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Original Article

Impact of Artificial Intelligence-Enabled Customer Interaction on Consumer Buying Intention: Evidence from Online Beauty and Personal Care Products in India

Aditya Prasad Das[1], Sunil Kumar Pradhan[2], Suman Kalyan Chaudhury[3]

[1,2,3]*Department of Business Administration, Berhampur University, Odisha, India.*

[3]*Corresponding Author : sumankchaudhury72@gmail.com*

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Abstract *- The purpose of this study is to examine how artificial intelligence–enabled customer interaction influences customer patronage towards e-commerce applications dealing with online beauty and personal care products in India. The study also explores the mediating effect of decision convenience and perceived control. The increasing adoption of AI features in online shopping applications, such as chatbots, personalized recommendations, automated customer support, and more, has improved consumers' online purchasing experience. However, empirical evidence explaining the mechanisms through which AI-enabled interactions affect consumer patronage, particularly in emerging economies like India, is underexplored. A structured, self-administered questionnaire was used to collect primary data from 477 Indian consumers with prior experience with AI-enabled online beauty and personal care platforms. The data were analysed using partial least squares structural equation modelling (PLS-SEM) to assess both the measurement and structural models. This study extends the AI and consumer behaviour literature by empirically validating the roles of decision convenience and perceived control as explanatory mechanisms linking AI-enabled customer interaction to customer patronage of AI-featured e-Commerce applications. The results show that AI-enabled customer interaction significantly enhances customers' decision convenience and moderately influences their perceived control over the application. Decision convenience has a strong positive effect on customer patronage and partially mediates the relationship between AI-enabled interaction and patronage. Perceived control, although positively related to patronage, does not demonstrate a significant mediating effect.*

Keywords *- Artificial Intelligence, Decision Convenience, Perceived control, Customer patronage, e-retail.*

1. Introduction

The fast development of Artificial Intelligence (AI) technologies and their use in e-commerce has transformed how fashion products are discovered, evaluated, and purchased by customers online. Technologies such as recommendation algorithms, virtual try-on tools, chatbots, visual search, and personalized content are now significantly shaping the online fashion experience for Generation Z (Gen Z) consumers, who are digitally native, mobile-first, and highly responsive to technology-mediated experiences. In the fashion industry, where trends shift very quickly, and purchase decisions are strongly influenced by aesthetics, peer influence, and personalization, AI has become essential to engage customers. For Gen Z, these systems not only help in shopping but also actively guide preferences, reduce decision effort, and stimulate impulse buying.

Many recent studies have examined the impact of AI-enabled personalization, recommendations, and automation in e-commerce; however, empirical evidence remains fragmented when it comes to understanding how these technologies influence online fashion buying behaviour among (Yeo et al. 2022; Ruiz-Viñals et al. 2024; Zaman et al 2025). Most existing research focuses on developed economies or treats online consumers as a homogeneous group, ignoring generational differences in technology perception, trust formation, and purchase motivation. In the Indian context, there is limited empirical work that explains how AI features shape Gen Z consumers' attitudes, satisfaction, trust, and purchase intentions in online fashion platforms. The significance of this study lies in its focus on AI–enabled customer interaction as a decision-support mechanism rather than a mere technological feature within e-commerce. Existing research largely treats AI as an experience enhancer or satisfaction driver, offering limited insight into how AI interactions restructure consumer decision processes and translate into sustained customer patronage (CP). By concentrating on online beauty and personal care products, a category where Indian consumers increasingly depend on AI chatbots, personalized recommendations, and virtual tools, the study addresses a relevant research gap. Therefore, this study aims to examine the impact of artificial intelligence technologies on online fashion buying behaviour among Gen Z consumers in India. It seeks to analyse how AI-driven features such as personalized recommendations, chatbots, predictive search, and automated customer support affect consumer perceptions, trust, satisfaction, and purchase intention. The study also aims to assess the extent to which AI enhances shopping experience and influences impulse buying and loyalty formation in online fashion retail. Moreover, the study intends to offer empirical insights that support both academic understanding of the customer decision-making process for fashion e-commerce platforms. It advances academic understanding by positioning Decision Convenience (DC) as the central explanatory mechanism linking AI interaction to buying intention and repeat patronage.

2. Theoretical Framework

The study is guided by the Stimulus–Organism–Response (S-O-R) model and is reinforced by insights from technology acceptance and consumer decision-making theories. In the online fashion market, AI features are intensively used as external *stimuli* that decide how Gen Z consumers process information, evaluate alternatives, and interact with fashion platforms. Unlike traditional online shopping methods, AI-driven stimuli actively adapt to user behaviour in real time, intensifying cognitive and affective reactions during the shopping journey. The *organism* component captures the consumers' internal states, including perceived usefulness, enjoyment, trust, satisfaction, and reduced decision effort arising from AI-based interactions. These internal evaluations determine the *response*, expressed through purchase intention, impulse buying, repeat purchase, and patronage toward the brand or platforms. The framework assumes that AI influences customer buying behaviour not directly, but by changing their perceptions and emotional engagement with the platform. By applying this integrated theoretical structure, the study explains how AI-driven retail environments convert technological inputs into behavioural outcomes among Gen Z consumers in online fashion shopping. Further, the Technology Acceptance Model (TAM) provides a foundation for understanding consumer responses to AI-enabled retail technologies. Initially developed to explain individual technology adoption, TAM has been extended to examine consumer interactions with AI-based advanced systems (Gansser & Reich, 2021; Mogaji et al., 2024). In contemporary retail contexts, AI facilitates personalized customer interaction through machine learning algorithms, smart recommendation systems, and virtual advisory tools, thereby influencing consumer decision processes rather than merely supporting system adoption (Choung et al., 2023; Petrescu et al., 2024). So, the process of moving beyond adoption-centric perspectives and examining how AI-enabled interactions reshape consumer decision-making and patronage behaviour can be explained based on these two theoretical frameworks.

3. Review of Literature

So many industries are nowadays trying to explore the potential of AI. The retail sector in India is emerging as one of the most prominent sectors where the potential of AI for supporting consumers is visible in making a better purchase experience (Jain & Gandhi, 2021). Retailers are trying to integrate even more advanced AI features, including chatbots and intelligent interfaces, into frontline retail platforms to improve customer interaction and engagement (Reis et al., 2020). This shift from transactional exchanges toward technology-mediated interactions has essentially changed consumer–service relationships (Loureiro et al., 2021; Petrescu et al., 2024). Similarly, the rapid dispersal of AI in the B2C retail sector is further evidenced by substantial investment growth, with AI start-ups gathering 1.8 billion US dollars across 374 retail deals between 2013 and 2018, followed by projections of exponential expansion in global AI economic value creation (George, 2023; Ouliel, 2021). Most AI applications in retail remain operationally focused, with nearly 74% deployed for back-end functions such as inventory optimization and logistics, and only 26% directly supporting customer interaction (Ouliel, 2021). Nevertheless, the recent industry is shifting its AI focus towards improving customer service, consumer intelligence, and personalized engagement, to ensure competitive advantage in the market (Petrescu et al., 2024).

The evolution of Retail 4.0, which is defined as the application of Industry 4.0 technologies within omnichannel retail environments, is a critical structural shift in the retail sector (Sakrabani et al., 2021; Haque et al., 2024). Retail 4.0 enables retailers to address some inefficiencies like stock-outs, price inconsistencies, and prolonged checkout times, which previously affected both consumer experience and operational efficiency (Mantur & Borgaon, 2020). Although many developed countries have adopted Retail 4.0, empirical evidence suggests that full-scale implementation remains limited, particularly in many developing markets (Har et al., 2022). This transitional phase creates scope for examining how AI integration into online retail (e-tail) contributes to improving personalization, expanded product assortments, and improved decision support (Haque et al., 2024).

AI features in retail applications include a range of facilities such as chatbots, virtual assistants, recommendations, augmented reality, and computer vision systems, which collectively support the customer decision-making process (Pillai et al., 2020; Hajishirzi et al., 2022). Artificial Intelligence–enabled Customer Interaction (AICI) refers to the extent to which AI features facilitate real-time, personalised, and responsive interactions between consumers and online retail platforms. These features use data from various sources, including text, voice, images, and facial expressions, allowing retailers to respond dynamically to consumer needs during the shopping process (Davenport et al., 2019). Prior studies show that AI interaction improves consumer flexibility, task efficiency, and decision confidence by lowering time pressure and simplifying complex evaluations (Parasuraman & Colby, 2014; Pillai et al., 2020). Therefore, consumers perceive AI as a useful element that aids options evaluation and enhances purchase confidence (Grewal et al., 2017; Elmashhara et al., 2023). The perceived usefulness of technology strongly influences the consumers' affective and cognitive responses while evaluating complex decisions (Choung et al., 2023). So, decision convenience (DC) reflects consumers' perception that a shopping task requires minimal time, effort, and cognitive resources to reach a purchase decision (Niza Braga & Jacinto, 2022). In modern retail environments, AI is deployed specifically to assist consumers in evaluating alternatives, reducing information asymmetry, and supporting purchase decisions through interactive systems (Chopra, 2019). Compared to other technology-related beliefs, perceived usefulness exhibits stronger explanatory power in shaping technology-related evaluations across diverse application settings, including retail and e-commerce (Marotta, 2023). As such, the ease of use of any technology is considered a critical determinant of its adoptability by consumers. A complex or poorly designed interface increases resistance toward system usage and adaptability (Nakod, 2019). The use of AI in retail contexts largely tries to simplify certain things while improving the ease of use. Thus, the ease of use of AI has been shown to improve accessibility, lower cognitive burden, and encourage favourable consumer attitudes toward such intelligent systems (Dwivedi et al., 2023; Panagoulias et al., 2024).

AI is capable of autonomously processing complex data and can streamline interaction and influence consumer purchase decisions by simplifying information search and comparison processes (Hoffman & Novak, 2017; Davenport et al., 2019). Such systems enhance perceived ease and contribute to consumer convenience during shopping. Prior studies report a significant association between DC and positive consumer attitudes toward AI technologies (Wang et al., 2023; Schiavo et al., 2024). However, empirical evidence remains limited regarding how these technology perceptions translate into sustained consumer behaviour outcomes, especially CP. Perceived control (PC) is yet another element that is observed to play a key role in online purchases. It is defined as the degree to which consumers feel they have control over the shopping process, customizable options, and ability to manage interactions with technology during online purchases (Bleier et al., 2019). Although PC has been linked to satisfaction and trust in technology, its impact varies depending on complexity and technology intensity involved in the task (Lu et al., 2023). As computer intelligence becomes embedded within AI interfaces, it increasingly shapes how users evaluate and interact with such systems when it comes to problem-solving ability (Balakrishnan & Dwivedi, 2021). From a consumer perspective, higher PC over the system enhances functional efficiency and task performance, thereby contributing to favourable evaluations of AI assistance (Fritsch et al., 2022). Digital and voice-based assistants exemplify this shift, functioning as personal intelligent agents that leverage conversational data to provide context-sensitive responses and decision support (Moussawi et al., 2021). These systems are categorized as intelligent due to their ability to interpret customer queries, learn from prior interactions, and autonomously adjust recommendations while keeping certain control in the hands of the user. However, studies have also shown that excessive automation or opaque AI decision-making can weaken perceived control, leading to resistance from customers (Lu et al., 2023; Longoni et al., 2019). In the context of online retail, PC has been found to positively influence satisfaction, confidence in decisions, and repeat use of such technology, though its effect may be contingent on consumers' familiarity with AI (Cui et al., 2022; Cicek et al., 2025).

Finally, CP is nothing but the intention to continue using a product or service. It includes consumer behaviours like repurchase and recommending the product to others (Zeithaml et al., 1996; Jones & Kim, 2010). Prior studies consistently show that convenience-driven and value-enhancing purchase experiences are key determinants of sustained CP (Molinillo et al., 2017; Syah & Olivia, 2022). Similarly, favourable engagement with technologies enhances shopping experiences and repeat purchase behaviour, particularly when consumers experience reduced effort and greater decision clarity (Renko & Druzijanic, 2014; Pillai et al., 2020). So, the present study tries to figure out how AI-based online buying experiences are leading to strong CP. It also tries to explore the mediating role of customer DC and PC over the AI technology influencing customer buying behaviour.

4. Method

4.1. Research Design and Context

This study uses a quantitative survey design to investigate the impact of AI–enabled Customer Interaction (AICI) on Customer Patronage (CP), with Decision Convenience (DC) and Perceived Control (PC) acting as mediating mechanisms. The empirical context was online beauty and personal care retailing in India. This category consists of a large product variety, information asymmetry, frequent use of AI-powered recommendation features, chatbots, and virtual assistance, and strong reliance on interactive digital interfaces during purchase decisions. India witnessed a tremendous growth of AI-enabled e-commerce applications across various retail platforms, and the ever-growing market of beauty and personal care products through online channels motivated this study.

4.2. Target Population and Sampling

The population identified for the study is Indian consumers aged 18–30 years who often purchase beauty and personal care products online and have interacted with AI-based interfaces during their purchase process. A screening question was included at the beginning of the questionnaire to ensure that only respondents in a certain age group and with prior experience of AI-enabled interaction in online beauty and personal care products qualified for participation.

A quota-based sampling strategy was employed to approximate stratified representation across gender and education level, reflecting the demographic composition of Indian online buyers. Data were collected from consumers residing in both urban and semi-urban regions across multiple Indian states to enhance generalizability. A total of 550 questionnaires were distributed online, out of which 477 valid responses were retained after data screening, yielding a strong effective sample size suitable for structural equation modelling (Hoyle & Gottfredson, 2015)

4.2.1. Tools

Data has been collected using a structured self-administered questionnaire comprising previously validated scales adapted to the study context. All constructs were measured using multiple items on a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). AICI was measured by capturing consumers' perceptions of responsiveness, personalization, informativeness, and interactivity of AI-driven interfaces during online shopping. DC was estimated based on the extent to which AI-interaction reduced cognitive effort, simplified product comparison, and accelerated purchase decisions.

PC captures consumers' sense of autonomy, choice flexibility, and control over the shopping process facilitated by AI. CP was measured through behavioural intentions like repeat purchase intention, preference, and continued engagement with the same online retailer or e-commerce platform. The questionnaire was pre-tested with a small group of respondents to ensure clarity, relevance, and contextual suitability, leading to a few minor refinements.

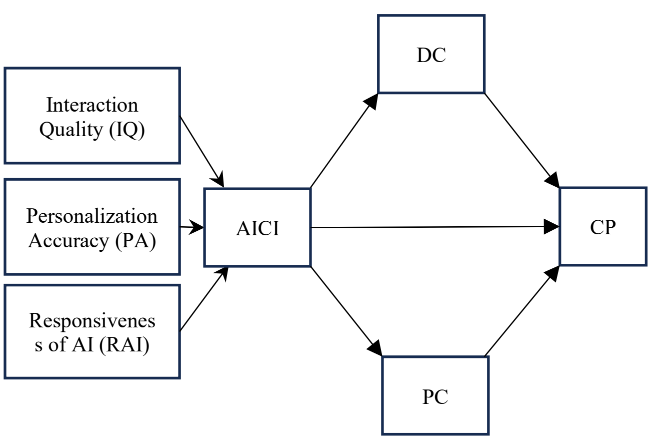

Fig. 1 Conceptual Model

4.2.2. Conceptual Model and Hypotheses

In Figure 1, the conceptual model is presented, which shows a clear path diagram establishing the relationship between the variables. The first order relationship to ensure the AICI is manifested by three constructs, such as the quality of interaction of the AI (IQ), accuracy in the personalisation advice produced by AI (PA), and responsiveness of the AI features (RAI). After ensuring the second-order construct (AICI), it is used with the other two constructs (DC and PC), which leads to the exogenous variable CP. DC and PC are used as the mediating variables in the structural model. Based on this conceptual model, we state the following hypothesis.

H1: AICI has a significant positive effect on DC among online beauty and personal care consumers in India.
H2: AICI has a significant positive effect on PC among online beauty and personal care consumers in India.
H3: DC has a strong positive impact on CP in online beauty and personal care platforms.
H4: PC has a strong positive effect on CP in online beauty and personal care platforms.
H5: DC fully mediates the relationship between AICI and CP.
H6: PC fully mediates the relationship between AICI and CP.

Table 1. Demographic Profile of Respondents (N = 477)

Variable	Category	Frequency	Percentage
Gender	Male	228	47.792
	Female	249	52.208
Age	<20 years	173	36.268
	21–25 years	191	40.042
	26–30 years	113	23.689
Education	Graduate	198	41.509
	Postgraduate	221	46.332
	Other Higher Qualifications	58	12.159
Employment status	Employed	362	75.892
	Unemployed	115	24.108
Earnings per annum	Below 2 Lakhs	168	35.222
	2 to 12 Lakhs	201	42.138
	More than 12 Lakhs	108	22.640
Online Purchase Frequency	Monthly	144	30.189
	2–3 times/month	213	44.650
	Weekly	120	25.161

5. Findings and Discussion

Table 1 presents the demographic profile of the 477 respondents surveyed for the study. The sample exhibits a balanced gender composition, with a slightly higher representation of female respondents (52.21%) compared to males (47.79%), which is appropriate given the focus on online beauty and personal care products where female participation is typically higher. The age distribution indicates that the sample is predominantly young, with nearly three-fourths of the respondents falling below 35 years, reflecting the strong engagement of younger consumers with AI-enabled online retail platforms. In terms of education, a highly educated sample is evident, as close to 88% of the respondents possess graduate or postgraduate qualifications, suggesting adequate familiarity with digital technologies and AI-driven interfaces. A substantial proportion of respondents are employed (75.89%), indicating stable purchasing power within the sample. The income distribution shows a concentration in the low- to middle-income brackets, aligning with the profile of urban Indian online shoppers who actively engage with digital commerce platforms. Finally, the online purchase frequency data reveal high platform engagement, with nearly 70% of respondents purchasing at least two to three times a month or more, supporting the relevance of examining AI-enabled customer interaction and its influence on CP in this context.

Table 2 reports the descriptive statistics for the key study constructs and provides initial evidence on respondents' perceptions of AI-enabled customer interaction and its outcomes. The mean values for all constructs exceed the midpoint of the scale, indicating generally favorable evaluations among Indian online beauty and personal care consumers. DC records the highest mean (M = 4.083), suggesting that respondents strongly perceive AI-enabled interactions as reducing effort and simplifying purchase decisions. CP(M = 4.012) and AI-enabled customer interaction (M = 3.941) also show high mean scores, reflecting positive engagement with AI-driven interfaces and a strong tendency to continue using and supporting these platforms. Perceived control, though slightly lower (M = 3.872), still indicates that consumers feel a reasonable level of autonomy and control during AI-assisted online shopping. The standard deviation values are moderate across constructs, implying acceptable variability without excessive dispersion in responses. Skewness and kurtosis values fall within acceptable thresholds, indicating no severe deviations from normality and suggesting that the data are suitable for subsequent multivariate analysis using PLS-SEM.

Table 2. Descriptive Statistics of Study Constructs

Construct	Mean	SD	Skewness	Kurtosis
AI-Enabled Customer Interaction	3.941	0.682	-0.714	0.613
Decision Convenience	4.083	0.641	-0.892	0.824
Perceived Control	3.872	0.705	-0.621	0.489
Customer Patronage	4.012	0.668	-0.803	0.771

The first-order measurement model assessing the reliability and convergent validity of the three dimensions forming AI-Enabled Customer Interaction (AICI) is given in Table 3. All indicator loadings are observed to be greater than 0.70, confirming construct reliability. Similarly, Cronbach's alpha values range from 0.838 to 0.861, and composite reliability (CR) values range from 0.891 to 0.910, both exceeding accepted standard values. This result confirms the internal consistency and reliability. Further, average variance extracted (AVE) values for all constructs are well above 0.50, demonstrating adequate convergent validity and indicating that each construct explains a substantial proportion of variance in its indicators.

Table 3. Rotated factor loading and reliability-validity measures (first-order model)

Construct	Item	Loading	α	CR	AVE
Interaction Quality (IQ)	IQ1	0.823	0.846	0.896	0.743
	IQ2	0.857			
	IQ3	0.801			
Personalization Accuracy (PA)	PA2	0.842	0.861	0.910	0.771
	PA3	0.879			
	PA4	0.816			
Responsiveness of AI (RAI)	RAI1	0.798	0.838	0.891	0.732
	RAI2	0.841			
	RAI4	0.826			

Table 4, given below, presents the measurement assessment of the higher-order construct AI-Enabled Customer Interaction (AICI). The regression weights indicate that Interaction Quality with AI features shows a significant impact on AICI. The other two constructs, Personalization Accuracy with a value of $\beta = 0.356$ and Responsiveness of AI with a β value of 0.229, also significantly predict AICI. All three paths are statistically significant, confirming that each dimension makes a distinct contribution to the formation of AICI. The Variance Inflation Factor (VIF) values confirm the absence of multicollinearity concerns among the three constructs. It can be affirmed that AICI can now be used as a higher-order formative construct in the subsequent structural model analysis that is composed of interaction quality, personalization accuracy, and responsiveness.

Table 4. Formative Weights and Collinearity (AICI)

Path	Weight	t-value	p-value	VIF
IQ → AICI	0.412	5.984	0.000	2.118
PA → AICI	0.356	4.731	0.000	1.984
RAI → AICI	0.229	2.146	0.032	1.762

The reflective measurement model used in the structural analysis is given in Table 5. All indicator loadings are above 0.70, confirming strong item reliability. Cronbach's alpha values range from 0.835 to 0.863, and Composite Reliability (CR) values range from 0.892 to 0.902, and are within the acceptable range of internal consistency across all constructs. The AVE values also exceeded 0.50, confirming adequate convergent validity. Discriminant validity is supported by the HTMT values, which are above 0.80 for all constructs, indicating that all the constructs are empirically distinct from one another and suitable for the structural model.

Table 5. Rotated factor loading and reliability-validity measures (Structural model)

Construct	Item	Loading	α	CR	AVE	HTMT
AI-Enabled Customer Interaction (AICI)	AICI1	0.812	0.863	0.902	0.697	0.834
	AICI3	0.847				
	AICI4	0.831				
	AICI5	0.789				
Decision Convenience (DC)	DC1	0.824	0.842	0.895	0.739	0.859
	DC2	0.861				
	DC3	0.843				
Perceived Control (PC)	PC2	0.806	0.835	0.892	0.734	0.857
	PC3	0.858				
	PC5	0.827				
Customer Patronage (CP)	CP1	0.834	0.854	0.901	0.753	0.867
	CP4	0.869				
	CP3	0.841				

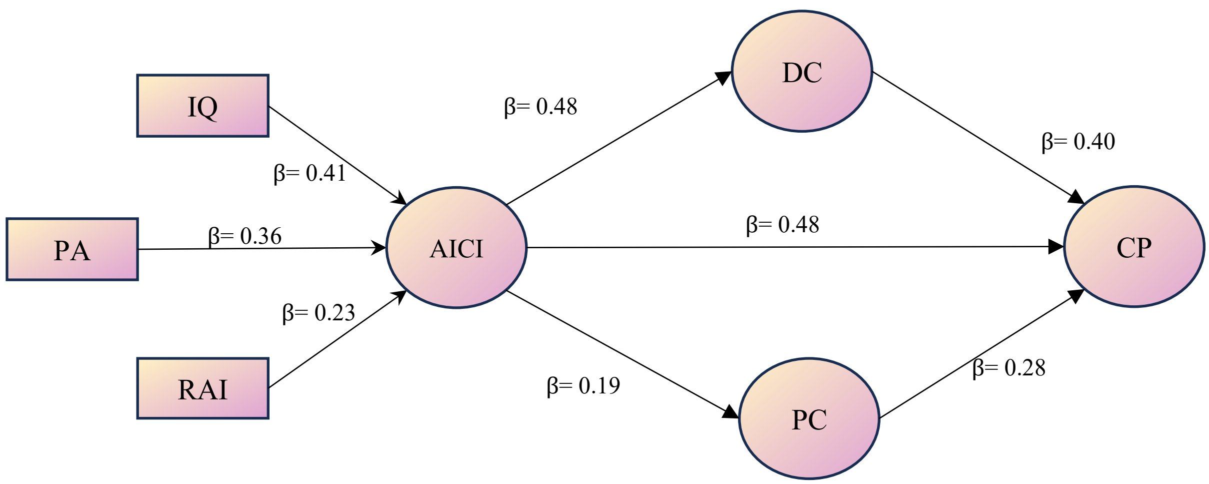

Fig. 2 Structural Path model with Standardised Coefficients

Table 6. Structural model results

Hypothesis	Path	β	t	p
H1	AICI → DC	0.482	8.913	0.000
H2	AICI → Perceived Control	0.198	1.912	0.056
H3	DC → CP	0.401	7.442	0.000
H4	PC → CP	0.276	5.184	0.000

The structural model path diagram with standardised coefficients is presented in Figure 2. Table 2 provides more detailed information on the relationships between the constructs. It can be observed that AICI has a significant positive effect on DC ($\beta = 0.482$, $t = 8.913$, $p < 0.001$), supporting the hypothesis H1. It confirms that AI features are useful to simplify the consumer decision-making process in online beauty and personal care platforms. In contrast, the effect of AICI on PC is weak and not significant at the 5% level ($\beta = 0.198$, $t = 1.912$, $p = 0.056$). We thus reject the hypothesis H2, claiming that AI-enabled interactions do not automatically translate into a stronger sense of control among Indian consumers, and it actually gives a feeling of algorithmic dominance or reduced autonomy. DC, however, is observed as a key driver of CP with $\beta = 0.401$ and $p < 0.001$, strongly supporting H3. Similarly, PC significantly predicts CP with $\beta = 0.276$ and $p < 0.001$, supporting hypothesis H4. These observations indicate that DC exhibits the dominant explanatory power linking AICI to CP, whereas PC plays a secondary and less consistently triggered role in the Indian online beauty and personal care market.

The significant effect of AICI on DC supports the argument that AI features reduce cognitive effort and time spent during product evaluation. Some prior studies also confirm that AI-based personalization and automation simplify complex choice environments and support faster, more correct decisions (Grewal et al., 2017; Pillai et al., 2020;

El Abed & Castro-Lopez, 2024). In beauty and personal care products, consumers face information overload related to ingredients, skin suitability, product comparisons, and, more importantly, doubts about the suitability of the product for a skin type. Here, AI-driven interaction appears to function mainly as a decision simplifier. The significant impact of DC on CP confirms that consumers reward platforms that make buying easy, leading to repeat visits and sustained patronage (Inman & Nikolova, 2017; Cui et al., 2022).

On the other hand, the insignificant relationship between AICI and PC reveals an important insight. Although AI features guide consumers efficiently, they do not necessarily increase users' sense of autonomy or control over the shopping process. This finding is confirmed by some scholars arguing that algorithm-driven recommendations may sometimes be perceived as opaque or overly directive, limiting consumers' feeling of agency (Balakrishnan & Dwivedi, 2021; Grassini, 2023). In the Indian e-commerce platforms, especially for beauty products, where personal preferences and self-expression matter, consumers may accept AI assistance for convenience but remain cautious about the mechanized control of automated systems. This explains why perceived control, although significant in predicting CP, is not strongly predicted by AI-enabled interaction itself. Similar findings were reported in studies examining AI trust and autonomy trade-offs in e-retail environments (Esch et al., 2020; Hassan et al., 2025). Therefore, DC is an important element through which AI-enabled customer interaction leads to increased CP, where PC plays a supportive but weaker role. Existing technology acceptance and smart AI-based retail in consumer markets are not uniform across psychological and behavioural outcomes. Rather than assuming that advanced AI automatically empowers users, the evidence suggests that its value lies more in friction reduction and cognitive support. This extends the claim of some prior works on smart retailing by positioning convenience, not control, as the key driver of patronage (Pillai et al., 2020; Choung et al., 2023; Petrescu et al., 2024).

Table 7. Mediation Analysis

Hypothesis	Indirect Path	Effect	t	p	Mediation
H5	AICI → DC → CP	0.193	6.112	0.000	Partial
H6	AICI → PC → CP	0.055	1.743	0.081	**Not supported**

The mediation effects of DC and PC in the relationship between AICI and CP are presented in Table 7. The results indicate that DC significantly mediates the relationship between AICI and CP, thus supporting hypothesis H5. The indirect effect of AICI on CP through DC is statistically significant, confirming partial mediation. This implies that AICI enhances CP not only directly but also indirectly by simplifying decision-making processes and reducing cognitive effort. Some prior studies also posit similar facts emphasizing the role of AI in minimizing information overload and facilitating efficient choices, which in turn encourage customer loyalty (Grewal et al., 2017; Pillai et al., 2020; El Abed & Castro-Lopez, 2024). In contrast, the mediating role of PC is not significant and thus rejects the hypothesis H6, as the indirect effect of AICI on CP via PC is statistically insignificant. Although PC has a direct and significant influence on CP (as shown in the structural model), AICI is not able to strengthen this perception of control among consumers. The customers are skeptical while using advanced AI features and fear that they may be losing their autonomy and decision-making to the machine. This suggests that AI systems, while efficient, may be perceived as directive, suppressing the feeling of autonomy in the decision process (Balakrishnan & Dwivedi, 2021; Grassini, 2023; Hassan et al., 2025). In emerging digital markets like India, consumers may prioritize speed and ease over control when interacting with AI, especially for routine or low-risk product categories such as beauty and personal care. The absence of strong mediation through PC adds an interesting point to the study by challenging the assumption that AI adoption automatically empowers consumers. Instead, the findings also suggest a more nuanced dynamic in which AI primarily functions as a decision facilitator rather than a control-enhancing agent. This contributes to smart retail and AI-consumption literature by demonstrating that convenience-driven mechanisms outweigh autonomy-driven mechanisms in the advancing AI use in marketing (Inman & Nikolova, 2017; Cui et al., 2022; Choung et al., 2023).

6. Implications

The findings of this study are useful for both managerial and theoretical decision-making as far as AI-based online retailing is concerned. It is suggested that retailers should prioritize AI features that reduce consumer effort and simplify decision-making, rather than overemphasizing consumer control mechanisms that may not strongly influence patronage. Moreover, investment in AI technology can directly strengthen customer loyalty. From a theoretical point of view, the study advances the literature on AI and consumer behavior by demonstrating that DC is a significant determinant of patronage in the case of AI-enabled smart buying behaviour. The study also adds to the existing literature the fact that efficiency-oriented AI benefits may outweigh autonomy-related concerns for consumers in digitally intensive retail environments.

7. Limitations and Scope

The study has a few limitations while paving the path for directions for future research. First, the analysis focuses on a single product category, i.e., online beauty and personal care, which restricts the generalizability to other sectors. Second, although demographic information was captured, the study does not explicitly compare AI interaction effects across generational cohorts based on age, gender, education levels, or income groups. Even though prior research suggests that AI awareness, technology familiarity, and risk tolerance vary substantially across these segments (Nouraldeen, 2023), the study acknowledges this limitation. Third, the model emphasizes behavioral mechanisms such as DC and PC but does not directly account for consumer awareness, knowledge, or literacy regarding AI use, which may limit the understanding of how consumers interpret and respond to AI features during their purchase decisions. So future studies can extend this work by adopting a multi-generational or cross-demographic comparative design to examine whether the effects of AI-enabled customer interaction differ between Gen Z, Millennials, and older cohorts. Moreover, a comparative study across gender and education levels could provide some interesting outcomes in the Indian context. Future studies may also try to explore the role of AI-interaction and brand-related behaviours such as brand trust, brand reputation, and brand value to understand better the strategic implications of AI adoption on brand image creation. Finally, a comparative study on consumer behavior in AI versus non-AI retail experiences would provide a different understanding of the developing role of AI in contemporary online retailing.

8. Conclusion

The study concludes that AI-enabled customer interaction plays a significant role in affecting the CP in online beauty and personal care buying behaviour. The findings confirm that AI features such as chatbots, personalized recommendations, and responsive interfaces significantly simplify consumer decision-making ability, which in turn leads to strong patronage behavior. DC exhibits a strong psychological mechanism mediating between AI interaction and patronage. It confirms that consumers value reduced effort, faster choices, and cognitive relief more than a heightened sense of control in this product category. Although PC positively affects patronage, AI features do not significantly strengthen customer perception, suggesting that Indian consumers prioritize efficiency over autonomy. The study highlights that the effectiveness of AI in online retail lies less in empowering consumers with control and more in streamlining their decision processes, offering a focused and contemporary explanation of how AI-driven customer interaction helps improve customer patronage.

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