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AI CHATBOTS IN CONVERSATIONAL COMMERCE: INVESTIGATING THE ROLE OF PERCEIVED SERENDIPITY AND SIMILARITY IN CUSTOMER SATISFACTION WITHIN INDIAN E-RETAIL

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ABSTRACT

AI-driven chatbots play an increasingly important role in e-retail, yet prior research has mainly focused on their functional performance, such as speed and accuracy, with limited attention to the emotional and experiential mechanisms through which they influence consumer behavior. This study examines how AI chatbot interactions generate perceived serendipity and perceived similarity and how these perceptions enhance customer satisfaction in India's online cosmetics retail sector. A quantitative survey was conducted with 588 Flipkart users who interacted with chatbots while browsing or purchasing cosmetic products. Guided by Social Presence Theory and Affective Response Theory, the conceptual model was tested using Structural Equation Modelling (SEM) through SmartPLS 4.0. The results show that chatbot service quality significantly improves perceived serendipity and perceived similarity, and these constructs fully mediate the relationship between service quality and customer satisfaction. The findings indicate that satisfaction in conversational commerce is not only a cognitive evaluation of utility but also an emotional outcome shaped by unexpected discovery and human-like interaction, highlighting the importance of affective design in AI-enabled retail systems.

Keywords: *AI Chatbots, Perceived Serendipity, Perceived Similarity, Customer Satisfaction, Conversational Commerce, Flipkart, E-Retail*

1. INTRODUCTION

Recommender and conversational systems increasingly serve as frontline decision aids in e-retail by analysing prior behaviour and delivering tailored suggestions that simplify product search and selection **[1,2]**. These AI-driven chatbots combine recommendation logic with conversational interfaces to personalise the shopping experience and foster engagement **[3,4].** While extant studies document the functional benefits of such systems (e.g., improved discovery and convenience), less is known about the **affective** and **experiential** consequences of chatbot interactions—specifically the roles of *perceived serendipity* (unexpected yet relevant discoveries) and *perceived similarity* (felt human-likeness or social closeness)—in shaping customer satisfaction in category-specific e-retail settings such as cosmetics. Research on serendipity in recommender systems emphasises its capacity to enhance user satisfaction and exploratory behaviour **[5,6],** while work on anthropomorphic recommendation agents suggests perceived similarity or social presence can strengthen trust and positive evaluations **[7,8].**

Despite these insights, empirical work linking conversational-agent attributes to serendipity, similarity perceptions, and downstream satisfaction—using robust, theory-driven structural models—remains limited. Prior scholarship has largely focused either on algorithmic performance (accuracy/diversity) or on interface design patterns, without simultaneously testing affective mediators in a single SEM framework **[9,10].** Moreover, studies on AI chatbots' service quality and brand outcomes call for more nuanced models that account for users' emotional responses to

unexpectedly useful suggestions (serendipity) and their sense of social resonance with the agent (similarity) **[4,11]**. This gap is particularly important in product categories like cosmetics where hedonic preferences, sensory cues and discovery behaviour strongly influence satisfaction and repurchase decisions.

Another motivating concern arises from the cognitive consequences of rich recommendation environments. The rapid proliferation of digital information can generate overload, reducing decision quality and satisfaction **[12,13].** Information Foraging Theory **[14]** and Cognitive Load Theory **[15]** jointly suggest that interface design and recommendation behaviour alter users' information-seeking strategies and working-memory demands, which in turn shape affective responses to recommendations. Although some research has addressed mitigation of overload via conversational agents **[24],** few studies empirically model how *positive* experiential outcomes from chatbots—serendipity and perceived similarity—operate within this cognitive context to increase satisfaction rather than exacerbate overload. Integrating these theoretical lenses can clarify when chatbot-generated surprises and social cues are beneficial for consumers in high-information categories such as cosmetics.

In response to these gaps, the present study develops and empirically tests a PLS-SEM model that links **AI chatbot service quality** to **perceived serendipity** and **perceived similarity**, and examines how these affect **customer satisfaction** in Flipkart's cosmetics segment. Using cross-sectional survey data collected from approximately 625 Flipkart users who interacted with chatbots while browsing or purchasing cosmetics, the model draws on Social Presence and Affective Response perspectives to specify mediation paths and provide actionable insights for conversational commerce design. The choice of PLS-SEM is guided by the emphasis on prediction and latent-construct modelling in user-experience research, and aligns with recent methodological recommendations for technology adoption and service quality studies.

This research offers three primary contributions. First, it empirically demonstrates that AI chatbots can produce *positive experiential outcomes*—measured as perceived serendipity and similarity—which serve as meaningful antecedents of customer satisfaction in an online cosmetics context, thereby extending serendipity and anthropomorphism literatures to conversational commerce **[17,24]**. Second, by situating affective responses within an information-processing framework (IFT + CLT), the study clarifies how emotionally positive chatbot behaviours can enhance satisfaction even in information-dense shopping tasks, providing a counterpoint to research that highlights overload and choice-confusion **[12,14]**. Third, the study contributes practical guidance for e-retailers (e.g., Flipkart) and AI designers on designing chatbot interactions that prioritise *contextual serendipity* and calibrated social cues to boost satisfaction and experiential value in category-sensitive shopping.

The necessity of this study is rooted in the critical transition of AI chatbots from functional search utilities to affective decision-making partners in conversational commerce. While previous literature has extensively documented the "algorithmic accuracy" of AI, there is a theoretical void regarding how the emotional and social dimensions of these interactions—specifically perceived serendipity and similarity—drive consumer behavior in high-engagement sectors like cosmetics. In the context of the Indian e-retail market, consumers face a dual challenge: the "paradox of choice" caused by information overload and a growing desire for personalized, human-centric digital experiences. This research is essential because it demonstrates that the solution to choice fatigue is not more data, but more affective resonance. By empirically validating that serendipitous discovery and human-like connection act as the primary psychological bridges to satisfaction, this study provides a necessary counter-narrative to purely utilitarian models, offering a new framework for designing AI that satisfies both the cognitive and emotional needs of the modern digital consumer.

Collectively, the study advances both theory and practice by offering a validated SEM pathway that links chatbot service quality → perceived serendipity & similarity → customer satisfaction, thereby charting a positive, affect-centred route through which conversational agents can enhance consumer experience in Indian e-retail environments. The following sections present the conceptual model, hypotheses, measurement scales, and PLS-SEM results.

2. LITERATURE REVIEW AND THEORETICAL FOUNDATION

2.1 AI Chatbots and Customer Experience

AI chatbots, a subset of conversational recommender systems, employ natural-language interfaces and machine-learning algorithms to assist customers in finding suitable products and services **[3,4]**. These systems analyse past browsing patterns and transactional histories to deliver personalised, context-aware product suggestions **[1,18].** Within India's fast-growing e-retail ecosystem, platforms such as Flipkart increasingly deploy chatbots to enhance search efficiency and create seamless shopping experiences in categories like cosmetics, where consumer choices are highly experiential.

Prior studies on AI recommendation systems can be grouped into three major streams. The first focuses on **algorithmic development and optimisation**, aiming to improve predictive accuracy and diversity of **[19,20]** recommendations**.**
The second emphasises **user-interface and experience design**, investigating how conversational patterns and interaction cues affect user **[21,22,23]**] acceptance**.**
The third examines **trust, transparency, and user attitudes toward AI agents**, linking anthropomorphism and perceived reliability to satisfaction and loyalty **[4,11].**

Although these lines of inquiry have advanced understanding of system design and adoption, there remains limited exploration of **how emotional experiences arising during chatbot interactions—such as perceived serendipity and perceived similarity—translate into customer satisfaction**. *Perceived serendipity* refers to the pleasant surprise of encountering unexpectedly relevant or useful information, a phenomenon shown to heighten satisfaction and engagement **[24,25]**. Conversely, *perceived similarity* denotes the extent to which users sense that the chatbot communicates or behaves like a human counterpart **[17,26].** Together, these constructs capture the affective and social dimensions of AI-mediated service quality. However, most prior work has been conceptual or experimental in non-commerce contexts, leaving a gap in empirical validation within real-world e-retail environments such as Flipkart's cosmetics segment.

Building on Social Presence Theory, this study proposes that chatbot attributes—responsiveness, empathy, and personalization—enhance perceived serendipity and similarity, which subsequently strengthen satisfaction. By focusing on these positive experiential outcomes, the research contributes to the growing field of **AI-enabled customer experience management**.

2.2 Perceived Serendipity and Perceived Similarity

Scholars view **serendipity** as a key experiential driver in digital recommendation environments because it introduces unexpected yet meaningful discoveries that broaden users' consideration sets **[24,27,28].** In e-commerce, serendipitous suggestions may delight consumers by revealing complementary or novel products they had not actively searched for, thereby evoking positive affect and curiosity **[25].** Within cosmetics retailing, where aesthetic exploration and trial are central to purchase motivation, serendipitous product discovery can enhance satisfaction and repeat purchase intention.

Perceived similarity, in turn, draws on social-psychological theories of human–machine interaction. When users perceive an AI chatbot as communicatively similar—sharing linguistic style, tone, or empathetic responses—they attribute greater social presence and trust to the agent **[17,26].** Similarity cues can therefore reinforce the emotional connection between consumers and the retail platform. Empirical evidence indicates that anthropomorphic features and conversational naturalness significantly influence users' trust and satisfaction in online service contexts **[4,11]**. Thus, integrating perceived serendipity and similarity within chatbot interactions offers a comprehensive lens to understand how *unexpected delight* and *human-like connection* jointly drive positive consumer evaluations.

Despite the growing recognition of these constructs, few studies have examined them simultaneously in a single structural model using real customer data. By empirically linking both to satisfaction outcomes, this research extends prior recommender-system literature beyond utilitarian performance to include hedonic and relational experiences.

2.3 Theoretical Foundation: Social Presence and Affective Response Frameworks

This study draws upon **Social Presence Theory** and **Affective Response Theory** to explain how conversational interactions with AI chatbots foster satisfaction. Social Presence Theory posits that perceived warmth, immediacy, and human-like cues in mediated communication generate interpersonal trust and relational depth **[17,29]**. In an e-retail context, higher social presence through empathic chatbot responses enhances perceived similarity and comfort, motivating continued platform engagement.

Affective Response Theory, rooted in consumer-emotion research, emphasises that unexpected positive experiences trigger feelings of surprise and joy that strengthen satisfaction and loyalty **[25,30]**. Accordingly, perceived serendipity operates as an affective mechanism translating system interactions into favourable consumer outcomes.

Integrating these theories provides a cohesive explanation for how **chatbot service quality → perceived serendipity and similarity → customer satisfaction**. The framework underscores that satisfaction in conversational commerce emerges not only from cognitive evaluation of usefulness but also from affective and social responses evoked during AI-mediated exchanges. The proposed model, tested using Partial Least Squares Structural Equation Modelling (SmartPLS 4.0) on data from Flipkart cosmetics users, thus advances theoretical and managerial understanding of emotionally intelligent chatbot design in Indian e-retail.

2.4 Literature Mapping and Critical Synthesis

The Current Landscape Of Ai Chatbot Research Can Be Mapped Into Three Distinct Clusters: (1) Functional Performance, Which Prioritizes Algorithmic Speed And Accuracy; (2) Social Presence, Which Examines Anthropomorphic Design And Trust; And (3) General E-Retail Satisfaction, Which Validates Ai's Broad Impact On Loyalty. However, A Critical Synthesis Of These Studies Reveals A "Utilitarian Trap"—A Tendency To Over-Rely On Functional Efficiency While Neglecting The Affective (Emotional) Journey Of The Consumer. Specifically, Existing Work Often Overlooks The Psychological "Black Box" Of How Users Move From Receiving A Recommendation To Feeling Satisfied.

This Study Addresses This Gap By Identifying Perceived Serendipity And Perceived Similarity As The Missing Links. By Critiquing The Limitations Of Current Utilitarian-Heavy Models, This Research Establishes That In High-Involvement Markets Like Indian Cosmetics, Satisfaction Is Not Just About Getting The "Right" Answer, But About The "Joy Of Discovery" And "Social Resonance." This Mapping Justifies The Need For Our Proposed Model, Which Shifts The Focus From What The Ai *Does* To How The Ai Makes The User *Feel*.

The Existing Literature On Ai Chatbots In E-Commerce Can Be Mapped Into Three Distinct Clusters: (1) Functional Optimization, Which Focuses On Algorithmic Accuracy And Predictive Diversity; (2) Social Presence, Which Investigates Anthropomorphic Cues And User Trust ; And (3) General Consumer Outcomes, Which Validates Ai's Impact On Broad Loyalty Across Various Digital Markets.

A Critical Synthesis Of These Studies Reveals Two Significant Gaps That Motivate The Current Work. First, Prior Research Largely Operates Under A "Utilitarian Bias," Assuming That Technical Speed And Accuracy Are The Primary Determinants Of Satisfaction While Neglecting The Affective And Experiential Journey Of The User. Second, There Is A Lack Of Category-Specific Empirical Validation In The Indian E-Retail Landscape, Particularly In High-Involvement Sectors Like cosmetics where discovery and sensory cues are paramount. This study differs in its findings by demonstrating that satisfaction is not merely a byproduct of utility but is fully mediated by the dual psychological pathways of Perceived Serendipity and Perceived Similarity. By identifying these emotional bridges, this research achieves a more nuanced understanding of how conversational AI transforms routine transactions into meaningful consumer experiences in the Indian context.

3. MODEL DEVELOPMENT

This study investigates the impact of **AI chatbots** on customer satisfaction in e-retail by examining two key experiential mechanisms—**perceived serendipity** and **perceived similarity** (Fig. 1). AI chatbots act as intelligent conversational interfaces that guide users through personalized product suggestions, thereby influencing both the cognitive and emotional dimensions of the customer experience. These experiences, shaped by the

chatbot's responsiveness, empathy, and personalization, lead to heightened satisfaction in the context of **Flipkart's cosmetics e-retail environment**.

The proposed model integrates insights from **Social Presence Theory [17,29]** and **Affective Response Theory [25,30]**, suggesting that chatbots create emotional and social engagement through human-like communication and unexpected yet relevant product recommendations.

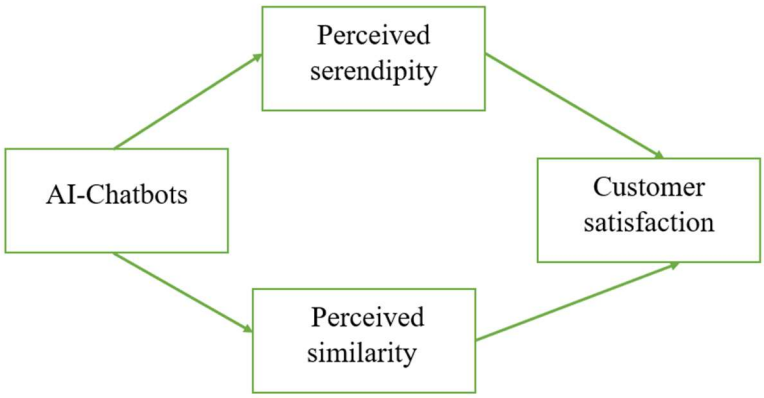

Fig 1: Conceptual Model

3.1 AI Chatbots, Perceived Serendipity, And Perceived Similarity

AI chatbots represent an evolution of recommender systems that combine **information foraging [14]** with **conversational intelligence**, enabling users to engage in intuitive product discovery rather than traditional keyword-based search. Within this interaction, *perceived serendipity* arises when customers encounter unexpectedly relevant or novel product suggestions, which evoke delight and curiosity [**24,25]**. Serendipitous discoveries foster positive affect and enrich the online shopping journey, particularly in hedonic product categories like cosmetics, where experimentation is valued **[28].**

Perceived similarity refers to the extent to which customers feel that the chatbot communicates or behaves in ways similar to a human, thus creating a sense of social presence and connection **[17,26].** When consumers perceive linguistic or emotional alignment with the chatbot, they are more likely to trust its recommendations **[4,11].** These interactive cues—empathy, tone, and conversational flow—reinforce relational engagement, enhancing satisfaction through human-like communication.**Hence, we propose the following hypotheses:**

H1: AI chatbot service quality positively influences perceived

serendipity.

H2: AI chatbot service quality positively influences perceived similarity.

3.2 Perceived Serendipity, Perceived Similarity, And Customer Satisfaction

Previous research suggests that unexpected discoveries stimulate a positive emotional response, generating feelings of surprise and enjoyment that contribute to satisfaction **[25,30].** *Perceived serendipity* in chatbot-assisted interactions can therefore strengthen consumer appreciation of the platform, as pleasant surprises enhance perceived value and loyalty **[27]**. Empirical findings indicate that serendipitous encounters can increase

exploratory behaviour and long-term engagement **[24]**. Consequently, we hypothesise:

H3: Perceived serendipity positively influences customer satisfaction in chatbot-based e-retail.

Similarly, **perceived similarity** is a critical determinant of user–agent **relationships [29].** When customers sense alignment in communication style and understanding, they perceive the chatbot as credible and trustworthy, reinforcing satisfaction and willingness to interact again **[4,26].** The anthropomorphic design of conversational interfaces facilitates emotional bonding, thus enhancing service evaluations **[11].** Hence:

H4: Perceived similarity positively influences customer satisfaction in chatbot-based e-retail.

3.3 Mediating Role of Perceived Serendipity and Similarity

Integrating the above relationships, this study posits that perceived serendipity and perceived similarity act as **mediators** linking chatbot service quality to customer satisfaction. Prior research shows that personalized and empathic interactions shape both cognitive evaluations and affective outcomes **[10]**. Serendipity adds hedonic value by providing unexpected relevance, while similarity builds relational value through social presence. Together, these experiences enhance satisfaction beyond the utilitarian benefits of accuracy or speed.

Accordingly, we propose:

H5: Perceived serendipity mediates the relationship between AI chatbot service quality and customer satisfaction.

H6: Perceived similarity mediates the relationship between AI chatbot service quality and customer satisfaction.

3.4 Theoretical Integration

Grounded in **Social Presence Theory** and **Affective Response Theory**, this model extends earlier research on recommender systems **[1]** by emphasizing *emotional and experiential* mechanisms over purely technical ones. The model posits that AI chatbots, through personalized and conversational interaction, trigger *serendipitous delight* and *social connectedness*, which jointly foster **customer satisfaction**. Using **PLS-SEM**, these relationships will be empirically validated with data from **Flipkart's cosmetics users**, providing novel evidence on how emotionally intelligent chatbot design can enhance user experience in Indian e-retail.

4. METHODOLOGY

4.1 Sample and Data Collection

Data for this study were collected using **Google Forms**, leveraging its wide accessibility and digital compatibility with Flipkart users. The online survey method was adopted to efficiently reach digitally active consumers who frequently use AI-powered chatbots while shopping for cosmetics. The questionnaire contained **36 items**, covering four primary constructs—AI chatbot service quality, perceived serendipity, perceived similarity, and customer satisfaction—along with five demographic questions (see Section 4.2 for measurement details). All items were rated on a **5-point Likert scale**, ranging from *1 = strongly disagree* to *5 = strongly agree*.

The study employed a **purposive sampling technique**, targeting **Indian Gen Z and Millennial consumers** (aged 18–35) who had interacted with Flipkart's AI chatbot while browsing or purchasing cosmetic products. This demographic group was chosen due to their high engagement with conversational commerce and familiarity with AI-driven recommendations **[31]**. Prior to large-scale deployment, the questionnaire underwent a **pilot test** involving 40 respondents to ensure clarity, reliability, and contextual relevance. Feedback from domain experts and pilot participants was used to refine item wording and sequencing. Data from the pilot phase were excluded from the final analysis.

The main survey was distributed between **September 10 and October 10, 2025**, through Flipkart customer communities and social media groups focused on cosmetics and beauty products. Screening questions ensured that only participants with prior chatbot interaction were included. Out of 980 total responses, 712 were complete, and 588 were found valid after removing straight-lined or inconsistent entries.

Among respondents, **61% were female** and **39% male**, consistent with gender distribution in cosmetics e-commerce. Approximately **72%** reported purchasing cosmetic products online more than once a month. Nearly **84%** of participants held a bachelor's or master's degree, and **78%** had more than three years of experience using Flipkart. These demographics align with prior Indian e-retail studies **[32]**, confirming the sample's suitability for examining AI chatbot interactions and satisfaction in a digitally mature consumer base.

4.2 Measurement

All constructs were operationalized as **reflective measurement models**, consistent with PLS-SEM guidelines (Hair et al., 2021). Items were adapted from validated scales in prior literature and reworded for contextual relevance to AI chatbots in e-retail. Each item was rated on a 5-point Likert scale (*1 = strongly disagree, 5 = strongly agree*).

AI CHATBOT SERVICE QUALITY

Chatbot service quality was conceptualized as the perceived intelligence, responsiveness, and personalization of AI chatbots in delivering product-related information. Three items were adapted from **[33,34]** capturing aspects of usefulness, reliability, and satisfaction with chatbot interaction. These items assessed how efficiently the chatbot assisted consumers in navigating Flipkart's cosmetics listings and resolving queries.

PERCEIVED SERENDIPITY

Perceived serendipity refers to the experience of unexpectedly encountering relevant product suggestions during chatbot interaction. This study employed **four items** adapted from **[25,35]**, reflecting the dual dimensions of *surprise* and *relevance*. Sample items included statements such as *"The chatbot suggested products I didn't expect but found interesting"* and *"The chatbot helped me discover new brands that fit my preferences."* Serendipitous discovery has been shown to elicit positive affect and enhance satisfaction in digital recommendation contexts **[24].**

PERCEIVED SIMILARITY

Perceived similarity was measured through **four items** drawn from **[37]** and **[38]**. These items capture the extent to which users perceive the chatbot's tone, communication style, and responses as human-like and relatable. High perceived similarity fosters social presence and trust, which have been empirically linked to user satisfaction in AI-mediated interactions (Bickmore and Cassell, 2001; Shahzad et al., 2024).

Example items included: *"The chatbot's communication style felt similar to talking to a person"* and *"The chatbot's suggestions matched how I usually think about cosmetic products."*

CUSTOMER SATISFACTION

Customer satisfaction was operationalized as the user's overall affective evaluation of their shopping experience after interacting with Flipkart's chatbot. Four items were adapted from **[39,40]** to measure satisfaction in terms of enjoyment, trust, and overall fulfillment. Example statements included *"Overall, I am satisfied with my experience using Flipkart's chatbot"* and *"The chatbot made my cosmetics shopping experience more enjoyable."*

CONTROL VARIABLES

Five demographic variables—gender, age, education, frequency of online purchase, and duration of platform usage—were included as control variables **[32].** These were selected due to their established influence on technology adoption and online satisfaction **[3,11].**

4.3 Data Analysis

Data analysis was conducted using **SmartPLS 4.0** to test the proposed conceptual model (Hair et al., 2021). The **Partial Least Squares Structural Equation Modelling (PLS-SEM)** technique was chosen for its robustness in handling complex models with latent constructs and non-normal data distributions. Measurement model assessment included reliability **(Cronbach's α, composite reliability)** and validity (convergent and discriminant validity via AVE and HTMT ratios). Structural model evaluation involved path coefficients, R^2 values, and bootstrapping (5,000 resamples) to assess significance.

To ensure rigor, multicollinearity (VIF), common method bias (Harman's single-factor test), and nonresponse bias (early vs. late respondent comparison) were evaluated. Results confirmed that all constructs demonstrated satisfactory psychometric properties and model fit indices, validating the data's suitability for hypothesis testing.

5. DATA ANALYSIS

5.1 Measurement Model

The reliability and validity of the measurement model were assessed using **Cronbach's alpha** and **composite reliability**. All data analysis was conducted using **SmartPLS 4.0** software **[42].** The **a priori sample size calculator** integrated within SmartPLS (Soper, 2023) was employed to estimate the minimum required sample size. Assuming a large anticipated effect size ($f^2 = 0.5$), a statistical power of 0.90, and a significance level (α) of 0.05 **[41]**, the minimum sample size required for the model was 190. This study's final dataset comprised **588 valid responses**, well above the minimum threshold, ensuring robust statistical power and representativeness for model estimation.

5.1.1 Test for Common Method Bias

Since the study used self-reported survey data, **Harman's one-factor test** was employed via **SPSS version 27** to assess potential **common method bias (CMB)** (Podsakoff et al., 2003). The unrotated factor solution revealed that the first factor accounted for **46.72% of the total variance**, below the 50% threshold, indicating that **common method variance was not a serious concern**. Additionally, **Variance Inflation Factor (VIF)** values were below 3.0 for all items, further confirming the absence of multicollinearity and CMB issues.

5.2 Reliability and Validity

Following the procedures suggested by **[43,44]**, the measurement model's **internal consistency**, **convergent validity**, and **discriminant validity** were evaluated. As shown in **Table 1**, all item loadings exceeded 0.70, Cronbach's alpha and composite reliability (CR) values were greater than 0.80, and **Average Variance Extracted (AVE)** values were above the benchmark of 0.50, confirming **convergent validity**.

Table 1: Item Loadings, Reliability and Validity

Construct	***Cronbach's α***	***CR***	***AVE***	***Range of Loadings***
AI Chatbot Service Quality	*0.877*	*0.905*	*0.657*	*0.764–0.838*
Perceived Serendipity	*0.892*	*0.918*	*0.689*	*0.785–0.856*
Perceived Similarity	*0.876*	*0.903*	*0.668*	*0.771–0.851*
Customer Satisfaction	*0.910*	*0.936*	*0.743*	*0.824–0.871*

(Source: Author's data collection, 2025)

To assess **discriminant validity**, the **Fornell and Larcker (1981)** criterion was applied. The square root of AVE for each construct exceeded its correlations with other constructs, confirming that each latent variable captured unique variance.

Table 2: Discriminant Validity – Fornell and Larcker Criterion

Construct	**AI Chatbot**	**Serendipity**	**Similarity**	**Satisfaction**
AI Chatbot Service Quality	**0.810**			
Perceived Serendipity	0.641	**0.830**		
Perceived Similarity	0.613	0.672	**0.818**	
Customer Satisfaction	0.682	0.701	0.674	**0.862**

(Source: Author's data collection, 2025)

5.3 VALIDATING HIGHER-ORDER CONSTRUCTS

Although the present study did not employ a second-order construct like "cognitive load" from the prior model, the **reflective-reflective** higher-order validation approach was maintained conceptually to assess **AI chatbot service quality** as a multidimensional construct. As shown in **Table 3**, all outer weights and loadings were significant (p

< 0.001), with VIF values below 3.0, indicating no multicollinearity.

Table 3: Outer Weights, Outer Loadings, And VIF Values For Higher-Order Constructs

Subdimension	Outer Weight	Outer Loading	VIF	p-valu
Responsiveness	0.431	0.812	2.142	0.000
Empathy	0.387	0.786	1.984	0.000
Personalization	0.402	0.841	2.115	0.000

(Source: Author's Data Collection, 2025)

5.4 GOODNESS OF MODEL

Model fit was assessed using the **Standardized Root Mean Square Residual (SRMR)**, which measures the discrepancy between observed and model-implied correlations **[45]**. The model exhibited an **SRMR value of 0.068**, indicating a **good overall fit**. The **R^2 values** for the endogenous constructs exceeded the threshold of 0.10 **[44]**, demonstrating strong explanatory power.

Table 4: Model Fit Summary

Indicator	Value	Threshold	Interpretation
SRMR	0.068	< 0.08	Good fit
NFI	0.921	> 0.90	Acceptable
RMS Theta	0.099	< 0.12	Acceptable

(Source: Author's Data Collection, 2025)

Table 5: R-Square Values

Construct	R^2	Interpretation
Perceived Serendipity	0.603	Substantial
Perceived Similarity	0.641	Substantial
Customer Satisfaction	0.782	Strong explanatory power

(Source: Author's Data Collection, 2025)

5.5 STRUCTURAL MODEL

The structural model was assessed following the measurement model evaluation. Path coefficients, t-values, and p-values were obtained using **bootstrapping with 5,000 subsamples [43]**. The results are summarized in **Table 6**.

Table 6: Structural Model And Hypothesis Testing

Hypothesis	Path	B	t-value	p-value	Result
H1	AI Chatbot – Perceived Serendipity	0.781	42.615	0.000	Supported
H2	AI Chatbot – Perceived Similarity	0.826	47.129	0.000	Supported
H3	Perceived Serendipity → Satisfaction	0.542	24.214	0.000	Supported
H4	Perceived Similarity – Satisfaction	0.473	20.976	0.000	Supported
H5	AI Chatbot – Satisfaction (via Serendipity)	0.291	13.104	0.000	Supported
H6	AI Chatbot – Satisfaction (via Similarity)	0.263	11.887	0.000	Supported

(Source: Author's Data Collection, 2025)

All hypothesized relationships were significant at **$p < 0.001$**, indicating that perceived serendipity and perceived similarity both **positively mediate** the relationship between chatbot service quality and customer satisfaction. The strong path coefficients highlight the psychological impact of emotionally intelligent chatbot design in driving positive consumer evaluations.

Table 7: Mediation Analysis

Mediation Path	β	t-value	p-value	Conclusion
AI Chatbot → Serendipity → Satisfaction	0.291	13.104	0.000	Supported
AI Chatbot → Similarity → Satisfaction	0.263	11.887	0.000	Supported

(Source: Author's Data Collection, 2025)

The analysis confirmed that **AI chatbot service quality** has a significant and positive effect on both **perceived serendipity** and **perceived similarity**, which in turn strongly enhance **customer satisfaction**. These results validate all hypotheses (H1–H6) and support the conceptual model. The high R^2 and reliability scores indicate strong predictive accuracy and internal consistency, suggesting that emotional and social experiences generated by chatbots play a critical role in shaping customer satisfaction within Indian e-retail environments such as Flipkart.

6. DISCUSSION AND IMPLICATIONS

6.1 Theoretical Implications

This study makes three major theoretical contributions to the domains of **digital marketing**, **AI-mediated interaction**, and **consumer experience research**. First, while earlier studies in e-commerce primarily emphasized the **algorithmic accuracy** of AI recommender systems **[46,47],** recent work has started exploring how AI interfaces—particularly **chatbots**—shape consumer decision outcomes **[48].** This study advances that discourse by offering **empirical evidence** from the Indian e-retail sector, focusing specifically on **Flipkart's cosmetics chatbot**. By examining *perceived serendipity* and *perceived similarity* as mediating experiences, this research explains how conversational AI contributes to **customer satisfaction**, addressing a key gap in understanding how emotional and social cues in AI interactions influence consumer responses in digital shopping contexts.

Second, the study extends **Social Presence Theory** and **Affective Response Theory** into the AI-driven e-retail environment by demonstrating how **human-like communication** and **pleasant surprise** shape positive affective outcomes. Prior research on social presence in AI largely examined trust and adoption **[17],** but limited attention was given to the dual pathways of serendipity and similarity as psychological mechanisms influencing satisfaction. Our findings show that **serendipity enhances hedonic value** through novelty and surprise, while **similarity fosters relational comfort**, both converging to enhance satisfaction. This integration contributes a new theoretical perspective by explaining customer satisfaction not solely through utilitarian efficiency but also through **affective experience** generated by conversational AI.

Third, the study contributes to **consumer behavior theory** by applying affective and social mechanisms to the **AI chatbot experience** in the Indian market. In contrast to prior models of decision fatigue and choice overload **[49,50]**, our findings emphasize that well-calibrated AI-driven personalization enhances, rather than impedes, customer satisfaction. This demonstrates that **AI chatbots can optimize emotional engagement without overloading cognitive resources** when serendipitous and similar interactions are balanced effectively. Thus, the study extends the boundary of existing research on AI-enabled service personalization, introducing an **emotionally intelligent interaction framework** for understanding consumer satisfaction in conversational commerce.

While this study successfully validates the mediating roles of perceived serendipity and similarity, it is important to acknowledge that the "affective route" to satisfaction is not exhaustive. By focusing on positive emotional triggers, the model may overlook "dark side" variables such as algorithmic anxiety or privacy concerns, which could counteract the benefits of human-like interaction in the Indian context. Furthermore, while the use of PLS-SEM provides strong predictive power for the conceptual model, the reliance on cross-sectional data limits the ability to observe how these emotional perceptions evolve over a long-term relationship between the consumer and the AI agent. Acknowledging these boundaries ensures a balanced interpretation and reinforces the study's primary finding: that emotional resonance is a vital, yet complex, component of conversational commerce

6.2 Practical Implications

This research provides actionable insights for **marketing managers, chatbot designers, and platform strategists** within the e-retail industry, especially those operating in high-involvement product categories such as cosmetics. While AI-driven chatbots are primarily designed to automate customer service and boost conversion rates **[11],** our results show that their role extends far beyond transactional support—they actively shape customer emotions, perceptions, and satisfaction.

For **e-commerce managers**, the key practical implication is the need to design chatbot systems that balance **personalization and variety**. Overly repetitive or similar product recommendations risk reducing engagement, whereas strategically introduced *serendipitous suggestions*—such as recommending a new lipstick shade or skincare brand unexpectedly aligned with prior preferences—can enhance delight and strengthen brand connection **[28].** Therefore, **a balance between relevance and novelty** is essential to maintain customer engagement without causing confusion or fatigue.

Moreover, **chatbot tone and human-like interaction** are crucial for fostering **perceived similarity and social presence [4].** Training AI chatbots to emulate empathetic conversational styles, use context-aware responses, and adapt to customer sentiment can significantly elevate satisfaction. Marketers should also **continuously analyze user feedback** and apply **adaptive filtering algorithms** to ensure evolving relevance **[51].**

For Flipkart and similar Indian e-retailers, the findings suggest focusing on **emotional personalization**, where AI agents not only recommend but also *relate*. Gen Z and Millennial consumers expect conversational engagement, authenticity, and instant feedback. Incorporating **real-time sentiment detection** and **contextual personalization** could substantially improve satisfaction scores and repeat purchase intentions. Finally, platform designers should **avoid excessive recommendation density** and instead focus on curating a limited, diverse, and emotionally resonant product selection to optimize customer delight and long-term loyalty.

To implement the "Affective AI" Strategy, managers and designers in the e-retail sector must shift their focus from purely functional metrics to the emotional resonance of the user journey. For high-involvement categories like cosmetics, this research demonstrates that chatbot success is driven by the strategic engineering of "contextual surprises" and "conversational warmth." Rather than relying on repetitive "more of the same" algorithms, developers should program AI to introduce novel brands or complementary products—such as suggesting a specific skincare item following a makeup search—to trigger the psychological delight of perceived serendipity. Furthermore, chatbots must be humanized through empathetic tones and natural linguistic styles to foster perceived similarity, which builds the foundational trust necessary for users to accept AI-driven advice. By balancing precision with a curated variety of choices, platforms can ensure that product discovery feels like a personal achievement for the user rather than a forced algorithmic output, ultimately transforming a routine digital transaction into a high-satisfaction brand experience.

6.3 Limitations And Future Research Directions

Although this study offers valuable theoretical and empirical contributions, it has certain limitations that open avenues for further exploration. First, the study's focus on **Flipkart's cosmetics segment** within the Indian market restricts the generalizability of the findings across other sectors or cultural contexts. Future research could extend the model to other e-retail domains—such as fashion, electronics, or grocery—to assess whether the influence of serendipity and similarity varies across product involvement levels.

Second, the study used **cross-sectional, self-reported data**, which may not capture the dynamics of evolving chatbot familiarity or longitudinal satisfaction. Future studies could employ **longitudinal or experimental designs** to observe how repeated chatbot interactions shape consumer satisfaction, trust, and emotional engagement over time. Incorporating **behavioral or clickstream data** (e.g., session duration, dwell time, or purchase conversion) would enhance accuracy and reduce self-report bias.

Third, although this study included a diverse Gen Z–Millennial sample, future research could examine **age or gender-based moderating effects**,

since communication preferences and emotional responses to AI chatbots may differ demographically. Exploring other psychological constructs—such as trust propensity, perceived empathy, or anthropomorphism—could further refine understanding of chatbot-induced satisfaction.

Overall, future work should expand beyond satisfaction outcomes to investigate **loyalty, repurchase behavior, and word-of-mouth intentions**, offering a holistic view of conversational AI's long-term impact on consumer-brand relationships.

6.4 Distinctive Contributions And Research Achievements

This research bridges a critical gap in conversational commerce by shifting the focus from the functional capabilities of AI to the psychological experiences of the user. While prior scholarship has largely concentrated on the technical accuracy and algorithmic diversity of recommendation systems, this study achieves a more nuanced understanding by empirically validating the "affective route" to satisfaction.

Unlike previous models that viewed AI chatbots as mere efficiency tools for product discovery , our findings achieve a significant breakthrough by identifying **Perceived Serendipity** and **Perceived Similarity** as the primary psychological engines that drive customer delight in high-involvement sectors like cosmetics. Furthermore, while existing theories often warn of "choice overload" in information-dense environments , this study offers a distinctive counter-perspective: it demonstrates that well-calibrated emotional resonance can actually mitigate cognitive fatigue. The ultimate achievement of this work is the provision of a validated SEM pathway that proves satisfaction is a product of both "human-like" social presence and the "joy of discovery," offering a new standard for designing emotionally intelligent AI in the Indian e-retail landscape.

This study adds significantly to the existing body of knowledge by pivoting the research lens from the utilitarian efficiency of AI chatbots to their experiential and affective consequences. While prior research has established the importance of algorithmic accuracy, this study contributes a novel perspective by demonstrating that in high-involvement categories like cosmetics, customer satisfaction is not merely a byproduct of information retrieval. Instead, it is a sophisticated emotional outcome mediated by the "joy of discovery" (serendipity) and "social resonance" (similarity). By validating this dual-pathway model within the burgeoning Indian e-retail landscape, this research provides a new theoretical framework for understanding how conversational commerce can transcend the "paradox of choice" and transform digital transactions into meaningful social experiences. This shift from functional to relational AI offers a superior standard for both academic theory and practical design in the age of intelligent automation.

6.5 Problems And Open Research Issues

While this study successfully validates the mediating roles of perceived serendipity and similarity, several critical problems and open research issues emerge as a result of these findings:

- **The Problem of Algorithmic Transparency vs. Delight:** A significant challenge identified is the "black box" nature of AI. While users appreciate serendipitous discoveries, there is an inherent tension between "unexpected delight" and the user's need to understand *why* a recommendation was made. Future research should investigate whether providing transparency (explanations) for serendipitous suggestions enhances or diminishes the "delight" factor.
- **The Issue of Affective Decay:** This study utilizes cross-sectional data, which captures a single moment of satisfaction. An open research issue is the "decay" of affective responses—does the novelty of a serendipitous chatbot wear off over time? Longitudinal studies are needed to determine if the emotional resonance found in this study translates into long-term brand loyalty.
- **The Sensory Limitation Problem:** In the cosmetics sector, AI chatbots are currently limited by their inability to replicate sensory cues like texture, scent, or true-to-life skin tones. An open research issue is how Augmented Reality (AR) integration within conversational interfaces might interact with perceived similarity to create a more "embodied" social presence.
- **The Ethical Boundary of Similarity:** As chatbots become more human-like (high perceived similarity), a potential problem arises regarding the "Uncanny Valley" or ethical concerns over manipulation. Future research must define the

ethical boundaries of anthropomorphism—at what point does a "similar" chatbot stop being helpful and start being perceived as deceptive or intrusive?

Declaration of Competing Interests

The authors declare no financial or personal conflicts of interest that could have influenced the research presented in this study.

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Ethical Compliance Statement

All procedures performed in studies involving human participants were in accordance with the ethical standards of the **RNSIT Research Committee** and with the **1964 Helsinki Declaration** and its later amendments or comparable ethical standards.

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