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[THE IMPACT OF AI-DRIVEN PERSONALIZATION ON ONLINE PURCHASE INTENTIONS: THE MEDIATING ROLES OF CONSUMER TRUST AND PERCEIVED RELEVANCE]

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ABSTRACT

This study investigates the impact of AI-driven personalization on online purchase intentions, focusing on the mediating roles of consumer trust and perceived relevance. Grounded in the Stimulus-Organism-Response (SOR) theory, the research conceptualizes AI personalization as a technological stimulus that influences consumers' internal evaluations, ultimately shaping their behavioral intentions. Data were collected through a structured questionnaire from 429 university students in three public sector universities in the Hazara Division, Pakistan. Using Hayes' PROCESS Macro (Model 4) for parallel mediation analysis, the results revealed that AI-driven personalization significantly enhances purchase intentions both directly and indirectly through consumer trust and perceived relevance. Confirmatory factor analysis confirmed the distinctiveness of the study constructs, and the four-factor model demonstrated the best model fit. The findings offer important theoretical contributions by extending the application of SOR theory in AI and e-commerce contexts, and practical implications for digital marketers and platform designers aiming to enhance consumer engagement. The study concludes that trust and relevance are critical mechanisms through which AI personalization drives online consumer behavior.

Keywords: AI-Driven Personalization, Online purchase intentions, Consumer trust, Consumer perceived relevance, Stimuli-organism-Response theory

Introduction

The increase in digital technologies and online shopping growth have revolutionized the way consumers seek, assess, and purchase products. In all this, artificial intelligence (AI) has emerged as a primary means of providing intelligent, real-time personalization; it facilitates businesses to personalize products, services, and communication strategy on the basis of big data of consumers (Jarek & Mazurek, 2019). AI personalization utilizes machine learning algorithms and predictive analytics to develop customized user experiences such as product suggestions, dynamic pricing, personalized content, and chatbot conversations (Zarouali, 2025). As competition in the digital market increases, organizations increasingly utilize AI personalization to capture attention and influence online purchasing decisions that are decisive in consumer loyalty in online environments(Afridi et al., 2018; Khan et al., 2022). But the efficacy of AI personalization doesn't solely come from the sophistication or accuracy of the technology. It strongly depends on how consumers view it, particularly in terms of trust in the technology and the applicability of the personalized choices (Ibrahim, 2022). Personalized content can ease decision-making, but effectiveness in steering buying intentions highly depends on consumer trust. This trust is to do with users having confidence that the AI system will handle their personal data in a responsible manner, provide quality recommendations, and act on their behalf (Jauhari et al., 2024; Wang et al., 2024). Trust becomes yet more crucial in AI-driven systems where the system is usually working autonomously and not transparent. Also, perceived relevance, or the extent to which the personalized content aligns with the user's values and needs, is essential for behavior guidance and satisfaction (Duong et al., 2024; Ibrahim & Khan, 2025). If personalization is irrelevant or untimely, it creates frustration, decreases engagement, or makes privacy a problem (Ibrahim et al., 2025; Khatib et al., 2023).

Even with growing investment in AI marketing platforms, existing studies continue to be scant and ambiguous regarding the influence of AI personalization on consumer behavior and the reasons behind the significant influence of factors such as trust and relevance in this context (Ahmed et al., 2024; Sajid et al., 2025). Most existing studies consider personalization in isolation, excluding the interaction between technology and consumer cognitive processes. In addition, issues such as algorithm explainability and data privacy concerns necessitate an improved comprehension of the psychological elements that make AI more or less effective in marketing (Bhardwaj et al., 2024; Nkembuh, 2024). To address these gaps, this research proposes and examines a model that considers the influences of consumer trust and perceived relevance on the relationship between AI personalization and online purchase intention. By integrating insights from consumer psychology, human–AI interaction, and digital marketing, the research not only contributes to our theoretical understanding of technology's impact on behavior but also offers practical implications for companies looking to expand AI utilization in customer interactions. The research is framed through the Stimulus–Organism–Response (S-O-R) theory (Mehrabian & Russell, 1974), a prominent model in consumer behavior scholarship. The S-O-R model predicts that the environment (such as AI-based personalization) influences inner feelings and thoughts (the organism—relevance and trust), which in turn influence behavior by developing the intention to purchase. This model allows us to grasp the psychological mechanisms that are involved in the transfer of digital stimulation to consumer conduct, particularly in complex, data-oriented, and technology-rich settings such as online shopping. Applying the S-O-R model, this research sees AI personalization not just as a technology function but as an experience that profoundly impacts psychology and behavior.

Literature Review and Hypotheses Development

AI-Driven Personalization and Online Purchase Intentions

In the modern networked digital economy, the contribution of artificial intelligence (AI) to altering consumer experiences is evident and more critical. Perhaps its most significant application is AI-powered personalization (Das et al., 2023; Lim & Zhang, 2022). It leverages real-time information and machine learning to deliver personalized product recommendations, dynamic content, and marketing messages tailored to customer interests (Nkembuh, 2024; Sodiya et al., 2024). This transformation has altered the way consumers interact, away from static, blanket approaches to responsive and forecast personalization mechanisms. Consequently, online buying intentions—consumers' intention to purchase online—have become crucial in determining the impact of AI on consumer behavior (Nkembuh, 2024; RC & Dulloo, 2024; Venkateswaran, 2023). Traditional forms of personalization have been associated with increased consumer satisfaction and loyalty for decades. Nonetheless, AI has greatly increased the speed, accuracy, and utility of personalization (Afridi et al., 2023; Bleier et al., 2019). Even though mounting evidence suggests that AI personalization has a positive effect on consumer intent (RC & Dulloo, 2024; Sodiya et al., 2024; Teepapal, 2025), scholars are still investigating the intricate psychological variables—such as trust and perceived relevance—that influence this relationship. This has prompted a more critical examination of not only whether AI-powered personalization works, but why and how it influences online purchasing behavior.

AI personalization has revolutionized the online buying experience by enabling businesses to produce one-to-one marketing moments in real time (Lim & Zhang, 2022; Teepapal, 2025). In contrast with mass marketing in large segments, AI makes possible very detailed customization. AI adjusts dynamically to specific consumer actions and circumstance (Arora et al., 2024). Technologies such as collaborative filtering, deep learning, and natural language processing consider previous behavior, preferences, time of day, and even affect to make effective product suggestions and content (Das et al., 2023; Vallabhaneni et al., 2024). Personalized experience is highly associated with increased consumer satisfaction, loyalty, and particularly purchase intentions. Personalized suggestions minimize cognitive effort and allow consumers to make faster, more confident decisions (Broklyn et al., 2024; Mishra, 2025). For instance, research by Arora et al. (2024) found that personalization boosts the feeling of convenience and enjoyment, both important factors in consumer purchasing behavior. In online shopping, personalization is linked with higher consumer interaction and brand interaction, which contributes to heightening the likelihood of purchasing (Arora & Mishra, 2023; Arora & Sahney, 2018). Additionally, AI-based personalization is related to emotional impact and decision quality. Bleier et al. (2019) identified that when customers are made to feel a company gets them, they feel the happiness that contributes to higher buying intentions. A meta-analysis conducted by Teepapal (2025) indicated that personalization, particularly when algorithmically optimized, markedly increases the purchase intention across diverse product categories and digital media.

However, AI personalization should be implemented responsibly and thoughtfully. Ineffective or obtrusive personalization can result in backfire, damage to trust and reducing the purchase intention (Afridi, Khan, et al., 2021; Afridi, Shahjehan, et al., 2021; Bhardwaj et al., 2024; Sodiya et al., 2024). Therefore, the effectiveness of AI personalization in influencing buying intentions is dependent not just on the technology but on consumers' perception that personalization. In the S-O-R framework, AI personalization is the stimulus (S) an environmental stimulus that affects the consumer. The consequent behavior, buying intention (R), is determined by how the consumer interprets this stimulus. Even without mediation, the stimulus will induce a response when personalization is perceived as relevant, convenient, and enjoyable. The concept lends credence to the S-O-R theory that proposes that some stimuli could straightaway elicit behavioral intentions when cognitive conditions are salient (Mehrabian & Russell, 1974).

H1: AI-driven personalization positively influences online purchase intentions.

Mediating Roles of Consumer Trust

In the modern data-driven economy, artificial intelligence (AI) has revolutionized the way companies engage with customers, particularly through customized marketing techniques. Through the analysis of large data sets, such as browsing habits, click history, and context in real-time, AI systems are able to make personalized product recommendations and offer promotional messages (Arora et al., 2024; Bitra, 2025; Mishra, 2025). While most sing the praises of AI personalization for enhancing user experience and reducing choice overload, it also poses new problems for how consumers make decisions. Contrary to physical shopping, where consumers rely on social signals, AI personalization operates by opaque algorithms that tend to leave consumers in the dark regarding how or why recommendations are being provided (RC & Dulloo, 2024; Vallabhaneni et al., 2024; Venkateswaran, 2023). This confusion can cause unease, particularly around how personal information is collected, interpreted, and utilized. With growing awareness of issues of privacy and algorithmic bias, consumers' sense of safety, control, and trust come to have a greater impact on how they respond to personalization initiatives (Nkembuh, 2024; Venkateswaran, 2023). With this evolving landscape, what in the past was deemed secondary for personalization, it is now a fundamental concern for scholars and business executives. Trust is not an nice extra; it is fast turning out to be indispensable for personalization to be able to shape consumer behavior online effectively (Afridi et al., 2017; Bergquist et al., 2024; Cao & Le, 2024). In AI-supported digital spaces, where algorithms interact with consumers in ambiguous and autonomous manners, trust stands as the unavoidable imperative to ensure successful personalization. Trust in AI encompasses beliefs regarding the system's capability, honesty, dependability, and benevolence (Chen, 2010; Colquitt et al., 2007). When users are not clear about how their data is utilized or where decisions are arrived at, trust may reduce perceptions of risk and uncertainty (Duong et al., 2024; Han et al., 2021). AI personalization is largely based on data gathering and profiling, which frequently results in privacy issues. González-Cánovas et al. (2024) discovered that perceived loss of control over personal information can greatly decrease trust. The decrease in trust can weaken the impact of personalization on consumer behavior. In contrast, systems that facilitate transparency, clarity, and fairness in personalization establish greater trust and have a greater likelihood of influencing consumers (Bhardwaj et al., 2024; RC & Dulloo, 2024). Trust is also crucial for emotional satisfaction. It reduces the demand for cautious information processing (Afridi et al., 2020; Ginting et al., 2023). When people trust in a system, they tend to take its output more at face value without questioning them. This results in faster and surer decisions (Ginting et al., 2023; Han et al., 2021).

Trust enhances user adoption of personalization attributes, stimulates participation, and influences behaviors like willingness to provide information, accept suggestions, and purchase products (Cardoso et al., 2022; Shie et al., 2022). Isac et al. (2024) examined this mediation and confirmed that trust completely mediates the influence of AI personalization on purchase intent in high involvement purchase scenarios. Their findings indicate that in the absence of trust, even the most sophisticated AI systems can fail to convert consumer interest into concrete intent. Under this model, AI-facilitated personalization (S) initiates an internal appraisal process of consumer trust (O), which determines the response (R) of purchase intention. The S-O-R model indicates that internal psychological states are significant mediators between stimulus and response. Trust reduces uncertainty and enables consumers to perceive AI personalization in a positive way, thus bringing about the desired behavior. Without trust being the organismic response, the stimulus will not bring about the desired behavior.

H2: Consumer trust plays a key role in the relationship between AI-driven personalization

and online purchase intentions.

Mediating Role of Perceived Relevance

As artificial intelligence continues to gain popularity in digital marketing, the capacity to provide timely, personalized, and contextually relevant content has emerged as a primary driver for online platforms (Bleier et al., 2019). Personalization systems based on artificial intelligence seek to break through the noise of digital data by providing consumers with personalized recommendations that resonate with their tastes, behaviors, and situations at hand (Fared et al., 2021; Ginting et al., 2023). Yet with so much personalized content to choose from on the internet, consumers increasingly pick and choose what of real interest to them and what can serve their purposes. Being personalized is no longer sufficient. Consumers of today evaluate content according to its relevance, querying: Is this helpful for me at this moment? Does this suit what I desire or require? (Bhardwaj et al., 2023; Chen et al., 2022). This increasing consumer selectivity implies that how applicable personalized experiences appear is now an important variable in whether consumers interact with, overlook, or reject AI-based recommendations (Duong et al., 2024; Ferreira et al., 2023). While personalization increases, subjective assessment of its utility—not its technological sophistication—is what guides consumer responses (Tucker, 2014). In this increasingly significant context, perceived relevance becomes not only a target for personalization but also a psychological sieve through which individuals evaluate and react to AI-driven activities in e-commerce (Sodiya et al., 2024; Teepapal, 2025). Another significant connection between AI personalization and purchase intention is perceived relevance. This is how consumers determine the usefulness or suitability of content or a recommendation depending on what they need or prefer at the moment (Tam & Ho, 2006). When personalization is well-matched to a consumer's interests, they perceive it as useful but not intrusive (Tucker, 2014). Relevance is what drives emotional and cognitive engagement for digital media.

Relevance is essential for both emotional and cognitive engagement on digital platforms. The Elaboration Likelihood Model (Geng et al., 2021; Hoyer et al., 2024) presumes that if consumers perceive information as relevant, they are more likely to process it comprehensively and react in a positive manner. Relevant personalized product recommendations can generate emotional involvement and reduce the perceived cost of search, both of which enhance purchase intent (Bleier et al., 2019). Perceived relevance has been found to be the "value lens" for making sense of personalization. Stojanova et al. (2023) showed that high relevance in location-based advertising improves consumers' attitudes towards the brand and their chances to act. Furthermore, Trzebiński et al. (2022) established that personalized advertisements considered highly relevant lead to increased click-through and conversion rates.

In the context of AI, the better a system can predict and reflect consumer preferences, the greater the perceived relevance and the stronger the resulting behavior. Hoyer et al. (2024) confirmed that perceived relevance partly mediates the relationship between AI-based personalization and purchase intentions, especially in mobile commerce and dynamic pricing situations. According to the S-O-R model, AI-driven personalization (S) prompts an evaluation of relevance (O). When consumers perceive relevance as high, their internal cognitive state improves, leading to a stronger behavioral response (R)—specifically, the intention to purchase. Perceived relevance serves as a bridge, helping consumers assess the usefulness and suitability of AI outputs, transforming a technological stimulus into meaningful action.

H3: Perceived relevance plays a key role in the relationship between AI-driven personalization and online purchase intentions.

Conceptual Model

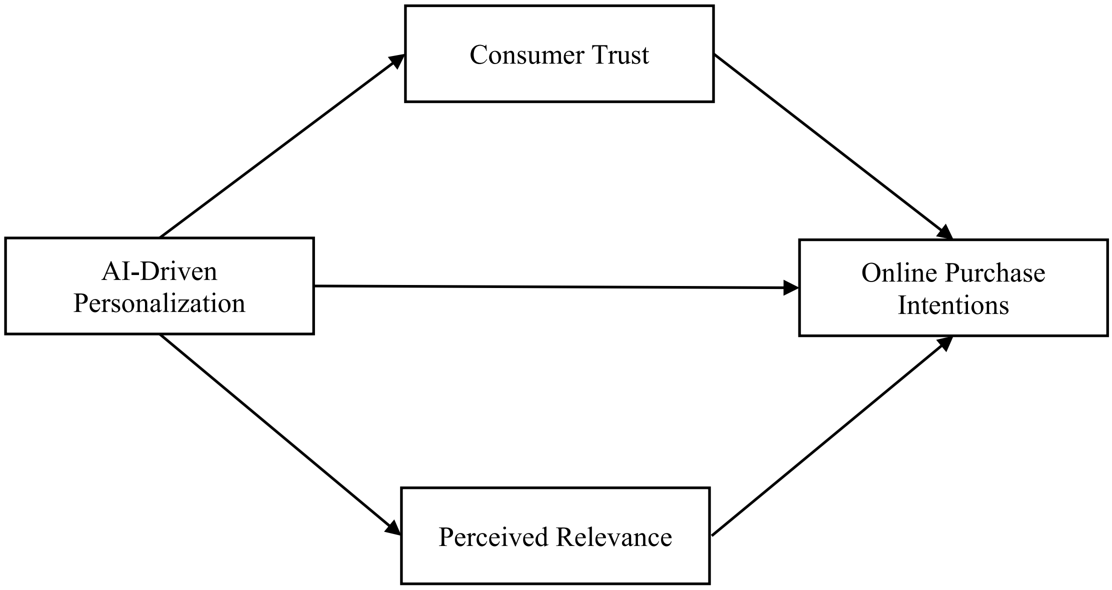

Figure No.1: Conceptual Model

Methodology

Participant and Procedure

The study targeted university students who were actively engaged in online purchasing, as this demographic is considered tech-savvy and familiar with digital platforms where AI-driven personalization is commonly implemented. A convenience sampling technique was employed for data collection. A total of 600 structured questionnaires were distributed across three major public sector universities in the Hazara Division, Pakistan—Hazara University, University of Haripur, and Abbottabad University of Science and Technology (AUST). Out of these, 429 questionnaires were returned and deemed valid for analysis, resulting in a response rate of approximately 71.5%.

The sample comprised 54% male and 46% female respondents, with an average age of 21.8 years (SD = 2.4). A majority of the participants reported having made at least one online purchase in the past three months, supporting the relevance of their input to the research topic. Participants were informed about the confidentiality and academic purpose of the study, and consent was obtained prior to participation.

Measures

All the items were scored on a five-point Likert scale from 1 (Strongly Disagree) to 5 (Strongly Agree).

AI-Driven Personalization was assessed on a 4-item measure based on (Bleier &

Eisenbeiss, 2015). The items reflected participants' belief about the extent to which online sites personalized recommendations or content according to their interests. An example item is: "The website offers me product suggestions that are in line with my interests." The scale showed high reliability with Cronbach's alpha of 0.87.

Consumer Trust was measured with a 5-item scale that rated participants' trust in online retailers utilizing AI to tailor experiences based on (Awad & Krishnan, 2006).). An example item is: "I trust online stores that use AI to understand my preferences." The scale's internal consistency was found to be acceptable at Cronbach's alpha = 0.83.

Perceived Relevance was assessed with a 4-item scale that measured how relevant consumers perceived the AI-personalized content or recommendations borrowed from (Tam & Ho, 2006). An example item is: "The recommendations I receive feel relevant to my needs." This scale showed high reliability with a Cronbach's alpha of 0.85.

Online Purchase Intentions were assessed using a 3-item scale of the extent to which participants were likely to make purchases on the basis of customized recommendations drawn from (Pavlou, 2003). An example item includes: "I am more likely to buy a product if it is suggested based on my historical behavior." The scale had adequate internal consistency with a Cronbach's alpha of 0.82.

All the items were borrowed from proved sources and reduced slightly to fit the context of online AI personalization. Pilot testing was carried out with 30 respondents to ascertain clarity and consistency of the tool before actual data collection.

Descriptive Statistics and Inter-construct Correlation

Table 1 presents the means, standard deviations, and Pearson correlation coefficients among the key study variables. All variables show moderate to high mean values, suggesting favorable participant perceptions. AI-driven personalization shows a strong positive correlation with online purchase intentions ($r = .67$, $p < .01$), supporting the hypothesized direct effect. Moreover, consumer trust ($r = .60$, $p < .01$) and perceived relevance ($r = .66$, $p < .01$) are also significantly correlated with purchase intentions, indicating their potential mediating roles in the relationship between personalization and consumer behavior.

Table No. 1

Descriptive Statistics and Correlation Matrix

Variable	Mean	SD	1	2	3	4
1. AI-Driven Personalization	3.89	0.72	1			
2. Consumer Trust	3.76	0.68	.62**	1		
3. Perceived Relevance	3.81	0.71	.58**	.64**	1	
4. Purchase Intentions	3.94	0.75	.67**	.60**	.66**	1

Note: *N = 429; *$p < .01$

Model fit Summary

As shown in Table 2, the four-factor model demonstrates the best model fit ($\chi^2 = 318.47$, df = 164, CFI = 0.94, TLI = 0.92, RMSEA = 0.052, SRMR = 0.038), indicating a clear distinction among the four constructs: AI-Driven Personalization, Consumer Trust, Perceived Relevance, and Purchase Intentions. Compared to the one-, two-, and three-factor models, the four-factor structure meets commonly accepted fit criteria, supporting the discriminant validity of the measurement model.

Table No. 2

Model Fit Indices

Model	χ^2	df	CFI	TLI	RMSEA	SRMR
One-Factor Model	1042.76	170	0.61	0.56	0.125	0.098
Two-Factor Model	781.34	169	0.72	0.68	0.108	0.085
Three-Factor Model	546.21	167	0.84	0.81	0.086	0.063
Four-Factor Model	**318.47**	164	**0.94**	**0.92**	**0.052**	**0.038**

Results

To test the direct impact of AI-Driven personalization on online purchase and the mediating roles of Consumer Trust and Perceived Relevance in the relationship between AI-Driven Personalization and Online Purchase Intentions, we used PROCESS Macro (Model 4) developed by Andrew F. Hayes in SPSS. This model allows the examination of multiple mediators operating in parallel while controlling for their shared variance. Bootstrapping with 5000 resamples was applied to obtain bias-corrected 95% confidence intervals.

The results indicate that AI-Driven Personalization has a significant total effect on Online Purchase Intentions ($B = 0.584$, $p < .001$). When mediators were included in the model, the direct effect remained significant ($B = 0.278$), suggesting partial mediation.

Both Consumer Trust ($B = 0.146$) and Perceived Relevance ($B = 0.160$) showed significant indirect effects, as their bootstrapped confidence intervals did not include zero. This confirms that these two variables independently and significantly mediate the relationship between AI personalization and purchase intentions.

These results validate the proposed theoretical framework and suggest that enhancing trust and perceived relevance are key mechanisms through which AI personalization influences consumer behavior.

Table No.3

Results Summary

Path	B	SE	95% CI	Significance
Total Effect (X → Y)	0.584	0.048	[0.489, 0.678]	Significant
Direct Effect (X → Y)	0.278	0.053	[0.174, 0.382]	Significant
Indirect Effect via Trust	0.146	0.032	[0.089, 0.217]	Significant
Indirect Effect via Relevance	0.160	0.035	[0.096, 0.236]	Significant

Discussion

The present study explored the influence of AI-driven personalization on online purchase intentions, examining the mediating roles of consumer trust and perceived relevance through the lens of Stimulus-Organism-Response (SOR) theory. Consistent with the SOR framework (DEMETRAKOS, 2025), personalization through AI (Stimulus) elicits internal psychological assessment like trust and relevance (Organism), which subsequently influence behavioral intentions (Response), i.e., whether to purchase online.

The results showed that AI-based personalization greatly contributes to online buying intentions both directly and indirectly by means of consumer trust and perceived relevance. These findings corroborate prior research that has established the persuasive potential of personalized information in influencing consumer behavior (Gantumur, 2025; Iqbal et al., 2024). Nevertheless, this study extends beyond the fact that it empirically tests both trust and relevance as parallel mediators—providing a more nuanced explanation of the psychological processes behind the link between personalization and intention.

Contrary to some previous studies that have concentrated on the role of personalization in enhancing user satisfaction or loyalty (Iyelolu et al., 2024), the current study sets purchase intention as the primary outcome and makes causal inferences by applying Hayes' PROCESS Model 4 for mediation analysis. Additionally, while prior work has often treated trust or relevance as singular mediators, this study shows that both independently contribute to explaining how consumers cognitively and emotionally process AI-personalized experiences.

The significance of consumer trust as a mediator supports earlier assertions that personalization enhances perceptions of transparency and care, which are foundational to trust-building (Tasnim et al., 2025). At the same time, the role of perceived relevance highlights the consumer's need for cognitive congruence; when AI-based suggestions align with their preferences and needs, they feel more understood and thus more inclined to act (Han et al., 2021; Sunkar, 2025).

From an SOR theory perspective, this study strengthens the conceptual argument that technological stimuli (AI personalization) influence consumers not directly, but through internal evaluative states—trust and perceived relevance—that lead to observable behaviors like purchase decisions. This mediation-based view offers a richer explanation compared to direct-only stimulus-response models.

Theoretical Contribution and Novelty

What is particularly novel about this study is the simultaneous testing of consumer trust and perceived relevance as parallel mediators within the same model. While both constructs have been explored in isolation, their combined explanatory power in a personalization context has been largely overlooked. This nuanced analysis not only deepens theoretical understanding but also provides a more practical framework for e-commerce platforms aiming to design AI-based systems that build both emotional security (trust) and cognitive alignment (relevance) with users.

Furthermore, the study expands the application of SOR theory into the domain of AI in marketing, showing that human responses to machine-generated content still rely heavily on psychological interpretations, not just functional utility.

Practical Implications

The findings of this study have practical insights for e-commerce websites, online marketers, and creators of AI systems. To begin with, the big mediating roles of perceived relevance and consumer trust underscore the importance of formulating AI personalization systems not only that provide accurate recommendations, but also transmit transparency and ethical interaction. In order to build trust, online retailers need to make it explicitly clear how they collect and use individual information, provide easy-to-understand privacy options, and securely protect customer data. These measures can ensure customers and enhance their trust in AI-powered platforms.

Additionally, the role of perceived relevance requires AI recommendations to rise above static algorithms and render contextually appropriate content that aligns with consumers' immediate context, preferences, and purchasing habits. E-commerce sites can benefit from using context-aware personalization that incorporates such as recent browsing history, device type, location, and time of day. This creates a more contextual and immersive shopping experience that fuels purchase intent.

Since this study was conducted among university students—a digitally native cohort of tech-conscious consumers in their own right—the findings have implications for the promise of age-targeted strategies aimed at younger online consumers. Websites should consider implementing interactive recommendation tools, gamified incentives, and real-time personalization to better engage this group. In addition, back-channel feedback on recommended content can refine AI algorithms in the long run so that future recommendations are more relevant and trustworthy.

Conclusion

This study sought to investigate the influence of AI-driven personalization on online purchasing intentions, specifically the mediating roles of consumer trust and perceived relevance. By applying the Stimulus-Organism-Response (SOR) theory, the findings provide robust empirical support for the proposition that AI-driven stimuli influence consumer behavior by internal cognitive and affective appraisals. Perceived relevance and consumer trust also emerged as robust mediators, highlighting their significant roles in mapping personalized experiences into purchasing intentions.

The results corroborate the evidence that while AI-powered personalization directly affects consumer buying behavior, it is immensely boosted when customers believe they can trust the site and obtain recommendations placed within context. Not only does this strengthen the psychological processes involved in online consumer participation, but it also further develops the theoretical use of the SOR model in artificial intelligence and online shopping contexts.

In general, this research aids in gaining a better insight into how personalized digital settings influence consumer choices and offers actionable recommendations for marketers, online business strategists, and AI creators. By specifically considering both technology correctness and consumer psychology, organizations can better capitalize on AI to drive and improve customer buying behavior in the age of digitalization.

Limitation and Future Research Directions

While this study offers valuable insights into the mechanisms through which AI-driven personalization influences online purchase intentions, several limitations should be acknowledged. First, the sample was limited to university students from three public sector universities in the Hazara Division of Pakistan, which may limit the generalizability of the findings to other demographic groups, regions, or countries. Future research should consider more diverse and representative samples, including individuals from different age groups, professions, and socio-economic backgrounds, to validate the model across broader populations.

Second, the study relied on cross-sectional, self-reported data, which may be subject to biases such as social desirability or common method variance. Longitudinal or experimental designs could be employed in future studies to better capture causal relationships and behavioral changes over time in response to AI personalization.

Third, this research focused only on two mediators—consumer trust and perceived relevance—within a parallel mediation model. While these constructs are central to the personalization process, future studies could explore additional mediating or moderating variables, such as perceived privacy risk, personalization skepticism, digital literacy, or emotional engagement, to gain a more comprehensive understanding of the personalization–intention link.

Lastly, the study used Andrew Hayes' Model 4 for parallel mediation; future research could adopt serial mediation models or moderated mediation frameworks to explore more complex psychological pathways and boundary conditions. As AI technology continues to evolve, further research is also needed to assess how different types of AI (e.g., generative AI, conversational AI, machine learning algorithms) differently impact consumer perceptions and behaviors.

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