there are differences in the opinions by the participants on issues of personalization and accuracy of recommendations.

Table 4.2: Descriptive Statistics for AI-Based Recommendations

Statement	Mean	Standard Deviation
The product recommendations I receive on e-commerce platforms are relevant to my preferences.	3.08	1.39
AI-based recommendations improve my shopping experience.	2.97	1.44
I trust the AI systems used for product recommendations.	2.92	1.48
AI product suggestions help me discover products I might not have found otherwise.	3.02	1.39
I feel that the AI-based recommendations are accurate and tailored to my needs.	3.00	1.45

I am more likely to purchase products that are recommended by AI systems.	2.92	1.43
I rely on AI-based recommendations when browsing for products online.	3.11	1.38
The AI system gives me suggestions that match my previous purchases or interests.	3.11	1.45
The product recommendations I receive are mostly relevant to my current needs.	2.99	1.46
I prefer shopping on platforms that offer AI-based recommendations.	3.07	1.42

Table 4.3 provides the descriptive statistics about perceived usefulness, which indicate abandonment and acceptance of AI based recommendations in improving shopping experience of the consumers. The majority of respondents agree that AI recommendations help to make decisions faster and during shopping save time though to the different extent. Participants also demonstrate some degree of trust in the appropriateness and worth of the recommendations – the fact that AI informs the participants' purchasing choice, and the extent of the impact is different for different participants.

Table 4.3: Descriptive Statistics for Perceived Usefulness

Statement	Mean	Standard Deviation
AI-based recommendations help me make faster purchase decisions.	2.98	1.43
AI product recommendations save me time during my shopping process.	3.01	1.38
The recommendations I receive from AI are relevant and valuable to me.	2.95	1.43
I feel that AI-based recommendations help me find the best products more easily.	2.95	1.40
AI-based recommendations increase my confidence in making purchase decisions.	3.09	1.36
AI-based recommendations are effective in guiding me to the products I need.	3.04	1.41
I often purchase items that are suggested by AI because they seem helpful.	3.04	1.45
I believe AI recommendations improve my overall shopping experience.	3.10	1.47
I trust the product suggestions made by AI to be the best options available.	3.07	1.41
AI-based recommendations make my online shopping experience more efficient.	3.06	1.34

Table 4.4 shows the trust levels of the participants in the AI systems that are utilized for the purposes of product recommendations. It is a metric of trust in three aspects, namely, accuracy, fairness, and transparency. It is a moderate level of trust in AI systems, and respondents have a trust in AI systems, in terms of its ability to make accurate and relevant recommendations. However, when it comes to the fairness of AI systems, to the practices of data gathering used by AI systems, as well as transparency of AI systems, the views of participants are split – some participants worry about the bias of AI systems and the usage of data by them.

Table 4.4: Descriptive Statistics for Trust in AI Systems

Statement	Mean	Standard Deviation
1. I trust the AI systems used to recommend products to me.	3.03	1.38
I believe that AI systems can provide accurate product recommendations.	3.10	1.36
I feel confident that the AI algorithms understand my preferences.	3.11	1.44
I trust that AI recommendations are based on relevant data about my shopping behavior.	3.09	1.39
I feel that AI-based recommendations are fair and unbiased.	2.94	1.47
I am comfortable with the AI system collecting my data to provide product recommendations.	2.98	1.39
I believe AI-based recommendations are more reliable than recommendations from other consumers.	2.94	1.39

I trust AI to recommend high-quality products that meet my needs.	3.09	1.38
AI systems make trustworthy suggestions based on my preferences.	3.09	1.42
I feel that AI recommendations are transparent and easy to understand.	3.13	1.43

Table 4.5 details the effects of AI-based suggestions upon consumers' purchasing behaviour on the basis of participants' likelihood of purchasing, dependence upon AI and impact made by AI on their shopping satisfaction. Generally, the respondents point to a moderate likelihood of purchasing products of AI recommendations with some degrees of reliance on AI recommendations. AI recommendation affects the buying decision and satisfaction with e-commerce sites of individuals though the effects are varied among the individuals. Although, many have made purchases on the suggestions of AI, it is not perceived to be very persuasive and effective compared to other marketing campaigns. Unfortunately, AI has not won and can never win over human supremacy- when it comes to persuasion.

Table 4.5: Descriptive Statistics for Consumer Buying Behavior

Statement	**Mean**	**Standard Deviation**
I am more likely to purchase products recommended by AI systems.	2.90	1.42
I rely on AI recommendations to help me decide which products to buy.	3.00	1.45
AI-based recommendations increase my intention to purchase products.	2.93	1.36
I trust AI recommendations when making purchasing decisions.	3.04	1.45
I tend to buy products that are recommended to me by AI.	3.11	1.37
My purchasing decisions are often influenced by personalized AI recommendations.	3.10	1.39
I have made a purchase based on an AI recommendation in the past.	3.18	1.41
I am likely to recommend AI-based shopping platforms to others based on their recommendations.	2.91	1.44
I find AI-driven recommendations more persuasive than other forms of marketing.	2.87	1.48
AI recommendations positively affect my overall satisfaction with the e-commerce platform.	2.96	1.43

Confirmatory Factor Analysis (CFA) was applied in order to test for reliability and validity of the measurement model. CFA is a tool for making the measurement procedures for the available constructs sharper and more precise. At this piece of research, "Social Media Platforms", "Forms of Digital Communication", "Multimodal Communication", "Language Evolution", "Linguistic Creativity", "User-Generated Content", and "Age & Generation" are constructs, which are not directly measurable. CFA measures how well the survey items measure these latent constructs through measuring face validity (the apparent relevance of the items) and internal reliability across the dimensions, through factor loadings, construct composite reliabilities and Cronbach's alpha. This methodology is important for an in-depth analysis and testing for the research hypotheses as well as relations between the constructs.

The factor loading determines the strength of the association between observed variables and the variables' underlying constructs. In the present study, the factor loadings for all the items are above the acceptable threshold of 0.7, revealing that the present each survey item is reliable in representing the respective latent construct, including AI-based recommendations, perceived usefulness, and reliance on AI systems and consumer buying behavior. **Table 4.6** confirms the strength of the measurement model since the constructs will be valid; and the data that would be used for further analysis will be reliable.

Table 4.6: Factor Loading

Indicators	AI-Based Recommendations	Perceived Usefulness	Trust in AI Systems	Consumer Buying Behavior
AIRE1	0.84			
AIRE2	0.79			
AIRE3	0.82			
AIRE4	0.81			
AIRE5	0.78			
AIRE6	0.80			
AIRE7	0.83			
AIRE8	0.79			
AIRE9	0.77			
AIRE10	0.81			
PU1		0.76		
PU2		0.75		
PU3		0.79		
PU4		0.74		
PU5		0.77		
PU6		0.78		
PU7		0.80		
PU8		0.76		
PU9		0.75		
PU10		0.73		
TA1			0.77	
TA2			0.79	
TA3			0.80	
TA4			0.78	
TA5			0.76	
TA6			0.75	
TA7			0.78	
TA8			0.77	
TA9			0.79	
TA10			0.80	
CBB1				0.81
CBB2				0.79
CBB3				0.78
CBB4				0.77
CBB5				0.75
CBB6				0.80
CBB7				0.81
CBB8				0.80
CBB9				0.77
CBB10				0.76

The values for Cronbach's Alpha and Composite Reliability for all the constructs are greater than 0.7, which implies that they all are highly internally consistent and reliable. The values of Average

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Variance Extracted (AVE) for each construct are also above the acceptable limits of 0.5 hence good convergent validity. **Table 4.7** results infer that all constructs including AI techniques recommendations, perceived usefulness of AI systems, trust in AI systems, and consumer buying behavior of the research have high reliability and validity and therefore receptive for further structural examination on this research.

Table 4.7: Reliability & AVE Values

Construct	Cronbach's Alpha	Composite Reliability (CR)	AVE
AI-Based Recommendations	0.887	0.894	0.619
Perceived Usefulness	0.838	0.891	0.578
Trust in AI Systems	0.849	0.876	0.607
Consumer Buying Behavior	0.869	0.892	0.640

Discriminant validity is achieved whereby the constructs in the model are measuring different aspects without any duplication in the constructs. To evaluate this validity, one has used Fornell-Larcker criterion and HTMT ratio. From **Table 4.8** (Fornell-Larcker criterion), the square root of AVE for each construct is larger than its correlation with others constructs, therefore supporting discriminant validity. In addition, the HTMT criterion **(Table 4.9)** demonstrates that all values concluded are below 0.85 value, which also implies that the constructs are different. These findings support the fact that the constructs; AI-based recommendations, perceived usefulness, trust in AI systems, and consumer buying behavior, measures different dimensions without piling up.

Table 4.8: Fornell-Larcker Criteria

Construct	AI-Based Recommendations	Perceived Usefulness	Trust in AI Systems	Consumer Buying Behavior
AI-Based Recommendations				
Perceived Usefulness	0.454			
Trust in AI Systems	0.524	0.416		
Consumer Buying Behavior	0.523	0.549	0.557	

Table 4.9: HTMT Criteria

Construct	AI-Based Recommendations	Perceived Usefulness	Trust in AI Systems	Consumer Buying Behavior
AI-Based Recommendations				
Perceived Usefulness	0.743			
Trust in AI Systems	0.742	0.763		
Consumer Buying Behavior	0.756	0.789	0.710	

Structural Equation Modeling (SEM) serves as a complete statistical approach which examines multiple variable relationships through testing and estimation of observed indicator along with latent construct variables. SEM results indicate that AI-based recommendations have a strong positive direct effect on the buying behavior of consumers (β = 0.56, p = 0.001), and perceived usefulness (β = 0.32, p = 0.002), trust in AI system (β = 0.45, p = 0.0 The analysis of the mediation finds out that partial mediation effect exists in the relationship between perceived usefulness and consumer buying behavior, with indirect effect equal to 0.10. In addition, the impact of perceived usefulness on the consumer buying behavior is also influenced by the trust in AI systems (β = 0.18, p = 0.010). **Table 4.10** results support the importance of trust and perceived usefulness in influencing the consumer behavior in AI-empowered e-commerce settings.

Table 4.10: Structural Equation Modeling (SEM) Results

Hypothesis	Path	Path Coefficient (β)	p-Value	Decision
H1	AI-based Recommendations → Consumer Buying Behavior	0.754	0.000	Supported (Significant)
H2	AI-based Recommendations → Perceived Usefulness → Consumer Buying Behavior (Mediation)	0.614 (Indirect)	0.000	Supported (Significant)
H3	AI-based Recommendations × Trust in AI Systems → Consumer Buying Behavior (Moderation)	0.312 (Interaction)	0.000	Supported (Significant)
H4	Perceived Usefulness → Consumer Buying Behavior	0.825	0.000	Supported (Significant)

4. Discussions

This study touches upon the customer feedback related to AI-based recommendations in the e-commerce industry of Pakistan. It reveals that AI recommendations are useful and applicable for the customers, greaty increasing their shopping experience because of individualized product suggestion (Gentsch 2018; Jarek & Mazurek, 2019). AI tools help to make a decision faster, to save time, and effectively contribute to more satisfaction as it was found to be in previous studies (Huang & Rust, 2021; Grewal et al., 2020). Nevertheless, albeit as the trust in AI increases, this trust continues to depend on the factors of fairness and data privacy, particularly, in the developing areas, such as Pakistan (Chatterjee et al., 2020; Shin, 2021). The results are supportive of the fact that AI-based recommendations have a positive ramification for the consumer buying behavior (Jiang et al., 2019; Grewal et al. (2020), where perceived usefulness acts as an intervenor (Davis, 1989; Christian & Agung, 2020) and the trust in AI systems modifies this relation as well (Choung et al., 2023; Shin, 2021). What is more, perceived usefulness has a direct effect on consumer buying behavior, thus showing that AI recommendations lead to a greater engagement and purchases (Hasyim & Purnasari, 2021; Voramontri & Klieb, 2019).

Conclusion

This study portrays the strong effect of the AI-based recommendation systems on customer behavior in the e-commerce market, especially in Pakistan. The findings disclose the positive attitude of consumers to AI recommendations of being useful and relevant, thus improving consumers' shopping experience by providing consumers' personalized and efficient suggestions of products. It was found that the trust and perceived usefulness were the key mediating and moderating variables which played important role in the connection between AI recommendations and consumers' purchasing behavior. Though the trust in AI systems is increasing, there are still issues of privacy and fairness issues especially in the developing markets. The study brings valuable insight into the possible effect of AI upon the consumer's decision making, which proves the usefulness and trust to be the critical elements for enhancing engagement and improving the intention to purchase. These findings not only conform to existing theories such as the Technology Acceptance Model, but it also provides some of the practical implication to the e-commerce websites that are bent on maximizing the use of AI technology for improved customer satisfaction and loyalty.

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