Exploring the Psychological Mechanisms behind AI Chatbot Adoption

Mariem Sboui

Department of Marketing, University of Tunis

DOI: https://doi.org/10.47772/IJRISS.2025.91200071

Received: 14 December 2025; Accepted: 21 December 2025; Published: 31 December 2025

ABSTRACT

Objective: This study examines the fundamental determinants influencing the intention to adopt AI chatbots in the telecommunication services context in an emerging market. Specifically, it investigates the influence of perceived ease of use (PEOU)**,** perceived usefulness (PU), initial trust, and technology anxiety on chatbot usage intention.

Methodology: Data were collected via an online survey administered to 321 Tunisian higher education students. The hypotheses were tested using structural equation modeling (SEM) with SmartPLS4 (Partial Least Squares 4).

Results: The findings reveal that initial trust and perceived usefulness (PU) have a significant and positive effect on intention to use chatbots. In contrast, perceived ease of use (PEOU) and technology anxiety were found to be non-significant predictors.

Managerial/societal implications: Managers should prioritize incorporating initial trust-building elements in chatbot design by proposing privacy protection mechanisms and transparent conversation. They must also reinforce the perceived usefulness of chatbots through their ability to address user needs efficiently.

Originality: This study enriches the growing literature on the Technology Acceptance Model (TAM), shedding light on the psychological factors that shape users' decisions to engage with AI-chatbot services.

Keywords: Chatbot services**,** perceived ease of use (PEOU**)**, perceived usefulness (PU), initial trust, technology anxiety.

INTRODUCTION

Artificial Intelligence (AI) has undergone remarkable advancements in recent years, transforming societal behaviors and organizational processes. Its widespread incorporation into business operations has reshaped the functioning of various industries, leading to enhanced automation, efficiency, and driving customer-centric innovation (Rashid and Kausik, 2024). One of the most rapidly evolving areas is AI-enabled marketing communication, where the adoption of advanced technologies, particularly interactive messaging services known as “chatbot e-services”, has experienced substantial growth (Desaulniers, 2016). An increasing range of brands are shifting from traditional customer service to chatbot-powered digital solutions, which offer scalability, consistency, and cost-efficiency (Forbes, 2017). The emergence of AI-based marketing has empowered organizations to integrate conversational agents as a pivotal component of their customer service strategies, significantly improving customer experience (Mehta et al., 2022; Wang, 2024).

Chatbots represent a fascinating field of communication between humans and AI (Liu et al, 2024). These programs communicate with users via natural language, employing voice, text, or both, simulating a human interaction (Liu et al, 2024). By serving as a 24/7 touchpoint providing customer responses, chatbots offer the potential for a significant cost reduction opportunity by reducing the need for a human agent (Bakhshi et al.,

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue XII December 2025

2018). According to a recent industry report, the global chatbot market is expected to grow to around $4.9 billion by 2032[1].

Despite the many benefits that conversational agents offer for improving services, customers have expressed frustration with chatbots due to ambiguous questions and inadequate responses (Elliott, 2018). Trust represents a key determinant in fostering the adoption of chatbots (Jyothsna et al, 2024). Trust holds significant importance in shaping user behavior and has been incorporated into the technology adoption model to predict future actions (Kelly et al, 2023). While several studies have investigated the role of trust across various technologies, little research has centered on initial trust in AI chatbots (Jyothsna et al, 2024). This highlights the need for additional investigation on this topic in Tunisia. In this country, individuals express a strong distrust of new technologies (Mostafa and Kasamani, 2022).

Additionally, prior studies show that, even for young users, rapidly transforming digital technologies generate technostress (Prior and Dwyer, 2023; Liu *et al.*, 2021). Hence, digital natives may experience apprehension or unease when interacting with new technology, specifically in emerging markets. Following the suggestion of Park *et al*. (2019), we examined "technology anxiety" as an individual characteristic that may obstruct the adoption of AI chatbots. Therefore, examining the impact of technology-related anxiety on the adoption of AI chatbots is important in the context of developing markets (Khanfar et al., 2024).

To enhance the prediction power of Tunisia scholars' acceptance of AI-assisted literature reading, this study employed the widely established Technology Acceptance Model (TAM) (Davis, 1989). TAM remains a dominant framework for predicting users' behavioral intentions to accept and use a new technology or system. Perceived ease of use (PEOU) and perceived usefulness (PU), two key elements in TAM, have been supported by extensive research demonstrating a significant predictive power for users' behavioral intention. Notably, these functional constructs may be less prominent among users familiar with digital tools, thereby calling into question the generalizability of TAM assumptions in these contexts (Bayaga and Du Plessis, 2023). Furthermore, one of the notable limitations of the Technology Acceptance Model (TAM) lies in its premise that users engage in a fully rational decision-making process when adopting novel technology (Ahn,2023). However, it is increasingly recognized that emotional drivers often impact user decisions rather than solely rational decisions (Ahn,2022). This highlights the crucial need to examine users' psychological states in the adoption of new technology (Ahn,2023).

This study addresses this research gap by integrating technology anxiety and initial trust into an extended TAM to examine the factors of chatbot adoption among students in an emergent market. By focusing on this underexplored segment, the study contributes to a more contextually grounded understanding of chatbot adoption in the telecommunication sector, offering theoretical insights and practical implications for marketers and service designers.

THEORETICAL BACKGROUND

Chatbot services

Chatbots, also referred to as conversational Agents (CA), are artificial intelligence (AI)-based systems designed to communicate with users through natural language processing (NLP). As defined by Ciechanowski et al. (2019, p. 540), a chatbot "*is a software program that interacts with users using natural language*". Owing to their ability to interact with customers continuously 24 hours a day and seven days a week, irrespective of standard working hours, companies are rapidly integrating chatbots to improve efficiency, competitiveness, and customer service (Sharma et al., 2022; Hyun et al., 2022; Troshani et al., 2021).

Chatbots have become increasingly popular in various service sectors, including banking (Lubbe and Ngoma, 2021; Pillai and Sivathanu, 2020), hospitality (Alotaibi and Hidayat-ur-Rehman, 2025), and e-commerce (Araújo and Casais, 2020). However, literature related to chatbot adoption in telecommunication services is relatively scant, particularly in the specific context of emerging countries (Fallaque, 2024; Sboui et al, 2024). Previous research within the telecommunications sector has investigated the role of chatbot interactions to improve customer satisfaction (Shin *et al*., 2023; Fallaque, 2024), yet a significant gap remains in comprehending how these agents stimulate intention to use chatbots in this sector within emerging markets.

The Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), developed by Davis (1989), is grounded in the Theory of Reasoned Action (TRA) and provides a valuable framework for investigating users' acceptance behaviors of information technologies. This model has been widely applied in the era of information systems (IS) and chatbot-related studies (De Cicco et al., 2022).

The TAM posits that user engagement with a specific information technology application, such as chatbots, depends on their behavioral intention, which refers to the extent to which a user is inclined to perform a particular behavior (Qatawneh et al, 2024). The model suggested that "perceived ease of use (PEU)" and "perceived usefulness (PU)" were the two main crucial factors of user acceptance (Marikyan and Papagiannidis, 2024). PEOU represents users' anticipation of an uncomplicated and intuitive interaction (Na et al., 2022), while PU refers to an individual's belief in significant advantages and enhanced performance that adoption of technology offers (Bailey et al., 2022). According to this framework, users are likely to adopt the chatbot given its user-friendly nature, and they perceive it as highly performant.

In the era of AI, TAM is widely acknowledged as the most prevalent theoretical framework for assessing usage intentions and customer acceptance across multiple technological applications (Kelly et al., 2023; Ibrahim et al., 2025). A broad range of empirical studies has consistently confirmed its effectiveness in explaining and predicting users' intentions to adopt and utilize various IT systems and applications (King and He, 2006).

By leveraging TAM, this study can comprehensively assess the factors driving the intention to use the chatbot services, thereby providing actionable insights to enhance customer engagement in emerging markets.

Hypothesis Development

Perceived ease of use and usage intention

Perceived ease of use represents "*the degree to which a person believes that using a particular system would be free of effort*" (Radner and Rothschild, 1975). It refers to the extent to which a system operates smoothly without specialized knowledge or specific expertise from users (Amin *et al*., 2014; Jo, 2022). Ease of use is a determinant of technology acceptance, insofar as consumers are likely to adopt technology that is easily understood and user-friendly (Davis, 1989). Previous studies show that when users experience minimal effort in operating technologies, their overall adoption enhances, leading to higher engagement (Chen et al., 2022; Iqbal and Campbell, 2023).

In the context of chatbot adoption, the concept of "perceived ease of use" is widely examined (Araújo and Casais, 2020; De Cicco et al., 2022; Gopinath and Kasilingam, 2023; Li et al., 2023). Specifically, prior studies have investigated its effect on usage intention (Pillai and Sivathanu, 2020; Maduku et al., 2024; PAN et al, 2025). The greater the PEOU of an innovative technology by consumers, the more likely they are to adopt it (Alotaibi and Hidayat-ur-Rehman,2025). hence, the following hypothesis:

H1: Perceived ease of use positively influences chatbot usage intention

Perceived usefulness and usage intention

Perceived Usefulness is related to the degree to which a technological system enhances user efficiency and aligns with their preferences (Gani et al., 2024). When customers consider a system or application an effective means of facilitating their tasks, they are more likely to use it again (Muslichah, 2018). Any service that saves customers time and offers personalized services and flexibility improves users' attitude toward the service provider (Eger et al, 2021).

Previous research has highlighted the relevance of the PU on the customers' intention to use emergent technologies (Gümüş & Çark, 2021; PAN et al, 2025). In the context of chatbots, when customers recognize the tangible benefits of using a chatbot, such as smoother interactions or process automation, their intention to adopt the technology enhances (Zhang et al., 2023). Hence, favorable evaluations of a chatbot's utility improve users' willingness to interact with it (Song et al., 2024), as people are more predisposed to adopt technologies that demonstrate clear advantages (Portz et al., 2019). Chatbot systems that offer personalized suggestions and predict user needs enhance the perception of usefulness.

Given these insights, users who recognize the chatbot as useful in facilitating the completion of various tasks are more likely to intend to use it in the future. Therefore, PU is a crucial determinant of intention in chatbot services. Hence, we posit the following hypothesis:

H2: Perceived usefulness positively influences chatbot usage intention

Initial trust and usage intention

Trust was identified as the most significant factor in predicting attitude and the intention to use an AI system (Zarifis and Cheng, 2023). This concept is defined as the willingness of one party to be vulnerable to the actions of another based on positive expectations about the latter's motivations or behavior (Hong and Cha, 2013). Trust manifests in two main forms: initial trust and ongoing trust (Pena et al., 2021). Trust building is a dynamic process marked by a gradual transition from initial trust to ongoing trust development (Chakraborty et al., 2022; Siau and Wang, 2018). Initial trust assumes that users have no information before the preliminary encounter (Talwar et al., 2020).

Initial trust refers to "*trust in an unknown party or without prior use*" (Fan et al., 2020). It represents a form of trust that arises without prior experience and is distinct from experiential trust due to its temporal dimension (Koufaris and Hampton-Sosa, 2004). In the realm of emerging technologies, numerous studies highlighted the importance of investigating initial trust, particularly when consumers are confronted with uncertainty before utilizing new technologies (Li et al., 2008; Mostafa and Kasamani, 2022; Talwar et al., 2020). Specifically, in the case of chatbots, existing literature has emphasized the pivotal role of initial trust on customer usage intention (Jyothsna et al, 2024; Mostafa and Kasamani, 2022; Kaabachi et al, 2019). Consequently, our study suggests that initial trust toward chatbots can enhance consumers' intention to adopt and use them. Hence, we can posit the following hypothesis:

H3: Initial trust in chatbots positively influences chatbot usage intention.

Anxiety and usage intention

Technological anxiety represents the extent to which a customer feels apprehensive or uneasy when using a technology (Meuter et al., 2005; Pillai et al., 2024). This emotional response engenders trepidation and fear toward adopting new technological tools (Venkatesh, 2000). Recognized as a substantial psychological barrier, technological anxiety has been established to reduce individuals' willingness to engage with technology and brings confusion (Meuter et al., 2005). The literature has shown that technological anxiety leads to avoidance of novel technology, becoming a major impediment to adoption (Lam et al., 2008; Mani and Chouk, 2018; Wang et al., 2020). It even risks overshadowing the advantage of technology and diverting the consumer's engagement (Man et al., 2024). This implies that individuals with high levels of technological anxiety are less inclined to use or adopt technology (Alboqami, 2023; Pillai and Sivathanu, 2020), hence the following hypothesis:

H4: Technology anxiety negatively affects the intention to adopt chatbots.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue XII December 2025

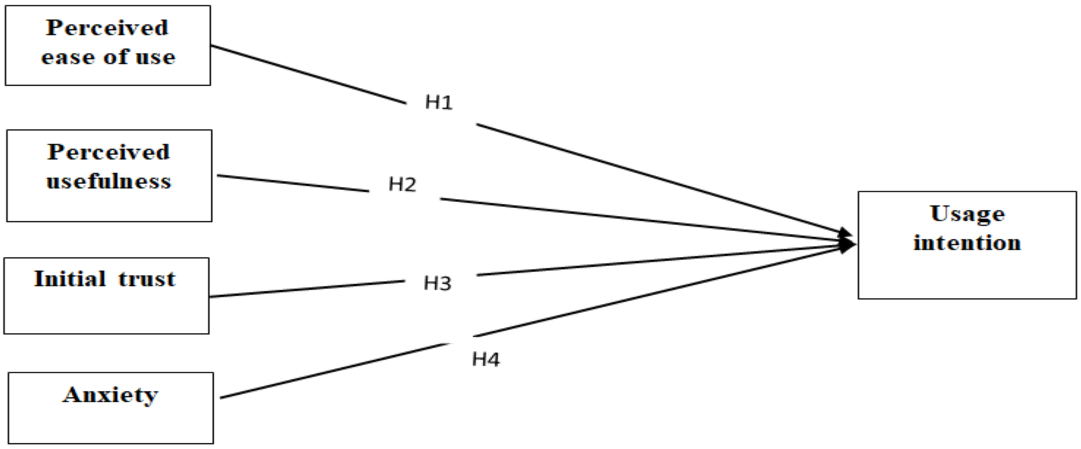

Figure 1. Conceptual Framework

Source(s) : The authors' own work

METHODOLOGY

Data Collection and Sample

To investigate the adoption of chatbot technologies among digital-native users in an emerging market context, data were collected with an online survey administered via Google Forms. The target population consisted of university students in Tunisia, who are generally considered digital natives (Dinh and Park, 2023). A convenience sampling method was used, given its appropriateness for reaching the intended population efficiently and effectively (Jager et al., 2017).

Before the data collection phase, the questionnaire underwent a readability check. A pilot test with five students was conducted to ensure item clarity. The final questionnaire, available in English and Arabic, was distributed through email and social media. The data collection process spanned eight weeks. To simulate real chatbot interaction, participants were first invited to interact with "Djingo Damdoum", a customer service chatbot developed by the telecommunication company of Orange Tunisia. Notably, this locally developed chatbot supports Tunisian dialect, French, and Modern Standard Arabic, enhancing linguistic accessibility. Following this interaction, participants were asked to pose between three and six questions to the chatbot on topics like services, promotions, or problem resolution in the language of their choice. The final sample is composed of 321 respondents, including 77 males (24%) and 244 females (76%).

Measures

The constructs of the current study were measured using validated scales, slightly modified and adapted from the literature. The items for the constructs Perceived Ease of Use (PEU) and Perceived Usefulness (PU) were taken from Davis's study (1989). The chatbot's initial trust measure scale was adapted from Oliveira *et al.* (2014). The items developed by Meuter et al. (2005) were used to inspect technology anxiety. All items were measured on seven-point Likert scales, with 1 "strongly disagree" and 7 "strongly agree." The study constructs and their sources are presented in Table 1.

Table 1. Variables measures

Constructs	**Items**	**Sources**
Ease of Use	EU1. My interaction with chatbots would be clear and understandable	Davis (1989)
	EU2. I would find chatbots easy to use	
	EU3. Learning to operate chatbots would be easy for me	

Perceived Usefulness	PU1. I find chatbot services useful in the purchasing process	Davis (1989)
	PU2. Using chatbot services enables me to accomplish the purchasing process quickly	
	PU3. Using chatbot services increases my efficiency in the purchasing process	
	PU4. Overall, I find Chatbot useful to me.	
Technology anxiety	TA1. I feel apprehensive about using technology	Meuter et al. (2005)
	TA2 Technical terms sound like confusing jargon to me	
	TA3 I have avoided technology because it is unfamiliar to me	
	TA4 I hesitate to use most forms of technology for fear of making mistakes I cannot correct	
Chatbot initial trust	CIT1 Chatbots seem dependable	Oliveira et al. (2014)
	CIT2 Chatbots seem secure	
	CIT3 Chatbots were created to help the client	
	CIT4 Chatbots seem trustworthy	
Usage Intention	UI1. I intend to use chatbot services the next time I make an online purchase	Venkatesh et al. (2003)
	UI2. I will probably use chatbot services the next time I make an online purchase	
	UI3. I have decided to use chatbot services the next time I make an online purchase	

RESULTS

Common Method Bias Analysis :

Data were analyzed by the PLS-SEM estimation method using Smart PLS4, which is widely applied in social sciences. To examine common method variance (CMV), the method recommended by Podsakoff et al. (2003) has been used. Hartman's single-factor technique showed that the single factor explained 19.47% of the total variance, which is lower than 50%, indicating the nonexistence of significant common method bias (Fuller et al., 2016).

Exploratory Factor Analysis

To assess the reliability and validity of the measurement scales, we applied the exploratory factor analysis using principal component analysis. Item CIT3 was excluded because its communality (0.429) is below 0.5. All remaining constructs demonstrated satisfactory reliabilities (above 0.7).

Measurement Model

The results presented in Table 2 confirm the reliability and validity of the robustness of the measurement model. Indeed, all Cronbach's α values are above 0.7, indicating strong internal consistency. All outer loadings were above 0.7 (Hair et al., 2019), indicating good indicator reliability. Except for item AT4, which was eliminated due to its outer loading of 0.617 (i.e., below the recommended threshold of 0.7). Report composite reliability (CR) values exceed 0.7, validating the internal consistency of each construct (Hair et al., 2019). Additionally,

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue XII December 2025

Average Variance Extracted (AVE) indicators confirm convergent validity as they exceed 0.5 (Henseler et al., 2016). As shown in Table 3, all HTMT values are below 0.9, indicating discriminant validity (Henseler et al., 2015).

Table 2. Reliability and Convergent Validity Assessment

	Cronbach's alpha	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**	**Average variance extracted (AVE)**
CIT	0.965	0.965	0.977	0.935
EU	0.813	0.842	0.886	0.721
PU	0.930	0.934	0.950	0.828
TA	0.824	0.833	0.894	0.738
UI	0.955	0.956	0.971	0.918

Table 3. Discriminant Validity (HTMT Criterion)

	CIT	**EU**	**PU**	**TA**	**UI**
CIT					
EU	0.266				
PU	0.350	0.486			
TA	0.055	0.065	0.154		
UI	0.481	0.288	0.590	0.42	

Structural Model

First, we assessed the multi-collinearity issues. Following the recommendations of MacKenzie et al. (2012), the item CIT4 is eliminated since its variance inflation factor value is above 10 (VIF 25.738). The structural Model is shown in Figure 2.

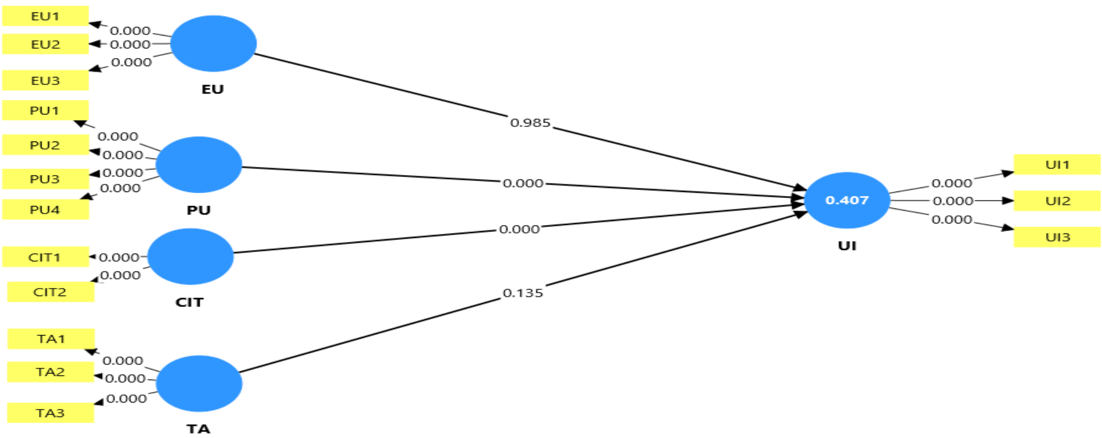

Figure 2: Structural Model

Subsequently, we analyzed the hypothesized relationships between the constructs. The results illustrated in Table 4 show that the hypotheses H2 and H3 are supported, while H1 and H4 are rejected. Among the variables that influence chatbot usage intention, perceived usefulness was found to have the most significant effect (β=0.468, t=8.931), followed by chatbot initial trust (β=0.309, t=6.336).

Table 4. Results

		Original sample (O)	T statistics	P values	Remarks
H1	**EU -> UI**	0.001	0.018	0.985	Not supported
H2	**PU -> UI**	0.468	8.931	0.000	Supported
H3	**CIT -> UI**	0.309	6.336	0.000	Supported
H4	**TA -> UI**	-0.088	1.495	0.135	Not supported

DISCUSSION

Drawing on TAM theory, this study investigates the impact of initial trust and technology anxiety on chatbot usage intention.

The results of this research confirm that initial trust has a significant influence on intention to use chatbots. This result aligns with the majority of previous research findings (Sboui et al, 2024; Rajaobelina et al., 2021; Kasilingam, 2020; Moussawi et al., 2021), confirming that when individuals have high initial trust in chatbots, they are more likely to intend to use these chatbots. Thus, increased initial trust in chatbots fosters the intention to engage with these systems and reduces behavioral ambiguity towards them (Sboui et al, 2024).

Moreover, the findings highlight the critical role of perceived usefulness (PU) in shaping the intention to use chatbot AI. Existing research (Ismatullaev and Kim, 2024; Norzelan et al., 2024; Davis et al, 1989; Rafique et al., 2020) reveals that users' perceptions of the technology's usefulness have a significant effect on their intention to adopt it. As users recognize the benefits and importance of chatbot services functionality to their needs, their adoption of the technology increases (Topsakal, 2024).

In contrast, the results showed that perceived ease of use was not a significant factor in the intention to adopt chatbots. This result diverges from the traditional TAM framework, which consistently highlights PEOU as a key determinant of intention. Our results align with prior studies suggesting that as users develop proficiency in digital tools, the role of ease of use becomes less impactful in their adoption of technologies (Liu et al., 2016; Van Eeuwen, 2017; Gopinath & Kasilingam, 2023; Topsakal, 2024). In digital environments, highly educated Internet surfers frequently use AI systems for various tasks; these interactions contribute to reducing the perceived skills required to interact with chatbots (Gopinath and Kasilingam, 2023). The participants in our study seem to be relatively familiar with open AI chatbots and did not perceive ease of use as an essential determinant for chatbot adoption. They seek to gather the needed knowledge rather than requiring the ease-of-use characteristic of an AI system (Chen and Barnes, 2007). Thus, the willingness to adopt novel technology such as chatbots is primarily driven by its perceived usefulness, rather than the ease of use of systems (Topsakal, 2024).

Furthermore, technology anxiety does not play a significant role in shaping customers' intention to use AI chatbots, contrary to our hypothesis and previous research (Li et al. 2021; Melián-González et al, 2021). However, this outcome aligns with the results of Foroughi et al (2025). This finding may be explained by the fact that students tend not to perceive chatbots as risky or overly complex, likely due to their habitual and frequent interaction with digital technologies and chatbot services. As a demographic characterized by high digital literacy and the effortless incorporation of technology into daily life (Ayanwale and Ndlovu, 2024; Tian et al., 2024; Ragheb et al., 2022), students are generally more at ease when engaging with digital innovations. Moreover, as noted by Foroughi et al. (2025), the interaction with conversational agents is often voluntary rather than obligatory, which may alleviate anxiety commonly associated with new technologies. Thus, it has been proved that older people are more anxious about novel technologies than younger people (Mariano et al., 2022; Wang et al., 2020), offering a perspective for future research into older people's intention to use chatbots.

Theoretical Implications

Our study offers several significant theoretical contributions to the existing body of literature. First, it seeks to integrate key research variables to develop a holistic framework for forecasting user adoption of AI-driven customer chatbot services. The strength of our model builds on an extended version of the Technology Acceptance Model (TAM) framework, by adding two additional factors: technology anxiety, as suggested by Dinh and Park (2023) and Ko and Chang (2019), and initial trust as recommended by Mostafa and Kasamani (2022). To the best of our knowledge, the present work is among the first to explore the combined impact of these two psychological factors with the cognitive determinants of the TAM, providing novel theoretical insights into the mechanisms driving technology adoption. Thus, the integrated conceptual model of the present study serves as a guidepost for future research on the adoption of chatbots, specifically among higher graduate students in Tunisia.

Second, although our study focuses on the “tech-savvy sailors”, perceived ease of use and technology anxiety are not significant factors in predicting chatbot usage intention. These results contradict the traditional assumptions of TAM, which generally assert ease of use as a key factor and anxiety as a psychological inhibitor included in extended models of TAM. For instance, the younger generation in emerging markets possesses higher exposure to technology and digital expertise (Dinh and Park, 2023), considering ease of use as a less important determinant, while instrumental benefits like perceived usefulness gain prominence. Similarly, the lack of a significant relationship between technology anxiety and intention highlights the limited relevance of this construct for digitally native users familiar with AI tools. These findings open new avenues for expanding TAM theories in future research by underscoring the need to refine current theoretical frameworks to specific technological contexts.

Finally, the effect of initial trust on intention to adopt chatbots has received minimal attention from scholars (Ameen et al., 2021; Prakash et al., 2023). Hence, following prior studies' perspectives (Foroudi et al., 2018; Van den Broeck et al., 2019), our study contributes to the literature by demonstrating that initial trust emerged as a strong determinant, reinforcing the theoretical argument that early perceptions of system’s trustworthiness and credibility are critical in shaping technology adoption, particularly when users have limited familiarity with the system.

Managerial implications

From a managerial standpoint, the study offers valuable insights for marketing managers on the strategic implementation of conversational agent service within the emerging market context. First, building initial trust with the chatbot is identified as a priority. Companies should embed design features that improve perceptions of credibility, such as privacy protection mechanisms, transparent conversation, and empathetic communication styles. These strategies contribute to a more trustworthy user experience. Second, communication strategies should emphasize the functional advantages of chatbot use, particularly their ability to offer rapid support can reinforce the perceived usefulness (Arce-Urriza et al, 2025). Specifically, managers should focus on bolstering the positive factors that influence adoption, such as the utility of chatbots in providing effective assistance. By reinforcing the perceived usefulness of chatbots through their ability to address user needs efficiently, organizations can enhance the willingness to adopt chatbot services, particularly among the young generation. Finally, while ease of use and technological anxiety may be less significant among students, these determinants could play an important role in other demographic segments. Thus, tailored strategies based on users’ digital proficiency are recommended.

Limitations and Future Research Directions

Despite its significant contributions, this study has several limitations that should be taken into account in future research. First, the survey was conducted with only university students, thereby limiting the generalizability of the findings to other populations. Future studies should broaden the sample to include a more representative sample population in different contexts.

Second, this study explored technology anxiety as an exogenous variable. Future research could explore its moderating effect to gain deeper insights into its effect on behavioral intention. In addition, the inclusion of other determinants like chatbot anthropomorphism and social influence would strengthen the prediction of the research model.

Finally, another limitation is the use of cross-sectional data. Future studies could adopt a longitudinal approach to capture changes in customers' experiences with chatbots over time.

REFERENCES

1. Ahn, H. (2022). Emotional intelligence as a personality trait that predicts consumption behavior: The role of consumer emotional intelligence in persuasive communication. Sustainability, 14, 15461.
2. Ahn, H. (2023). Unrevealing voice search behaviors: Technology acceptance model meets anthropomorphism in understanding consumer psychology in the US market. Sustainability, 15(23), 16455.
3. Alboqami, H. (2023). Factors affecting consumers' adoption of AI-based chatbots: The role of anthropomorphism. American Journal of Industrial and Business Management, 13(4), 195–214.
4. Alotaibi, M., & Hidayat-ur-Rehman, I. (2025). An empirical analysis of user intention to use chatbots for airline tickets consultation. Journal of Science and Technology Policy Management, 16(1), 204–228. https://doi.org/10.1108/JSTPM-03-2024-0087
5. Ameen, N., Tarhini, A., Reppel, A., & Anand, A. (2021). Customer experiences in the age of artificial intelligence. Computers in Human Behavior, 114, 106548.
6. Amin, M., Rezaei, S., & Abolghasemi, M. (2014). User satisfaction with mobile websites: The impact of perceived usefulness (PU), perceived ease of use (PEOU) and trust. Nankai Business Review International, 5(3), 258–274.
7. Applied Psychology, Vol. 88 No. 5, pp. 879-903, doi: 10.1037/0021-9010.88.5.879.
8. Araújo, T., & Casais, B. (2020). Customer acceptance of shopping-assistant chatbots. In Á. Rocha, J. L. Reis, M. K. Peter, & Z. Bogdanović (Eds.), Marketing and smart technologies (Vol. 167, pp. 278–287). Springer Singapore. https://doi.org/10.1007/978-981-15-1564-4_26
9. Arce-Urriza, M., Chocarro, R., Cortiñas, M., & Marcos-Matás, G. (2025). From familiarity to acceptance: The impact of generative artificial intelligence on consumer adoption of retail chatbots. Journal of Retailing and Consumer Services, 84, 104234.
10. Ayanwale, M. A., & Ndlovu, M. (2024). Investigating factors of students' behavioral intentions to adopt chatbot technologies in higher education: Perspective from expanded diffusion theory of innovation. Computers in Human Behavior Reports, 14, 100396.
11. Bailey, D. R., Almusharraf, N., & Almusharraf, A. (2022). Video conferencing in the e-learning context: Explaining learning outcome with the technology acceptance model. Education and Information Technologies, 27(6), 7679–7698. https://doi.org/10.1007/s10639-022-10949-1
12. Bakhshi, N., van den Berg, H., Broersen, S., de Vries, D., Bouazzaoui, H. E., & Michels, B. (2018). Chatbots Point of View. Deloitte. Retrieved December 20, 2022, from https://www2.deloitte.com/content/
13. Bayaga, A., & Du Plessis, A. (2023). Ramifications of the Unified Theory of Acceptance and Use of Technology (UTAUT) among developing countries' higher education staffs. Education and Information Technologies. https://doi.org/10.1007/s10639-023-12194-6
14. behavioral research: a critical review of the literature and recommended remedies", Journal of
15. Chen, Y.-H., & Barnes, S. (2007). Initial trust and online buyer behaviour. Industrial Management & Data Systems, 107(1), 21–36.
16. Ciechanowski, L., Przegalinska, A., Magnuski, M., & Gloor, P. (2019). In the shades of the uncanny valley: An experimental study of human–chatbot interaction. Future Generation Computer Systems, 92, 539–548. https://doi.org/10.1016/j.future.2018.01.055

17. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008
18. De Cicco, R., Iacobucci, S., Aquino, A., Romana Alparone, F., & Palumbo, R. (2021, November). Understanding users' acceptance of chatbots: an extended TAM approach. In International Workshop on Chatbot Research and Design (pp. 3-22).
19. Desaulniers, S. (2016). Chatbots rise, and the future may be 're-written'. Development, 82(2), 13–30. https://doi.org/10.1111/mono.12296
20. Dinh, C. M., & Park, S. (2024). How to increase consumer intention to use Chatbots? An empirical analysis of hedonic and utilitarian motivations on social presence and the moderating effects of fear across generations. Electronic Commerce Research, 24(4), 2427-2467.
21. Eger, L., Komárková, L., Egerová, D., & Mičík, M. (2021). The effect of COVID-19 on consumer shopping behaviour: Generational cohort perspective. Journal of Retailing and Consumer Services, 61, 102542. https://doi.org/10.1016/j.jretconser.2021.102542
22. Elliott, C. (2018). Chatbots are killing customer service. Here's why. European Conference on Knowledge Management, Vol. 25, pp. 1115-1122.
23. Fallaque, C.A.H. (2024), "Impact of chatbots on satisfaction and loyalty in Lima's telecom sector",
24. Følstad, A., Araujo, T., Papadopoulos, S., Law, E. L. C., Granmo, O. C., Luger, E., & Brandtzaeg, P. B. (2020). Chatbot research and design. Amsterdam: Springer International Publishing.
25. Forbes. (2017). How chatbots improve customer experience in every industry: An infographic. Retrieved from https://www.forbes.com/
26. Foroudi, P., Gupta, S., Sivarajah, U., & Broderick, A. (2018). Investigating the effects of smart technology on customer dynamics and customer experience. Computers in Human Behavior, 80, 271-282.
27. Fuller, C. M., Simmering, M. J., Atinc, G., Atinc, Y., & Babin, B. J. (2016). Common methods variance detection in business research. Journal of Business Research, 69(8), 3192–3198.
28. Gani, M. O., Rahman, M. S., Bag, S., & Mia, M. P. (2024). Examining behavioural intention of using smart health care technology among females: Dynamics of social influence and perceived usefulness. Benchmarking: An International Journal, 31(2), 330–352.
29. Gopinath, K., & Kasilingam, D. (2023). Antecedents of intention to use chatbots in service encounters: A meta-analytic review. International Journal of Consumer Studies, 47(6), 2367–2395. https://doi.org/10.1111/ijcs.12933
30. Gümüş, N., & Çark, Ö. (2021). The effect of customers' attitudes towards chatbots on their experience and behavioral intention in Turkey. Interdisciplinary Description of Complex Systems, 19(3), 420–436. https://doi.org/10.7906/indecs19.3.6
31. Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24.
32. Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: Updated guidelines. Industrial Management & Data Systems, 116(1), 2–20.
33. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8
34. Hong, I.B. and Cha, H.S. (2013), "The mediating role of consumer trust in an online merchant in
35. Ibrahim, F., Münscher, J.-C., Daseking, M., & Telle, N.-T. (2025). The technology acceptance model and adopter type analysis in the context of artificial intelligence. Frontiers in Artificial Intelligence, 7, 1496518. https://doi.org/10.3389/frai.2024.1496518
36. Ismatullaev, U. V. U., & Kim, S. H. (2024). Review of the factors affecting acceptance of AI-infused systems. Human Factors, 66(1), 126–144. https://doi.org/10.1177/00187208211064707
37. Jager, J., Putnick, D. L., & Bornstein, M. H. (2017). II. More than just convenient: The scientific merits of homogeneous convenience samples. Monographs of the society for research in child development, 82(2), 13-30.
38. Jo, H. (2022). Continuance intention to use artificial intelligence personal assistant: Type, gender, and use experience. Heliyon, 8(9), e10585. https://doi.org/10.1016/j.heliyon.2022.e10585
39. Jyothsna, M., & Kryvinska, N. (2024). Exploring the chatbot usage intention: A mediating role of chatbot initial trust. Heliyon, 10, e33028.

40. Kaabachi, S., Ben Mrad, S., & O'Leary, B. (2019). Consumer's initial trust formation in IOB's acceptance: The role of social influence and perceived compatibility. International Journal of Bank Marketing, 37(2), 507–530. https://doi.org/10.1108/IJBM-12-2017-0270
41. Kasilingam, D. L. (2020). Understanding the attitude and intention to use smartphone chatbots for shopping. Technology in Society, 62, 101280.https://doi.org/10.1016/j.techsoc.2020.101280
42. Kelly, S., Kaye, S.-A., & Oviedo-Trespalacios, O. (2023). What factors contribute to the acceptance of artificial intelligence? A systematic review. Telematics and Informatics, 77, 101925.
43. Khanfar, A. A., Kiani Mavi, R., Iranmanesh, M., & Gengatharen, D. (2024). Determinants of artificial intelligence adoption: Research themes and future directions. Information Technology and Management. https://doi.org/10.1007/s10799-024-00435-0
44. King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. Information & Management, 43(6), 740–755. https://doi.org/10.1016/j.im.2006.05.003
45. Koufaris, M., & Hampton-Sosa, W. (2004). The development of initial trust in an online company by new customers. Information & Management, 41(3), 377–397. https://doi.org/10.1016/j.im.2003.08.004
46. Lam, S. Y., Chiang, J., & Parasuraman, A. (2008). The effects of the dimensions of technology readiness on technology acceptance: An empirical analysis. Journal of Interactive Marketing, 22(4), 19–39. https://doi.org/10.1002/dir.20115
47. Li, B., Chen, Y., Liu, L., & Zheng, B. (2023). Users' intention to adopt artificial intelligence-based chatbot: A meta-analysis. The Service Industries Journal, 43(15–16), 1117–1139. https://doi.org/10.1080/02642069.2023.2217756
48. Li, L., Lee, K. Y., Emokpae, E., & Yang, S.-B. (2021). What makes you continuously use chatbot services? Evidence from Chinese online travel agencies. Electronic Markets, 31, 575–599. https://doi.org/10.1007/s12525-020-00441-6
49. Li, X., Hess, T. J., & Valacich, J. S. (2008). Why do we trust new technology? A study of initial trust formation with organizational information systems. The Journal of Strategic Information Systems, 17(1), 39–71. https://doi.org/10.1016/j.jsis.2008.01.001
50. Liu, M., Yang, Y., Ren, Y., Jia, Y., Ma, H., Luo, J., Fang, S., Qi, M., & Zhang, L. (2024). What influences consumer AI chatbot use intention? An application of the extended technology acceptance model. Journal of Hospitality and Tourism Technology, 15(4), 667–689.
51. Liu, Z., Shan, J., & Pigneur, Y. (2016). The role of personalized services and control: An empirical evaluation of privacy calculus and technology acceptance model in the mobile context. Journal of Information Privacy and Security, 12(3), 123–144.
52. Maduku, D. K., Rana, N. P., Mpinganjira, M., Thusi, P., Mkhize, N. H.-B., & Ledikwe, A. (2024). Do AI-powered digital assistants influence customer emotions, engagement and loyalty? An empirical investigation. Asia Pacific Journal of Marketing and Logistics, ahead-of-print.
53. Makridakis, S. (2017). The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. Futures, 90, 46–60. https://doi.org/10.1016/j.futures.2017.03.006
54. Man, S. S., Ding, M., Li, X., Chan, A. H. S., & Zhang, T. (2024). Acceptance of highly automated vehicles: The role of facilitating condition, technology anxiety, social influence and trust. International Journal of Human–Computer Interaction.
55. Mani, Z., & Chouk, I. (2018). Consumer resistance to innovation in services: Challenges and barriers in the Internet of Things era. Journal of Product Innovation Management, 35(5), 780–807.
56. Marikyan, D., & Papagiannidis, S. (2024). Technology acceptance model: A review. TheoryHub Book. https://eprints.ncl.ac.uk/302879
57. Mehta, P., Jebarajakirthy, C., Maseeh, H. I., Anubha, A., Saha, R., & Dhanda, K. (2022). Artificial intelligence in marketing: A metanalytic review. Psychology & Marketing, 39(11), 2013–2038. https://doi.org/10.1002/mar.21738
58. Melián-González, S., Gutiérrez-Taño, D., & Bulchand-Gidumal, J. (2021). Predicting the intentions to use chatbots for travel and tourism. Current Issues in Tourism, 24(2), 192–210. https://doi.org/10.1080/13683500.2020.1722216
59. Meuter, M. L., Bitner, M. J., Ostrom, A. L., & Brown, S. W. (2005). Choosing among alternative service delivery modes: An investigation of customer trial of self-service technologies. Journal of Marketing, 69(2), 61–83. https://doi.org/10.1509/jmkg.69.2.61.60759

60. Mostafa, R. B., & Kasamani, T. (2022). Antecedents and consequences of chatbot initial trust. European journal of marketing, 56(6), 1748-1771.
61. Moussawi, S., Koufaris, M., & Benbunan-Fich, R. (2021). How perceptions of intelligence and anthropomorphism affect adoption of personal intelligent agents. Electronic Markets, 31(2), 343–364. https://doi.org/10.1007/s12525-020-00411-w
62. Muslichah, M. (2018). The effect of self-efficacy and information quality on behavioral intention with perceived usefulness as intervening variable. Journal of Account Business and Management, 25(1), 21–34.
63. Na, S., Heo, S., Han, S., Shin, Y., & Roh, Y. (2022). Acceptance model of artificial intelligence (AI)-based technologies in construction firms: Applying the Technology Acceptance Model (TAM) in combination with the Technology–Organisation–Environment (TOE) framework. Buildings, 12(2), 90.
64. Norzelan, N. A., Mohamed, I. S., & Mohamad, M. (2024). Technology acceptance of artificial intelligence (AI) among heads of finance and accounting units in the shared service industry. Technological Forecasting and Social Change,198,123022. https://doi.org/10.1016/j.techfore.2023.123022
65. Oliveira, T., Faria, M., Thomas, M. A., & Popovič, A. (2014). Extending the understanding of mobile banking adoption: When UTAUT meets TTF and ITM. International journal of information management, 34(5), 689-703.
66. Pan, L., Luo, H., & Gu, Q. (2025). Incorporating AI literacy and AI anxiety into TAM: Unraveling Chinese scholars' behavioral intentions toward adopting AI-assisted literature reading. IEEE Access.
67. Pillai, R., & Sivathanu, B. (2020). Adoption of AI-based chatbots for hospitality and tourism. International Journal of Contemporary Hospitality Management, 32(10), 3199–3226.
68. Pillai, R., Ghanghorkar, Y., Sivathanu, B., Algharabat, R., & Rana, N. P. (2024). Adoption of artificial intelligence (AI) based employee experience (EEX) chatbots. Information Technology & People, 37(1), 449–478. https://doi.org/10.1108/ITP-04-2022-0287
69. Podsakoff, P.M., MacKenzie, S.B., Lee, J.-Y. and Podsakoff, N.P. (2003), "Common method biases in
70. Portz, J. D., Bayliss, E. A., Bull, S., Boxer, R. S., Bekelman, D. B., Gleason, K., & Czaja, S. (2019). Using the technology acceptance model to explore user experience, intent to use, and use behavior of a patient portal among older adults with multiple chronic conditions: Descriptive qualitative study. Journal of Medical Internet Research, 21(4), e11604. pp. 927-939, doi: 10.1016/j.ijinfomgt.2013.08.007
71. Prakash, A. V., Joshi, A., Nim, S., & Das, S. (2023). Determinants and consequences of trust in AI-based customer service chatbot. The Service Industries Journal, 43(9–10), 642–675. https://doi.org/10.1080/02642069.2023.2166493
72. predicting purchase intention", International Journal of Information Management, Vol. 33 No. 6,
73. Qatawneh, N., Aljaafreh, A., Allymoun, O., & Aladaileh, R. (2024). Critical success factors influencing the behavioral intention to adopt smart home technologies. IEEE Access.
74. Rafique, H., Almagrabi, A. O., Shamim, A., Anwar, F., & Bashir, A. K. (2020). Investigating the acceptance of mobile library applications with an extended technology acceptance model (TAM). Computers & Education, 145, 103732.
75. Ragheb, M. A., Tantawi, P., Farouk, N., & Hatata, A. (2022). Investigating the acceptance of applying chatbot (artificial intelligence) technology among higher education students in Egypt. International Journal of Higher Education Management, 8(2). https://doi.org/10.24052/ijhem/v08n02/art-1
76. Rajaobelina, L., Prom Tep, S., Arcand, M., & Ricard, L. (2021). Creepiness: Its antecedents and impact on loyalty when interacting with a chatbot. Psychology & Marketing, 38(12), 2339-2356.
77. Rashid, A. B., & Kausik, M. A. K. (2024). AI revolutionizing industries worldwide: A comprehensive overview of its diverse applications. Hybrid Advances, 7, 100277.
78. Sboui, M., Baati, O., & Sfar, N. (2024). Influencing factors and consequences of chatbot initial trust in AI telecommunication services: A study on Generation Z. The TQM Journal.
79. Song, X., Gu, H., Li, Y., Leung, X. Y., & Ling, X. (2024). The influence of robot anthropomorphism and perceived intelligence on hotel guests' continuance usage intention. Information Technology & Tourism, 26(1), 89–117. https://doi.org/10.1007/s40558-023-00275-8
80. Tian, W., Ge, J., Zhao, Y., & Zheng, X. (2024). AI chatbots in Chinese higher education: Adoption, perception, and influence among graduate students—An integrated analysis utilizing UTAUT and ECM models. Frontiers in Psychology, 15, 1268549.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue XII December 2025

81. Topsakal, Y. (2024). How familiarity, ease of use, usefulness, and trust influence the acceptance of generative artificial intelligence (AI)-assisted travel planning. International Journal of Human–Computer Interaction. https://doi.org/10.1080/10447318.2024.2426044
82. Van den Broeck, E., Zarouali, B., & Poels, K. (2019). Chatbot advertising effectiveness: When does the message get through? Computers in Human Behavior, 98, 150–157. https://doi.org/10.1016/j.chb.2019.04.009
83. Van Eeuwen, M. (2017). Mobile conversational commerce: Messenger chatbots as the next interface between businesses and consumers [Master's thesis, University of Twente]. http://purl.utwente.nl/essays/71706
84. Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. Information Systems Research, 11(4), 342–365.
85. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478.
86. Wang, C. L. (2024). Editorial – What is an interactive marketing perspective and what are emerging research areas? Journal of Research in Interactive Marketing, 18(2), 161–165.
87. Zhang, B., Zhu, Y., Deng, J., Zheng, W., Liu, Y., Wang, C., & Zeng, R. (2023). “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, 39(9), 1887–1903. https://doi.org/10.1080/10447318.2022.2124345
88. **Note:**[1] https://www.precedenceresearch.com/chatbot-market Report