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The relevance of task technology fit and affective responses in predicting chatbot user's sustained use: Moderating role of cognitive innovativeness

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ABSTRACT

Business enterprises increasingly leverage artificial intelligence tools, particularly chatbots, to improve client relations and drive sustainable growth. There is a dearth of empirical research on the post-adoption behavior of individuals who have adopted chatbots. However, this study examines the impact of task-technology fit (TTF), affective response model (ARM), and cognitive innovativeness on post-adoption behavior, specifically the intention to continue using a chatbot, which extends beyond the confines of the expectation-confirmation model (ECM). Notably, previous studies had not collectively tested these predictors, marking the uniqueness of this study. The authors empirically validated data from 401 travel chatbot users through structural equation modeling (SEM) and artificial neural network (ANN) analyses. Task-technology fit emerged as the most potent predictor of satisfaction and sustained use. Contrary to expectations, anthropomorphism exhibited a detrimental effect on continuance intention. Additionally, this research offers intriguing perspectives into the catalytic role of users' cognitive innovativeness, identifying two significant and non-significant moderations. The study offers implications for academia, travel management, and chatbot developers.

Keywords: chatbot; TTF; SEM-ANN; perceived anthropomorphism; perceived playfulness

1. INTRODUCTION

Moore's law asserts that "the number of transistors on an integrated circuit doubles approximately every two years" [1]. The principle has catalysed technological advances [2] and artificial intelligence [3]. The advent of big data and computing has contributed to AI's upward trajectory over the last decade, percolating most business sectors [4]. Conversational agents, one of AI's tools, are gaining prominence in customer service [5]. Artificially intelligent agents can take various forms such as embodied avatars, disembodied chatbots, or conversational interfaces like Alexa and Siri [6], [7], [8]. The current research focuses on conversational commerce, which, according to Balakrishnan and Dwivedi [9], involves buying using virtual agents, particularly disembodied text-based chatbots.

Chatbots referred to as chatterbots, talk bots, interactive agents, or just bots, utilize advanced natural language processing (NLP) to simplify interactions between computers and humans [10]. Chatbots first emerged as virtual healthcare bots named ELIZA in 1966, providing predetermined answers to users' questions [11]. Over time, chatbots have significantly evolved in functionality, efficacy, and finesse, delivering numerous benefits to retailers. They have the potential to reduce customer service personnel expenses, offer immediate responses, handle multiple users simultaneously, foster leads through active user engagement, furnish precise information requested by customers, encourage repeat customers, track customer data for insights and marketing strategies, ensure accessibility across multiple channels, and guarantee a smooth customer journey.

The advantages of chatbots have spurred a significant rise in adoption, projecting retail sales through them to hit $112 billion by 2023—15 times more than the $7.3 billion in 2021 [12]. Between 2023 and 31, the CAGR is expected to reach 23.9%, and robust adoption is expected in the Asia-Pacific region, driven by the incremental growth of e-commerce [13]. Among the several verticals that have adopted chatbots for customer service, travel, and tourism stand out as key players [14]. Online travel agencies (OTAs) have employed chatbots to facilitate services such as reservations/bookings and recommendations [15]. Travelers benefit from chatbots by specifying the destination details, time, date, price preference, class, and other customized services, without the hassle of navigating and interacting with customer service for a booking query [16].

While chatbots offer manifold benefits, their sustained use in the future remains challenging. Factors contributing to this challenge include concerns about information security [17], affective challenges, technical complexities [18], and the inability of bots to replicate genuine human-human emotional connections [19]. Despite the existing research, the literature provides minimal evidence on the predictors of continued intent among chatbot users. Commonly explored theories include trust [20], social presence [21], and social response [22] as well as models such as the technology acceptance model (TAM) [23]. To address this gap, this research introduces a novel framework that integrates the extended expectation-confirmation model (ECM), task-technology fit (TTF), and affective response model (ARM) to predict travel chatbot users' sustained use and satisfaction.

Complementarities between ECM and TTF have been explored in the context of e-food delivery [24] and e-learning [25]. Notably, the inclusion of ARM, focusing on affective responses, such as anthropomorphism and playfulness, in the framework is understudied in the literature. Furthermore, the authors delve into the less-examined interacting role of users' cognitive innovativeness, defined as the "desire for new experiences to stimulate new minds" [26], with interactive technologies [27], and its role in predicting post-adoption chatbot user behavior.

The authors' research queries address the following gaps: How relevant are task-technology fit, affective responses, and ECM constructs in predicting chatbot users' satisfaction and sustained use? Does the level of cognitive innovativeness among chatbot users influence their continuance intentions? This study aims to contribute valuable insights into the current understanding of chatbot adoption and sustained use by addressing these questions.

Additionally, this research innovates by utilizing a hybrid method of CB-SEM and ANN analyses, unveiling the predictors of satisfaction and sustained intent. These findings offer actionable insights for academia, OTAs, destination marketers, and chatbot developers.

2. THEORETICAL BACKGROUND AND PROPOSITIONS DEVELOPMENT

To empirically examine OTA chatbot user satisfaction and continuance intention, the authors sought to create a model (Figure 1) that included ECM, TTF, perceived anthropomorphism, and perceived playfulness

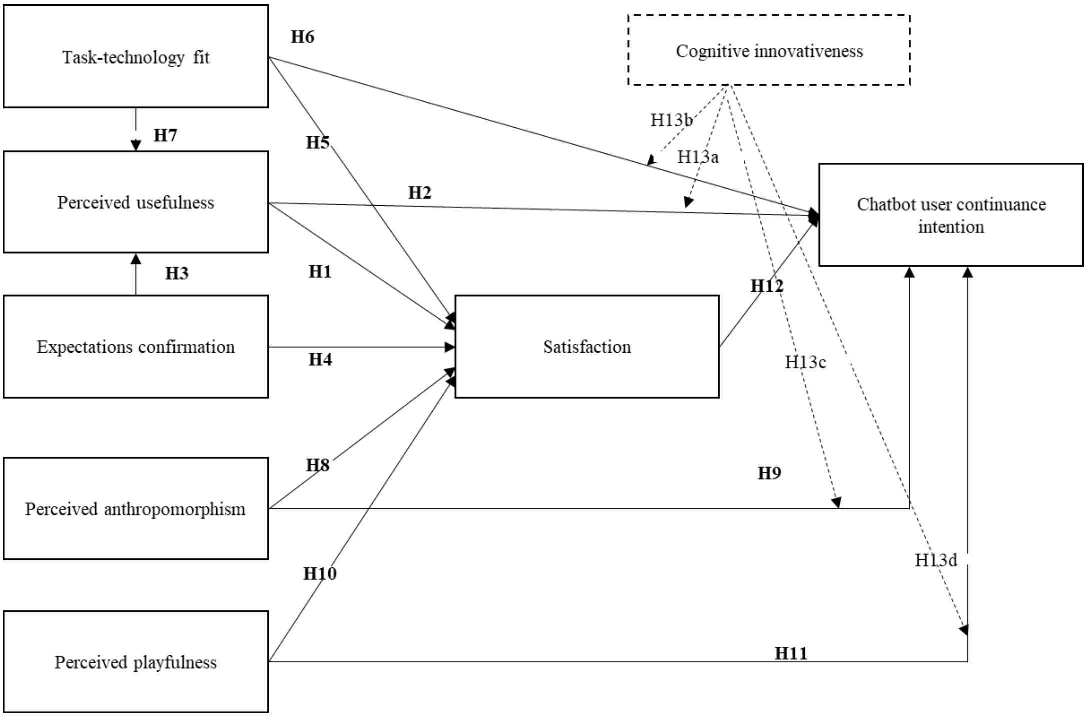

Figure 1. Conceptual framework

2.1 Expectation-Confirmation Model (ECM)

The expectation-confirmation model (ECM) was based on the expectation-confirmation theory (ECT) proposed by Oliver [28], which included a consumer behavior model [29]. ECT postulates that after using a product or service, customers often evaluate its performance based on how well it matches their expectations (a measure of confirmation). This confirmation is directly related to customer satisfaction and subsequent repurchase intentions [30]. Previous researchers found ECM to be a superior and more relevant framework for examining the intention to continue engaging in e-commerce [29]. Based on the ECM, the authors included three primary factors to predict continuance intention: perceived usefulness, expectation confirmation, and satisfaction.

Users perceive that utilizing chatbots for tasks such as seeking information improves their satisfaction. Consequently, customers, in return for high satisfaction, continue to use chatbots [24], [31]. Scholars have argued that perceived usefulness (PU) has a strong impact on satisfaction and continued intention to use information systems [30], [32], [33]. Hence, the following is an overview of the propositions about PU:

> **H1 and H2:** PU positively impacts chatbot user satisfaction and continuance intention respectively.

Chatbot users experience favorable confirmation when they perceive that the actual performance of chatbots exceeds their earlier expectations. As a result of this favorable confirmation, more significant satisfaction levels were established [34]. Many ECM-based studies have indicated positive correlations between satisfaction, expectations confirmations, and perceived utility in diverse realms [35], [36], [37]. Hence, the following propositions:

> **H3:** Confirmation of chatbot users' expectations causes favorable effects on perceived usefulness.

> **H4:** Confirmation of chatbot users' expectations causes favorable effects on user satisfaction.

Satisfaction, the most important antecedent of post-adoption behavior [30], [38], is the “subjective sum of interactive experiences” [39], [40]. The interactive encounters with chatbot services lead to satisfaction, encouraging sustained use intent [31]. Hence, the researchers postulate the following proposition:

> **H12:** Chatbot user satisfaction positively affects their continuance intentions.

2.2 Task-Technology Fit (TTF)

Numerous information systems scholars have adopted postulates in task-technology fit theory to elucidate IS adoption and usage. Task-technology fit (TTF) can be measured as the level of content derived from the compatibility between the information system and user tasks. TTF is a crucial determinant for gauging user performance levels and satisfaction [41], [42]. In chatbot usage, when there is a strong alignment between the task and technology, users consider it helpful and express their satisfaction [43], [44]. Previous research in human-computer interaction has explored the correlations among TTF, satisfaction, and continued use [45], [46], [47]. Hence, the following propositions are postulated:

H5: TTF impacts chatbot user satisfaction.

H6: TTF impacts the continued use of chatbot users.

While TTF refers to technical support for task completion, perceived usefulness (PU) concerns an individual's conviction that technology will enable them to achieve their tasks [39]. Both TTF and PU affect the successful implementation of technology. Previous researchers have claimed positive TTF-PU relations [24], [43], [48] with contradicting evidence from Dishaw and Strong [47], owing to individual differences, organizational context, and technology complexity. The academic debate surrounding TTF-PU prompted the authors to empirically investigate this link in conversational commerce. Hence, the following proposition:

H7: TTF impacts the perceived utility of chatbot users positively.

2.3 Affective response model (ARM)

The affective response model (ARM) comprises a body of knowledge that investigates emotional/affective experiences and their impact on human behavior. ARM is relevant in cases where individuals are exposed to computer-mediated communication as a direct stimulus. [49], which aligns with the research's primary aim. The ARM is a comprehensive framework that integrates a range of affective concepts categorized into five distinct dimensions: "the residing, the temporal, the particular/general stimulus, the object/behavior stimulus, and the process/outcome stimulus" [50]. The ARM dimensions explain the affective nature of these concepts and their relations. One of the postulates of ARM states that "affective concepts of category 4 (induced affective states) influence category 6.2 (particular affective evaluation based on outcome towards behavior on a particular object)" [50]. The concept of an induced affective state refers to the emotions experienced by individuals as a result of their interactions with an object. On the other hand, outcome-based affective evaluation involves the assessment of emotional responses that arise from engaging in a specific behavior associated with a particular object [50]. In line with this, researchers have argued that perceived playfulness and perceived anthropomorphism are induced affective states (emotions) [50], [51], and satisfaction is a particular affective evaluation [50]. Therefore, these induced affective states positively impact satisfaction. Moreover, the proposed future directions of the ARM advocate for further research into the impact of affected states on continuance intention [50].

Furthermore, previous studies in ICT, have utilized ARM to examine the role of affective concepts in various behavioral outcomes, such as online buying behavior [52], adoption of information technology [49], and acceptance of mobile payment systems [53]. However, the extent to which perceived playfulness and perceived anthropomorphism predict continuance intention during a human-chatbot interaction has been less investigated and hence included in the current research framework.

A significant increase in research in computer-mediated environments (CME) has emphasized investigating the affective responses associated with human-computer interaction. One such affective state is perceived anthropomorphism. Airenti [51] describes anthropomorphism as the ascription of “human mental and affective states” to artificial entities. Perceived anthropomorphism (PA) refers to how users perceive anthropomorphism during user-chatbot interactions [54], [55]. PA is an emotional response elicited by interactions with an object [55]. ARM justifies the perceived anthropomorphism and satisfaction relations with the OTA chatbot [50]. Previous scholars have confirmed a positive relationship between perceived anthropomorphism and satisfaction [56], [57], and continuance intention [58]. Therefore, the following propositions were developed:

> **H8 and H9:** The user perceptions of anthropomorphism positively affect satisfaction and continued use in the future respectively.

Perceived playfulness defined as the “experience of emotions, inspiration, curiosity, and feeling of being immersed,” impacts satisfaction according to the ARM framework. Previous studies also support this assertion [33], [59], [60]. Furthermore, users of web portals tend to revisit the platform later if they perceive the interaction to possess playful attributes [61]. Similarly, users of augmented reality (AR) applications express intentions to use them again in the future when they perceive the experience as playful [62]. Hence, in addition to satisfaction, users’ perceptions of playfulness, influence their intention to continue usage. Therefore, the authors propose the following propositions:

> **H10 and H11:** Perceived playfulness of chatbot users positively impacts their satisfaction and continuance intention respectively.

2.4 Moderating role of cognitive innovativeness

Cognitive innovativeness connects to an individual's inclination to actively participate in and derive pleasure from novel experiences that stimulate cognition. This consumer trait is delineated into two dimensions: The internal cognitive innovativeness dimension refers to individuals’ liking of “unusual cognitive processes that are focused on explanatory principles and cognitive schemes” [63]; The corresponding external dimension is an inclination towards “finding out facts, how things work, and learning to do new things.” [63]; The current study employs the scale developed by Huang and Liao [27] to measure both dimensions.

Customers with a high level of cognitive innovativeness derive satisfaction from expending mental energy to accomplish their goals, prioritizing task execution, and considering the utility and user-friendliness of the product. They engage in a thorough analysis and assessment of various attributes before making purchasing decisions, extending this approach to AI technologies [27]. In the current research context, the chatbot cues perceived by users include usefulness, playfulness, task-technology fit, and anthropomorphism. Therefore, cognitive innovative technology users perceive usefulness, task-technology fit, playfulness, and anthropomorphism as impacting positive user behavior, specifically their continued intention to use chatbots. Researchers have found corroborating evidence on cognitive innovativeness moderating the impact of perceived usefulness on relationship behavior among highly cognitively innovative consumers [27]. In addition, the presence of anthropomorphism or human-like characteristics in technology is considered a desirable trait by cognitive innovative users due to its association with innovation. Researchers deduced that users’ innovativeness moderated anthropomorphism and self-congruence links [64]. Furthermore, TTF motivates users after evaluating the system features for decision-making [65]. Evidence shows that TTF and personal innovativeness impact user decision-making behavior [66]. However, the catalytic role of cognitive innovativeness on TTF and user behavior is relatively less explored.

The arguments above suggest that highly cognitive innovative users enhance the significant influence of usefulness, anthropomorphism, and task-technology fit on user behavioral outcomes. Conversely, highly cognitive innovative consumers diminish the impact of perceived playfulness on relationship behavior [27]. This is attributed to consumers with limited cognitive innovativeness being more impulsive and playful compared to their counterparts with higher cognitive innovativeness [26], [27]. Hence, the following propositions:

> **H13a-d:** Cognitive innovativeness moderates the influence of users' perceptions of usefulness, anthropomorphism, TTF, and playfulness on continuance intention respectively.

3. METHODOLOGY

3.1 Instrument design

A preliminary study involving 60 OTA chatbot users evaluated the survey instrument's validity and reliability. Cronbach alpha values were in the range of 0.81 to 0.91. The pilot study's findings and expert suggestions led to the design of the final survey form (***Table 2***), which included questions on eight constructs, supplemented by demographic information. Each question was assessed using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Four items for task-technology fit from Wu and Chen [43] and Zhou et al. [67] and five survey questions for perceived usefulness from Nguyen et al. [31] and Pillai and Sivathanu [68] were adopted. Scale of Nguyen et al. [31] for confirmation (three items) was adopted. Satisfaction from Chung et al. [69], perceived anthropomorphism from Balakrishnan et al. and Han et al. [54], [70], and perceived playfulness from Hsu et al. [59] were utilized for the study. Three items for continuance intention from Balakrishnan et al. [54] and eight questions for cognitive innovativeness from Huang et al. [27] included.

3.2 Sample collection

A quantitative research approach was employed to examine the determinants of chatbot user behavior. The convenience sampling method was used to gather data from individuals with prior experience in travel booking using chatbots, given constraints in accessing respondents. Most researchers have adopted this approach and found it quick, less expensive, and effective [71], [72], [73]. To mitigate uncertainty and ensure representativeness, the researchers focused on managing the sample's representativeness, collecting data from diverse locations and days, and incorporating a large sample [74]. The survey was conducted in India's top 5 tier 1 cities - Delhi, Chennai, Bengaluru, Hyderabad, and Mumbai, as identified by Times Property (2023). Tier 1 cities were selected for the study due to their ability to attract a varied populace, leading to a mix of cultures and new ideas, and providing ample employment options [75]. The targeted respondents for the study were adult OTA chatbot users. Before commencing the survey, respondents were subjected to screening items: 1. Are you familiar with chatbot services from online travel agencies (OTAs)? 2. Please specify the OTA whose chatbot you had used, to filter the desired audience. Those who answered affirmatively to both questions were provided the option to either scan a laminated QR code, generated using a QR code generator and proceed to fill out the validated questionnaire online (Google Forms) or complete a physical questionnaire handed over by the researchers. To ensure clarity, the survey instrument incorporated a comprehensive definition of chatbots and an overview of travel chatbots in India, featuring platforms like Travel Triangle, Red Bus, and Make My Trip, accompanied by images of chat screens. This was followed by items representing the relevant constructs (refer to ***Table 2***) and inquiries about the respondents' socio-demographic profiles. The initial responses received totaled 553 during August and September 2023; however, 152 participants did not complete the survey (including both online and offline) and were removed using Mahalanobis distance [76], yielding a final sample of 401 responses.

Male respondents (64%) outnumbered female respondents (36 %). The majority of responders (45%) fell within the range of the 26-35 age bracket, followed by users aged 36-45 (22%). This is in accordance with the age profile of chatbot users, as millennials are more interested in novel technologies [77]. A significant proportion of the sample audience (74.7 percent) said they utilized chatbot services 1-2 times a month (64.7 percent) for 1-2 minutes (75 percent). Table 1 presents the target sample’s demographic characteristics.

Table 1. Socio-demographic statistics

Demographic information		**Percentage**
Gender	Male	64
	Female	36
Age	<25	21
	26-35	45
	36-45	22
	>45	12
Highest level of education	High School	7
	Undergraduate	63
	Postgraduate	20
	Doctorate	10
Annual Income (in Rs.)	< 2.5 Lakhs	10
	2.5-5 Lakhs	15
	5-7.5 Lakhs	35
	7.5-10 Lakhs	18
	>10 Lakhs	22
Frequency of chatbot use	3 – 4 times a week	2.9
	1 – 2 times a week	12.3
	Once/twice a month	64.7
	< once a month	20.1
Average time of use	< 1 minute	5
	1 – 2 minutes	75
	>2 minutes	20

3.3 Constructs validation

Since the study comprised self-reported measures, common-method bias (CMB) needed to be eliminated, for which the following procedural remedies were followed. The brief introduction to the questionnaire included phrases guaranteeing the privacy of all responses. In addition, the items used for assessing the constructs were developed at an easy level of understanding. Furthermore, a statistical remedy, the common latent factor (CLF) approach was followed. The difference in the values of confirmatory factor analysis (CFA) with CLF and without CLF was low (<0.2), ideal according to Gaskin. J [78], confirmed no bias in the research data. Hence, CLF was not retained for further path analysis.

4. RESULTS

4.1 Structural Equation Modelling (SEM)

The primary aim of covariance-based structural equation modeling (CB-SEM) is to evaluate the fit between a theoretical model (Figure 1) and empirical data obtained from real-world settings. In contrast to PLS-SEM, which is primarily used for exploratory research, CB-SEM is best suited for explanatory research [79]. The authors, therefore analyzed the current data using CB-SEM as a first step.

The current research incorporated four multi-variate assumptions: linearity, normality, multicollinearity, and homoscedasticity. Linearity was achieved through OLS linear regression for each independent and dependent variable pair. The corresponding p-values were less than 0.05. Data demonstrated normality, as evidenced by skewness and kurtosis values being less than their respective tripled standard errors, aligning with the normality criterion outlined by Belsley and Gaskin [80], [81]. Additionally, the skewness and kurtosis coefficients (***Table 2***) were between -1 and 1, thus validating the data to be normal [82]. Full collinearity was assessed using VIF and tolerance values of all the constructs, with a random variable (random values between 0 and 1) assigned as the dependent variable. All VIF values (in Table 4) were well below the optimal value of 5.0, according to Belsley [81]. The tolerance values ranged from 0.366 to 0.916 (Table 4), close to zero indicating no collinearity issues [76].

AMOS 26.0 tested the measurement model's validity, reliability, and model fit. All factors were retained for subsequent examination since their loadings were over 0.5. (***Table 2***). The composite reliability exceeded 0.9 for all variables, surpassing the 0.7 threshold recommended by Hair Joseph F. [76]. Additionally, the average variance extracted (AVE) surpassed 0.5, providing evidence that all variables achieved convergent validity concerning the measurement model of the study (***Table 2***). The framework achieved discriminant validity as per Fornell and Larcker [83] criterion. As intended, the diagonal values representing $\sqrt{AVE}$, exceeded the shared correlations between constructs. Table 3 exhibits this result. Furthermore, the model fit indices were also on par with Bentler et al. [84], [85], [86] (displayed in Table 5).

Table 2. Convergent validity of measurement model

Constructs	Items	Factor loading	CR	AVE	Skewness	Kurtosis
Task-technology Fit (TTF)	Chatbots are fit for the requirements of my travel booking.	0.847	0.889	0.668	-0.060	-1.079
	Using chatbots fits with my booking experience.	0.798			0.034	-0.913
	Chatbots help address the booking requirements.	0.827			-0.085	-0.930
	In general, the functions of chatbots fully meet my travel needs.	0.796			-0.029	-0.873
Perceived usefulness (PU)	Chatbots are helpful for my travel planning.	0.801	0.913	0.676	-0.118	-0.872
	Chatbots improve the efficiency of my travel planning.	0.836			-0.137	-0.956
	Chatbots improve my performance in travel planning (save time).	0.833			0.093	-1.097
	Chatbot helps me to perform many things more conveniently.	0.821			0.059	-1.001
	Overall, I feel that chatbots are very useful for travel planning.	0.821			-0.044	-1.028
Confirmation (CONF)	My experience with chatbots was greater than my expectations.	0.881	0.886	0.721	0.035	-0.923
	The service level provided by chatbots was greater than what I expected.	0.832			-0.062	-0.904
	In general, most of my expectations from using chatbots were confirmed.	0.833			-0.083	-0.948
Satisfaction (SAT)	I am satisfied with the chatbot.	0.861	0.917	0.689	-0.025	-1.147
	I am content with the chatbot.	0.810			-0.185	-0.925
	Chatbot did a good job.	0.813			-0.113	-0.979
	The chatbot did what I expected.	0.831			-0.167	-0.988
	I was satisfied with the experience of conversing with a chatbot.	0.834			-0.003	-1.096
Perceived anthropomorphism (PA)	Chatbots are natural; I do not feel fake about them.	0.768	0.862	0.611	0.042	-0.996
	Chatbots are more human-like.	0.782			-0.035	-0.975
	Chatbots feel lifelike and not artificial.	0.772			-0.133	-0.988
	Chatbots are elegant in engaging.	0.803			-0.033	-0.894

Constructs	**Items**	**Factor loading**	**CR**	**AVE**	**Skewness**	**Kurtosis**
Perceived playfulness (PP)	When interacting with the OTA chatbot, I am not aware of the time as it elapses.	0.807	0.858	0.668	-0.115	-0.854
	When interacting with the OTA chatbot, I am not aware of distracting noise.	0.809			-0.104	-0.842
	When interacting with the OTA chatbot, I often forget other commitments.	0.836			-0.057	-1.076
Continuance intention (CI)	I intend to continue using chatbots in the future.	0.816	0.876	0.703	-0.123	-0.970
	I will always try to use chatbots when there is a need.	0.843			-0.186	-0.976
	I will strongly recommend others to use it.	0.855			-0.145	-1.042
Cognitive innovativeness (COG)	Finding out the meaning of words I do not know.	0.846	0.923	0.706	-0.075	-0.874
	Thinking about different ways to explain the same thing.	0.849			-0.088	-0.880
	Figuring out the shortest distance from one city to another.	0.867			0.006	-1.011
	Thinking about why the world is in the shape that it is in.	0.803			-0.291	-0.816
	Figuring out how many bricks it would take to build a fireplace.	0.836			-0.191	-0.868

Structural equation modeling (SEM) tests model fit and the relationships between constructs [84]. As explained in Table 5, the goodness of fit measures was within the ideal range. Hence, this suggests a strong fit for the model of the study. Figure 2 and Table 6 explain the propositions of the study.

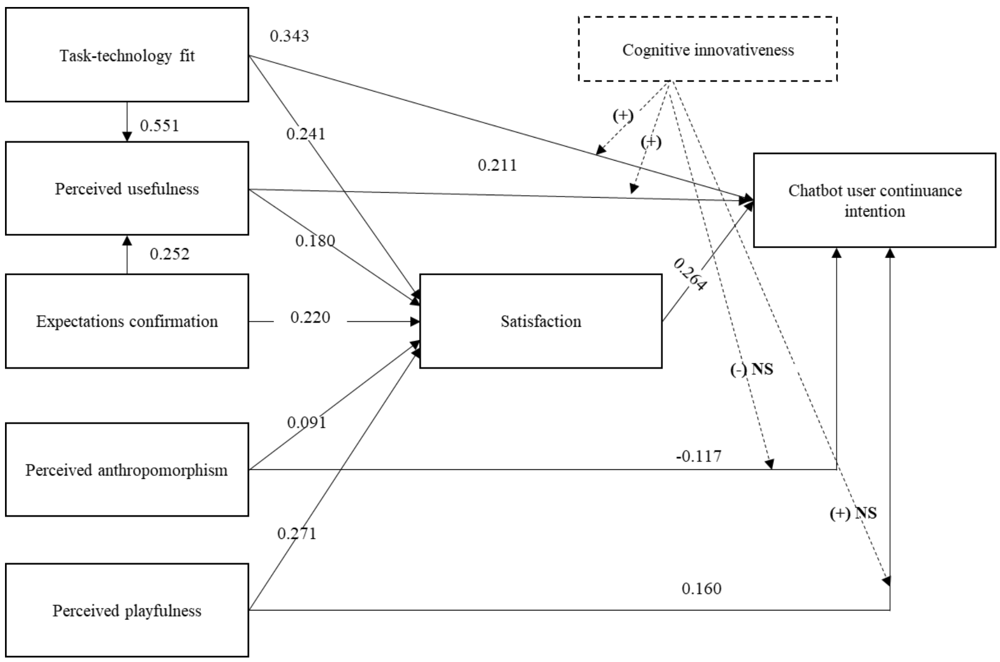

Figure 2. Standardized estimates - SEM analysis

Table 3. Fornell-Larcker criterion

	CI	TTF	PU	CONF	SAT	PP	PA	COG
CI	0.838							
TTF	0.768	0.817						
PU	0.721	0.714	0.822					
CONF	0.696	0.670	0.617	0.849				
SAT	0.740	0.724	0.660	0.658	0.830			
PP	0.695	0.696	0.628	0.602	0.699	0.817		
PA	0.029	0.181	0.045	0.043	0.191	0.146	0.781	
COG	-0.586	-0.587	-0.552	-0.576	-0.716	-0.564	-0.202	0.840

Table 4. Full collinearity assessment

Variables	Tolerance	VIF values	Cronbach alpha
TTF	0.385	2.597	0.889
PU	0.467	2.141	0.913
CONF	0.513	1.948	0.885
SAT	0.366	2.732	0.917
PP	0.502	1.991	0.858
PA	0.916	1.091	0.862
CI	0.385	2.597	0.876
COG	0.520	1.924	0.923

Note: Dependent variable: Random (values between 0 and 1)

Table 5. Comparison of model fit indices

Indicators	Measurement model	Structural model	Ideal criteria	Source
χ^2/df	1.450	1.544	≤3	[76]
GFI	0.911	0.919	≥0.90	[85]
NFI	0.934	0.941	≥0.90	[84]
RFI	0.925	0.932	≥0.90	[84]
TLI	0.975	0.975	≥0.90	[84]
CFI	0.978	0.978	≥0.50	[84]
RMSEA	0.034	0.037	≤0.05	[87]
PCLOSE	1.000	1.000	>.05	[76]
SRMR	0.0328	0.0325	<0.08	[76]

(Note: χ^2/df = Ratio of Chi-square value to degrees of freedom; GFI = Goodness of fit index; NFI = Normed fit index; RFI = Relative fit index; TLI = Tucker-Lewis index; CFI = Comparative fit index; RMSEA = Root mean square error of approximation; PCLOSE = p of close fit; SRMR = Standardized root mean square residual;)

The first predictor, PU, positively impacted satisfaction (SAT) (H1, $\beta = 0.180$, $t = 3.000$, $p = 0.003$) and continuance intention (CI) (H2, $\beta = 0.214$, $t = 3.644$, $p < 0.001$). The second predictor, expectation confirmation, influenced chatbot user satisfaction (H4, $\beta = 0.221$, $t = 3.731$, $p < 0.001$). The third predictor, TTF impacted satisfaction (H5, $\beta = 0.241$, $t = 3.112$, $p = 0.002$), continuance intention (H6, $\beta = 0.334$, $t = 4.354$, $p < 0.001$), and perceived usefulness (H7, $\beta = 0.551$, $t = 8.361$, $p < 0.001$), supporting their respective hypotheses. The fourth predictor, perceived anthropomorphism, revealed a favorable impact on SAT (H8, $\beta = 0.091$, $t = 2.371$, $p = 0.018$) and an unfavorable effect on CI (H9, $\beta = -0.119$, $t = -3.160$, $p = 0.002$). H8, but not H9, was supported. PP, the fifth predictor, indicated a favorable influence on the satisfaction of OTA chatbot users (H10, $\beta = 0.271$, $t = 4.368$, $p < 0.001$) and continued use (H11, $\beta = 0.158$, $t = 2.535$, $p = 0.011$). Additionally, expectation confirmation impacted perceived usefulness (H3, $\beta = 0.252$, $t = 4.118$, $p < 0.001$). Satisfaction of chatbot users led to a favorable impact on their continued use of chatbots (H12, $\beta = 0.276$, $t = 4.122$, $p < 0.001$). The R square value of CI is 0.72, which implies that the model accounted for 72.0 % of the variance in OTA chatbot users' sustained use.

Table 6. Propositions results

Propositions	Paths	Standardized Estimates	S. E	C.R	P-value	Support
H1	PU → SAT	0.180	0.065	3.003	0.003	Yes
H2	PU → CI	0.211	0.057	3.604	***	Yes
H3	CONF → PU	0.252	0.063	4.118	***	Yes
H4	CONF → SAT	0.220	0.065	3.722	***	Yes
H5	TTF → SAT	0.241	0.091	3.113	0.002	Yes
H6	TTF → CI	0.343	0.082	4.472	***	Yes
H7	TTF → PU	0.551	0.072	8.36	***	Yes
H8	PA → SAT	0.091	0.042	2.369	0.018	Yes
H9	PA → CI	-0.117	0.037	-3.106	0.002	No
H10	PP →SAT	0.271	0.067	4.369	***	Yes
H11	PP → CI	0.160	0.061	2.572	0.010	Yes
H12	SAT → CI	0.264	0.058	4.135	***	Yes

To explore the nature of the moderation effect further, the authors employed simple slope analysis and plotted the results using unstandardized estimates and intercepts as in Figure 3. The graph indicates that the impact of COG on the PU-CI (0.102; t = 2.068; p<0.05) and TTF-CI (0.109; t = 2.263, p< 0.05) relationships is positive and significant, supporting hypotheses H13a and H13b. However, the moderating effect of COG on PP-CI (-0.059; p = 0.206) was negative and insignificant, not supporting hypothesis H13d. The catalytic effect of COG on PA-CI relations was positive and insignificant (0.039; p = 0.241), not supporting H13c.

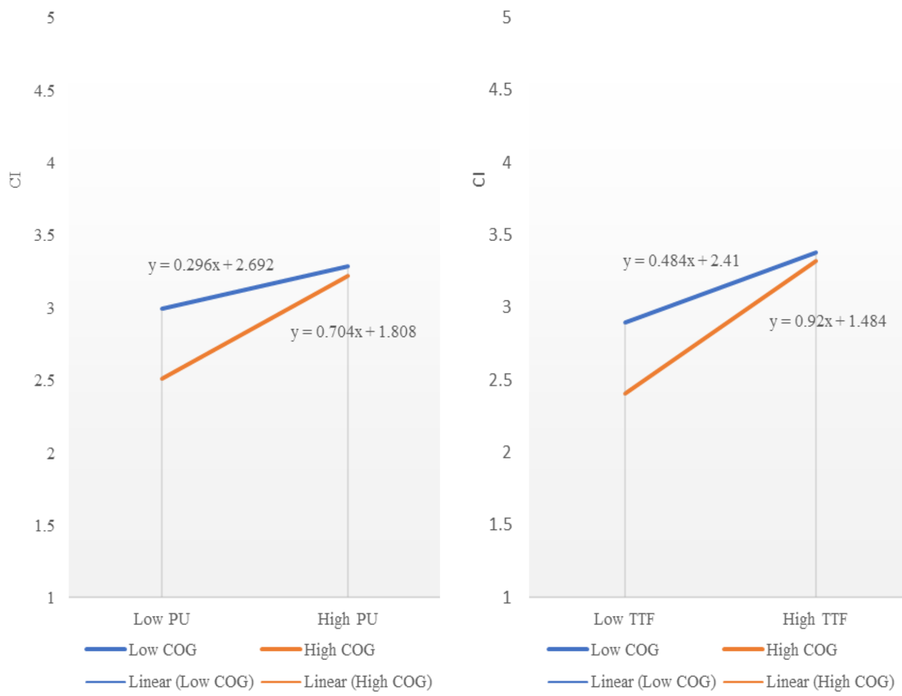

Figure 3. Slope analysis - COG as moderator

4.2 Artificial neural network (ANN)

The authors employed artificial neural network analysis (ANN) for significant drivers of SAT and CI based on the CB-SEM analysis, following Leong et al.'s [88] approach. Accordingly, TTF, PU, CONF, PA, and PP were fed as input neurons for ANN model 1, and TTF, PU, SAT, and PP were fed for model 2 using the SPSS 26.0 neural network module. PA was removed in model 2 since it had a negative influence on CI, as per SEM analysis. Each model has one output, irrespective of the number of input neurons [89]. The ANN diagram (Figure 4) has one hidden layer that allows signals to pass from each input neuron [90]. ANN without hidden layers is a mere linear regression incapable of detecting non-linearity [88]. ANN algorithm detects both linear and non-linear relationships [90], thus serving the purpose of the study. Nodes represented as H (1:1) imply the first node of the layer, similar to H (1:3) which implies the third node of the respective layer. The total number of nodes in models 1 and 2 is two [89]. The lower the number of nodes, the better the model fit. Too little may be problematic [88]. Two is ideal. The input and hidden layers utilized multilayer perceptron and sigmoid activation functions [89], [91]. Researchers designated seventy percent of the samples for training and thirty percent for testing processes (SPSS). To avoid the problem of overfitting, the study employed a ten-fold cross-validation approach and calculated the root mean square of errors (RMSE) (*Table 7*). The mean RMSE was lower: 0.442 and 0.364 (training) and 0.460 and 0.355 (testing) for models 1 and 2, respectively (*Table 7*). Low RMSE values indicate the precision of ANN models in predicting output neurons [88].

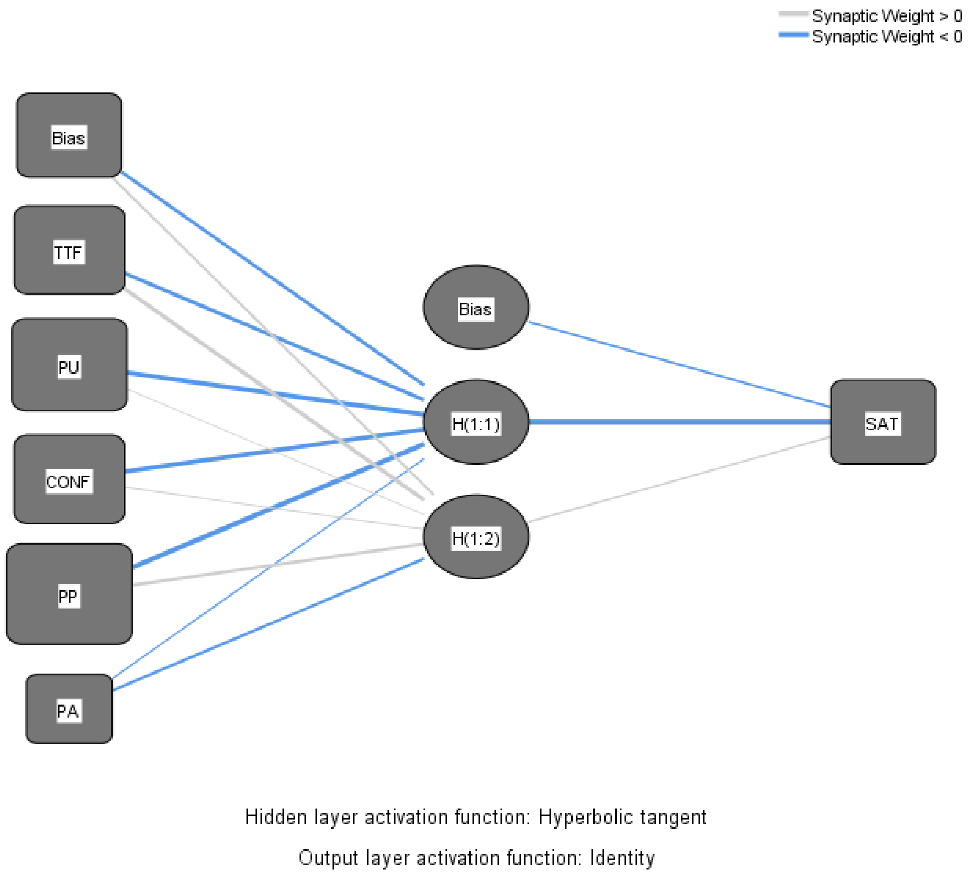

Figure 4. ANN - synaptic weights

The researchers performed a sensitivity analysis of models 1 and 2 to evaluate the predictive capabilities of each input neuron (Table 8). The normalized importance of the neurons was computed by dividing their respective importance by the maximum importance and afterward expressed as a percentage [88], [91]. The findings indicate that the most significant predictor was TTF, followed by PU with normalized importance of 89%, perceived playfulness at 82%, expectation-confirmation at 68%, and perceived anthropomorphism at 36% for model 1. For model 2, the order of significant predictors of CI is TTF (the normalized importance of 100%), perceived usefulness (82%), perceived playfulness (79%), and satisfaction (66%) (Table 8).

Table 7. RMSE values - Model 1 and 2

Network	Model 1				Model 2			
	Sum of square error (Training)	Sum of square error (Testing)	RMSE (Training)	RMSE (Testing)	Sum of square error (Training) (ESA)	Sum of square error (Testing) (ESA)	RMSE (Training) (ESA)	RMSE (Testing) (ESA)
1	70.093	17.456	0.508	0.368	30.200	21.141	0.333	0.405
2	52.203	25.626	0.424	0.483	46.980	6.713	0.402	0.247
3	58.079	23.484	0.463	0.425	35.698	16.285	0.363	0.354
4	41.699	36.104	0.393	0.525	42.965	9.728	0.399	0.273
5	59.839	26.35	0.466	0.459	33.693	20.993	0.349	0.410
6	51.043	24.505	0.420	0.468	40.932	13.033	0.376	0.341
7	59.491	24.868	0.463	0.448	38.307	18.320	0.372	0.384
8	56.908	31.688	0.450	0.514	29.694	19.792	0.325	0.406
9	48.168	21.867	0.415	0.425	36.506	14.649	0.361	0.348
10	50.089	25.769	0.415	0.484	36.853	15.784	0.356	0.379
Mean	54.761	25.772	0.442	0.460	37.183	15.644	0.364	0.355
SD	7.450	4.840	0.032	0.044	5.143	4.541	0.024	0.053

Table 8. Sensitivity analysis - Models 1 and 2

Neural networks	Model 1					Model 2			
	PU	PP	CONF	PA	TTF	PU	TTF	SAT	PP
NN (i)	0.520	0.820	0.680	0.200	0.860	0.712	1.000	0.747	0.719
NN (ii)	0.830	0.750	0.790	0.250	0.810	0.891	1.000	0.677	0.663
NN (iii)	1.000	0.740	0.750	0.320	0.440	1.000	0.843	0.600	0.711
NN (iv)	0.560	0.770	0.640	0.370	0.840	0.912	1.000	0.610	0.736
NN (v)	0.800	0.770	0.490	0.110	1.000	0.998	1.000	0.806	0.914
NN (vi)	1.000	0.570	0.620	0.300	0.950	0.928	1.000	0.788	0.851
NN (vii)	0.900	0.510	0.570	0.370	1.000	0.823	1.000	0.547	0.994
NN (viii)	0.700	1.000	0.750	0.130	0.860	0.744	1.000	0.684	0.751
NN (ix)	1.000	0.780	0.470	0.580	0.910	0.650	1.000	0.548	0.683
NN (x)	1.000	0.930	0.570	0.710	0.760	0.413	1.000	0.477	0.754
Average Importance	0.830	0.760	0.630	0.330	0.840	0.810	0.980	0.650	0.780
Normalized importance	89%	82%	68%	36%	100%	82%	100%	66%	79%

5. DISCUSSION

The principal goal of this study was to empirically investigate the relevance of ECM, TTF, and ARM in predicting OTA chatbot user satisfaction and sustained use in the future. The study's constructs add to the current corpus of literature on human-chatbot interaction.

The current research investigated five significant drivers of satisfaction (SAT) and continuance intention (CI). Among these, TTF has been identified as a crucial predictor of both SAT and CI through SEM and ANN analyses, as supported by Larsen et al. [92] and Yuan et al. [93]. Prior studies on post-adoption behavior have predominantly focused on IS models, specifically the technology acceptance model (TAM) [94], [95], [96], whereas TTF has received comparatively less consideration. Therefore, the relevance and contribution of TTF as a key antecedent of SAT and CI were empirically validated in the chatbot realm. The seamless integration of the chatbot with user tasks enhanced their satisfaction and continued intent. Furthermore, TTF has a favorable impact on the usefulness of chatbot users. The research conducted by You et al. [44] provided corroborating evidence.

Perceived usefulness (PU) ranked second among the predictors of SAT ($\beta = 0.180$, 89 %) and CI ($\beta = 0.211$, 82%), consistent with previous empirical findings [23], [31], [44]. The results emphasize users' benefit and value in determining their satisfaction and continued intent. Furthermore, expectation-confirmation (CONF) ranked fourth and played a crucial role in driving SAT ($\beta = 0.220$, 68%) and PU ($\beta = 0.252$), in agreement with the results of Nguyen et al. [31], thereby substantiating the ECM postulates proposed by Bhattacharjee [30]. This suggests that meeting or exceeding user expectations positively impacts their usefulness and satisfaction.

Perceived anthropomorphism (PA) exerted a notable impact ($\beta = 0.091$) on the satisfaction levels of chatbot users. It was identified as the fifth predictor of satisfaction. In a meta-analytical study, researchers predicted the influential role of anthropomorphism on satisfaction [97]. The results of the present study validate this assertion. According to Li and Sung [98], utilizing anthropomorphism or human-like cues to enhance the perceived proximity between humans and artificially intelligent agents, leads to satisfaction. And satisfied users are inclined to continue using chatbots in the future. However, PA negatively impacted users' continued intentions. Two potential factors may account for this phenomenon. Firstly, individuals may experience temporary satisfaction with a particular technology or trait, but, this satisfaction might not translate into a lasting inclination to use it in the future, as the novelty wears off. For example, individuals who engage in reading a book or attending a theatrical performance typically do not seek to repeat the experience, even if they were satisfied the first time [99]. This pattern is similar to that observed in mobile games. Secondly, it is worth noting that users may have short-term satisfaction with the anthropomorphic trait of chatbots while intending to shift towards an alternative solution (e.g., engaging with a human agent, or embodied agents) in the long run.

Chatbot users were satisfied because of their playful experiences during their interactions with OTA chatbots. Perceived playfulness (PP) had a positive impact on SAT ($\beta = 0.271$, 82%) and CI ($\beta = 0.160$, 79%), supported by past empirical evidence [33], [62].

Interestingly, current research sheds light on the nuanced ways in which cognitive innovativeness (COG) interacts with predictors to shape users' continued use. The first noteworthy finding was that COG exhibited a positive moderating effect on TTF-CI and PU-CI relationships. This suggests that individuals with higher COG perceive a stronger positive impact of a technology's alignment with their tasks and its perceived usefulness on CI, as supported by Huang and Liao [27], highlighting how COG shapes technology acceptance, usefulness, and continued usage. In contrast, there was an insignificant negative moderating influence of COG on perceived playfulness and continuance intention link. This implies that individuals with high COG were not influenced by the playful aspects of technology when forming their intention to continue its use. This observation suggests that these individuals might prioritize the practical and functional aspects of technology more than the emotional or playful aspects [26], [27]. This insight underscores the diverse motivations that drive chatbots' continued use. Yet another interesting finding was that cognitive innovativeness had an insignificant catalytic effect on the PA-CI relation. This suggests that regardless of one's cognitive innovativeness level, the extent to which a technology exhibits human-like qualities may not substantially impact the intention to continue using it.

5.1 Theoretical implications

This research contributes to the advancement of theoretical understanding in several pivotal areas within the literature on human-chatbot interaction. The inclusion of TTF, perceived anthropomorphism, and perceived playfulness in the ECM enriched the framework of the study. This extension acknowledges the significance and relevance of these predictors in shaping user expectations and confirmation post-adoption, thereby contributing to an insightful understanding of chatbot user interactions.

The study is based on multiple theories (ECM, TTF, ARM), which offer novel perspectives on human-chatbot interaction. They shed light on the predictors of post-adoption behavioral outcomes which have been relatively less explored in chatbot literature. The application of advanced analytical techniques (SEM and ANN) reinforces the credibility and robustness of the authors' findings, setting a precedent for further research employing similar methodologies. In addition, the investigation into cognitive innovativeness as a moderator in post-adoption behavior underscores the role of consumer traits in the landscape of technology interactions.

In sum, these implications collectively advance the academic discourse in the fields of chatbots, technology adoption, and consumer behavior.

5.2 Practical implications

When designing and deploying chatbots, Indian online travel agencies must prioritize the alignment between tasks and technology as a predominant attribute. Chatbot functionalities catering to travel planning requirements make chatbots highly appealing and useful, leading to prolonged usage.

In situations where customers encounter difficulties during online ticket booking or travel planning processes, they often seek assistance. When chatbots provide useful and personalized responses with anthropomorphic cues, customers become delighted and exhibit favorable behavior. However, chatbot conversations must be just anthropomorphic without falling into the uncanny valley. Care must be taken to avoid novelty wearing-off and anticipate a potential switch to alternate solutions, ensuring continued use, in the future.

The efficacy of chatbots' responses can be further enhanced by acquiring additional knowledge about their users' travel plans and assisting them in reaching their destinations, similar to their human counterparts. When this level of service exceeds users' expectations, it leaves a lasting positive impression, fostering satisfaction. Therefore, it is recommended that the OTA management regularly updates customer expectations, as they are subject to change. Additionally, marketers should incorporate playfulness to an appropriate degree while designing chatbots as it contributes to a pleasant experience among travel chatbot users.

Furthermore, while dealing with highly cognitive innovative travelers, optimizing functional and useful aspects of chatbots is crucial to encourage sustained use in the future. Highly cognitive innovative individuals do not prioritize playful and anthropomorphic traits as significantly. Hence the optimal level of playfulness and anthropomorphism in the chatbot design is essential to cater to a diverse range of users. These insights have implications for chatbot deployment and marketing strategies, laying the foundation for more personalized chatbot interactions.

6. CONCLUSION

The proliferation of AI technologies and the emergence of a self-evolving digital literacy boom have contributed to the advancement of conversational commerce. Recently chatbots have gained significant popularity in travel, owing to their ability to provide an efficient mode of business-client communication. Notwithstanding the efficacy of OTA chatbots to automate customer service and enhance sales, it is crucial to comprehend the predictors of post-adoption behavior. The current empirical study investigated the drivers predictive of the satisfaction and sustained use of OTA chatbots using a hybrid analysis approach (SEM-ANN). The findings reveal that OTA managers should consider the following predictors of SAT ranked based on their importance: TTF, PU, PP, CONF, and PA. Furthermore, it was found that TTF, PU, PP, and SAT best predicted the continuance intention. Task-technology fit evolved as the potent predictor, suggesting more emphasis during chatbot design. Moreover, it is recommended that chatbot developers and OTA management be mindful when incorporating anthropomorphism and playfulness, specifically when catering to highly cognitive innovative users. The affective responses represent a novel contribution with significant relevance in the literature on text-based chatbots, alongside other predictive factors.

Despite the comprehensive research approach, the current study contains the following limitations. The current study gathered responses from chatbot users in tier-1 cities. Future researchers could expand their scope to include tier 2 and tier 3 cities in India to investigate chatbot user behavior. Moreover, the study employed a hybrid SEM-ANN approach to determine the predictors of CI. However, as an extension, necessary condition analysis (NCA) could be applied to determine which factors are necessary for chatbot users' intention to continue using them. Therefore, a more hybrid SEM-ANN-NCA could be employed by future researchers, similar to the works of Huang and Fu [100]. Perceived anthropomorphism had a positive impact on satisfaction; however, it is worthwhile to investigate the potential uncanny valley effects owing to anthropomorphic cues of chatbots. Also, other affective responses, e.g., cognitive absorption, scepticism, and fear of technology may be investigated in the future. Moreover, scholars could conduct a comparative analysis between themed chatbots and conventional OTA chatbots based on the current conceptual framework. Furthermore, the potential impact of website features on continued chatbot usage could be studied in the future.

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