Journal of Research in Interactive Marketing

Determinants of chatbot continuance intention in airlines: theory and evidence

Aashish Mehra
School of Business, Galgotias University, Greater Noida, India
Justin Paul
University of Puerto Rico, San Juan, Puerto Rico, USA and Korea University Business School, Seoul, South Korea
Sneha Rajput
Department of Marketing, Prestige Institute of Management and Research, Gwalior, India
Govind Soni
Retail and Fashion Merchandise, Footwear Design and Development Institute, Chhindwara, India, and
Serhat Ata
Department of International Trade and Finance, Faculty of Business, Düzce University, Duzce, Turkey

Received 10 July 2025
Revised 18 September 2025
24 November 2025
6 December 2025
Accepted 10 December 2025

Abstract

Purpose – The purpose of the current study is to evaluate the continuance intentions (CIs) of chatbot users in airlines and/or air travel booking companies, which is explored by integrating the extended technology acceptance model (TAM).

Design/methodology/approach – The paper presents empirical evidence by conducting data analysis on 467 travelers, using AMOS. The current study has undertaken six constructs as factors of trust (TRU), which lead to customer experience (CEXP) and finally CI to use airline chatbots. The CEXP to CI path is also mediated by the need for interaction (NFI) and anthropomorphism (ANTH).

Findings – The findings indicate that TAM variables (extended) play a major role in shaping users' trust in chatbots used by airlines, which is crucial for enhancing the CEXP. ANTH plays a significant role in CEXP, directly influencing CEXP and CI, whereas the NFI does not. Ultimately, the CEXP of using airline chatbots significantly impacts their intention to continue.

Originality/value – The study addresses the role of human–AI interaction with a unique proposition wherein extended TAM variables influence CI via trust and CEXP.

Keywords AI-enabled chatbot, Airlines, Trust, Anthropomorphism, Continuance intention, Extended TAM, Structural modeling

Paper type Research article

1. Introduction

Companies are increasingly utilizing artificial intelligence (AI) technologies, including speech recognition, machine learning (ML) and natural language processing (NLP) (Li *et al.*, 2023). AI is transforming industries globally, enabling businesses to streamline operations with smarter tools, engage customers and boost efficiency. With advancements in ML, NLP and speech recognition, AI systems can perform tasks much faster and with remarkable precision, surpassing human capabilities (Sharma *et al.*, 2025).

Chatbots interact with customers using text, voice and visuals (Islam *et al.*, 2024), becoming integral across various industries, including retail, banking, healthcare and travel. AI-enabled chatbots significantly enhance hospitality and tourism experiences (Husnain *et al.*, 2025) by using NLP and ML to answer questions, solve problems and handle tasks like bookings and

Journal of Research in Interactive Marketing
© Emerald Publishing Limited
e-ISSN: 2040-7130
p-ISSN: 2040-7122
DOI 10.1108/JRIM-07-2025-0386

payments seamlessly. In the airline and travel booking sector, AI-driven chatbots assist with inquiries and bookings, as exemplified by Koninklijke Luchtvaart Maatschappij N.V.'s (a.k.a. Royal Dutch Airlines) "BlueBot", which managed over 1.7 million inquiries in its first year (Forbes, 2024).

In the airline industry, convenience, usefulness and trust influence continued chatbot usage. Trust is critical, as users must feel confident in the chatbot's accuracy and ability to handle transactions securely (Wirtz *et al*., 2018). However, service failures pose a barrier to acceptance (Cheng *et al*., 2022). Despite growing use of chatbots and their adoption, a notable contextual and theoretical gap persists (Ngo *et al*., 2025). To address this gap, the current study investigates the following questions:

RQ1. Which attributes of chatbots of airlines and online travel agencies (OTAs) influence their consumers' trust and subsequent experience with chatbots?

RQ2. In what ways do the attributes of airline and OTA chatbots affect consumers' trust and overall experience with these chatbots?

RQ3. To what extent does the impact of chatbot attributes on consumer trust depend on the consumer experience, influencing their intention to continue using them?

This study identifies six key attributes influencing chatbot usage: perceived usefulness (PUSE), perceived ease of use (PEOU), perceived enjoyment (PENJ), social influence (SINF), response time (RTIM) and perceived security (PSEC). Between these attributes and customer experience (CEXP) with chatbots, trust (TRUS) serves as a mediating variable and, finally, CEXP mediates the relationship between trust and continuance intention (CI) of users (CINT) in using airline and/or OTA chatbots. Two additional mediating factors, namely, need for interaction (NFI) (the preference to switch from chatbots to human agents) (NFIN) and anthropomorphism (ANTH) (the perception of human-like traits in non-human agents), are also examined for their indirect effects on CI to use airline and/or OTA chatbots.

The remainder of this paper includes a literature review, theoretical background, methodology, main findings, discussion of findings, implications and limitations of this study.

2. Literature review

2.1 Chatbots in airlines

Chatbots are automated computer programs designed to simulate human-like interactions through interfaces that are either text or voice-based (Wang and Lo, 2025). AI-powered chatbots significantly enhance efficiency in customer service through advancements in AI technology; they offer 24/7 support, resolve basic issues and problems, handle tasks like answering frequently asked questions and provide product recommendations (Gao *et al*., 2025). "Anthropomorphism" has led to more affiliation between customers and service providers by cultivating emotional bonds, thus lowering costs by using fewer staff (Epley *et al*., 2007) and handling multiple customers from different time zones, thus freeing human resources for other tasks.

AI chatbots have become increasingly popular with the airline industry. Now airline customers can acquire more accurate information related to air travel, such as flight schedules, booking, boarding and/or check-in information (including luggage) and updates, thus enhancing the CEXP. Jiménez-Barreto *et al*. (2021) confirmed the direct impact of CEXP and self-determined interaction on attitude towards and satisfaction.

3. Theoretical background, research voids and hypotheses development

3.1 Theoretical background

The section presents the background theories incorporated in the proposed research model (Figure 1). The majority of factors in the study are adapted from the two most popular models of

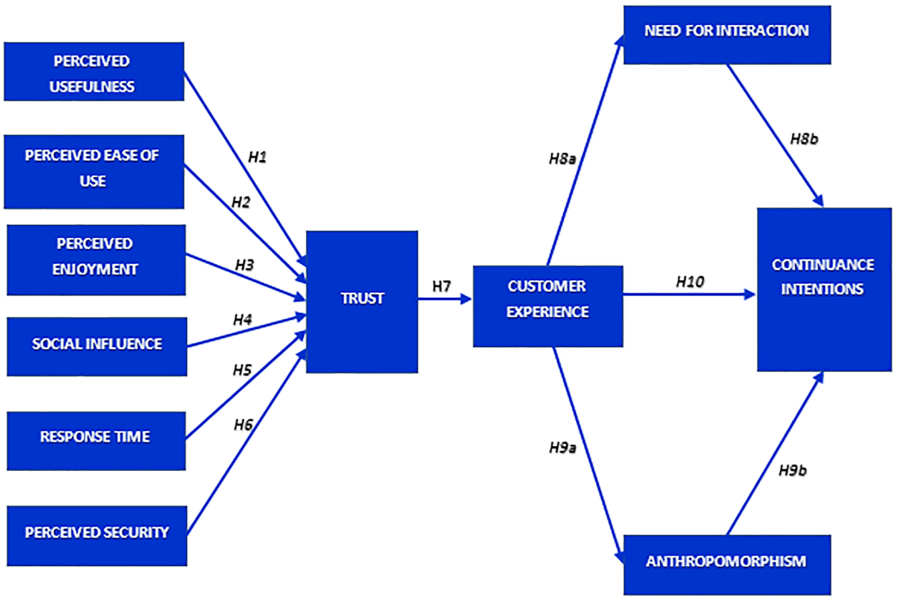


Figure 1. Research model

technology adoption, namely, the technology acceptance model (TAM): six factors, and the unified theory of acceptance and use of technology (UTAUT): two factors; all the rest of the factors were adapted from other models and/or theories (one factor from each model) such as social response theory, expectancy violations theory and SEEK (three-factor model) (see Table 1).

3.1.1 TAM (technology acceptance model). TAM explains the phenomenon of user acceptance as a theory based on the expansion of the theory of reasoned action (Davis, 1989). The two main factors in TAM that measure user acceptance are PUSE and PEOU (Gao *et al*., 2025).

Table 1. Summary of constructs

Codes used	Model	Original Source	Cited in
PUSE	TAM	Davis (1989)	Oghuma *et al*. (2016)
PEOU	TAM 2	Davis *et al*. (1989)	Dasgupta *et al*. (2011)
PENJ	TAM 3	Davis *et al*. (1992)	Lee *et al*. (2005)
SINF	UTAUT	Venkatesh *et al*. (2003)	Venkatesh *et al*. (2012)
RTIM	Social response theory and expectancy violations theory	Bailey and Pearson (1983)	Cheng (2011)
PSEC	Extended TAM	Hartono *et al*. (2014)	Aggarwal and Rahul (2018)
TRUS	Extended TAM	Gefen *et al*. (2003)	Chong *et al*. (2012)
CEXP	UTAUT	Chan *et al*. (2010)	Hong *et al*. (2011)
NFIN	NA	Dabholkar *et al*. (1996)	Xie *et al*. (2020)
ANTH	Three-factor model — the sociality, effectance and elicited agent knowledge (SEEK)	Epley *et al*. (2007)	Rosen *et al*. (2024)
CINT	In addition to TAM	Bhattacherjee (2001)	Bhattacherjee and Lin (2015)

Source(s): Compiled by authors

TAM emphasizes external variables' role in defining internal decision-making processes of individuals; these external factors exert both direct and indirect effects on PUSE, mainly through PEOU (Berbar, 2023). As the design of AI-powered chatbot technologies is based on users' needs, PEOU is a critical necessity (Gao *et al*., 2025). PSEC has been included in this study, as the traveler's perception of security, privacy protection and quality of the application they are using is of utmost concern (Pillai and Sivathanu, 2020). PENJ also affects chat users' behavior positively as they feel engaged and entertained with chatbots. People have fun in interacting, which leads to a better understanding of their enhanced user experience such that chatbot developers can deliver a better service quality (Wut *et al*., 2024). Trust (TRUS) has been investigated in several distinct contexts; however, scant research is present addressing trust in chatbots. "Usefulness" and "ease of use" are the two factors that majorly drive initial trust and behavioral intention. CINT, an additional factor from TAM, is crucial for this study. Thus, the framework shown in Figure 1 combines six factors extracted from TAM (including extended TAM), namely, PUSE, PEOU, PSEC, PENJ, TRUS and CINT, along with other factors to measure customer user experience mediated by trust with an AI chatbot in the airline industry.

3.1.2 UTAUT (unified theory of acceptance and use of technology). The UTAUT model (Venkatesh *et al*., 2003) explains the variance in user behavior and behavioral intention through performance expectancy, effort expectancy and SINF. Dwivedi *et al*. (2019) proposed to include missing paths, such as from facilitating conditions to behavioral intentions and the inclusion of the attitude of users mediating between performance expectancy and effort expectancy to behavioral intention. Similarly, CEXP has been added later on as part of the extended UTAUT.

SINF is a crucial factor from UTAUT theory, as it considers that consumers believe in reference groups and their advice to use certain products or services, and these beliefs affect consumers' trust and behavior in using new technologies (Mostafa and Kasamani, 2022). Thus, we included SINF as an antecedent to chatbot trust.

CEXP is an individual's perception and response in relation to the use of a product, service or system (Shahzad *et al*., 2024). The user experience with AI chatbots entails the satisfying feeling a user has when interacting with chatbots seamlessly (Pizzi *et al*., 2021). This study develops an understanding of two mediating elements in the proposed framework: the NFIN and ANTH. The "need for interaction" is crucial for interpersonal communication (Baumeister and Leary, 1995). Studies document the impact of ANTH on usage or purchase intention (Sestino and D'Angelo, 2023).

3.2 Research voids and hypotheses development

While chatbots were first developed in 1966, significant work on chatbots has existed since 2016, although the co-existence with airlines is a rare phenomenon. A significant milestone was reached in 2007 when British Airways launched its chatbot, marking a pivotal moment in the evolution of conversational AI in the airline industry. The pioneer studies elaborated on the use of Facebook Messenger online chat for business activities by Dutch Airlines, like issuing boarding passes through the same (Olson, 2016). Studies are conducted for chatbot interaction in the context of airlines on user-generated and user engagement (Son *et al*., 2023) and the self-service technology adoption model (Lee, 2013).

The current study is undertaken to present an empirical framework using UTAUT and TAM variables having influence on TRUS and CINT, mediated by NFI and ANTH. Rare studies using TAM constructs along with TRUS and CINT are conducted in the airline industry (Quililan *et al*., 2025), thus leaving a void. Also, empirical studies on CINT determinants for chatbots are limited (Nguyen *et al*., 2021).

Many studies extensively explored the prediction of trust in AI-powered chatbot systems to identify ways to quantify and recognize factors such as social presence, ANTH and credibility (Gkinko and Elbanna, 2023). Therefore, trust-enhancing attributes like usefulness, ease of use, RTIM, social presence, security, transparency, enjoyment, etc. require more research (Zierau *et al*., 2020).

Six factors were hypothesized to have been connected with trust as part of the first-order measurement model, namely, PUSE, PEOU, PENJ, SINF, RTIM and PSEC, which are vital for this paper. Thus, the study is a novel attempt to study the connection of TAM variables along with trust, NFI and ANTH in the airline industry. There is a need to explore the role of NFI, as well as the humanized characteristics of a chatbot, i.e. ANTH, in mediating the relationship between trust and CI. Empathic chatbot-led services enhance CEXP (Juquelier *et al*., 2025).

Based on the literature and considering the research gap, the following hypotheses were formed.

3.2.1 PUSE → Trust. In AI-based chatbots, PUSE is a key determinant of adoption intentions (Li *et al*., 2023). PUSE impacts adoption in travel planning, such as business-to-consumer travel search engines and tourism apps (Coves-Martínez *et al*., 2023). In the adoption of new technologies such as chatbots, PUSE and PEOU are major drivers of initial trust and behavioral intention. The overall experience fosters trust when any airline consumer perceives that its chatbot has high utility and a consistent performance. Therefore, the hypothesis posits:

H1. PUSE influences TRUS in airline chatbot service.

3.2.2 PEOU → Trust. PEOU refers to how seamlessly a system operates without requiring extra effort or skills from users. Higher trust levels are linked to greater PEOU. The TAM theory supports the positive relationship between TRUS and PEOU (Gefen *et al*., 2003). A higher PEOU strengthens initial trust, driving chatbot adoption (Mostafa and Kasamani, 2022). The logic behind the strengthened trust is that easier the product is to use, the more confidence it gives to the consumer, who is fearless in using the product and thus can perform better with easy navigation (Ashfaq *et al*., 2025). PEOU can instill trust among chatbot users of airlines. Thus, the hypothesis posits:

H2. PEOU influences trust in the airline chatbot service.

3.2.3 PENJ→ TRUS. PENJ is defined as the "pleasure derived from engaging with a system, independent of any performance outcomes" (Venkatesh, 2000; Mehra *et al*., 2020). Customers who enjoy using chatbots are more inclined to use them again and feel they have sufficient time to complete the tasks, ultimately increasing their trust in the chatbots. The reason behind such a connection between PENJ and trust is the positive feeling associated and the emotional attachment (Mamun *et al*., 2023). Conversely, diminished PENJ can hinder trust and negatively impact the user experience (Pereira *et al*., 2022). The fun element in airline chatbots is expected to enhance trust in them. Hence, the hypothesis posits:

H3. PENJ influences trust in the airline chatbot service.

3.2.4 SINF → Trust. People often see using AI services as aligning with social group (peer and/or social group, friends and relatives) norms (Gursoy *et al*., 2019). Using the same product (as the group) leads to validation; moreover, at times, there is a sense of pressure to adopt to align oneself with the community (Sasahara *et al*., 2021). Chi *et al*. (2020) examined the attitude of tourists towards the use of AI devices in airlines (utilitarian) and hospitality (hedonic) services and compared the two services. Their findings suggest that SINF was a weaker determinant of user attitude towards AI devices in airline services in comparison to hospitality services and further recommended that SINF in the airline context needs to be explored further; hence, we included SINF. The hypothesis framed is:

H4. SINF influences trust in the airline chatbot service.

3.2.5 RTIM → Trust. RTIM in chatbot interactions is a critical social cue, shaping conversational flow, relational engagement and user satisfaction (Zhang *et al*., 2024a, b). Users in typical customer service scenarios expect quick responses. Much delay in response could lead to conversational disengagement and dissatisfaction (Zhang *et al*., 2024a, b, July).

Prompt RTIM builds trust and enhances the user experience. The literature about RTIM and TRUS has not been explored in the field of chatbots, specifically in airlines and tourism. Thus, the hypothesis is:

H5. RTIM influences trust in airline chatbot service.

3.2.6 PSEC→ Trust. PSEC is the subjective likelihood that the personal information of users will not be illegally stored, accessed or manipulated by others (Flavián and Guinalíu, 2006). PSEC is linked to trust; users lose trust in the company if the security of their personal data, such as information viewed by outsiders or information leaks, is not being protected by the company and/or service provider (Siagian *et al*., 2022). Trust, defined as confidence in security and privacy, is crucial for user behavior and influences users' intentions (Hooda *et al*., 2022), and it is a must in airline chatbot service. Hence, the hypothesis is:

H6. PSEC influences trust in airline chatbot service.

3.2.7 Trust → CEXP. The relationship between TRUS and CEXP across domains has been depicted in both ways, i.e. effect of TRUS on CEXP and vice versa as well; several studies, like Siqueira *et al*. (2023), adapted the former relationship – in contrast, Kushwaha *et al*. (2021) adapted the effect of trust in CEXP, although in a business-to-business context. We adapted trust in the CEXP relationship, as the trust-enhancing attributes such as PUSE, PEOU, PSEC, RTIM, SINF and PENJ would motivate the chatbot user to go for an enhanced experience, and based on the trust so built, it will eventually lead to a CINT if satisfied with the enhanced experience. Trust in the quality of the chatbot ensures better CEXP (Jenneboer *et al*., 2022) in the airline industry. Hence, the following hypothesis is framed:

H7. TRUS positively influences CEXP in the airline chatbot service.

3.2.8 CEXP → NFIN. Defining CEXP is challenging due to its diverse meanings (Lemon and Verhoef, 2016). CEXP encompasses cognitive, emotional, sensorial and behavioral responses influenced by communication, brand identity and environmental factors. These experiences shape consumer expectations during all interactions. In chatbot interactions, studies examine trust, satisfaction or actions that affect the overall experience (Hoyer *et al*., 2020), while human-like features enhance engagement. However, complex interactions may lead to disappointment (Solvvy, 2021), eventually leading to the need for a personal interaction to solve a specific problem. This situation may arise in an airline chatbot interaction in case it lacks meticulous programming. Thus, the hypothesis is:

H8a. CEXP influences the NFIN in the airline chatbot service.

3.2.9 NFIN→ CINT. NFIN is "the importance of human interaction to the customer in service encounters" (Dabholkar and Bagozzi, 2002). Interaction, satisfaction and CINT are interconnected, though users may perceive human-like chatbots as threatening (Schmitt, 2020). Expectation confirmation theory explains how expectations shape customer perceptions. When chatbot performance meets expectations, it leads to confirmation and satisfaction. Consequently, chatbot interactions influence CINT by shaping beliefs, expectations and satisfaction (Nguyen *et al*., 2021). Chatbots' creepiness with an increased integration of AI in airlines, utilizing technology anxiety and the need for human interaction, is found to influence perceived creepiness, further affecting customer satisfaction and loyalty (Lacap *et al*., 2025). Hence, NFIN is a mediating variable that affects CINT. Thus, the hypothesis is:

H8b. NFIN influences CINT in the airline chatbot service.

3.2.10 CEXP → ANTH. "Alexa, play rhymes" sounds like speaking to a human, categorizing the social responses of computers as "anthropomorphism" (Nass and Moon, 2000) and believe that the object possesses human characteristics (Zhou *et al*., 2019). The SEEK model elaborates on "ANTH" through sociality, effect and elicited knowledge

(Rosen *et al*., 2024). AI-enabled chatbots are considered to make conversations and interactions with customers using a high degree of ANTH (human-like) (Alalwan *et al*., 2025).

Marketing literature lacks consensus on whether ANTH in chatbot experiences enhances or limits users' intention to reuse chatbots (Schmitt, 2020). Although excessive human-like features may lower satisfaction and future purchase intentions, incorporating humor can enhance CEXP (Shin *et al*., 2022). Thus, the following hypothesis is proposed:

H9a. CEXP influences ANTH in airline chatbot service.

3.2.11 ANTH → CINT. ANTH in AI is pivotal as it helps humans. Be it pandemic times (Miner *et al*., 2020) or online shopping (Fu *et al*., 2023), ANTH is the leading characteristic in AI (Lee *et al*., 2023).

The impact of ANTH can be positive (Zhang *et al*., 2022) as well as negative (Crolic *et al*., 2022). Factors like customer traits and predispositions, gender of chatbots, design, impacts and use are also the triggers of ANTH (Blut *et al*., 2021). Much literature presented ANTH in relation to CINT (Lee and Li, 2023). At times, it weakens the CINT in industries like retail, as it needs more customer engagement, i.e. human interaction (Lim *et al*., 2021). However, airline chatbots' ANTH can efficiently resolve many consumer queries and issues, encouraging its adoption. Thus, the hypothesis is:

H9b. ANTH influences CINT in the airline chatbot service.

3.2.12 CEXP → CINT. CINT is a user's intent to keep using services (Bhattacherjee, 2001). The quality of chatbot service and its assistance influences CINT; timely responses foster trust and satisfaction (Gao *et al*., 2015). Aw *et al*. (2022) found that digital voice assistance can boost CINT. Implementing empathy into AI chatbot interfaces can significantly boost CEXP (Juquelier *et al*., 2025) and ultimately enhance satisfaction. The airline industry lacks exploration of chatbot-related CINT, presenting opportunities for further research. Thus, the hypothesis is:

H10. CEXP influences CINT in the airline chatbot service.

4. Methodology

Using 467 responses from users of AI-based chatbots from airline companies, data were collected through online and offline modes via purposive sampling and were contacted at major airports in India (Indore, Gwalior, Bhopal and Mumbai) for offline data, were aged 18–75 and had used its "chatbot" for any inquiry (track luggage, general inquiries, etc.). Eight capable research scholars of the authors were deputed (two in each of the four cities) to lead a team of carefully scrutinized 8–12 master of business administration students for distribution and collection of questionnaires at the exit gates of the mentioned airports. In total, 950 individuals were contacted; however, 467 agreed to respond (296 in physical mode and the rest through email and/or social media), yielding a 34.6% response rate including 286 males and 181 females from Madhya Pradesh and Mumbai, India.

4.1 Instrument design and data collection

A seven-point Likert scale instrument for this was adapted after a thorough review of the various sources (Table 1).

4.2 Data analysis tools

The measure was standardized assessing reliability and validity. Confirmatory factor analysis (CFA) was used to confirm the constructs (factors), and structural equation modeling (SEM) was used to establish the hypothesized model.

4.3 Sample descriptive

The study included all age groups: 18–30 years, 31–45 years, 46–60 years and 61–75 years; with representation of 114, 187, 103 and 63 as the number of respondents for respective age groups. From the age group first, 86 were males; from group second, 79 males were there, and from group third, 48 were males; the rest were females.

5. Results

5.1 Reliability and discriminant validity

Reliability (Cronbach's alpha) values were above 0.7 (Nunnally, 1994). Discriminant validity ensured that the two measures are significantly correlated (Venkatraman, 1989). The average variance extracted values were 0.5, and composite reliability was 0.7 (Fornell and Larcker, 1981), as per the threshold, ranging from 0.842 to 0.931 and 0.625 to 0.772, respectively (Table 2).

5.2 Common method bias (CMB)

The Harman's single factor and the unmeasured latent method construct have been used for this research (Podsakoff *et al*., 2003) for all, and the results entailed that no biases in the data were found, as common method bias (29.06%) was well within the permissible limits of 50% (Harman, 1976).

5.3 Measurement model testing

CFA, an extension of exploratory factor analysis, is used to assess whether measurements align with construct essence (Hair *et al*., 1992). Goodness-of-fit (GoF) indices (chi-square minimum / degrees of freedom (CMIN/DF), goodness-of-fit index (GFI), comparative fit index (CFI), adjusted goodness-of-fit index (AGFI), normed factor index (NFI), root mean residual (RMR) and root mean square error of approximation (RMSEA)) were evaluated to measure model fitness (Byrne, 2010). After data reassessment, all indices met the minimum threshold limits, confirming enhanced model fitness: CMIN/DF (1.191), GFI (0.908), CFI (0.988), AGFI (0.894), NFI (0.932), RMR (0.030) and RMSEA (0.020). Figure 2 shows the final measurement model with all 11 constructs (Table 3).

5.4 Structural model

The final structural model (revised) is depicted in Figure 3. Path analysis findings, as illustrated in Table 3, indicate that a better match to the data is presented by the GoF indices. All indices were found as per threshold: CMIN/DF (1.212), GFI (0.906), CFI (0.987), AGFI (0.895), NFI (0.930), RMR (0.045) and RMSEA (0.021). Results show the following relationships: PUSE ($\beta = 0.203$, $p < 0.001$), PEOU ($\beta = 0.195$, $p < 0.001$), PENJ ($\beta = 0.243$, $p < 0.001$), RTIM ($\beta = 0.187$, $p < 0.001$) and PSEC ($\beta = 0.266$, $p < 0.001$), all five had a highly significant and positive influence on TRUS; SINF ($\beta = 0.070$, $p < 0.036$) had a slightly significant and positive influence on TRUS; TRUS ($\beta = 0.290$, $p < 0.001$) had a significant and positive influence on CEXP; similarly, CEXP ($\beta = 0.585$, $p < 0.001$) on ANTH and ANTH ($\beta = 0.488$, $p < 0.001$) on CINT were strong predictors of airline chatbot users' behavior towards using its chatbot. However, CEXP ($\beta = -0.449$, $p < 0.001$) on NFIN and NFIN ($\beta = -0.182$, $p < 0.001$) on CINT had a negative influence; finally, CEXP ($\beta = 0.431$, $p < 0.001$) had a highly significant and positive influence on CINT.

5.5 Mediation testing

The mediation analysis where CEXP is an independent variable and CINT is the dependent variable, along with NFIN and ANTH acting in the capacity of mediating variables. Following Baron and Kenny (1986), we used bootstrap procedures with 5,000 samples and a 95% bias-corrected bootstrap confidence interval.

Table 2. Discriminant validity

	CR	AVE	ANTH	PUSE	PENJ	PEOU	SINF	RTIM	PSEC	TRUS	CEXP	NFIN	CINT
ANTH	0.925	0.711	*0.843*										
PUSE	0.910	0.669	0.194	*0.818*									
PENJ	0.907	0.660	0.173	0.521	*0.812*								
PEOU	0.906	0.707	0.217	0.487	0.408	*0.841*							
SINF	0.869	0.688	0.010	0.006	0.034	0.021	*0.830*						
RTIM	0.842	0.640	0.058	0.407	0.418	0.253	0.012	*0.800*					
PSEC	0.920	0.698	0.174	0.590	0.573	0.562	0.019	0.514	*0.835*				
TRUS	0.869	0.625	0.178	0.652	0.656	0.587	0.091	0.561	0.729	*0.791*			
CEXP	0.905	0.706	0.567	0.307	0.291	0.251	0.032	0.051	0.242	0.263	*0.840*		
NFIN	0.911	0.719	−0.437	−0.181	−0.098	−0.090	−0.047	−0.056	−0.132	−0.140	−0.436	*0.848*	
CINT	0.931	0.772	0.671	0.200	0.157	0.149	0.011	0.038	0.132	0.174	0.625	−0.495	*0.879*

Note(s): Correlation significance <0.05. Diagonal elements are equal to the square roots of AVEs

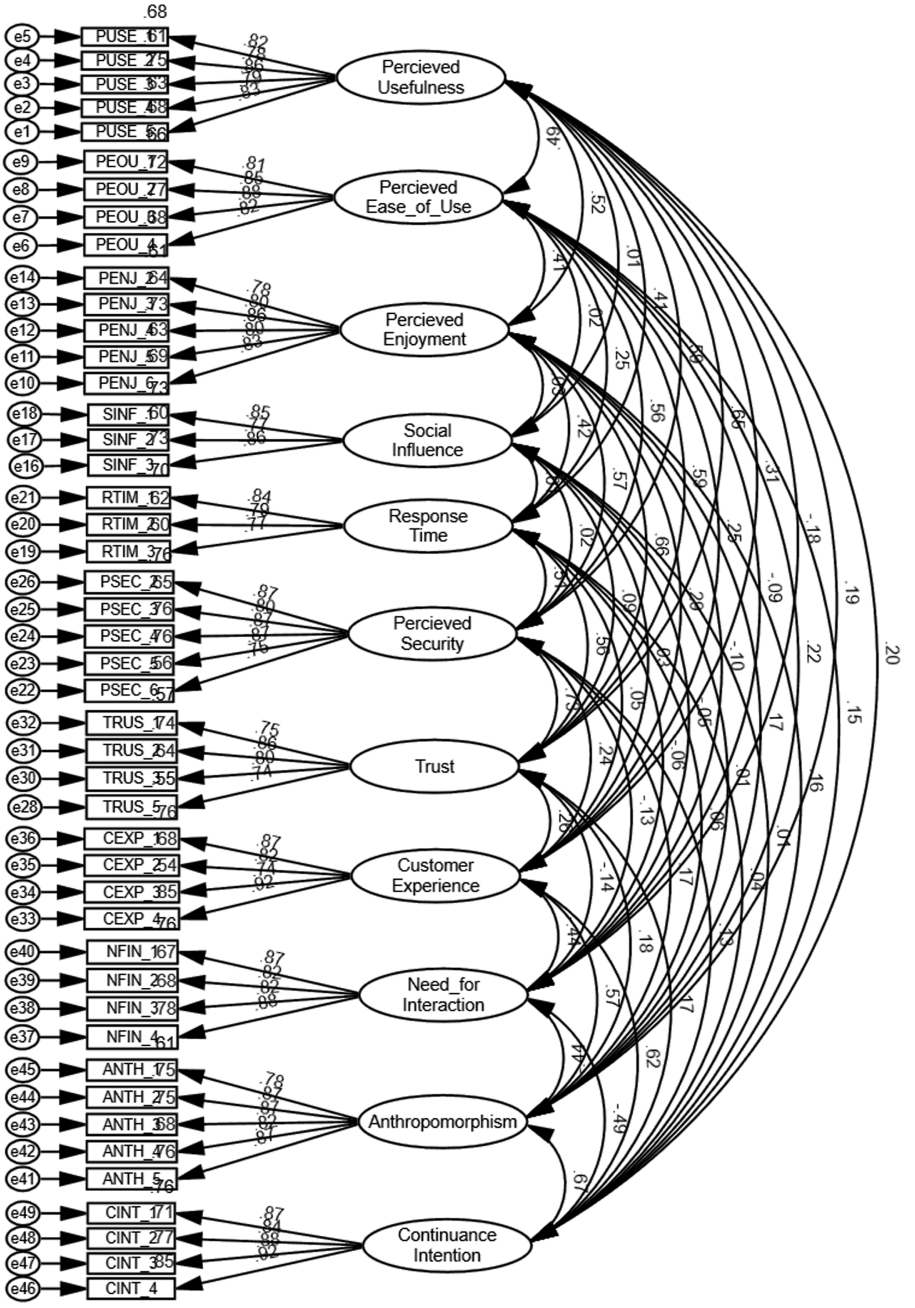


Figure 2. Measurement model. **Source:** AMOS output

The mediation influence of NFI on the CEXP and CINT relationship is minimal, as the indirect effects are statistically not so significant ($\beta = 0.077$, $p < 0.000$) (with lower bound 0.035 and upper bound 0.133); on the contrary, ANTH is positively mediating (highly) the

Table 3. The goodness-of-fit indices of the measurement model (final) and SEM (revised-final) of the adoption of airline chatbots

			Absolute fit measures				Incremental fit measures		Parsimony fit measure
	χ^2	Df	χ^2/df	GFI	RMSEA	RMR	NFI	CFI	AGFI
Criteria			$1<\chi^2/df$	≥0.90	≤0.08 <0 .1	≤0.08 <0 .1	≥0.90	≥0.90	≥0.90
CFA	1112.543	934	1.191	0.908	0.020	0.030	0.932	0.988	0.894
Structural model	1112.526	918	1.212	0.906	0.021	0.045	0.930	0.987	0.895

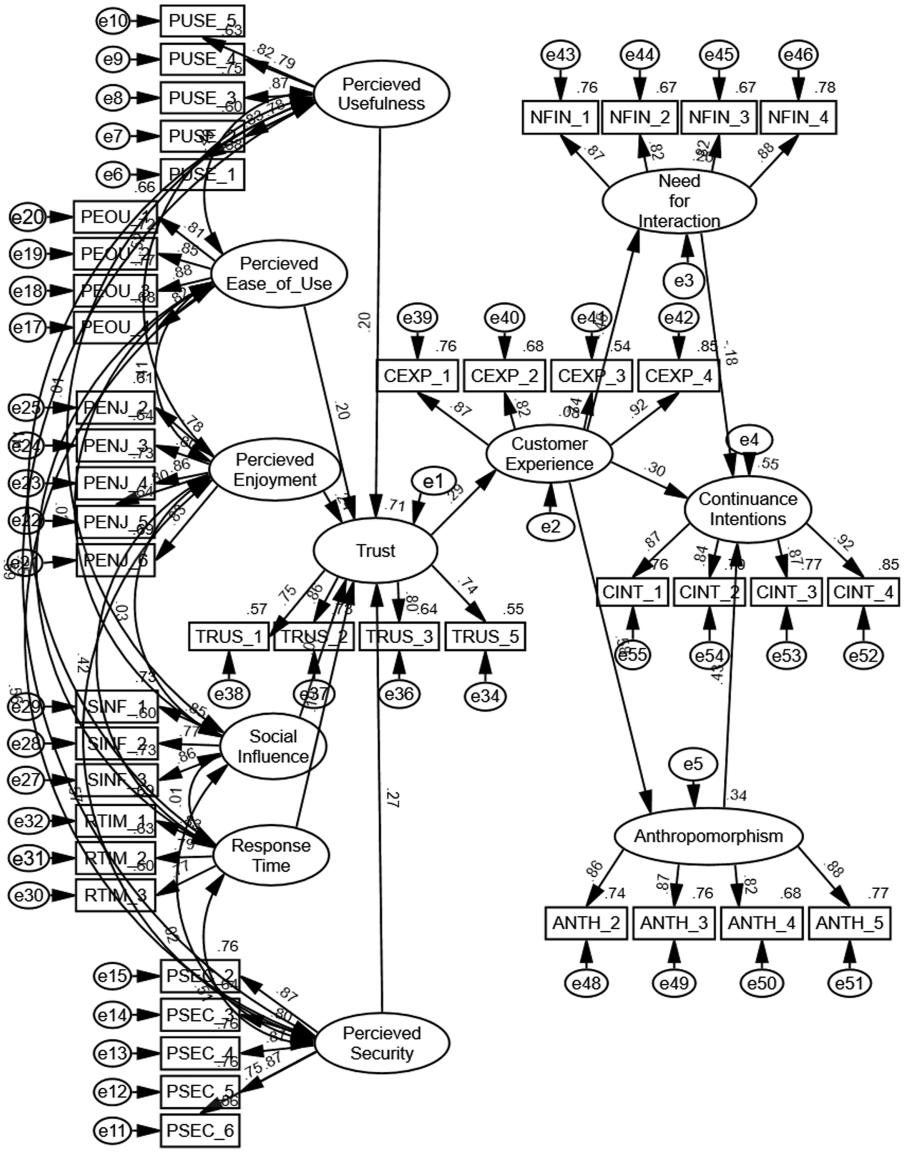


Figure 3. Structural model (path analysis). **Source:** AMOS output

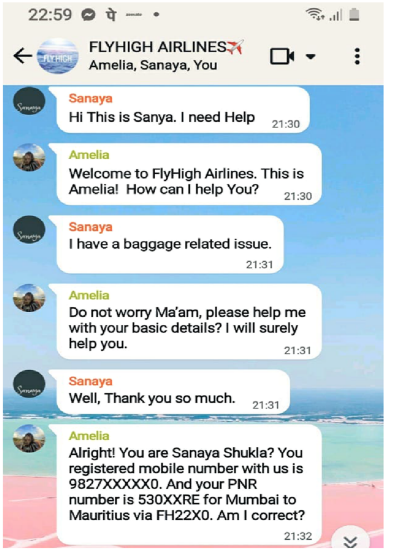
relationship between CEXP and CINT, as the indirect effects are statistically significant ($\beta = 0.237$, $p < 0.000$) (with lower bound 0.169 and upper bound 0.323). Based on these results, we reject H8 and accept H9.

6. Discussion and implications

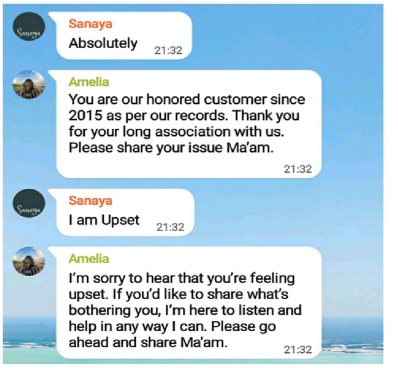
This section presents the discussion of the findings through a storytelling narrative (Wang, 2025), followed by a discussion of hypotheses.

6.1 Storytelling narrative

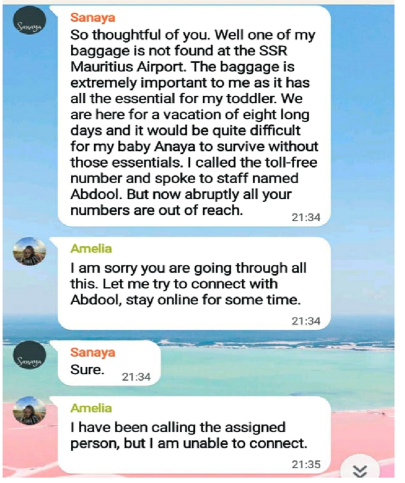
The following story (as shown in images A to F) underlines the novel contributions of the study:



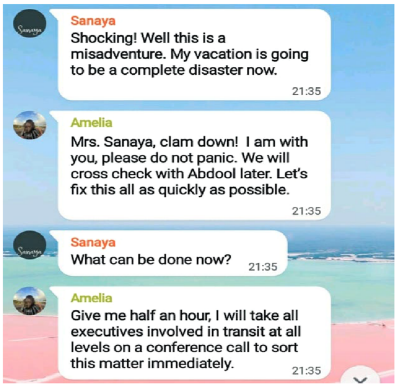
(a)



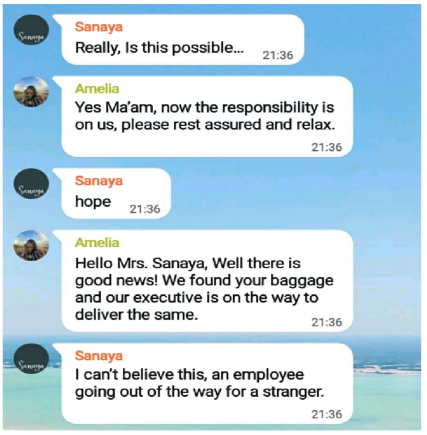
(b)



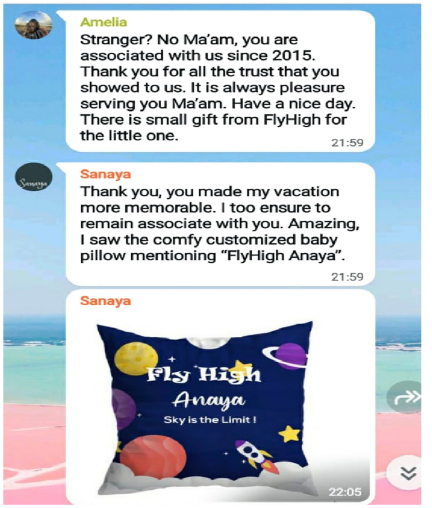
(c)



(d)



(e)



(f)

Source(s): Images a to f: Created by the authors

Summary of story: The story clearly entails how easily (PEOU) Sanaya could communicate with an airline Amelia (chatbot) and used it (PUSE) to find her lost baggage in very little time (RTIM). She could share her sensitive information (PSEC) with ease and was inspired to use the chatbot freely, which could have been suggested by any of her acquaintances and/or relatives (SINF). Eventually, she enjoyed using the chatbot (PENJ). She had built a trustworthiness (TRUS) based on her great experience (CEXP), and at the end, she decided to continue using the airline's chatbot (CINT) without even needing to talk to any employee (NFIN) and completely understanding the value of "computer to human interaction," which was having human-like emotions (ANTH) too. Thus, the storyline clearly delineates the use of various constructs in our study.

6.2 Discussion of hypotheses

PUSE had a significant and positive effect on trust (H1). It clearly signifies that the customer is looking for the utility and value of airline chatbot service that includes its seamless performance and consistency, which is expected to solve the problem of the user. Wherein PEOU affects the trust positively and significantly and is consistent with much of the literature (H2) (Choudhury and Shamszare, 2023), it shows how important it is for an airline chatbot user to feel comfortable and confident while using the service, thus making the user mentally relaxed.

The effect of PENJ on trust (Rouibah *et al*., 2016) is also seen. These positive emotions are the foundation of building trust. Airline and/or OTA consumers used to enjoy their chatbot service and feel pleased. The enjoyment associated with airline chatbot service helps to reduce doubt and makes the user more confident (H3).

SINF partially affected trust, supported by rare studies (Amrollahi *et al*., 2024). There are chances that recommendations from reference groups may not perfectly align with the needs of airline chatbot users, and they feel that their opinion is stronger compared to the suggestions or recommendations given by their known. Here, cultural differences must not be ignored to understand the fact that there can be contradictions in the opinion (H4).

RTIM significantly affects trust for an airline chatbot service (H5). The lesser time taken in response generates a high level of reliability and vice versa; the higher the RTIM, the higher the chance of uncertainty (Efendić *et al*., 2020). PSEC (H6) significantly affects trust (supported

by Siagian *et al*., 2022), as the user shares sensitive information with the airline chatbot, like travel dates, destinations, budget or queries related to payments, to name a few. In such cases, more certainty that the information will be kept confidential is needed. Further, the trust influences CEXP positively and significantly. Trust is the foundation of an enduring positive relationship, leading to a positive experience, thus supporting H7.

H8a, the impact of CEXP on NFI, was found to be insignificant. Thus, when airline customers are accustomed to chatbot service for inquiry, etc. they prefer to interact as little as possible with its personnel. Similarly, the NFI does not influence CI, as the customer has a tendency to choose solitude and be more confident in using the chatbot's automation. Thus, when the NFI is lesser, the CI can be higher and vice versa (H8b).

H9a and H9b, where the airline chatbot experience was found to positively and significantly affect ANTH, and ANTH was also significantly affecting its CI, respectively. Subsequently, the more human-like qualities in the chatbot will help airline customers to have a strong emotional connection with the brand, and they would also like to continue with such interactions.

CEXP affects positively CI (H10). Further (H8), NFIN is not mediating the CEXP and CI relationship, as the indirect effects are statistically insignificant. However, ANTH is positively mediating the relationship between CEXP and CI (H9), as the indirect effects are statistically significant. Based on these results, we reject H8 and accept H9.

6.3 Implications for practice

The study adds to existing literature on the theory of technology acceptance (extended TAM). The adoption of chatbots by airline customers by examining the prediction of the most crucial determinants (factors) of users' intention to use airline and/or OTA chatbots. The study fills the gap by analyzing an integrated model that amalgamates mainly TAM, extended TAM, UTAUT and other theories, including social response theory and expectancy violations theory and the SEEK model for the first time. The study uniquely defines new causal paths in the proposed model (integrated): TRUS → CEXP → CINT, CEXP → NFIN → CINT and CEXP → ANTH → CINT except CEXP → NFIN → CINT, which, in fact, was an expected result. This study significantly contributes to the body of technology acceptance and its adoption.

From the manager's perspective, travelers, entrepreneurs and professionals –who do not have enough time to devote to travel-related inquiries, including check-in information, ticket booking and/or cancellation, etc., will frequently use the airline and/or OTA chatbot if it is excellent. Thus, airlines, while designing their chatbot, must focus on enhancing all the dimensions (factors) used in the study. For the same, a "trial chatbot" can be used to know more about the user's perception, expectations from the same and a simplified procedure for users. Nowadays, the testimonials and feedback have more impact; in line with this, existing users can be encouraged to write content and promote it to potential customers.

As PSEC enhances trust, the managers must share the trust level maintained by the chatbot, reflecting transparency and ethical dimensions being followed by the company. Further, value-added features like sharing memories of last travel, making a customized itinerary or other services like free upgradation and improvised check-in and boarding information (along with real-time signage displayed by the bot showing where to move, e.g. how to reach to the boarding gate, etc.) can significantly impact to build the user's trust in having a great experience while using an airline chatbot. Thus, managers must ensure that the chatbot does not become so monotonous and complicated that it increases the anxiety of any user. Rather, the user gets a feeling of belongingness (care) or a kind of affiliation (i.e. the anthropomorphic effect – as depicted in the "Amelia" story) so that he becomes absolutely convinced to adopt the chatbot.

From the developers' and marketers' perspective, the study's findings suggest that the developers and marketers of AI-driven chatbots should emphasize the SINF (SI) factor (which

was found to be weak) while developing, designing and promoting the AI-based chatbots for airlines in India, such that more and more people traveling by airlines adopt the use of chatbots for booking of tickets and/or travel enquiry, etc., and they start recommending it to others in their respective social and/or peer groups. The user can be incentivized for referring the chatbot in their network.

7. Limitations and directions for research

Digital transformation has a profound influence on society and business (Paul *et al*., 2024; Patil *et al*., 2025; Raman and Paul, 2025). We recommend future researchers may include more cities and states for comparative analyses with the largest airports in other countries. While many variables relate to chatbot use by airline customers, such as marketer–customer interaction (Cheng and Jiang, 2021) and human–machine interaction (Kaczorowska and Spychalska, 2019), future investigations could integrate additional relevant variables to create a more comprehensive model. Comparing countries is another scope, as countries' level of advancement varies. Similarly, longitudinal studies can definitely provide a richer and more dimensional view of the paths established in the study. Lastly, adding various demographics like nationality, employment level, gender and age group can add more insights to the literature contextually.

8. Conclusion

The study examines the factors affecting chatbot users' continuity and loyalty intention. Chatbot users who frequently prefer airline travel, such as doctors, students, teachers, entrepreneurs, employees, etc., constituted the primary data sources, and the data were analyzed by applying tests such as reliability, validity, CFA and SEM. The study was found to be critical in identifying the impact of influencing factors in chatbot use on users' experience, trust, NFI and intention to continue. Following CFA, all 11 factors were found to be significant predictors for capturing the determinants of perception of chatbot use on intention to continue using airline chatbots. Among these factors, PUSE, PEOU, PENJ, RTIM and PSEC were found to be the factors that fully affect trust, whereas trust was found to fully affect CEXP, CEXP was found to fully affect customer ANTH and the combined significant effect of CEXP and ANTH was found on CINT to continue using airline and/or OTA chatbot. Therefore, as the results indicate, the model used in the study is approved.

Appendix

Measurement items

Construct	Items	Factor Loads
Perceived Usefulness	I find the airline chatbot useful in my daily life.	PUSE_1 0.825
	Using the airline chatbot helps me to accomplish things more quickly.	PUSE_2 0.778
	Using the airline chatbot helps me get my web check-in quickly.	PUSE_3 0.864
	Using the airline chatbot helps me get my mobile boarding pass quickly.	PUSE_4 0.795
	Using the airline chatbot helps me to perform many things more conveniently.	PUSE_5 0.825

(*continued*)

Continued

Construct	Items	Factor Loads
Perceived Ease of Use	My interaction with the airline chatbot is clear and understandable.	PEOU_1 0.812
	Interaction with the airline chatbot does not require a lot of my mental effort.	PEOU_2 0.85
	It is easier to use airline chatbot to inquire about my journey details.	PEOU_3 0.877
	I find the airline chatbot to be easy to use.	PEOU_4 0.823
Perceived Enjoyment	I enjoy a conversation with the airline chatbot.	PENJ_1 (0.834)*
	It is fun and pleasant to share a conversation with the airline chatbot.	PENJ_2 0.782
	The conversation with the airline chatbot is exciting.	PENJ_3 0.797
	I enjoy choosing products more if they are recommended by the airline chatbot than if I choose them myself.	PENJ_4 0.856
	Using airline chatbot is unpleasant.	PENJ_5 0.797
	I was absorbed in the conversation with the airline chatbot.	PENJ_6 0.828
Social Influence	People (like, my family/friends) who are important to me think that I should use the airline/online travel company chatbot.	SINF_1 0.855
	People who could influence my behavior think that I should use the airline/online travel company chatbot.	SINF_2 0.775
	People whose valuable opinions I consider, suggests me to use the airline/online travel company chatbot.	SINF_3 0.856
Response Time	When I am using the airline/online travel company chatbot, system response is fast.	RTIM_1 0.837
	In general, the response time of the airline/online travel company chatbot system I use is consistent.	RTIM_2 0.789
	In general, the response time of the airline/online travel company chatbot system I use is reasonably fast.	RTIM_3 0.773
Perceived Security	I believe transactions conducted through airline/ online travel company chatbots will be secure.	PSEC_1 (0.713)*
	I believe my personal information will be kept confidential while using airline/ online travel company chatbots.	PSEC_2 0.872
	I am confident regarding the security measurements offered by airline/ online travel company chatbots.	PSEC_3 0.803
	Privacy in airline/ online travel company chatbots are well protected.	PSEC_4 0.872
	I do not worry about providing credit card information to airline/ online travel company chatbots.	PSEC_5 0.871
	Airline/ online travel company Chatbots is as secure as any airline/ online travel company website.	PSEC_6 0.751
Trust	I believe transactions conducted through airline chatbots will be secure.	TRUS_1 0.754
	I believe my personal information will be kept confidential while using airline chatbots.	TRUS_2 0.859
	I am confident regarding the security measurements offered by airline chatbots.	TRUS_3 0.803
	Privacy in airline chatbots is well protected.	TRUS_4 (0.702)*
	I do not worry about providing credit card information to airline chatbots.	TRUS_5 0.741

(*continued*)

Continued

Construct	Items	Factor Loads
Customer Experience	I enjoy using (brand) airline/ online travel company chatbots (e.g., Indigo, Spicejet, makemytrip, easemytrip etc.).	CEXP_1 0.87
	The experience of using (brand) airline/online travel company chatbots was interesting.	CEXP_2 0.823
	I am happy with the experience of using (brand) airline/ online travel company chatbots.	CEXP_3 0.735
	I feel excited to use airline/ online travel company chatbots.	CEXP_4 0.922
Need for Interaction	Human contact in providing services makes the process enjoyable for me.	NFIN_1 0.869
	Personal attention by the airline employee is very important to me.	NFIN_2 0.817
	I like interacting with the person who provide the airline services.	NFIN_3 0.823
	It bothers me to use a chatbot when I could talk to a airline person instead.	NFIN_4 0.882
Anthropomorphism	I feel the airline chatbot sound quite natural.	ANTH_1 0.78
	I feel the airline chatbot is just like human.	ANTH_2 0.868
	I feel the airline chatbot is very conscious.	ANTH_3 0.865
	The airline chatbot look as if it has life.	ANTH_4 0.825
	The airline chatbot moves elegantly.	ANTH_5 0.874
Continuance Intention	I intend to continue using this airline/online travel company chatbot in the future.	CINT_1 0.874
	I will always try to use this airline/travel chatbot whenever I am traveling through airlines.	CINT_2 0.841
	I will strongly recommend others to use this airline/ online travel company chatbot.	CINT_3 0.877
	I found that the chatbot of my airline/ online travel company to be worthy.	CINT_4 0.921

Note(s): *Items with factor loadings in parenthesis were being removed for fitting of the model; modification indices removal process in AMOS.

References

Aggarwal, A. and Rahul, M. (2018), "The effect of perceived security on consumer purchase intentions in electronic commerce", *International Journal of Public Sector Performance Management*, Vol. 4 No. 1, pp. 1-20, doi: 10.1504/ijpspm.2018.088691.

Alalwan, A.A., Algharabat, R., El Samen, A.A., Albanna, H. and Al-Okaily, M. (2025), "Examining the impact of anthropomorphism and AI-chatbots service quality on online customer flow experience–exploring the moderating role of telepresence", *Journal of Consumer Marketing*, Vol. 42 No. 4, pp. 448-471, doi: 10.1108/JCM-06-2024-6929.

Amrollahi, A., Kummer, T.F., Rajaeian, M. and Hadinejad, A. (2024), "Trust dynamics in sharing economy services during a crisis: a comparison between Airbnb and Uber", *International Journal of Tourism Research*, Vol. 26 No. 4, e2676, doi: 10.1002/jtr.2676.

Ashfaq, M., Makkar, M., Hoang, A.P., Dang-Pham, D., Do, M.H.T. and Nguyen, A.T. (2025), "Exploring customer stickiness during 'smart' experiences: a study on AI chatbot affinity in online customer services", *Journal of Research in Interactive Marketing*, doi: 10.1108/jrim-09-2024-0452.

Aw, E.C., Tan, G.W., Cham, T., Raman, R. and Ooi, K. (2022), "Alexa, what's on my shopping list? Transforming customer experience with digital voice assistants", *Technological Forecasting and Social Change*, Vol. 180, 121711, doi: 10.1016/j.techfore.2022.121711.

Bailey, J.E. and Pearson, S.W. (1983), "Development of a tool for measuring and analyzing computer user satisfaction", *Management Science*, Vol. 29 No. 5, pp. 530-545, doi: 10.1287/mnsc.29.5.530.

Baron, R. and Kenny, I. (1986), "The moderator-mediator variable distinction in social psychological research", *Journal of Personality and Social Psychology*, Vol. 51 No. 6, pp. 1173-1182, doi: 10.1037/0022-3514.51.6.1173.

Baumeister, R.F. and Leary, M.R. (1995), "The need to belong: desire for interpersonal attachments as a fundamental human motivation", *Psychological Bulletin*, Vol. 117 No. 3, pp. 497-529, doi: 10.1037/0033-2909.117.3.497.

Berbar, S. (2023), "User experience and technology adoption: the mediating effect of perceived ease of use on Senso-Aesthetic openness and behaviour intention", *2023 17th International Conference on Signal-Image Technology and Internet-Based Systems (SITIS)*, IEEE, pp. 38-45.

Bhattacherjee, A. (2001), "Understanding information systems continuance: an expectation-confirmation model", *MIS Quarterly*, Vol. 25 No. 3, pp. 351-370, doi: 10.2307/3250921.

Bhattacherjee, A. and Lin, C.P. (2015), "A unified model of IT continuance: three complementary perspectives and crossover effects", *European Journal of Information Systems*, Vol. 24 No. 4, pp. 364-373, doi: 10.1057/ejis.2013.36.

Blut, M., Wang, C., Wünderlich, N.V. and Brock, C. (2021), "Understanding anthropomorphism in service provision: a meta-analysis of physical robots, chatbots, and other AI", *Journal of the Academy of Marketing Science*, Vol. 49 No. 4, pp. 632-658, doi: 10.1007/s11747-020-00762-y.

Byrne, B. (2010), *Structural Equation Modeling with AMOS: Basic Concepts, Applications, and Programming*, 6th ed., Taylor & Francis, New York.

Chan, K.W., Yim, C.K. and Lam, S.S. (2010), "Is customer participation in value creation a double-edged sword? Evidence from professional financial services across cultures", *Journal of Marketing*, Vol. 74 No. 3, pp. 48-64, doi: 10.1509/jmkg.74.3.048.

Cheng, Y.M. (2011), "Antecedents and consequences of e-learning acceptance", *Information Systems Journal*, Vol. 21 No. 3, pp. 269-299, doi: 10.1111/j.1365-2575.2010.00356.x.

Cheng, Y. and Jiang, H. (2021), "Customer–brand relationship in the era of artificial intelligence: understanding the role of chatbot marketing efforts", *The Journal of Product and Brand Management*, Vol. 31 No. 2, pp. 252-264, doi: 10.1108/jpbm-05-2020-2907.

Cheng, X., Zhang, X., Cohen, J. and Mou, J. (2022), "Human vs. AI: understanding the impact of anthropomorphism on consumer response to chatbots from the perspective of trust and relationship norms", *Information Processing and Management*, Vol. 59 No. 3, 102940, doi: 10.1016/j.ipm.2022.102940.

Chi, O.H., Gursoy, D. and Chi, C.G. (2020), "Tourists' attitudes toward the use of artificially intelligent (AI) devices in tourism service delivery: moderating role of service value seeking", *Journal of Travel Research*, Vol. 61 No. 1, pp. 170-185, doi: 10.1177/0047287520971054.

Chong, A.Y.L., Chan, F.T. and Ooi, K.B. (2012), "Predicting consumer decisions to adopt mobile commerce: cross country empirical examination between China and Malaysia", *Decision Support Systems*, Vol. 53 No. 1, pp. 34-43, doi: 10.1016/j.dss.2011.12.001.

Choudhury, A. and Shamszare, H. (2023), "Investigating the impact of user trust on the adoption and use of ChatGPT: survey analysis", *Journal of Medical Internet Research*, Vol. 25, e47184, doi: 10.2196/47184.

Coves-Martínez, Á.L., Sabiote-Ortiz, C.M. and Frías-Jamilena, D.M. (2023), "How to improve travel-app use continuance: the moderating role of culture", *Tourism Management Perspectives*, Vol. 45, 101070, doi: 10.1016/j.tmp.2022.101070.

Crolic, C., Thomaz, F., Hadi, R. and Stephen, A.T. (2022), "Blame the bot: anthropomorphism and anger in customer–chatbot interactions", *Journal of Marketing*, Vol. 86 No. 1, pp. 132-148, doi: 10.1177/00222429211045687.

Dabholkar, P.A. and Bagozzi, R.P. (2002), "An attitudinal model of technology-based self-service: moderating effects of consumer traits and situational factors", *Journal of the Academy of Marketing Science*, Vol. 30 No. 3, pp. 184-201, doi: 10.1177/00970302030003001.

Dabholkar, P.A., Thorpe, D.I. and Rentz, J.O. (1996), "A measure of service quality for retail stores: scale development and validation", *Journal of the Academy of Marketing Science*, Vol. 24 No. 1, pp. 3-16, doi: 10.1177/009207039602400101.

Dasgupta, S., Paul, R. and Fuloria, S. (2011), "Factors affecting behavioral intentions towards mobile banking usage: empirical evidence from India", *Romanian Journal of Marketing*, Vol. 1, pp. 6-28.

Davis, F.D. (1989), "Perceived usefulness, perceived ease of use, and user acceptance of information technology", *MIS Quarterly*, Vol. 13 No. 3, pp. 319-340, doi: 10.2307/249008.

Davis, F.D., Bagozzi, R.P. and Warshaw, P.R. (1989), "User acceptance of computer technology: a comparison of two theoretical models", *Management Science*, Vol. 35 No. 8, pp. 982-1003, doi: 10.1287/mnsc.35.8.982.

Davis, F.D., Bagozzi, R.P. and Warshaw, P.R. (1992), "Extrinsic and intrinsic motivation to use computers in the workplace", *Journal of Applied Social Psychology*, Vol. 22 No. 14, pp. 1111-1132, doi: 10.1111/j.1559-1816.1992.tb00945.x.

Dwivedi, Y.K., Rana, N.P., Jeyaraj, A., Clement, M. and Williams, M.D. (2019), "Re-examining the unified theory of acceptance and use of technology (UTAUT): towards a revised theoretical model", *Information Systems Frontiers*, Vol. 21 No. 3, pp. 719-734, doi: 10.1007/s10796-017-9774-y.

Efendić, E., Van De Calseyde, P.P. and Evans, A.M. (2020), "Slow response times undermine trust in algorithmic (but not human) predictions", *Organizational Behavior and Human Decision Processes*, Vol. 157, pp. 103-114, doi: 10.1016/j.obhdp.2020.01.008.

Epley, N., Waytz, A. and Cacioppo, J.T. (2007), "On seeing human: a three-factor theory of anthropomorphism", *Psychological Review*, Vol. 114 No. 4, pp. 864-886, doi: 10.1037/0033-295x.114.4.864.

Flavián, C. and Guinalíu, M. (2006), "Consumer trust, perceived security and privacy policy: three basic elements of loyalty to a web site", *Industrial Management and Data Systems*, Vol. 106 No. 5, pp. 601-620, doi: 10.1108/02635570610666403.

Forbes (2024), available at: https://www.forbes.com/sites/neilsahota/2024/03/29/navigating-the-skies-with-ai-how-airlines-are-transforming-air-travel/

Fornell, C. and Larcker, D.F. (1981), "Evaluating structural equation models with unobservable variables and measurement error", *Journal of Marketing Research*, Vol. 18 No. 1, pp. 39-50, doi: 10.2307/3151312.

Gao, S., Yang, Y. and Krogstie, J. (2015), "The adoption of smartphones among older adults in China", *IFIP Advances in Information and Communication Technology*, Vol. 44 No. 9, pp. 112-122, doi: 10.1007/978-3-319-16274-4_12.

Fu, J., Mouakket, S. and Sun, Y. (2023), "The role of chatbots' human-like characteristics in online shopping", *Electronic Commerce Research and Applications*, Vol. 61, 101304.

Gao, J., Opute, A.P., Jawad, C. and Zhan, M. (2025), "The influence of artificial intelligence chatbot problem solving on customers' continued usage intention in e-commerce platforms: an expectation-confirmation model approach", *Journal of Business Research*, Vol. 200, 115661, doi: 10.1016/j.jbusres.2025.11566.

Gefen, D., Karahanna, E. and Straub, D.W. (2003), "Trust and TAM in online shopping: an integrated model", *MIS Quarterly*, Vol. 27 No. 1, pp. 51-90, doi: 10.2307/30036519.

Gkinko, L. and Elbanna, A. (2023), "The appropriation of conversational AI in the workplace: a taxonomy of AI chatbot users", *International Journal of Information Management*, Vol. 69, 102568, doi: 10.1016/j.ijinfomgt.2023.102568.

Gursoy, D., Chi, O.H., Lu, L. and Nunkoo, R. (2019), "Consumers' acceptance of artificially intelligent (AI) device use in service delivery", *International Journal of Information Management*, Vol. 49, pp. 157-169, doi: 10.1016/j.ijinfomgt.2019.03.008.

Hair, J.F., Anderson, R.E., Tatham, R.L. and Black, W.C. (1992), *Multivariate Data Analysis with Readings*, 3rd ed., Macmillan Publishing Company, New York, NY.

Harman, H.H. (1976), *Modern Facthior Analysis*, 3rd ed., University of Chicago Press, Chicago, Illinois.

Hartono, E., Holsapple, C.W., Kim, K., Na, K. and Simpson, J.T. (2014), "Measuring perceived security in B2C electronic commerce website usage: a respecification and validation", *Decision Support Systems*, Vol. 62, pp. 11-21, doi: 10.1016/j.dss.2014.02.006.

Hong, W., Thong, J.Y., Chasalow, L.C. and Dhillon, G. (2011), "User acceptance of agile information systems: a model and empirical test", *Journal of Management Information Systems*, Vol. 28 No. 1, pp. 235-272, doi: 10.2753/MIS0742-1222280108.

Hooda, A., Gupta, P., Jeyaraj, A., Giannakis, M. and Dwivedi, Y.K. (2022), "The effects of trust on behavioral intention and use behavior within e-government contexts", *International Journal of Information Management*, Vol. 67, 102553, doi: 10.1016/j.ijinfomgt.2022.102553.

Hoyer, W.D., Kroschke, M., Schmitt, B., Kraume, K. and Shankar, V. (2020), "Transforming the customer experience through new technologies", *Journal of Interactive Marketing*, Vol. 51 No. 1, pp. 57-71, doi: 10.1016/j.intmar.2020.04.001.

Husnain, M., Zhang, Q., Usman, M., Hayat, K., Shahzad, K. and Akhtar, M.W. (2025), "How Chatbot negative experiences damage consumer-brand relationships in hospitality and tourism? A mixed-method examination", *International Journal of Hospitality Management*, Vol. 126, 104076, doi: 10.1016/j.ijhm.2024.104076.

Islam, M.S., Tan, C.C., Sinha, R. and Selem, K.M. (2024), "Gaps between customer compatibility and usage intentions: the moderation function of subjective norms towards chatbot-powered hotel apps", *International Journal of Hospitality Management*, Vol. 123, 103910, doi: 10.1016/j.ijhm.2024.103910.

Jenneboer, L., Herrando, C. and Constantinides, E. (2022), "The impact of chatbots on customer loyalty: a systematic literature review", *Journal of Theoretical and Applied Electronic Commerce Research*, Vol. 17 No. 1, pp. 212-229, doi: 10.3390/jtaer17010011.

Jiménez-Barreto, J., Rubio, N. and Molinillo, S. (2021), "Find a flight for me, Oscar! Motivational customer experiences with chatbots", *International Journal of Contemporary Hospitality Management*, Vol. 33 No. 11, pp. 3860-3882, doi: 10.1108/IJCHM-10-2020-1244.

Juquelier, A., Poncin, I. and Hazée, S. (2025), "Empathic chatbots: a double-edged sword in customer experiences", *Journal of Business Research*, Vol. 188, 115074, doi: 10.1016/j.jbusres.2024.115074.

Kaczorowska and Spychalska, D. (2019), "Chatbots in marketing", *Management*, Vol. 23 No. 1.

Kushwaha, A.K., Kumar, P. and Kar, A.K. (2021), "What impacts customer experience for B2B enterprises on using AI-enabled chatbots? Insights from Big data analytics", *Industrial Marketing Management*, Vol. 98, pp. 207-221, doi: 10.1016/j.indmarman.2021.08.011.

Lacap, J.P.G., Alminar, A., Baltazar, J.K.B., Cabral, R., Catibog, J.A., Cunanan, M. and Moratal, M. (2025), "Does chatbot interaction drive satisfaction and loyalty? Exploring technology anxiety, need for human interaction and creepiness", *Asia-Pacific Journal of Business Administration*, doi: 10.1108/apjba-03-2025-0155.

Lee, L.Y. (2013), "Hospitality industry web-based self-service technology adoption model", *Journal of Hospitality and Tourism Research*, Vol. 40 No. 2, pp. 162-197, doi: 10.1177/1096348013495695.

Lee, K.W. and Li, C.Y. (2023), "It is not merely a chat: transforming chatbot affordances into dual identification and loyalty", *Journal of Retailing and Consumer Services*, Vol. 74, 103447, doi: 10.1016/j.jretconser.2023.103447.

Lee, M.K.O., Cheung, C.M.K. and Chen, Z. (2005), "Acceptance of Internet-based learning medium: the role of extrinsic and intrinsic motivation", *Information and Management*, Vol. 42 No. 8, pp. 1095-1104, doi: 10.1016/j.im.2003.10.007.

Lee, S.E., Ju, N. and Lee, K.H. (2023), "Service chatbot: co-citation and big data analysis toward a review and research agenda", *Technological Forecasting and Social Change*, Vol. 194, 122722, doi: 10.1016/j.techfore.2023.122722.

Lemon, K.N. and Verhoef, P.C. (2016), "Understanding customer experience throughout the customer journey", *Journal of Marketing*, Vol. 80 No. 6, pp. 69-96, doi: 10.1509/jm.15.0420.

Li, B., Chen, Y., Liu, L. and Zheng, B. (2023), "Users' intention to adopt artificial intelligence-based chatbot: a meta-analysis", *Service Industries Journal*, Vol. 43 Nos 15-16, pp. 1117-1139, doi: 10.1080/02642069.2023.2217756.

Lim, X., Cheah, J., Ng, S.I., Basha, N.K. and Soutar, G.N. (2021), "The effects of anthropomorphism presence and the marketing mix have on retail app continuance use intention", *Technological Forecasting and Social Change*, Vol. 168, 120763, doi: 10.1016/j.techfore.2021.120763.

Mamun, M.R.A., Prybutok, V.R., Peak, D.A., Torres, R. and Pavur, R.J. (2023), "The role of emotional attachment in IPA continuance intention: an emotional attachment model", *Information Technology and People*, Vol. 36 No. 2, pp. 867-894, doi: 10.1108/itp-09-2020-0643.

Mehra, A., Paul, J. and Kaurav, R.P.S. (2020), "Determinants of mobile apps adoption among young adults: theoretical extension and analysis", *Journal of Marketing Communications*, Vol. 27 No. 5, pp. 1-29, doi: 10.1080/13527266.2020.1725780.

Miner, A.S., Laranjo, L. and Kocaballı, A.B. (2020), "Chatbots in the fight against the COVID-19 pandemic", *NPJ Digital Medicine*, Vol. 3 No. 1, 65, doi: 10.1038/s41746-020-0280-0.

Mostafa, R.B. and Kasamani, T. (2022), "Antecedents and consequences of chatbot initial trust", *European Journal of Marketing*, Vol. 56 No. 6, pp. 1748-1771, doi: 10.1108/EJM-02-2020-0084.

Nass, C. and Moon, Y. (2000), "Machines and mindlessness: social responses to computers", *Journal of Social Issues*, Vol. 56 No. 1, pp. 81-103, doi: 10.1111/0022-4537.00153.

Ngo, T.T.A., Phan, T.Y.N., Nguyen, T.K., Le, N.B.T., Nguyen, N.T.A. and Le, T.T.D. (2025), "Understanding continuance intention toward the use of AI chatbots in customer service among generation Z in Vietnam", *Acta Psychologica*, Vol. 259, 105468, doi: 10.1016/j.actpsy.2025.105468.

Nguyen, D.M., Chiu, Y.T.H. and Le, H.D. (2021), "Determinants of continuance intention towards banks' chatbot services in Vietnam: a necessity for sustainable development", *Sustainability*, Vol. 13 No. 14, 7625, doi: 10.3390/su13147625.

Nunnally, J.C. (1994), *Psychometric Theory*, 3rd ed., Tata McGraw-Hill Education, New York, NY.

Oghuma, A.P., Libaque-Saenz, C.F., Wong, S.F. and Chang, Y. (2016), "An expectation-confirmation model of continuance intention to use mobile instant messaging", *Telematics and Informatics*, Vol. 33 No. 1, pp. 34-47, doi: 10.1016/j.tele.2015.05.006.

Olson, P. (2016), "Businesses get their chatbots ready for Facebook Messenger", Forbes, available at: https://www.forbes.com/sites/parmyolson/2016/04/01/businesses-chat-bots-facebook-messenger/

Patil, K.P., Paul, J., Bharathi, S.V. and Pramod, D. (2025), "Unveiling the Metaverse retail environments: understanding consumer gratifications and buying behavior", *Journal of Research in Interactive Marketing*, Vol. 19 No. 7, pp. 1125-1144, doi: 10.1108/JRIM-07-2024-0326.

Paul, J., Ueno, A., Dennis, C., Alamanos, E., Curtis, L., Foroudi, P., Kacprzak, A., Kunz, W.H., Liu, J., Marvi, R., Nair, S.L.S., Ozdemir, O., Pantano, E., Papadopoulos, T., Petit, O., Tyagi, S. and Wirtz, J. (2024), "Digital transformation: a multidisciplinary perspective and future research agenda", *International Journal of Consumer Studies*, Vol. 48 No. 2, e13015, doi: 10.1111/ijcs.13015.

Pereira, T., Limberger, P.F., Minasi, S.M. and Buhalis, D. (2022), "New insights into consumers' intention to continue using chatbots in the tourism context", *Journal of Quality Assurance in Hospitality and Tourism*, Vol. 25 No. 4, pp. 1-27, doi: 10.1080/1528008X.2022.2136817.

Pillai, R. and Sivathanu, B. (2020), "Adoption of AI-based chatbots for hospitality and tourism", *International Journal of Contemporary Hospitality Management*, Vol. 32 No. 10, pp. 3199-3226.

Pizzi, G., Scarpi, D. and Pantano, E. (2021), "Artificial intelligence and the new forms of interaction: who has the control when interacting with a chatbot?", *Journal of Business Research*, Vol. 129, pp. 878-890, doi: 10.1016/j.jbusres.2020.11.006.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y. and Podsakoff, N.P. (2003), "Common method biases in behavioral research: a critical review of the literature and recommended remedies", *Journal of Applied Psychology*, Vol. 88 No. 5, pp. 879-903, doi: 10.1037/0021-9010.88.5.879.

Quililan, A.A., Cervantes, C.A., Sayco, D.M., Alcala, L.B.M., Hernandez, J.Z., Cuadra, J.M. and Gamad, L.C. (2025), "From reliance to satisfaction: trust in chatbots as the mediating Force in Low-Cost airline Websites", *2025 16th International Conference on E-Education, E-Business, E-Management and E-Learning (IC4e)*, IEEE, pp. 297-301.

Raman, R. and Paul, J. (2025), "Integrating metaverse technologies with online retail: machine learning-based topic modeling approach", *Journal of Decision Systems*, Vol. 34 No. 1, 2573315, doi: 10.1080/12460125.2025.2573315.

Rosen, Z., Long, M., Ford, B., Wendt, E.A., Cheeseman, M., Quinn, C., L'Orange, C., Volckens, J. and Pierce, J.R. (2024), "Anthropomorphism and motivating participation in citizen science projects", *Journal of Science Communication*, Vol. 23 No. 8, p. A04, doi: 10.22323/2.23080204.

Rouibah, K., Lowry, P.B. and Hwang, Y. (2016), "The effects of perceived enjoyment and perceived risks on trust formation and intentions to use online payment systems: new perspectives from an Arab country", *Electronic Commerce Research and Applications*, Vol. 19, pp. 33-43, doi: 10.1016/j.elerap.2016.07.001.

Sasahara, K., Chen, W., Peng, H., Ciampaglia, G.L., Flammini, A. and Menczer, F. (2021), "Social influence and unfollowing accelerate the emergence of echo chambers", *Journal of Computational Social Science*, Vol. 4 No. 1, pp. 381-402, doi: 10.1007/s42001-020-00084-7.

Schmitt, B. (2020), "Speciesism: an obstacle to AI and robot adoption", *Marketing Letters*, Vol. 31 No. 1, pp. 3-6, doi: 10.1007/s11002-019-09499-3.

Sestino, A. and D'Angelo, A. (2023), "My doctor is an avatar! The effect of anthropomorphism and emotional receptivity on individuals' intention to use digital-based healthcare services", *Technological Forecasting and Social Change*, Vol. 191, 122505, doi: 10.1016/j.techfore.2023.122505.

Shahzad, M.F., Xu, S., An, X. and Javed, I. (2024), "Assessing the impact of AI-chatbot service quality on user e-brand loyalty through chatbot user trust, experience and electronic word of mouth", *Journal of Retailing and Consumer Services*, Vol. 79, 103867, doi: 10.1016/j.jretconser.2024.103867.

Sharma, N., Payal, R. and Paul, J. (2025), "Hello! How can I help you? Role of technology appetite on AI adoption in the post-pandemic era", *R&D Management*, Vol. 55 No. 5, pp. 1560-1581, doi: 10.1111/radm.12771.

Shin, H., Bunosso, I. and Levine, L.R. (2022), "The influence of chatbot humour on consumer evaluations of services", *International Journal of Consumer Studies*, Vol. 47 No. 2, pp. 545-562, doi: 10.1111/ijcs.12849.

Siagian, H., Tarigan, Z.J.H., Basana, S.R. and Basuki, R. (2022), "The effect of perceived security, perceived ease of use, and perceived usefulness on consumer behavioral intention through trust in digital payment platform", *International Journal of Data and Network Science*, Vol. 6 No. 3, pp. 861-874, doi: 10.5267/j.ijdns.2022.2.010.

Siqueira, J.R., Bendixen, M., Reinoso-Carvalho, F. and Campo, R. (2023), "Key drivers of brand trust in a Latin American airline: the impact of Colombia's Avianca customer experience", *Journal of Marketing Analytics*, Vol. 11 No. 2, pp. 186-201, doi: 10.1057/s41270-023-00208-8.

Solvvy (2021), "States of chatbots report 2021", United States of America.

Son, H., Ahn, J., Chung, A.D. and Drumwright, M.E. (2023), "From the black box to the glass box: using unsupervised and supervised learning processes to predict user engagement for the airline companies", *International Journal of Information Management Data Insights*, Vol. 3 No. 2, 100181, doi: 10.1016/j.jjimei.2023.100181.

Venkatesh, V. (2000), "Determinants of perceived ease of use: integrating control, intrinsic motivation, and emotion into the technology acceptance model", *Information Systems Research*, Vol. 11 No. 4, pp. 342-365, doi: 10.1287/isre.11.4.342.11872.

Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003), "User acceptance of information technology: toward a unified view", *MIS Quarterly*, Vol. 27 No. 3, pp. 425-478, doi: 10.2307/30036540.

Venkatesh, V., Thong, J.Y.L. and Xu, X. (2012), "Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology", *MIS Quarterly*, Vol. 36 No. 1, pp. 157-178, doi: 10.2307/41410412.

Venkatraman, N. (1989), "Strategic orientation of business enterprises: the construct, dimensionality and measurement", *Management Science*, Vol. 35 No. 8, pp. 942-962, doi: 10.1287/mnsc.35.8.942.

Wang, C.L. (2025), "Demonstrating contributions through storytelling", *Journal of Research in Interactive Marketing*, Vol. 19 No. 1, pp. 1-4, doi: 10.1108/JRIM-01-2025-455.

Wang, Y.L. and Lo, C.W. (2025), "The effects of response time on older and young adults' interaction experience with Chatbot", *BMC Psychology*, Vol. 13 No. 1, p. 150, doi: 10.1186/s40359-025-02459-9.

Wirtz, J., Patterson, P., Kunz, W., Gruber, T., Lu, V., Paluch, S. and Martins, A. (2018), "Brave new world: service robots in the frontline", *Journal of Service Management*, Vol. 29 No. 5, pp. 907-931, doi: 10.1108/josm-04-2018-0119.

Wut, T.M., Chan, E.A.H. and Wong, H.S.M. (2024), "Does fun matter? Using chatbots for customer services", *Informatics*, Vol. 11 No. 4, p. 94, doi: 10.3390/informatics11040094.

Xie, Y., Chen, K. and Guo, X. (2020), "Online anthropomorphism and consumers' privacy concern: moderating roles of need for interaction and social exclusion", *Journal of Retailing and Consumer Services*, Vol. 55, 102119, doi: 10.1016/j.jretconser.2020.102119.

Zhang, B., Zhu, Y., Deng, J., Zheng, W., Liu, Y., Wang, C. and Zeng, R. (2022), "'I am here to assist your tourism': predicting continuance intention to use AI-based chatbots for tourism. Does gender really matter?", *International Journal of Human-Computer Interaction*, Vol. 39 No. 9, pp. 1887-1903, doi: 10.1080/10447318.2022.2124345.

Zhang, R.W., Liang, X. and Wu, S.H. (2024a), "When chatbots fail: exploring user coping following a chatbots-induced service failure", *Information technology and people*, Vol. 37 No. 8, pp. 175-195, doi: 10.1108/itp-08-2023-0745.

Zhang, Z., Tsiakas, K. and Schneegass, C. (2024b), "Explaining the wait: how justifying chatbot response delays impact user trust", *Proceedings of the 6th ACM Conference on Conversational User Interfaces*, pp. 1-16, doi: 10.1145/3640794.3665550.

Zhou, X., Kim, S. and Wang, L. (2019), "Money helps when money feels: money anthropomorphism increases charitable giving", *Journal of Consumer Research*, Vol. 45 No. 5, pp. 953-972, doi: 10.1093/jcr/ucy012.

Zierau, N., Hausch, M., Bruhin, O. and Söllner, M. (2020), "Towards developing trust-supporting design features for AI-based chatbots in customer service", *Proceedings in the Forty-First International Conference on Information Systems, India 2020 (ICIS)*.

Further reading

Paul, J. (2024), "Publishing in premier journals with high impact factor and Q1 journals: Dos and Don'ts", *International Journal of Consumer Studies*, Vol. 48 No. 3, e13049, doi: 10.1111/ijcs.13049.

Corresponding author

Justin Paul can be contacted at: profjust@gmail.com

For instructions on how to order reprints of this article, please visit our website:
www.emeraldgrouppublishing.com/licensing/reprints.htm
Or contact us for further details: **permissions@emeraldinsight.com**