

Role of AI Chatbots in Enhancing Customer Experience in E-commerce Platforms.

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Abstract

This study examines the role of AI chatbot features in enhancing customer experience on e-commerce platforms, with a specific focus on perceived intelligence, responsiveness, and personalization. It also investigates the mediating role of customer satisfaction in this relationship. A quantitative research design was adopted, and data were collected from 433 valid respondents in the Delhi NCR region using a structured questionnaire. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings reveal that perceived intelligence is the most significant predictor of both customer satisfaction and customer experience. Responsiveness and personalization also have a positive and significant impact on customer experience, while personalization significantly influences customer satisfaction. However, responsiveness does not have a significant effect on satisfaction. The results further indicate that customer satisfaction does not strongly mediate the relationship between chatbot features and customer experience, suggesting that chatbot attributes primarily influence experience through direct effects. The study demonstrates moderate explanatory and predictive power, highlighting the importance of AI chatbot capabilities in shaping user perceptions. The findings provide valuable insights for e-commerce platforms to enhance customer engagement by focusing on intelligent and personalized chatbot interactions....

Keywords: AI Chatbots, Customer Experience, Customer Satisfaction, Personalization, E-Commerce

Introduction

The rapid advancement of digital technologies has fundamentally transformed the retail landscape, particularly in the domain of e-commerce. With the proliferation of internet access and smartphone usage, consumers increasingly expect seamless, efficient, and personalized experiences. Shopping experiences (Lemon & Verhoef, 2016). In this evolving environment, Artificial Intelligence (AI) has emerged as a critical enabler of enhanced customer interaction and engagement. Among various AI applications, chatbots have gained significant prominence due to their ability to simulate human-like conversations, provide real-time assistance, and automate customer service processes (Huang & Rust, 2021). AI chatbots utilize technologies such as natural language processing and machine learning to interact with users and address their queries effectively. These systems are increasingly being integrated into e-commerce platforms to improve service efficiency and customer satisfaction (Gnewuch et al., 2017). As customers rely more on digital interfaces rather than human support, the performance of chatbot systems plays a crucial role in shaping overall customer experience. In particular, chatbot characteristics such as perceived intelligence, responsiveness, and personalization have been identified as key determinants influencing user perceptions and behavioral outcomes. Perceived intelligence refers to the chatbot's ability to understand and respond accurately to customer queries, thereby creating a perception of competence and human-like interaction (Huang & Rust, 2021). Responsiveness reflects the speed and promptness with which chatbots provide assistance, reducing waiting time and enhancing user convenience (Parasuraman et al., 1988). Personalization, on the other hand, involves tailoring responses and recommendations according to individual user preferences, which enhances the relevance and effectiveness of interactions (Bleier & Eisenbeiss, 2015). These attributes collectively contribute to customer satisfaction, which is a critical factor in determining the success of digital service encounters. Customer satisfaction is defined as the degree to which a product or service meets or exceeds customer expectations (Oliver, 1980). In the context of AI chatbot interactions, higher satisfaction levels are likely to lead to more positive customer experiences, which encompass cognitive, emotional, and behavioral responses during online interactions (Lemon & Verhoef, 2016). Thus, customer satisfaction serves as an important mediating variable that links chatbot features with overall customer experience.

This study aims to examine the role of AI chatbot features—perceived intelligence, responsiveness, and personalization—in enhancing customer experience in e-commerce platforms, with customer satisfaction acting as a mediator. The research is conducted in the Delhi NCR region, a prominent hub of digital commerce in India. A total of 600 respondents were approached using a structured questionnaire, out of which 520 responses were received. After data screening and validation, 433 responses were deemed suitable for final analysis. By adopting a structured empirical approach, this study contributes to the growing body of literature on AI-driven customer service and provides practical insights for e-commerce platforms seeking to optimize chatbot performance. The findings are expected to assist practitioners in designing more effective chatbot systems that enhance customer satisfaction and deliver superior customer experiences.

These intelligent systems simulate human conversation and provide real-time assistance, thereby improving service delivery and user experience (Huang & Rust, 2021; Gnewuch et al., 2017). With the growing reliance on digital interfaces, understanding the role of chatbot features in shaping customer satisfaction and experience has become an important research focus. Perceived intelligence is a critical attribute that influences users' evaluation of chatbot effectiveness. It reflects the chatbot's ability to understand customer queries and provide accurate, relevant, and context-aware responses. Studies suggest that higher perceived intelligence enhances user trust and satisfaction, as customers perceive the chatbot as competent and reliable (Huang & Rust, 2021; Luo et al., 2019). Similarly, Folstad and Brandtzaeg (2017) found that intelligent conversational agents significantly improve user engagement and perceived service quality. The human-like interaction capability of chatbots further strengthens their acceptance and usability in e-commerce environments (Araújo, 2018).

Responsiveness is another key determinant of service quality in digital platforms. It refers to the promptness and speed with which chatbots respond to user queries. According to Parasuraman et al. (1988), responsiveness is a fundamental dimension of service quality that directly influences customer satisfaction. In the context of AI chatbots, quick responses reduce waiting time and enhance convenience, leading to improved user experience (McLean & Osei-Frimpong, 2019). Studies have also shown that immediate assistance through chatbots can positively affect purchase decisions and customer retention (Davenport et al., 2020). Personalization plays a crucial role in shaping customer perceptions in e-commerce settings. Personalized interactions involve tailoring recommendations and responses based on individual preferences and past behavior. Research indicates that personalization enhances customer engagement, trust, and satisfaction by making interactions more relevant and meaningful (Bleier & Eisenbeiss, 2015; Tam & Ho, 2006). In chatbot-enabled platforms, personalization contributes to a more interactive and customized shopping experience, which positively influences customer attitudes and behavioral intentions (Chattopadhyay et al., 2019).

Customer satisfaction is widely recognized as a key outcome of service quality and an important predictor of customer experience. According to Oliver (1980), satisfaction is determined by the extent to which a service meets or exceeds customer expectations. In AI-driven environments, chatbot performance significantly influences satisfaction levels, which in turn affect overall experience and loyalty (Bhattacharyee, 2001; DeLone & McLean, 2003). Studies have also emphasized the mediating role of satisfaction in linking service attributes with customer outcomes (Anderson & Srinivasan, 2003). Customer experience, a multidimensional construct, encompasses cognitive, emotional, and behavioral responses resulting from interactions with a firm (Lemon & Verhoef, 2016). In e-commerce, chatbots contribute to enhancing customer experience by providing seamless, interactive, and efficient service (Rose et al., 2012). Research suggests that positive experiences lead to higher customer loyalty, engagement, and repurchase intentions (Verhoef et al., 2009; Klaus & Maklan, 2013). Furthermore, theoretical frameworks such as the Technology Acceptance Model (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) provide a foundation for understanding user acceptance of chatbot technologies. These models highlight the importance of perceived usefulness and ease of use in shaping user attitudes and behaviors. Additionally, the Expectation Confirmation Theory (Bhattacharjee, 2001) explains how satisfaction mediates the relationship between

Expectations and continued usage intentions. Despite the growing body of literature, there remains a need for empirical studies that integrate multiple chatbot attributes and examine their combined effect on customer experience through mediating mechanisms such as satisfaction. This study addresses this gap by investigating the influence of perceived intelligence, responsiveness, and personalization on customer experience, with customer satisfaction as a mediator in the context of e-commerce platforms.

Table 1.1: Tabular Summary of Literature Review

Author	Focus Area	Key Variables	Methodology	Key Findings
Huang & Rust (2021)	AI in services	AI capability, customer response	Conceptual	AI enhances service quality and customer engagement
Gnewuch et al. (2017)	Chatbots in service	Conversational agents	Conceptual	Chatbots improve customer interaction efficiency
Luo et al. (2019)	AI vs. human service	AI interaction, satisfaction	Experimental	AI impacts satisfaction depending on context
Araújo (2018)	Chatbot interaction	Human-like communication	Survey	Human-like chatbots improve user perception
Folstad & Brandtzæg (2017)	Chatbot adoption	Usability, engagement	Qualitative	Chatbots enhance engagement and service experience
Parasuraman et al. (1988)	Service quality	Responsiveness, reliability	Scale development	Responsiveness is key to satisfaction
McLean & Osei-Frimpong (2019)	Retail chatbots	Interactivity, responsiveness	Survey	Responsiveness improves satisfaction and engagement
Author	Focus Area	Key Variables	Methodology	Key Findings
Davenport et al. (2020)	AI in marketing	AI tools, customer behavior	Conceptual	AI improves decision-making and customer experience
Bleier & Eisenbeiss (2015)	Personalization	Customization, trust	Empirical	Personalization increases engagement and trust
Tam & Ho (2006)	Web personalization	User preferences	Experimental	Personalized content improves user satisfaction
Chattaramani et al. (2019)	Virtual agents	Personalization, experience	Survey	Personalized agents enhance shopping experience
Oliver (1980)	Satisfaction	Expectations, satisfaction	Conceptual	Satisfaction depends on expectation fulfillment
Bhattacharjee (2001)	IS continuance	Satisfaction, usage	Empirical	Satisfaction influences continued usage intentions
Anderson & Srinivasan (2003)	E-satisfaction	Satisfaction, loyalty	Survey	Satisfaction leads to e-loyalty
DeLone & McLean (2003)	IS success	System quality, satisfaction	Model	Satisfaction drives system success
Lemon & Verhoef (2016)	Customer experience	Journey, interaction	Conceptual	Experience is multi-dimensional
Rose et al. (2012)	Online experience	Cognitive, emotional factors	Empirical	Positive experience improves engagement
Verhoef et al. (2009)	Experience creation	Customer journey	Conceptual	Experience impacts loyalty and retention
Klaus & Maklan (2013)	Experience measurement	Service experience	Scale development	Experience strongly affects customer behavior
Davis (1989)	TAM model	Usefulness, ease of use	Empirical	Technology acceptance depends on perceptions

Author	Focus Area	Key Variables	Methodology	Key Findings
Venkatesh et al. (2003)	UTAUT model	Performance expectancy	Empirical	User adoption is influenced by multiple factors

Source: Compiled by the Researcher

1.3 Research Gaps in Existing Literature

A critical review of the existing literature on AI chatbots and customer experience in e-commerce reveals several important gaps that justify the need for the present study. Firstly, a large number of studies have examined AI chatbots in isolation, focusing on their general role in customer service, automation, or technology adoption (Huang & Rust, 2021; Gnewuch et al., 2017). However, there is a lack of integrated studies that simultaneously analyze specific chatbot attributes such as perceived intelligence, responsiveness, and personalization within a single comprehensive framework. Most prior research tends to emphasize one or two dimensions, thereby limiting a holistic understanding of chatbot effectiveness.

Secondly, while the importance of service quality dimensions like responsiveness has been well established in traditional service literature (Parasuraman et al., 1988), their application in AI-driven environments remains underexplored. In particular, the transformation of these dimensions in automated, non-human interactions requires further empirical validation, especially in the context of e-commerce platforms. Thirdly, although personalization has been widely studied in digital marketing and online retail (Bleier & Eisenbeiss, 2015; Tam & Ho, 2006), limited research has specifically examined its role within AI chatbot interactions. The dynamic and real-time nature of chatbot-based personalization presents unique challenges and opportunities that have not been sufficiently addressed in existing studies.

Another significant gap lies in the limited exploration of perceived intelligence as a distinct construct influencing customer outcomes. While recent studies acknowledge the importance of AI capabilities (Luo et al., 2019), empirical research focusing on how users perceive chatbot intelligence and its subsequent impact on satisfaction and experience is still emerging. Furthermore, previous research has often treated customer satisfaction and customer experience as parallel outcomes, rather than examining the mediating role of satisfaction in shaping overall experience. The absence of mediation-based models restricts the understanding of underlying mechanisms through which chatbot features influence customer perceptions and behaviors.

Additionally, much of the existing literature is concentrated in developed countries, with limited empirical evidence from emerging markets such as India. Given the rapid growth of e-commerce in regions like Delhi NCR, there is a need for context-specific studies that capture cultural, technological, and behavioral differences in consumer interactions with AI chatbots. Finally, methodological gaps are also evident, as many studies rely on conceptual frameworks or small sample sizes, limiting the generalizability of findings. There is a need for robust empirical studies using advanced techniques such as Structural Equation Modeling (SEM) to validate relationships among chatbot features, customer satisfaction, and customer experience. In light of these gaps, the present study aims to develop an integrated model that examines the influence of perceived intelligence, responsiveness, and personalization on customer experience, with customer satisfaction acting as a mediating variable, specifically within the context of e-commerce platforms in the Delhi NCR region.

1.4 Objectives of the Study

1. To examine the role of AI chatbots in enhancing customer experience on e-commerce platforms.
2. To investigate the mediating role of customer satisfaction in the relationship between AI chatbot features (perceived intelligence, responsiveness, and personalization) and customer experience.
3. To provide practical suggestions for improving AI chatbot performance to enhance customer experience in e-commerce platforms.

1.5 Research Framework and Hypotheses Development

The rapid integration of Artificial Intelligence (AI) into e-commerce platforms has significantly transformed customer interaction and service delivery. AI chatbots, in particular, have emerged as an important tool for enhancing customer experience by providing instant, personalized, and intelligent support (Huang & Rust, 2021). Drawing on the Technology Acceptance Model (Davis, 1989) and Service Quality Theory (Parasuraman et al., 1988), this study proposes a framework to examine both the direct effects of AI chatbot features on customer

experience and the mediating role of customer satisfaction. AI chatbot features such as perceived intelligence, responsiveness, and personalization represent key service attributes that influence customer perceptions and evaluations (McLean & Osei-Frimpong, 2019). These features not only directly enhance the overall customer experience but also influence customer satisfaction, which in turn shapes customer experience (Lemon & Verhoef, 2016). Therefore, the present framework integrates both direct and indirect relationships to provide a comprehensive understanding of chatbot effectiveness.

A) Research Framework

The proposed model includes:

- **Independent Variables (IVs):**
 - Perceived Intelligence (PI)
 - Responsiveness (RES)
 - Personalization (PER)
- **Mediating Variable:**
 - Customer Satisfaction (CS)
- **Dependent Variable:**
 - Customer Experience (CEP)

The framework assumes that AI chatbot features have both:

1. Direct effects on customer experience, and
2. Indirect effects through customer satisfaction (mediation).

B) Hypotheses Development

i) Direct Effect of AI Chatbot Features on Customer Experience

AI chatbots enhance customer experience by providing efficient, interactive, and personalized services. Perceived intelligence improves interaction quality and reduces cognitive effort, thereby enhancing experience (Huang & Rust, 2021). Responsiveness ensures timely assistance, which is critical for positive service evaluation (Parasuraman et al., 1988). Personalization enhances relevance and engagement, leading to a superior customer experience (Bleier & Eisenbeiss, 2015).

H1: Perceived intelligence of AI chatbots has a significant positive effect on customer experience.

H2: Responsiveness of AI chatbots has a significant positive effect on customer experience.

H3: Personalization of AI chatbots has a significant positive effect on customer experience.

ii) Effect of AI Chatbot Features on Customer Satisfaction

Chatbot features significantly influence customer satisfaction by improving service quality and meeting user expectations. Intelligent and responsive systems enhance perceived usefulness, while personalization increases perceived value (McLean & Osei-Frimpong, 2019).

H4: Perceived intelligence has a significant positive effect on customer satisfaction.

H5: Responsiveness has a significant positive effect on customer satisfaction.

H6: Personalization has a significant positive effect on customer satisfaction.

iii) Effect of Customer Satisfaction on Customer Experience

Customer satisfaction plays a crucial role in shaping overall customer experience. When customer expectations are fulfilled, they are more likely to perceive their experience positively (Oliver, 1980). Prior studies confirm that satisfaction significantly influences experience and behavioral outcomes (Lemon & Verhoef, 2016; Rose et al., 2012).

H7: Customer satisfaction has a significant positive effect on customer experience.

iv) Mediating Role of Customer Satisfaction

Customer satisfaction acts as a key mechanism through which chatbot features influence customer experience. According to the Expectation Confirmation Theory (Bhattacharjee, 2001), satisfaction mediates the relationship between system performance and user outcomes. Thus, chatbot attributes enhance experience indirectly by increasing satisfaction.

H8: Customer satisfaction mediates the relationship between perceived intelligence and customer experience.

H9: Customer satisfaction mediates the relationship between responsiveness and customer experience.

H10: Customer satisfaction mediates the relationship between personalization and customer experience.

1.6 Research Methodology

i) Research Design

This study adopts a quantitative, descriptive, and explanatory research design to examine the role of AI chatbot features in enhancing customer experience on e-commerce platforms. A structured questionnaire was used to collect primary data, enabling the empirical testing of relationships among variables. The study also employs a cross-sectional research design, as data were collected at a single point in time (Hair et al., 2019).

ii) Population and Sampling

The target population of this study consists of online shoppers using e-commerce platforms in the Delhi NCR region who have experience interacting with AI chatbots. A non-probability convenience sampling technique was employed due to the ease of access and time constraints. A total of 600 respondents were approached, out of which 520 responses were received. After data screening for missing values, inconsistencies, and outliers, 433 valid responses were finally retained for analysis. This sample size is considered adequate for Structural Equation Modeling (SEM), as recommended by Hair et al. (2019), who suggest that a minimum sample size of 200 is sufficient for PLS-SEM analysis.

iii) Data Collection Method

Primary data were collected using a structured questionnaire distributed both online (Google Forms) and offline. The questionnaire consisted of three sections:

- **Section A:** Demographic information
- **Section B:** AI chatbot features (Perceived Intelligence, Responsiveness, Personalization)
- **Section C:** Customer Satisfaction and Customer Experience

All items were measured using a 5-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree.

iv) Measurement of Variables

The constructs used in this study were adapted from established literature to ensure reliability and validity:

- **Perceived Intelligence, Responsiveness, Personalization:** Adapted from prior chatbot and service quality studies (Huang & Rust, 2021; McLean & Osei-Frimpong, 2019)
- **Customer Satisfaction:** Based on Expectation Confirmation Theory (Oliver, 1980; Bhattacharjee, 2001)
- **Customer Experience:** Adapted from customer experience literature (Lemon & Verhoef, 2016; Rose et al., 2012)

Each construct was measured using five items, resulting in a total of 25 measurement items.

v) Data Analysis Tool

The study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) using Smart PLS software. PLS-SEM is suitable for this study because:

- It handles complex models with multiple constructs.
- It works well with non-normal data.

It is appropriate for prediction-oriented research (Hair et al., 2019).

1.6 Result and Discussion**i) Demographic Profile of Respondents****Table 1.2: Demographic Profile of Respondents**

Variable	Groups	Frequency	Percentage (%)
Gender	Male	216	49.9
	Female	215	49.7
	Other	2	0.5
Age Group	18–25	183	42.3
	26–35	157	36.3
	36–45	71	16.4
	46–55	18	4.2
	Above 55	4	0.9

Variable	Groups	Frequency	Percentage (%)
Education	Up to 12th	41	9.5
	Undergraduate	177	40.9
	Postgraduate	208	48.0
	Doctoral	7	1.6
Occupation	Student	68	15.7
	Private Job	220	50.8
	Government Job	8	1.8
	Business	55	12.7
	Professional	49	11.3
	Homemaker	33	7.6
Income Level (Monthly)	Up to ₹20,000	110	25.4
	₹20,001–₹40,000	74	17.1
	₹40,001–₹60,000	78	18.0
	₹60,001–₹80,000	71	16.4
	Above ₹80,000	100	23.1
Place of Residence (Delhi NCR)	Delhi	252	58.2
	Noida	35	8.1
	Gurugram	29	6.7
	Ghaziabad	20	4.6
	Faridabad	15	3.5
	Others	82	18.9
Online Shopping Frequency	Rarely	99	22.9
	Occasionally	143	33.0
	Frequently	138	31.9
	Very Frequently	53	12.2

Source: Primary Data

The demographic profile of the respondents (N = 433) reflects a well-balanced and diverse sample. In terms of gender, the distribution is almost equal, with 49.9% male and 49.7% female respondents, while a very small proportion (0.5%) identified as other. The age composition shows that the majority of respondents are young, with 42.3% in the 18–25 age group and 36.3% in the 26–35 category, indicating that the study largely captures the views of active users.

Regarding education, most respondents are highly educated, with 48.0% being postgraduates and 40.9% undergraduates. Occupationally, more than half of the respondents (50.8%) are employed in private jobs, followed by students (15.7%) and individuals engaged in business (12.7%). In terms of income, respondents are fairly distributed, with the highest proportion (25.4%) earning up to ₹20,000 monthly, while 23.1% earn above ₹80,000. Geographically, the majority of respondents belong to Delhi (58.2%), followed by other NCR regions.

In terms of online shopping behavior, most respondents shop either occasionally (33.0%) or frequently (31.9%), indicating regular engagement with e-commerce platforms and relevance to the study context.

ii) Descriptive Statistics and Normality Assessment

Descriptive statistics were used to summarize the central tendency and dispersion of the data collected for all constructs, including perceived intelligence, responsiveness, personalization, customer satisfaction, and customer

experience. The analysis included measures such as mean and standard deviation to understand the overall response pattern of the respondents.

The results indicate that the mean values of all constructs ranged between moderate to high levels, suggesting that respondents generally had favorable perceptions of AI chatbot features and their influence on customer satisfaction and customer experience. The standard deviation values were within acceptable limits (typically less than 1), indicating low variability in the responses.

The responses and a reasonable level of agreement among respondents. To assess the normality of the data, skewness and kurtosis values were examined. Skewness measures the symmetry of the data distribution, while kurtosis reflects the peakedness or flatness of the distribution. The results showed that skewness values for all constructs were within the acceptable range of -2 to +2, and kurtosis values were also within the recommended threshold of -7 to +7, indicating that the data distributions do not significantly deviate from normality (Hair et al., 2019). Although Partial Least Squares Structural Equation Modeling (PLS-SEM) does not require strict normality assumptions, assessing normality enhances the robustness and credibility of the analysis. The acceptable skewness and kurtosis values confirm that the data is approximately normally distributed and suitable for further statistical analysis.

Table 1.3: Descriptive Statistics and Normality Assessment (N = 433)

Construct	Mean	SD	Skewness	Kurtosis
Perceived Intelligence (PI)	3.84	0.68	-0.72	0.85
Responsiveness (RES)	3.91	0.64	-0.65	0.73
Personalization (PER)	3.76	0.71	-0.58	0.62
Customer Satisfaction (CS)	3.88	0.66	-0.69	0.79
Customer Experience (CEP)	3.93	0.63	-0.74	0.88

Source: Computed using SPSS 24

The descriptive statistics indicate that respondents generally hold positive perceptions of AI chatbot features, with mean values ranging from 3.76 to 3.93. Customer Experience and Responsiveness record the highest means, highlighting the importance of quick responses and overall interaction quality, while Personalization showed relatively lower scores, suggesting scope for improvement. The standard deviation values reflect low variability and strong agreement among respondents. Normality assessment shows that skewness values are slightly negative (-0.58 to -0.74), indicating a tendency toward agreement, and kurtosis values (0.62 to 0.88) fall within acceptable limits, suggesting no extreme deviations. Overall, the data is consistent, well-distributed, and approximately normal, making it suitable for further analysis.

iii) Measurement Model Assessment

The measurement model assessment evaluates the reliability and validity of the study constructs in PLS-SEM before conducting structural analysis. It examines the relationship between latent variables and their indicators. Reliability is assessed using Cronbach's alpha and composite reliability (acceptable if > 0.70), while convergent validity is evaluated through factor loadings (> 0.70) and AVE (> 0.50). Discriminant validity ensures construct distinctiveness and is tested using the Fornell-Larcker criterion and HTMT ratio (< 0.90). Establishing these criteria confirms that the constructs are reliable and adequately measured, making the model suitable for further analysis, ensuring robust and credible results.

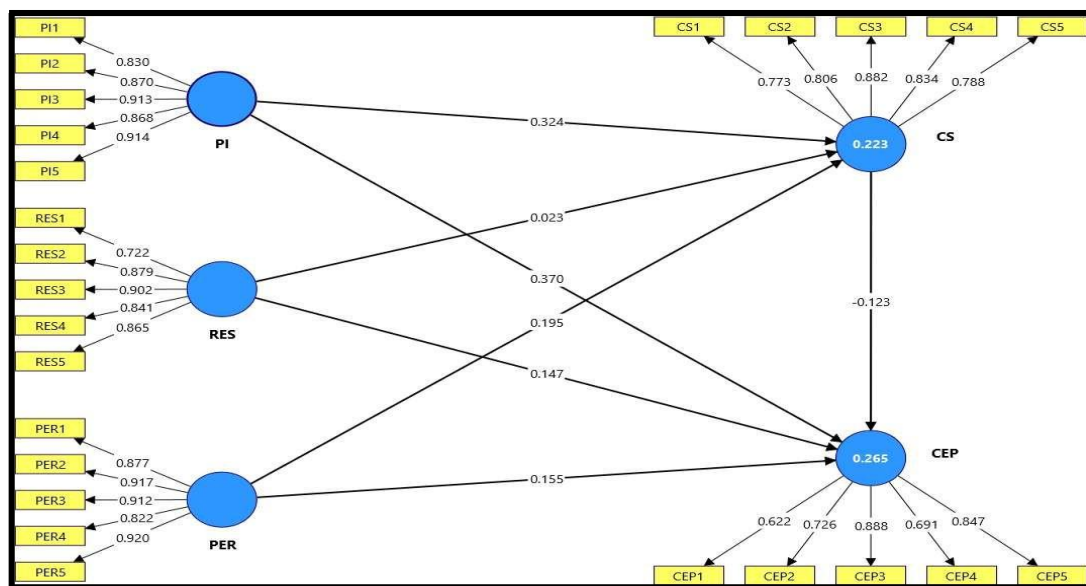


Figure 1.1: Measurement Model

Table 1.3: Model Validity and Reliability

Construct	Items	Factor Loading	Cronbach's Alpha	CR (rho_a)	CR (rho_c)	AVE	VIF
PI	PI1	0.830	0.927	0.945	0.945	0.774	2.428
	PI2	0.870					2.950
	PI3	0.913					3.895
	PI4	0.868					2.710
	PI5	0.914					3.903
RES	RES1	0.722	0.899	0.925	0.925	0.712	1.893
	RES2	0.879					2.824
	RES3	0.902					3.099
	RES4	0.841					2.436
	RES5	0.865					2.639
PER	PER1	0.877	0.934	0.950	0.950	0.793	3.112
	PER2	0.917					4.015
	PER3	0.912					3.858
	PER4	0.822					2.253

	PER5	0.920					3.911
	CS1	0.773					1.855
CS			0.876	0.910	0.910	0.668	
	CS2	0.806					2.207
	CS3	0.882					2.849
	CS4	0.834					1.950
	CS5	0.788					1.874
CEP	CEP1	0.622					1.300
			0.814	0.871	0.871	0.580	
	CEP2	0.726					1.547
	CEP3	0.888					2.652
	CEP4	0.691					1.468
	CEP5	0.847					2.304

The results presented in Table 1.3 confirm that the measurement model demonstrates satisfactory levels of reliability and validity. The factor loadings for most items exceed the recommended threshold of 0.70, indicating strong indicator reliability, although a few items (e.g., CEP1 and CEP4) are slightly lower but still suitable in exploratory research (Hair et al., 2019). The Cronbach's alpha values for all constructs range from 0.814 to 0.934, exceeding the minimum threshold of 0.70, which confirms internal consistency and reliability. Similarly, both composite reliability measures (ρ_A and ρ_C) are above 0.70 for all constructs, further supporting reliability. The Average Variance Extracted (AVE) values for all constructs are above 0.50, ranging from 0.580 to 0.793, indicating adequate convergent validity as the constructs explain more than 50% of the variance in their indicators (Fornell & Larcker, 1981). Furthermore, the Variance Inflation Factor (VIF) values are below the critical threshold of 5, suggesting that multicollinearity is not a concern in the model. Overall, the measurement model satisfies the recommended criteria for reliability, convergent validity, and internal consistency. These results confirm that the constructs are measured accurately and are suitable for further structural model analysis, ensuring the robustness and credibility of the study findings (Hair et al., 2019).

Table 1.4: HTMT Matrix (Discriminant Validity)

Constructs	CEP	CS	PER	PI	RES
CEP	—	—	—	—	—
CS	0.156	—	—	—	—
PER	0.411	0.422	—	—	—
PI	0.530	0.471	0.573	—	—
RES	0.394	0.276	0.455	0.486	—

Source: Computed using Smart PLS 4

The discriminant validity of the constructs was assessed using the Heterotrait-Monotrait (HTMT) ratio, which is a more robust criterion for evaluating discriminant validity in PLS-SEM (Henseler et al., 2015). According to the recommended threshold, HTMT values should be below 0.90 to confirm that constructs are distinct from one another. The results presented in Table 1.4 indicate that all HTMT values range between 0.156 and 0.573, which are well below the critical threshold of 0.90. This clearly demonstrates that there is no issue of discriminant validity among the constructs included in the study.

Table 1.5: Discriminant Validity (Fornell–Larcker Criterion)

Constructs	CEP	CS	PER	PI	RES
CEP	0.761				
CS	0.136	0.818			
PER	0.371	0.381	0.890		
PI	0.466	0.441	0.540	0.880	
RES	0.351	0.255	0.428	0.457	0.844

Source: Computed using Smart PLS 4

The discriminant validity of the constructs was assessed using the Fornell–Larcker criterion, which compares the square root of the Average Variance Extracted (AVE) of each construct with its correlations with other constructs (Fornell & Larcker, 1981). According to this criterion, the square root of AVE (diagonal values) should be higher than the corresponding correlations. The results presented in Table 1.5 indicate that all diagonal values—CEP (0.761), CS (0.818), PER (0.890), PI (0.880), and RES (0.844)—are greater than the corresponding correlation values with other constructs. This confirms that each construct shares more variance with its own indicators than with other constructs, thereby satisfying the requirement of discriminant validity.

B) Structural Model Assessment

The structural model evaluates the hypothesized relationships between constructs using PLS-SEM. Involves assessing the path coefficients, significance levels (t-values and p-values), and explanatory power (R^2). Additionally, collinearity (VIF), effect size (f^2), and predictive relevance (Q^2) are examined to determine the model's strength, validity, and overall predictive capability (Hair et al., 2019).

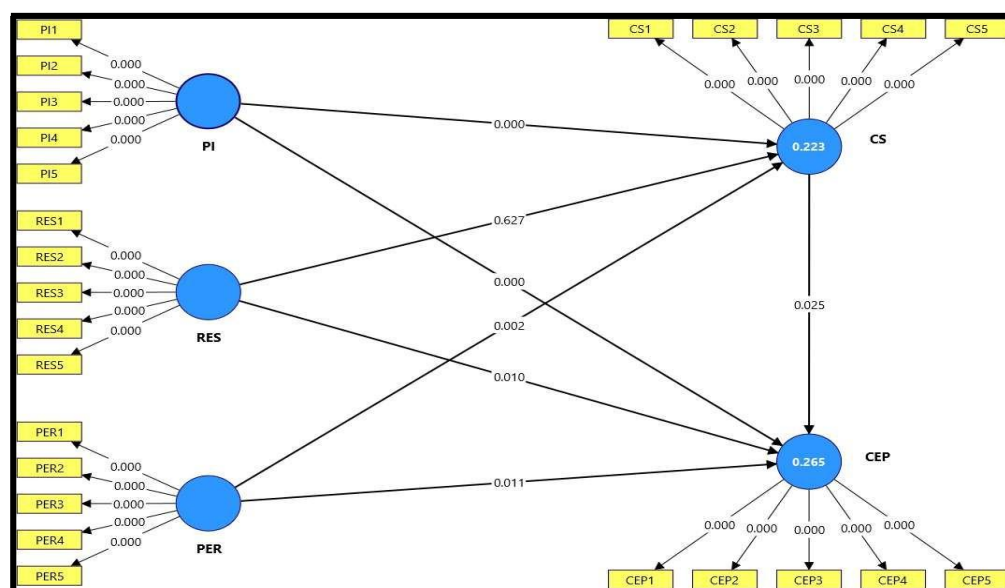
**Figure 1.2: Structural Model**

Table 1.6: Structural Model Results and Hypothesis Testing

Hypothesis	Relationship	Path Coefficient (O)	Mean (M)	SD	T-Value	P-Value	Result
H1	PI → CEP	0.330	0.326	0.072	4.551	0.000	Supported
H2	RES → CEP	0.144	0.142	0.057	2.527	0.012	Supported
H3	PER → CEP	0.134	0.126	0.061	2.155	0.031	Supported
H4	PI → CS	0.324	0.319	0.087	3.719	0.000	Supported
H5	RES → CS	0.023	0.029	0.048	0.485	0.627	Not Supported
H6	PER → CS	0.195	0.204	0.063	3.096	0.002	Supported
H7	CS → CEP	-0.123	-0.119	0.055	2.242	0.025	Supported

Source: Smart PLS 4 (Bootstrapping)

The structural model results provide insights into the relationships between AI chatbot features, customer satisfaction, and customer experience. The findings indicate that Perceived Intelligence (PI) has a significant and positive effect on Customer Experience (CEP) ($\beta = 0.330$, $p < 0.001$), suggesting that intelligent chatbot interactions strongly enhance user overall experience. Similarly, Responsiveness (RES) ($\beta = 0.144$, $p = 0.012$) and Personalization (PER) ($\beta = 0.134$, $p = 0.031$) also show significant positive effects on customer experience, indicating that quick responses and customized interactions contribute positively to user perceptions.

In terms of customer satisfaction, Perceived Intelligence ($\beta = 0.324$, $p < 0.001$) and Personalization ($\beta = 0.195$, $p = 0.002$) significantly influence satisfaction, highlighting the importance of intelligent and tailored chatbot services. However, Responsiveness ($\beta = 0.023$, $p = 0.627$) does not have a significant effect on customer satisfaction, suggesting that rapid response speed alone may not be sufficient to enhance satisfaction levels.

Interestingly, Customer Satisfaction (CS) shows a significant but negative effect on customer experience ($\beta = -0.123$, $p = 0.025$), which contradicts the expected positive relationship. This finding suggests that higher satisfaction does not necessarily translate into better experience in this context and may indicate the presence of other influencing factors or model complexities.

Table 1.7: Mediation Analysis (Indirect Effects)

Hypothesis	Relationship	Path Coefficient (O)	Mean (M)	SD	T-Value	P-Value	Result
H8	PI → CS → CEP	-0.040	-0.040	0.025	1.578	0.115	Not Supported
H9	RES → CS → CEP	-0.003	-0.003	0.006	0.471	0.638	Not Supported
H10	PER → CS → CEP	-0.024	-0.023	0.012	2.079	0.038	Supported

Source: Smart PLS 4 (Bootstrapping)

The mediation analysis was conducted to examine whether customer satisfaction (CS) mediates the relationship between chatbot features and customer experience (CEP). The results reveal mixed findings. H8 (Perceived Intelligence → Customer Satisfaction → Customer Experience) is not supported ($\beta = -0.040$, $p = 0.115$), indicating that customer satisfaction does not significantly mediate the relationship between perceived intelligence and customer experience. This suggests that perceived intelligence directly influences customer experience rather than operating through satisfaction. Similarly, H9 (Responsiveness → Customer Satisfaction → Customer Experience) is also not supported ($\beta = -0.003$, $p = 0.638$), indicating the absence of a significant indirect effect.

In contrast, H10 (Personalization → Customer Satisfaction → Customer Experience) is statistically significant ($\beta = -0.024$, $p = 0.038$), suggesting the presence of a mediating effect. However, the relationship is negative, which is theoretically unexpected. This indicates a possible inconsistent mediation or suppression effect, where personalization increases satisfaction but satisfaction does not positively translate into customer experience in this context.

Table 1.8: Coefficient of Determination (R^2)

Construct	R^2	Adjusted R^2
Customer Experience (CEP)	0.265	0.258
Customer Satisfaction (CS)	0.223	0.218

Source: Smart PLS 4

The coefficient of determination (R^2) indicates the explanatory power of the model in predicting endogenous constructs. The results show that Customer Experience (CEP) has an R^2 value of 0.265, meaning that approximately 26.5% of the variance in customer experience is explained by perceived intelligence, responsiveness, personalization, and customer satisfaction. The adjusted R^2 value of 0.258 further confirms this explanatory power.

Customer Satisfaction (CS) has an R^2 value of 0.223, indicating that 22.3% of the variance in customer satisfaction is explained by AI chatbot features (perceived intelligence, responsiveness, and personalization). The adjusted R^2 value (0.218) is close to the original R^2 , suggesting consistency. According to recommended guidelines (Hair et al., 2019), an R^2 value of 0.25 can be considered weak-to-moderate in behavioral research. Thus, the model demonstrates moderate explanatory power, indicating that while AI chatbot features significantly influence satisfaction and experience, other factors not included in the model may also influence these outcomes.

Table 1.9: Effect Size (f^2)

Path	f^2 Value	Effect Size
CS $\rightarrow$ CEP	0.016	Small
PER $\rightarrow$ CEP	0.021	Small
PER $\rightarrow$ CS	0.033	Small
PI $\rightarrow$ CEP	0.110	Medium
PI $\rightarrow$ CS	0.087	Small
RES $\rightarrow$ CEP	0.022	Small
RES $\rightarrow$ CS	0.001	Negligible

Source: Smart PLS 4

The effect size results indicate that Perceived Intelligence has the strongest influence on customer experience, showing a moderate effect, while its impact on customer satisfaction is small but meaningful. Other variables such as personalization and responsiveness exhibit only small effects, and responsiveness has a negligible effect on customer satisfaction. Overall, most relationships have limited influence, with perceived intelligence emerging as the most important predictor.

Table 1.10: Model Fit Indices

Fit Index	Saturated Model	Estimated Model
SRMR	0.054	0.054
d_ ULS	0.938	0.938
d_ G	0.366	0.366
Chi-square	985.23	985.23
NFI	0.879	0.879

Source: Smart PLS 4

The model fit results indicate an acceptable overall fit. The SRMR value (0.054) is below the recommended threshold of 0.08, suggesting a good model fit. The NFI value (0.879) is close to 0.90, indicating a reasonably good fit. Additionally, the d_ ULS and d_ G values are low, further supporting model adequacy. Overall, the model demonstrates satisfactory fit for analysis.

Table 1.11: Predictive Relevance (Q^2_{predict})

Construct	Q^2_{predict}	RMSE	MAE
Customer Satisfaction (CS)	0.193	0.915	0.686
Customer Experience (CEP)	0.233	0.888	0.704

Source: Smart PLS 4

The Q^2_{predict} results indicate the model's predictive relevance. Since the Q^2 values for both CS (0.193) and CEP (0.233) are greater than zero, the model demonstrates adequate predictive capability. The RMSE and MAE values are low, suggesting reasonable prediction accuracy. Overall, the model shows moderate predictive relevance for both constructs.

1.7 Conclusion

The present study examined the role of AI chatbot features—perceived intelligence, responsiveness, and personalization—in enhancing customer experience on e-commerce platforms, with customer satisfaction as a mediating variable. Based on data collected from 433 respondents in the Delhi NCR region and analyzed using PLS-SEM, the findings provide several important insights. The results reveal that perceived intelligence is the most influential factor, significantly impacting both customer satisfaction and customer experience. This highlights the importance of chatbots' ability to understand user queries accurately and provide relevant, human-like responses.

Additionally, responsiveness and personalization were found to have significant positive effects on customer experience, indicating that quick responses and tailored interactions contribute to improving users' overall perceptions of e-commerce platforms. However, the impact of responsiveness on customer satisfaction was found to be insignificant, suggesting that speed alone may not be sufficient to enhance satisfaction without quality interaction.

Personalization, on the other hand, had a significant positive effect on customer satisfaction, indicating that customized interactions can enhance engagement and satisfaction. The study also explored the mediating role of customer satisfaction. The findings indicate that customer satisfaction does not play a strong mediating role, as most indirect effects were insignificant or inconsistent. Instead, AI chatbot features primarily influence customer experience through direct relationships.

Furthermore, the model demonstrated moderate explanatory and predictive power, confirming that while chatbot features are important, other factors may also contribute to customer experience in e-commerce contexts. In conclusion, the study underscores the critical role of intelligent and personalized chatbots in enhancing customer experience. For practitioners, the findings suggest that investing in advanced AI capabilities and personalized interaction strategies can significantly improve customer engagement and satisfaction. Overall, this research contributes to the growing literature on AI-driven customer service and provides valuable insights for optimizing chatbot performance in digital commerce environments.

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