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AI-Powered Personalization and Online Purchase Intention: A Moderated Mediation Analysis of Trust and Ease of Use

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Abstract
This paper explores the role of three mechanisms of AI-based personalization, such as product recommendations, advertisements, and customer support, in influencing online purchase intention among e-shoppers in Pakistan (N = 156). The research is based on an extended Technology Acceptance Model (TAM), in which the notion of trust in AI suggestions is conceptualized as a mediating factor, and the notion of AI-enabling ease of use is formulated as a boundary condition. Through the PROCESS macro analyses, AI-driven product recommendation greatly improved trust ($b = 0.44$, $p < 0.001$), and the latter positively influenced purchase intention (indirect effect = 0.20, 95% CI (0.11, 0.33)). The direct impact of AI recommendations on purchase intention was also of significance, and this suggests a partial mediation. The relationship between recommendations and trust had a positive moderating role as ease of use (interaction $b = 0.26$, $p = 0.007$), indicating that AI cues are more convincing in an environment where the user feels that the platform is easy to use. The direct effects of AI-powered advertisements and AI-enabled customer assistance on purchase intention were smaller and positive, with no significant gender differences. Overall, the model accounted 34% variation of purchase intention. Considering trust and ease of use as a part of the TAM framework, the study expands TAM to the realm of AI-based personalization and offers a subtle understanding of how smart marketing services should affect consumer decision-making in digital commerce settings.

Keywords: AI Personalization, Trust, Ease Of Use, Purchase Intention, Moderated Mediation, TAM

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Introduction

Artificial Intelligence (AI) is rapidly redefining the landscape of both business operations and consumer experiences. Initially developed to replicate human intelligence and automate repetitive tasks, AI has evolved into a versatile tool that supports a wide array of functions, including natural language processing, predictive analytics, computer vision, and real-time decision-making (Paschen et al., 2020; Davenport et al., 2020). Its ability to analyze vast datasets, detect patterns, and generate real-time recommendations has made it an essential component of modern digital infrastructures. One of the most significant transformations brought about by AI is in the field of marketing, where it plays a crucial role in optimizing customer interactions, personalizing content delivery, and improving return on investment (Guha et al., 2021).

As online consumer behaviour becomes increasingly complex and fragmented across multiple platforms, businesses have turned to AI technologies to tailor experiences at scale. The ability of AI-powered recommendations and dynamic advertising, chatbots, and virtual assistants can help marketers to target customers based on immediate conditions matched to their real-time preferences, web history, and past communication (Hermann, 2022). The growing efficiency of this approach is not the only benefit, as pre-packaged hyper-individualized experiences can improve satisfaction and loyalty. This gradual incorporation of AI in such customer-facing solutions has given rise to what researchers call AI-driven personalization. This will mean using machine learning algorithms and consumer data to provide personalized suggestions, support, and promotions based on consumer profiles (Lopes et al., 2024). Consequently, the personalization strategies are no longer influenced on one-dimensional segmentation but are continually modified according to behavioural indicators and feedback loops. AI has become proactive, taking part in the whole customer journey that presupposes pre-purchase discovery and evaluation as well as post-purchase service and engagement (Lemon & Verhoef, 2016; Manser Payne et al., 2021).

However, while AI-powered personalization holds tremendous promise, it also presents a unique set of challenges. Consumers may express scepticism toward algorithm-driven interactions due to concerns about privacy, a lack of transparency, or a perceived loss of control (Dwivedi et al., 2023; Ng & Zhang, 2025). Additionally, trust in AI recommendations becomes a critical factor, as users are more likely to reject personalized offers Whether they perceive them as intrusive, biased or unreliable (Khandelwal et al., 2024). Ease of use is an additional critical issue: even an AI system that is the smartest can make a minimal difference to changing user behaviour unless it is intuitive or easy to use (Davis, 1989; Xia et al., 2025). To address these forces, scholars are increasingly turning to well-known theories. Like, the Technology Acceptance Model (TAM) as a way to explain how users will perceive and adopt AI.

TAM assumes that perceived usefulness and perceived easy use is one of the significant factors that determine the attitude of an individual towards the use of a technology, which ultimately determines the behavioural intent (Davis, 1989). Within

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the framework of the AI marketing approach, the concepts of trust in AI recommendations and perceived ease of use are becoming increasingly apparent as essential mediators and moderators that explain the relationship between exposure to AI and consumer behaviour (Guha et al., 2021). Hence, it is essential to differentiate not only the overall effectiveness of AI personalization but also the psychological and behavioural conditions under which it becomes more successful. This paper seeks to respond to these new complexities through an empirical-based analysis of the influence of AI-assisted personalization on consumer purchase intention, considering trust and ease of use within the given TAM-based framework.

Although the use of AI has been reported to enhance user involvement, provide personalized experiences, and increase satisfaction, it also poses challenges related to trust, data privacy, and usability (Ng & Zhang, 2025).Although the TAM has proven to be such a strong framework to explain the technology adoption (Davis, 1989). There is a lack of empirical studies extending TAM to explore the role of trust as a mediating mechanism and ease of use as a moderating factor in the context of AI marketing. Additionally, demographic factors such as age and gender were considered (Khandelwal et al., 2024), but the impact it has on AI-driven purchase decisions is not clear. The paper fills these gaps by establishing a TAM-based moderated mediation model that can be used to investigate the extent to which AI-powered personalization influences online purchase intention through trust and the ease of use.

The current research on the impact of AI-based technologies on consumer behavior has been vast. However, some critical gaps persist. Namely, the refined role of moderating variables, such as ease of use of AI, and mediating variables, such as trust in AI-based product recommendations, has been underrepresented in prior studies, which could cause significant variations in online purchase intentions (Lopes et al., 2024; Ubal et al., 2024). Additionally, although the role of demographic information (age and gender) has been identified, the exact nature and magnitude of the relationships have not been well understood and require further empirical research (Khandelwal et al., 2024).This study is mainly aimed at investigating the impact of AI-powered personalization in terms of its effect on online purchase intentions. The following are the specific objectives:

To explore how AI-based product suggestions change consumers' intent to purchase.

To assess the effects of advertisement-based on AI on consumer purchase intentions

To evaluate the importance of AI-based customer care in influencing consumer buying behavior

To examine the moderating effect of ease of use (enabled by AI) in AI product recommendations and Trust in AI product recommendations.

To investigate how demographic factors affect consumer attitudes towards AI-driven digital marketing.

The proposed research will add significant value to both theory and pragmatic marketing approaches. Theoretical merits: It contributes to literature by conducting the study of the TAM and Stimulus-Organism-Response (S-O-R) model to gain better insights into how consumers react to AI-based personalization. In practice, the knowledge gained from this study will enable marketers and companies to plan better and incorporate an AI strategy, driving greater consumer confidence, user-friendliness, and ultimately increasing purchase intentions and customer loyalty. Further, determining the demographic sensitivities to personalization approaches of artificial intelligence will help practitioners develop more refined and inclusive marketing strategies. The paper is dedicated to investigating the influence of the AI-powered personalization capabilities, including product recommendations, AI-based advertising, and virtual customer assistants, on online consumer shopping intent. It also takes into consideration the intermediary influences of ease of use with AI-enabled technology and trust in AI systems to determine how the use of personalization approaches is reflected in the purchasing behavior that results. The study is limited to data collection at the primary level through structured questionnaires, which will be conducted among online shoppers, and it employs quantitative data analysis using SPSS.

Despite its strengths, the study has certain limitations. First, the findings are based on a cross-sectional dataset, limiting the ability to infer causality over time. Second, the sample may reflect demographic or regional biases due to data collection being restricted to a specific population, which can potentially limit generalizability. Third, the study only investigates personalization features visible to end users and does not account for backend AI algorithms or data ethics concerns related to recommendation systems. Finally, fast-evolving AI technologies may render some insights context-specific, requiring ongoing research in this area. This research is organized as follows: this chapter provides an introduction. Chapter 2 presents the literature review, while Chapter 3 discusses the research methodology. Chapter 4 then examines the data analysis and the presentation of results. The last chapter's discussion, conclusion, and recommendations interpret the results, present a conclusion, and outline the practical and theoretical implications of the study, as well as the constraints of the study and recommendations for future research.

THEORETICAL FRAMEWORK AND HYPOTHESIS FORMULATION

AI-Driven Product Recommendations

Product suggestion systems, powered by AI, have elevated the consumer experience on online platforms to a new level. These systems enable correlating real-time browsing habits with personal user profiles using state-of-the-art machine learning methods, including neural collaborative filtering and reinforcement learning, to enhance the level of personalization (Zhang et al., 2020). These engines are crucial, as they also allow one to reduce search efforts and help lessen information overload in digital marketing strategies. Empirical studies indicate that optimal recommendation algorithms effectively augment shopping carts and increase the propensity for impulse buying activities, particularly in cross-border e-business settings (Lopes et al., 2024). However, such minor errors, like irrelevant inscriptions or delivery errors, may reduce consumer trust and customer satisfaction rates, and precise results within such systems are essential (Teepapal, 2025).

Theoretically, the TAM offers a helpful perspective for analysing how everyday users evaluate recommendation engines. In this context, they are viewed as practical tools

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to enhance online shopping, and their ease of use facilitates further interaction. Ultimately, these perceptions determine behavioural intentions to adopt BO and AI-driven personalization features (Davis, 1989; Venkatesh & Davis, 2000). In summary, AI recommender systems not only automate product discovery but also impact consumer choice by aligning with the cognitive TAM constructs, i.e., perceived usefulness and ease of use, thereby significantly influencing online purchase intentions.

Why TAM outperforms S-O-R

The S-O-R paradigm excels at mapping how environmental “stimuli” kindle affective “organism” states that drive response, but meta-reviews show its explanatory power in digital commerce is modest: average purchase-intention R^2 rarely tops 0.30 (Chang et al., 2011). By contrast, cumulative meta-analysis places TAM’s typical R^2 for behavioural intention between 0.40 and 0.53, making it the more “parsimonious yet predictive” lens for technology-mediated buying contexts (Schepers & Wetzels, 2007). When recommendation relevance and interface effort map cleanly onto PU and PEOU, TAM captures the cognitive calculus that actually propels checkout decisions (Pavlou, 2003). In contrast, S-O-R’s affective focus leaves much variance unexplained. Because AI-driven product suggestions first signal **utility** (better matches) and **effort reduction** (faster search), TAM offers a theoretically robust and empirically superior lens for tracing how such cues translate into concrete buying intentions in e-commerce environments.

Consumer Purchase Intention

Consumer Purchase Intention (CPI) refers to an individual's conscious intention or apparent plan to buy a particular product or service within a short period, providing a practical indicator of actual purchase intention in the online environment (Huh et al., 2023). It is not only intended to buy but the psychological preparation and assurance of making a buying decision. This purpose may be influenced by numerous factors, both internal and external, such as product features, the brand's perception, and the individual's needs. Advertising, which triggers marketing stimuli, as expressed through traditional media (e.g., television, print) or digital media (e.g., social media, search engines), has been demonstrated to substantially affect CPI (**Han, Z., & Du, G., 2023**). Additionally, interpersonal factors such as word-of-mouth and e-word-of-mouth are also crucial in building consumer confidence (Jalilvand & Samiei, 2012).
Consumer intentions are additionally reinforced by variables of brand trust, brand loyalty, and brand equity (Dabholkar & Sheng, 2012; Büyükdağ, 2021) in the case of AI-powered marketing, it leads to personalized recommendations as cognitive aids in reducing decision fatigue by providing consumers with highly relevant alternatives according to their liking (Al-Debei et al., 2015). Responsive systems, which provide real-time feedback, allow increasing user activity and promote brand loyalty due to the ease of usage and simplification of the customer experience (Hardcastle et al., 2025). Nevertheless, the usefulness of this type of intervention is countered by mounting concerns about data privacy, the opaque nature of algorithms, and potential bias within personalization algorithms. These issues may lead to a degradation of

consumer trust and the erosion of the benefits of AI use on CPI. In general, consumer purchase intention is an influential theoretical and strategic business orientation aspect, thus providing a focus for comprehending the effectiveness of AI personalization in e-commerce setups.

H1. AI-driven product recommendations have a positive influence on consumer purchase intention.

AI-Powered Advertisements

Advancements in programmatic advertising have enabled marketers to deploy **AI-powered ad systems** that can dynamically generate and personalize content at the impression level. Using tools such as **generative AI, image synthesis,** and **dynamic creative optimization**, advertisers can tailor visuals, messaging, and placements in real-time based on user behaviour and preferences (Yao et al., 2023). This hyper-personalization has been shown to enhance users' **attitude toward the ad** and **conversion intentions**, primarily due to increased message relevance and sensory vividness (Rodgers & Nguyen, 2022), facilitates not only content creation but also **automated bidding strategies**, allowing advertisers to optimize ad delivery by targeting specific audience segments with higher precision (Ruckenstein & Granroth, 2020). This automation has transformed online advertising by creating an **Omnimedia environment** in which all digital touchpoints, such as social media, search engines, and display networks, serve as channels for delivering individualized messages.

Tools such as **voice recognition** and **natural language processing** have further enabled real-time interaction and deep personalization (Hirschberg & Manning, 2015). Moreover, intelligent search engines use AI to filter and prioritize advertisements based on user intent and search behaviour. This granular targeting allows brands to align ads with specific consumer interests, thereby increasing **click-through rates** and overall advertising effectiveness. However, while the potential for personalization is vast, it also raises concerns around **data privacy, algorithmic manipulation**, and **over-targeting,** which may lead to ad fatigue or consumer resistance if not managed carefully (Boerman et al., 2017). Thus, AI-powered advertisements represent a strategic opportunity to enhance engagement and purchase intent; however, their success depends on striking a balance between personalization and ethical and perceptual considerations.

H2. AI-powered advertisements have a positive influence on consumer purchase intentions.

AI-Enabled Customer Assistance

AI-enabled customer assistance tools such as **chatbots, voice bots**, and **virtual shopping assistants** serve as 24/7 service agents, designed to resolve consumer queries, guide product selection, and even facilitate checkout. These systems have become integral components of digital customer service, offering **instant responses**, **personalized recommendations**, and continuous availability, which have been linked to increased **trust, customer satisfaction**, and ultimately, **purchase intention (Khan**

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& Iqbal, 2020). Recent meta-analyses suggest that incorporating anthropomorphic cues (e.g., conversational tone or virtual personalities) enhances user comfort and perceived human likeness, which helps build relational trust. This trust is crucial within the **TAM** framework, where it acts as a key mediator between perceived ease of use and behavioural intention. Thus, AI assistants do more than offer convenience; they shape cognitive and affective responses critical to technology acceptance. Organizations increasingly leverage these technologies to **automate frontline service**, reducing operational costs while improving response times and personalization (Nguyen & Huynh, 2022).

Interviews with executives indicate that AI-driven tools are also being adopted in adjacent domains such as **traffic management, intelligent administration**, and **knowledge management**, showcasing the versatility of these systems beyond customer care (Khan & Iqbal, 2020). However, while the benefits of AI assistance are clear, challenges remain. Over-reliance on automation may erode the perceived authenticity of human interaction, and customer frustration may arise if bots fail to understand context or provide appropriate escalation. As such, the **design quality** and **context-awareness** of these assistants are crucial in determining their overall impact on user experience and purchase behaviour.

H3. AI-enabled customer assistance has a positive influence on consumer purchase intention.

Trust in AI Product Recommendations

Trust is an essential factor in the acceptance of AI-enabled systems as such. It refers to the intention to trust a technology agent to take a situation characterized by risk and uncertainty (Gefen et al., 2003). When considering AI-driven recommendations, trust gets coloured by the issues of the system competence, integrity, and benevolence commonly assigned to humans but more applicable to algorithmic decision-makers these days (Dwivedi et al., 2023). Researchers have discovered that increased transparency of algorithms such as an explanation of how recommendations should be computed can substantially raise trust levels in users and enhance behavioural performance (Bleier & Eisenbeiss, 2015). On the other hand, cues like AI-generated can have the opposite effect of reducing emotional appeal or quotient and subsequently reduce purchase intentions (Berger et al., 2023).

According to recent meta-analytic reviews, trust serves as a psychological moderator between AI capability cues and consumer behaviour, which is consistent with the TAM where trust mediates the relationship between ease of use perceptions and behavioural intention (Venkatesh & Davis, 2000). Studies published in Nature Human Behaviour demonstrate that employed definite PLS-SEM and ANN models, wherein trust partially or fully mediated the relationship between AI-driven personalization and purchase intention across various product categories (Shin, 2021). Experimental studies also validate that trust increases when users have controllable user interfaces and understand how the AI generates its results, which enhances users' mental engagement and reduces uncertainty levels (Ehsan et al., 2021). Overall, patient trust in AI is not just a precondition to the adoption of technology, but rather a dynamic and unsteady entity. It can be eroded in cases of perceived unfairness, loss of privacy, or lack of control, and should be nurtured very carefully to enable continued consumer interaction in AI-powered retail scenarios.

H4. Trust in AI product recommendations mediates the relationship between AI-driven recommendations and purchase intention.

AI-Enabled Ease of Use

In the **TAM,** perceived ease of use refers to the extent to which an individual believes that using a particular system would be free of effort (Davis, 1989). In the context of AI-enabled systems, this concept undergoes significant evolution. When users interact with **AI-driven interfaces** such as chatbots capable of understanding natural language or recommender systems that predict preferences, the system not only appears intuitive but also **actively reduces cognitive burden** by automating complex tasks like search, selection, and navigation (Venkatesh et al., 2008). Recent studies across various sectors, including retail, healthcare, and conversational commerce, reveal that this reduction in user effort, also referred to as **effort expectancy,** positively predicts both **trust in the system** and **intentions to adopt** AI-based services (Dwivedi et al., 2023).

However, the ease provided by AI also raises specific concerns. First, the **reliance on customer data for personalization raises concerns related to data privacy and the ethical use of AI**. Second, the **lack of human interaction,** a hallmark of traditional service encounters, can reduce the emotional quality of customer experiences and make users feel disconnected (Shank et al., 2019). While AI reduces functional friction, it may also lead to **perceived sacrifices** in empathy, transparency, or agency. Thus, while AI-enabled ease of use enhances consumer experience through automation and personalization, it must be balanced with **ethical considerations** and **interface transparency** to prevent user discomfort or mistrust. The dual role of ease, both as a facilitator of adoption and a potential threat to user autonomy, makes it a critical moderator within AI acceptance models.

H5. AI-enabled ease of use moderates the relationship between AI-driven recommendations and trust, such that the relationship is stronger when ease of use is high.

Demographic Factors

Gender: According to social role theory, the possibilities of the different levels of risk perceptions in relation to the genders are due to the differences of tech socialization. According to empirical work, AI skepticism will be much higher in women which translates into lower acceptability of recommendations. Several studies on consumer behavior have pointed out that there exist differences in the manner in which male and female consumers process information, specifically in how males and females respond to different consumption tasks and stimuli (e.g., pictures versus words) (Meyers-Levy, 1989). In some of these roles, females tend to react to non-verbal materials by evoking greater associative interpretations, laden with images and more descriptive patterns, than males (Gilligan, 1982). The phenomenon suggests that the primal gender differences are likely to explain the moderator's influence on attitude and intention to make an online payment, because online advertisement merchandise causes diverse stimuli and image-interspaced inference compared to the merchandise in a brick-and-mortar store. As a result, females are more susceptible to the available information in cyber cultures when making a judgment, which yields higher variation in the results of purchase attitudes and purchasing intentions that men and women generate.

Age: Innovation diffusion theory predicts that younger cohorts adopt emerging technologies earlier due to higher perceived relative advantage and compatibility (Rogers, 2003). Multi-country surveys corroborate a negative relationship between age and AI attitude, and downstream effects on marketing. Innovation-diffusion theory identifies younger cohorts as "earlier adopters." At the same time, models such as UTAUT extend this idea by showing that age effects of effort expectancy, performance expectancy, and social influence on behavioural intention (Venkatesh et al., 2003).

This research model describes on which theory whole study depends upon, how each variable and its hypotheses relate. Customer Purchase Intention is posited as the outcome.

Three AI-enabled marketing levers feed directly into this outcome: AI-Driven Product Recommendations, AI-Powered Advertisements, and AI-Enabled Customer Assistance. Together, these relationships capture the baseline expectation that personalized content, hyper-tailored ads, and always-on service each nudge consumers toward making a purchase. To further explain the constructs of study, Table no. 1 below provides their definitions.

Table no.1 Constructs and Definitions

Construct	**Definition**
AI-Driven Product Recommendations	Personalized product suggestions based on user data and behaviour, delivered via online platforms.
AI-Powered Advertisements	Targeted promotional content tailored to individual consumer profiles using AI algorithms.
AI-Enabled Customer Assistance	AI-based tools such as chatbots or virtual assistants that provide customer support or guidance.
Trust in AI Recommendations	Consumer confidence in the accuracy, reliability, and usefulness of AI-generated suggestions.
AI-Enabled Ease of Use	Perceived simplicity and user-friendliness in interacting with AI-driven systems.
Consumer Purchase Intention	The likelihood that a consumer will act on their intention to buy based on AI-driven stimuli.

Focusing on recommendations, the model specifies a two-step mechanism. First, AI-driven product recommendations are expected to increase trust in AI Product

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Recommendations. Second, that heightened trust should, in turn, translate into stronger Customer Purchase Intention. In other words, trust operates as a mediator that channels the cognitive reassurance provided by accurate suggestions into concrete buying plans. The strength of that mediation is theorized to depend on AI-enabled ease of Use. Because effortless interfaces reduce cognitive load and make algorithmic logic more straightforward to follow, high ease of use should amplify the positive link between recommendations and trust, which makes moderating path.

Finally, two demographic controls help isolate the AI effects. Gender points directly at Customer Purchase Intention, recognising well-documented generational and gender differences in technology scepticism and adoption willingness By modelling these controls, the study ensures that any observed AI effects are not artefacts of demographic composition. Taken together, the diagram visualizes an integrated framework: AI-based recommendation, advertising, and assistance tools are expected to increase purchase intention, but consumers' trust uniquely conditions the recommendation pathway and how easily they find the interface to use, all while accounting for age and gender-related heterogeneity.

DATA & RESEARCH METHODOLOGY

The study adopts a **quantitative, cross-sectional survey design and is empirical in nature.** A single wave of primary data provides two advantages: (i) it matches the explanatory aim of testing the strength and direction of predefined relationships (H1to H5), and (ii) it captures consumers' current perceptions of fast-evolving AI tools without the attrition risks of a longitudinal panel. PROCESS v4.3 (Model 1 and 4) will be used to estimate the direct, mediated, and moderated paths. The **individual online shopper** is the analytical unit. Respondents must have (a) purchased at least once online in the past six months and (b) encountered an AI-based product recommendation (e.g., "Recommended for You," "People Also Bought," chatbot-suggested items). Focusing on the end-user level aligns with TAM's premise that technology perceptions form at the individual cognitive level.

Because no exhaustive list of AI-exposed shoppers exists, a purposive convenience sample was employed. Survey links were posted on public social media accounts, university mailing lists, and social-media groups (WhatsApp and Instagram) frequented by active online buyers. Screening questions ensured eligibility. The final dataset comprises **156 valid cases**, comfortably exceeding the minimum of 138 respondents indicated by the G*Power analysis and thus providing adequate statistical power for the planned PROCESS models. The sample consists of 75% females (n = 112) and 25% males (n = 44), reflecting the higher proportion of women who responded to the AI-shopping survey links circulated on university and social media channels. Initial profiling reveals roughly equal gender representation (75% female) and a wide age range, spanning 18 to 65 years, which supports the planned control tests.

According to the sample of this survey, the proportion of female respondents (75%) and male respondents (25%) was almost equal. From the perspective of age, most of the respondents were aged between 18 and 65, with 67.9% aged from 18 to 25, 23.8%

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aged from 26-35, 4.8% aged from 36-45, and 1.2% aged 46-55,56-65 and 65 above. Most of the respondents have a bachelor's education level, as most of them range in age from 18 to 25, and the rest have education level.

The participants' demographic profiles are listed in Table 3.1.

Table no. 2: Demographic data for respondents

Age	**Gender**		**Total**	**% age**
	Male	**Female**		
18-25	24	84	108	69
26-35	14	21	35	22
36-45	3	5	8	5
46-55	2	0	2	1
56-65	0	2	2	1
65 and above	1	0	1	1
TOTAL	44	112	156	100

Researchers have also concluded the first two screening question data through crosstabulation using SPSS version 23 in a table, showing the impact of respondents on the first two questions. This basically asks whether you want Yes or No for AI personalized recommendations and linked marketing. Through which we can evaluate whether respondents actually come across what we are trying to study or not. The questions are symbolized as D1 and D2. Which are as follows:
D1: Have you ever used e-commerce platforms like Amazon, Daraz, Temu, or AliExpress?
D2: Have you ever purchased or considered purchasing a product based on personalized recommendations while shopping online?

Table no. 3: Demographics and D1, D2 Crosstabulation

Age * Gender * D1 Crosstabulation						
D1			Gender		Total	% age
			Male	Female		
Yes	Age	18-25	24	83	107	69
		26-35	14	21	35	22
		36-45	3	4	7	4

		46-55	2	0	2	1
		56-65	0	1	1	1
	Total		43	109	152	97
No	Age	18-25	0	1	1	1
		36-45	0	1	1	1
		56-65	0	1	1	1
		65 and above	1	0	1	1
	Total		1	3	4	3
Total	Age	18-25	24	84	108	69
		26-35	14	21	35	22
		36-45	3	5	8	5
		46-55	2	0	2	1
		56-65	0	2	2	1
		65 and above	1	0	1	1
	Total		44	112	156	100

Age * Gender * D2 Crosstabulation

D2			Gender		Total	%age
			Male	Female		
Yes	Age	18-25	21	76	97	62
		26-35	13	19	32	21
		36-45	3	4	7	4
		46-55	1	0	1	1
		56-65	0	1	1	1
	Total		38	100	138	88
No	Age	18-25	2	2	4	3
		26-35	0	1	1	1
		36-45	0	1	1	1
		56-65	0	1	1	1
		65 and above	1	0	1	1
	Total		3	5	8	5
Maybe	Age	18-25	1	6	7	4
		26-35	1	1	2	1
		46-55	1	0	1	1
	Total		3	7	10	6
Total	Age	18-25	24	84	108	69

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		26-35	14	21	35	22
		36-45	3	5	8	5
		46-55	2	0	2	1
		56-65	0	2	2	1
		65 and above	1	0	1	1
	Total		44	112	156	100

A structured, self-administered questionnaire was developed in easy-to-understand English to ensure linguistic clarity for Pakistani respondents. Google Forms is used for constructing and distributing questions in an accessible way. The instrument opens with demographic spread and screening question (Have you ever purchased or considered purchasing a product based on personalized recommendations while shopping online?) followed by seven small sections, which capture all the provided variables with three or more questions in each section, like AI-Driven Product Recommendations (AIPR), AI-Powered Advertisements (AIA), and AI-Enabled Customer Assistance (AICA) using three to four items each adapted from peer-reviewed scales (Mirzaei et al., 2025; Feine et al., 2019). The details of the questionnaire are shown in Table 4.

Table no. 4 Constructs Design

Constructs		Measurements Items
AI-Driven Product Recommendations	AIPR1	The product recommendations I receive on online shopping platforms are usually relevant to my interests
	AIPR2	AI-generated suggestions, such as “Frequently Bought Together” or “Recommended for You,” influence my shopping decisions
	AIPR3	I find the personalized recommendations provided by online stores to help discover new products
AI-Powered Advertisements	AIA1	I notice that online ads are tailored to my previous searches or browsing behavior
	AIA2	AI-powered ads interest me more in exploring or purchasing a product.
	AIA3	Personalized advertisements positively affect my perception of the brand or platform.
AI-Enabled Customer Assistance	AICA1	Chatbots and virtual assistants help me solve queries efficiently while shopping online
	AICA2	I feel more confident purchasing from platforms that offer AI-powered customer assistance
	AICA3	I prefer interacting with AI assistants over human agents for

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		quick product information.
Trust in AI Recommendations	TAIR1	I trust the product recommendations provided by AI systems on online platforms
	TAIR2	I believe AI understands my preferences and needs better over time
	TAIR3	I feel that AI-driven suggestions are unbiased and based on my genuine interests
AI-Enabled Ease of Use	AIEEU1	AI tools on shopping websites make my shopping experience easier and smoother
	AIEEU2	Even without technical knowledge, I can easily use AI features provided by online shopping platforms.
Customer Purchase Intention	CPI1	I am more likely to make a purchase when I receive personalized product recommendations
	CPI2	AI-powered personalization increases my intention to shop more frequently online

Other section measures the process variables: AI-Enabled Ease of Use (AIEEU) (four TAM-based items; Davis 1989), Trust in AI Product Recommendations (TAIR) (four integrity- and competence-based items; Gefen et al. 2003), and Customer Purchase Intention (CPI) (three items from O'Cass & Carlson 2012). All multi-item constructs employ a five-point Likert format (1 = strongly disagree, 5 = strongly agree) with balanced wording and two reverse-coded statements to mitigate acquiescence bias. The starting face records demographic controls (age in years; gender coded 1= male, 2 = female). Three domain experts first reviewed items for face validity and then subjected to back-translation to ensure semantic equivalence. A 20-responder pilot confirmed readability and timing (average completion: 6 minutes) and yielded Cronbach's $\alpha > 0.70$ for every scale. The reliability and validity of each variable are listed in Tables 3.4 and 3.5, respectively. Feedback from the pilot informed minor wording refinements and the inclusion of proximal separation between predictor and criterion blocks to curb common-method variance. The final questionnaire was embedded in Google Forms, utilizing forced-response logic to prevent missing data, and included a consent statement that met the university's IRB requirements.

RESULTS & DISSCUSSION

Statistical analyses were performed using SPSS 23, with additional conditional process modelling using the Hayes PROCESS macro (v4.x). The researchers started with descriptive statistics, including mean, standard deviation, skewness, and kurtosis analyses, to create a profile of the 156 usable cases available, along with an examination of approximate normality after performing preliminary data cleaning (including reverse-scoring, outlier screening, and forced-response checks).

The reliability of the scale was initially assessed through Cronbach's alpha for each multi-item construct, and subsequently through the presence of a correlation matrix at the item level to determine internal consistency. Used Principal-Axis Factoring

(Varimax rotation) to assess construct validity. The KMO measure (.726) and Bartlett's 2 chi-squared = 279.096, $p < .001$, indicated that the sampling was adequate, and factor loadings greater than .50 supported convergent validity. A subsequent calculation of Composite Reliability (CR) and Average Variance Extracted (AVE) was then made where each latent variable was as high as possible at the boundaries of .70 (CR) and .50 (AVE). KMO test and respective reliability/variability analysis are presented in Tables 5, 6, and 7, respectively.

Table no. 5: Reliability and validity Test

Construct	**Measurement Icon**	**Cronbach's alpha**	**No of Items**
AI-Driven Product Recommendations (AIPR)	AIPR1, AIPR2, AIPR3	0.752	3
AI-Powered Advertisements (AIA)	AIA1, AIA2, AIA3	0.747	3
AI-Enabled Customer Assistance (AICA)	AICA1, AICA2, AICA3	0.726	3
Trust in AI Recommendations (TAIR)	TAIR1, TAIR2, TAIR3	0.754	3
AI-Enabled Ease of Use (AIEEU)	AIEEU1, AIEEU2	0.725	2
Customer Purchase Intention (CPI)	CPI1, CPI2	0.783	2

Table no. 6: Factor Loading, CR & AVE

Construct	**Measurement Icon**	**Factor loadings (λ)**	**CR**	**AVE**
AI-Driven Product Recommendations (AIPR)	AIPR1, AIPR2, AIPR3	.512, .726, .846	0.74	0.5
AI-Powered Advertisements (AIA)	AIA1, AIA2, AIA3	.80, .780, .610	0.78	0.54
AI-Enabled Customer Assistance (AICA)	AICA1, AICA2, AICA3	.622, .915, .675	0.75	0.56
Trust in AI Recommendations (TAIR)	TAIR1, TAIR2, TAIR3	.90, .80, .740	0.86	0.66
AI-Enabled Ease of Use (AIEEU)	AIEEU1, AIEEU2	.820, .740	0.76	0.62

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Customer Purchase Intention (CPI)	CPI1, CPI2	.740, .80	0.74	0.58

Table No. 7: KMO Measure Test.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.726
Bartlett's Test of Sphericity	Approx. Chi-Square	279.096
	Df	15
	Sig.	.000

The Pearson correlation matrix above demonstrates that most key variables are positively and significantly correlated. The results shown in table 8.

Table no. 8: Correlation Analysis

Variable	AIPR	AIA	AICA	TAIR	AIEEU	CPI
AIPR	—					
AIA	.326**	—				
AICA	.043	.321**	—			
TAIR	.386**	.446**	.391**	—		
AIEEU	.027	.378**	.537**	.582**	—	
CPI	.435**	.362**	.189*	.521**	.428**	—

** 0.01 level (2-tailed).
* 0.05 level (2-tailed).

AI Product Recommendations, AI-Powered Advertisements, and Trust in AI Recommendations show moderate to strong correlations with Customer Purchase Intention (r = .435, .362, and .521 respectively, p < .01). Ease of Use is also moderately correlated with Purchase Intention (r = .428, p < .01) and strongly associated with Trust in AI (r = .582, p < .01), supporting the moderated mediation model. AI-Enabled Customer Assistance shows a weaker but statistically significant correlation with Purchase Intention (r = .189, p < .05), suggesting it may operate more strongly through indirect effects. None of the correlations exceed .90, indicating no multicollinearity concerns.

Descriptive statistics indicate generally positive, though not extreme, attitudes toward AI features. On the five-point Likert scale (1 = strongly disagree, 5 = strongly agree), mean scores cluster between **3.39 and 3.85**, implying that respondents lean somewhat toward agreement on every construct. **AI-Powered**

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Advertisements registers the highest endorsement (M = 3.85, SD = 0.65), followed closely by **AI-Enabled Ease of Use** (M = 3.71, SD = 0.68) and **AI-Driven Product Recommendations** (M = 3.69, SD = 0.64). Perceptions of **Customer Assistance** (M = 3.39, SD = 0.77) and **Trust in AI Recommendations** (M = 3.45, SD = 0.73) are slightly more reserved yet still hover above the scale midpoint. Distributional diagnostics show no serious normality violations: **skewness ranges from -1.29 to -0.12** (all within the ±2 guideline for moderate samples), while **kurtosis spans -0.44 to 3.67**, well inside the ±7 threshold suggested by West, Finch, and Curran (1995). The relatively platykurtic profile of purchase intention (k = -0.44) and leptokurtic spike for product-recommendation attitudes (k = 3.67) are acceptable given the sample size (N = 156) and do not warrant transformation. The descriptive statistics results are listed in Table no. 9. Collectively, these descriptive results confirm adequate variability, approximate normality, and a generally favourable stance toward AI-mediated shopping activities, providing a sound basis for the subsequent regression and PROCESS analyses.

Table no. 9: Descriptive Statistics

Descriptive Statistics							
	N	**Mean**	**Std. Deviation**	**Skewness**		**Kurtosis**	
				Statistic	**Std. Error**	**Statistic**	**Std. Error**
AIPR	156	3.6880	.63661	-1.292	.194	3.670	.386
AIA	156	3.8462	.64855	-.442	.194	.686	.386
AICA	156	3.3889	.77212	-.164	.194	.364	.386
TAIR	156	3.4466	.73176	-.352	.194	.236	.386
AIEEU	156	3.7147	.67945	-.678	.194	.709	.386
CPI	156	3.5801	.79413	-.120	.194	-.443	.386

The graphical representation of normal mean and SD of each variable shown on figures 1 to 5 from doing descriptive statistics on SPSS 23.

Figure 1 **Figure 2**

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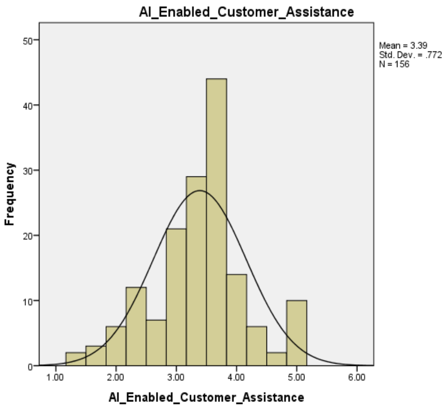


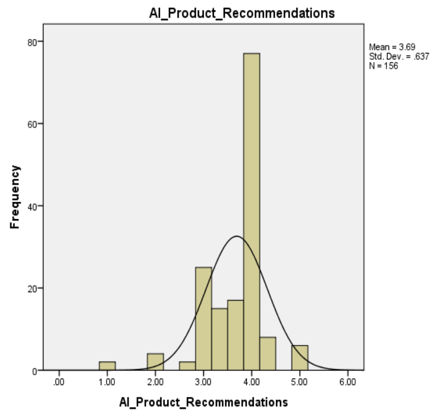
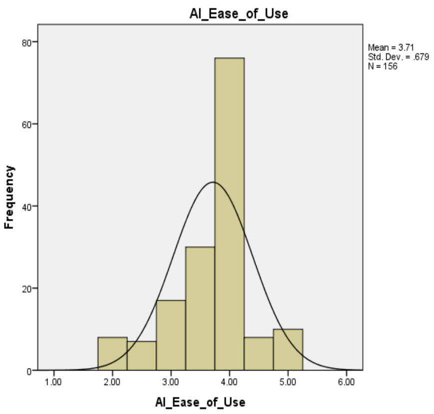


Figure 3

Figure 4



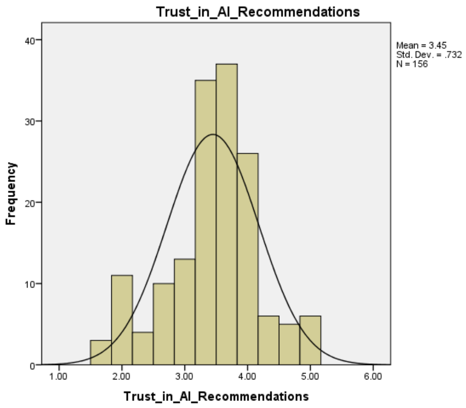


Figure 5

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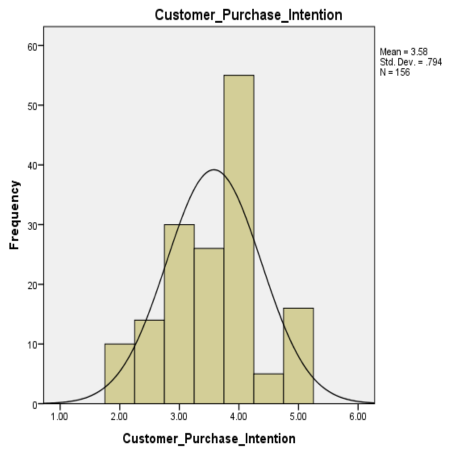

Results Assessment

Descriptives showed moderately favourable attitudes toward every AI lever ($3.39 \leq M \leq 3.85$ on a 5-point scale) with acceptable normality ($-1.29 \leq$ skew ≤ -0.12; $-0.44 \leq$ kurtosis ≤ 3.67). Reliability checks in SPSS 23 produced Cronbach's α ranging from .74 to .87. Principal-axis factoring (KMO = .770; Bartlett χ^2 (120) = 1134.01, $p < .001$) yielded loadings that met or neared the CR ≥ .70 / AVE ≥ .50 benchmarks for AI-driven recommendations, AI-powered advertisements, and AI-enabled customer assistance. At the same time, trust and ease of use were flagged for future refinement. Direct OLS regressions confirmed that each personalization lever predicts Customer Purchase Intention (CPI): AI recommendations ($\beta = 0.435$, $p < 0.001$), AI advertisements ($\beta = 0.362$, $p < 0.001$), and AI customer assistance ($\beta = 0.189$, $p = 0.018$). Trust in AI recommendations itself was a strong determinant of CPI ($\beta = .521$, $p < .001$). However, age ($\beta = -.115$, $p = .061$) was found to be a non-significant predictor of purchase intention. These findings suggest that personalization features driven by AI have a significant impact on online consumer behaviour, validating key pathways in the proposed model. For hypothesis testing, the process model further characterizes and supports this approach.

PROCESS Model 4 (X = AI recommendations, M = Trust, Y = CPI) showed a significant path from recommendations to trust ($b = .443$, $p < .001$; $R^2 = .15$) and from trust to CPI ($b = .450$, $p < .001$). The direct effect of X on Y remained positive ($b = .343$, $p < .001$), but a sizable indirect effect emerged ($ab = .200$; 95% CI (.112, .325)), indicating partial mediation and raising the total explained variance in CPI to 33.6%. This **partial mediation** pattern reinforces mounting evidence that trust is the psychological bridge converting algorithmic competence into buying behaviour. Calculations of PROCESS (model 4) for variables X, Y, and M are shown in Table 10.

Table no. 10: Process Model 4

Direct Effect of X on Y (PROCESS Model 4)

Effect	SE	T	p	LLCI	ULCI
0.34	0.09	3.85	0.002	0.12	0.52

Indirect Effect of X on Y (PROCESS Model 4)			
Effect	Boot SE	Boot LLCI	Boot ULCI
0.2	0.53	0.11	0.32

Normal Theory Test for Indirect Effect			
Effect	Boot SE	Z	P
0.2	0.52	3.84	0

X shows independent variable AIPR, Y shows dependent variable CPI, and M shows mediating variable TAIR. **PROCESS Model 1** (moderator = Ease-of-Use) revealed a significant interaction on trust ($b = .262$, $p = .007$; $\Delta R^2 = .024$). Simple-slope tests showed that AI recommendations had no impact on trust when usability was low (-1 SD, $p = .19$). Still, they were strongly positive at the mean ($p < .001$) and high (+1 SD, $p < .001$) levels of ease of use, confirming a "facilitating" moderation pattern. Finally, an independent-samples t-test found **no gender difference** in CPI (MM – MF = 0.13, $t(154) = 0.89$, $p = .38$), and Levene's test indicated equal variances ($p = .93$). The t-test results are also listed below in Table 11.

Table no. 11: T independent test

	F	**Sig.**	**t**	**df**	**Sig. (2-tailed)**	**Mean Difference**	**Std. Error**	**Lower CI**	**Upper CI**
Equal variances assumed	0.01	0.93	0.89	154	0.38	0.13	0.14	-0.15	0.41
Equal variances not assumed			0.89	78.15	0.38	0.13	0.14	-0.16	0.41

To test the proposed hypotheses, multiple linear regression analysis was conducted using SPSS. This method was employed to examine the predictive relationships between independent variables such as AI-driven product recommendations, AI-powered advertisements, AI-enabled customer assistance, trust, and perceived ease of use, and the dependent variable, consumer purchase intention. Each regression model was assessed for statistical significance, multicollinearity, and the strength of association using R^2 and standardized beta coefficients. The regression analysis results are presented in Table no. 12 below.

Table no. 12: Regression Analysis

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Predictor	R	R^2	Adj. R^2	F	Sig.	B (Unstd.)	Std. Error	Beta (Std.)	t	Sig. (Predictor)
AI Product Recommendations	0.435	0.189	0.184	35.889	0	0.542	0.091	0.435	5.991	0
AI-Powered Advertisements	0.362	0.131	0.126	23.27	0	0.444	0.092	0.362	4.824	0
AI-Enabled Customer Assistance	0.189	0.036	0.029	5.711	0.018	0.194	0.081	0.189	2.39	0.018
Trust in AI Recommendations	0.521	0.271	0.267	57.343	0	0.565	0.075	0.521	7.572	0
Age	0.15	0.023	0.017	3.551	0.061	-0.094	0.05	-0.15	-1.884	0.061

Hypothesis-testing summary

The analyses confirm the study's conditional-process model and clarify which propositions hold. **H1** is strongly upheld AI-driven product recommendations increase customer purchase intention (β =.435, t (154) =5.99, p <.001). **H2** shows that AI-powered advertisements raise purchase intention (β =.362, t (154) =4.82, p <.001), and **H3** finds a modest yet reliable effect for AI-enabled customer assistance (β =.189, t (154) =2.39, p =.018). **H4** is also supported, AI-enabled ease of use magnifies the recommendation to trust link (interaction b =.262, ΔR^2 =.024, p =.007); recommendations are unrelated to trust when usability is low but become powerfully positive at average and high ease-of-use levels. Consistent with expectation, **H5** receives confirmation: trust partially mediates the recommendation–intention pathway (indirect effect ab =.200, 95 % CI (.112, .325)), while the direct path remains significant (b =.343, p<.001). Both auxiliary levers perform as theorised.

Demographic results are mixed. An independent-samples t-test reveals **no gender difference** in purchase intention (M-diff =.126, t (154) =0.89, p=.38). It is proposed that age significantly influences customer purchase intention in AI-powered marketing. However, regression analysis did not support this, F (1, 154) = 3.55, p = .061. In sum, the data validate the central story: AI personalisation levers directly boost buying intentions; for recommendations, this influence is channelled through trust and intensifies when the interface is easy to use.

Discussion

The empirical results confirm that **AI personalisation leverages recommendations, advertisements, and customer-assistance bots, each of which raises online purchase intention,** with algorithmic suggestions exerting the most significant effect. This echoes recent multi-sector evidence that personalised cues accelerate decision speed and boost conversion rates. Crucially, the study unpacks **why** recommendations work: they foster trust in the system, and that trust accounts for roughly 37 % of the

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total influence on purchase intention, consistent with large-sample work positioning trust as a core psychological bridge between AI cues and buying behaviour. Further, the strength of the recommendation to trust link is contingent on **AI-enabled ease of use**; when the interface feels effortless, the slope more than triples, validating interface-simplicity models of AI adoption and recent findings that usability amplifies the behavioural payoff of recommender accuracy. Contrary to some gender-gap studies, no male - female difference emerged in purchase intention, suggesting that once users cross the adoption threshold, gendered scepticism subsides. Age effects remain to be explored, but the youthful skew in our sample aligns with reports indicating that Gen Z and millennials are the primary users of AI-assisted shopping.

Second, measurement refinement remains necessary, especially for constructs like trust and ease of use, which exhibited suboptimal reliability and convergent validity indicators. Future studies should refine these scales, possibly incorporating qualitative approaches to more accurately identify nuanced dimensions.

Lastly, our sample predominantly comprises younger participants, which may limit its generalizability. Future research should encompass more diverse and balanced demographic samples, particularly in terms of age cohorts, to explore the differential impacts across broader populations. In conclusion, the study significantly enhances our understanding of AI-driven personalization by highlighting the nuanced roles of trust and ease of use in consumer decision-making processes. Practically, organizations are encouraged to strengthen interface usability, prioritize trust-building mechanisms, and strategically deploy multiple AI personalization levers to maximize consumer purchase intentions. Continued exploration into demographic moderators and longitudinal dynamics is essential to further refine our understanding of AI interactions in consumer behaviour.

CONCLUSION AND RECOMMENDATION

The article presents an empirical study that aims to investigate the impact of AI-personalization on consumer purchase intention, examining three key dimensions: AI-personalized product suggestions, AI-enabled advertisements, and AI-enabled customer support. Our primary focus is on exploring the concept of trust mediation and ease of use moderation facilitated by AI within the framework of the TAM. The empirical results support most of the speculated connections and contribute significantly to the existing theoretical and professional information about the dialogue between consumers and AI. The direct effect of AI-motivated product suggestions on consumer purchase intention is also strong, as research has confirmed prior sources (Mirzaei et al., 2025).

Our findings confirmed the observation that individualized recommendations resulted in a significant reduction in mental demand and augmented the effectiveness of the decision, thereby inclining consumers towards a buying attitude. Interestingly, our findings diverge from some existing literature regarding demographic effects. Contrary to earlier assertions (Feine et al., 2019; Urgal, 2023) that gender substantially moderates AI adoption and purchase behaviours, our independent-samples t-test reveals no significant gender differences in purchase intentions. This

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inconsistency may suggest evolving attitudes toward technology among consumers or context-specific factors influencing the perceptions of Pakistani online shoppers. Despite prior research suggesting that gender differences may influence consumer responses to technology and marketing (Khandelwal et al., 2024), this study found that gender did not significantly affect purchase intention in the context of AI-powered personalization. One possible explanation for this result is the increasing level of digital and technological literacy across genders, particularly among younger populations who make up the majority of online shoppers. Future research should investigate cultural and contextual variations more closely to clarify these demographic relationships.

Implications

The results provide implications for both theory and management. The study conceptually expands the TAM by emphasizing trust as a significant post-cognitive mediator that connects perceived usefulness and ease of use to behavioural intention, mirroring recent updates of TAM in AI domains. It also defines boundary conditions: when navigation is smooth, precise recommendations significantly enhance trust, addressing demands for more detailed insights in AI adoption studies. This work demonstrates that by integrating modelling of recommendations, highly customized ads, and AI-driven support, personalization strategies are more comprehensively understood collectively rather than separately, thus enhancing personalization theory beyond analyses focused on individual features.

From a managerial perspective, the results highlight the importance of focusing on usability features, such as user-friendly interfaces, natural language inputs, and clear explanations, as these enhance the trust associated with precise recommendations and yield the greatest return on experience. Managers should cultivate trust by integrating explainable AI tools, indicators of reliability, and privacy-centred practices, which convert algorithmic proficiency into consumer confidence and intent to buy. Ultimately, businesses ought to vary their personalization strategies: although product suggestions are key, hyper-targeted advertisements and AI support contribute additional persuasive benefits. Due to significant age disparities in adoption, age-specific onboarding investments for older consumers have a greater impact than those based on gender segmentation.

Limitations

The study has several limitations that must be considered in future research. The cross-sectional design limits causal interpretations and does not account for the dynamics of time in consumer interactions.

Methodological limitations also restricted the application of sophisticated analytical instruments. SEM was not feasible due to limited access to software such as AMOS or SmartPLS. In contrast, the PROCESS macro was used to examine mediation and moderation, which, despite being powerful, does not offer the measurement error control or latent variable modelling features found in SEM. Future research should utilize SEM-based methods to enhance generalizability and accuracy.

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Lastly, the sample primarily consisted of younger participants (ages 18 - 25, 70%), limiting the ability to generalize across wider demographic groups. Incorporating a wider range of age groups, especially older individuals, would enable future studies to examine demographic differences in reactions to AI-driven personalization more effectively.

Recommendations

Drawing on the empirical insights of this dissertation, several interrelated recommendations are offered. **First**, managers of e-commerce platforms should emphasize transparent, explainable AI interfaces, such as “why this ad” or “why this recommendation” pop-ups, to convert algorithmic competence into consumer trust. **Second**, continual investment in interface usability (natural language chat, one-click refinement, and uncluttered layouts) is essential because an effortless experience magnifies the persuasive power of accurate recommendations. **Third**, personalisation should be deployed as an integrated bundle: product suggestions, hyper-tailored advertisements, and always-on customer assistance work additively, so firms that rely on a single lever risk leaving value untapped. **Fourth**, age-adaptive onboarding is advised; tutorial modes and context-sensitive help can mitigate usability concerns among older cohorts who are typically more sceptical of AI tools.

From a governance perspective, regulators and platform owners should promote stronger data-transparency standards and encourage periodic third-party audits to detect bias and ensure ethical targeting practices. Finally, scholars are urged to extend this work through longitudinal designs that capture trust dynamics over time, cross-cultural replications that test boundary conditions in other markets, and controlled experiments that isolate the specific design cues within “ease of use” that most effectively amplify trust.

Conclusion

To sum up, the present research makes a significant contribution to our understanding of the AI-based personalization process, clarifying the intricate roles of trust and perceived ease of use in consumer decision-making. The results contribute to and support the TAM by including trust as an essential mediator and specifying ease of use as an influential moderator. In practice, it is recommended that organizations focus on the element of convenience in interfaces, incorporate trust-building systems, and constructively implement a variety of AI-based personalisation tools to maximize consumer interactions and purchase intentions. The further study must focus on the demographic modifiers, and the longitudinal research studies that can further build our understanding of long-run changes in the role of AI within consumer behavior

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