A Technology Acceptance Perspective on Chatbot Adoption: Perceived Human-Likeness and Emotional Response

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ABSTRACT

Considering recent AI-driven advancements, conversational agents (chatbots) have become fundamental to digital interactions, requiring an assessment of determinants impacting their adoption. This study investigates the effect of anthropomorphism and technology anxiety on chatbot adoption. This study investigates the effects of anthropomorphism and technology anxiety on perceived usefulness (PU), perceived ease of use (PEU), and usage intention in the context of chatbot services. Data were collected via an online survey administered to 380 Tunisian higher education students. Using structural equation modeling with Smart PLS4, the findings confirm the crucial role of (PU) and (PEOU) in predicting usage intention. In contrast, anthropomorphism and anxiety do not significantly influence adoption. These results contribute to the literature by demonstrating that, despite heightened interest in human-likeness and psychological reactions to AI chatbots, traditional cognitive factors remain the primary drivers of chatbot service adoption.

Keywords: Chatbots, Anthropomorphism, Technology Anxiety, Technology Acceptance Model (TAM)

INTRODUCTION

The rapid development of artificial intelligence (AI) and conversational agents has significantly transformed how individuals interact with digital systems. Chatbots (or conversational agents), in particular, have become key tools in various sectors such as education, retail, tourism, entertainment, and telecommunication (Christensen et al, 2024; Sboui et al., 2024; Liu et al., 2020; McLean and Osei-Frimpong, 2019), offering immediate assistance and enhanced user engagement. Hence, the global chatbot market was valued at approximately USD 7.76 billion in 2024 and is projected to grow at a CAGR of 23.3% between 2025 and 2030. As these conversational agents gain momentum, understanding the determinants of chatbot acceptance remains an essential research priority.

The question of how closely machines should resemble humans—and how individuals respond to increasingly human-like forms of AI—has long been a central topic in emerging technology research (Breazeal, 2003; Kühne & Peter, 2023). Over time, AI has evolved from early text-based chatbots such as ELIZA to personalized voice assistants like Alexa, and more recently to advanced humanoid robots such as Sophia. This progression reflects a shift from simple surface-level imitation to deeper and more sophisticated forms of human resemblance (Fetterolf & Hertog, 2023; Rajaraman, 2023).

AI anxiety, understood as a psychological response to the growing humanisation of machines, has therefore become an increasingly important area of inquiry—particularly as advanced AI systems begin to challenge traditional notions of human agency (Xi et al., 2024). While some scholars argue that anthropomorphism heightens anxiety toward AI, others suggest that a richer set of human-like cues can instead reduce technology-related stress (Li & Sung, 2021; Epley, 2007; Lee et al., 2020).

Grounded in the Technology Acceptance Model (TAM), this study addresses these gaps by examining how anthropomorphism shapes users' anxiety toward chatbots in Tunisia. According to the Oxford Insights Report (2023), Tunisia is ranked among the top African nations for AI preparedness, with strong infrastructure and policies supporting AI-driven technologies like chatbots. This makes Tunisia an ideal setting for exploring the factors influencing chatbot adoption.

The present research contributes to the existing literature in several ways. First, it answers the calls for further research on anthropomorphism (Thomaz et al. 2020). In addition, to the best of our knowledge, this is the first attempt to extend TAM with two key antecedents of chatbot acceptance: anthropomorphism and technology anxiety, specifically within the realm of AI chatbots, as a key determinant influencing consumer adoption. Furthermore, the theoretical model in this study is empirically examined within the telecommunication industry sector as recommended by (Gatzioufa and Saprikis,2022), where chatbots are widely implemented to enhance customer engagement.

Theoretical Background and Hypothesis Development

Chatbots Across Industries

A chatbot refers to a software application designed to simulate textual interactions with users. These intelligent virtual assistant agents have gained popularity across various domains such as customer support and information delivery, reying to artificial intelligence to comprehend user queries and provide timely and relevant responses (Kumar & Rose, 2019). By automating routine interactions, chatbots help organisations to enhance customer service efficiency while providing round-the-clock assistance (Adamopoulou & Moussiades, 2020).

Chatbots are currently used to assist services in different fields, such as banking, hospitality, and e-commerce (Lubbe and Ngoma, 2021; Pillai and Sivathanu, 2020; Alotaibi and Hidayat-ur-Rehman, 2025; Araújo and Casais, 2020; Ashfaq et al., 2020). However, literature related to chatbot intention in telecom services is relatively scant.

Chatbots generate substantial value for both users and businesses by improving accessibility, personalization, and operational effectiveness. They offer 24/7 accessibility, allowing users to obtain information and services without temporal restrictions (Mehta et al., 2020). For businesses, they reduce operational costs by automating repetitive tasks, thereby optimizing resource allocation (Mital et al.,2021). Consequently, chatbots have revolutionized digital communication by offering a powerful blend of personalization, efficiency, and accessibility across a wide range of industries.

Technology acceptance model (TAM)

The TAM, proposed by Davis in 1986, is rooted in the Theory of Reasoned Action (TRA) and provides a valuable framework for investigating users' adoption behaviors of new technologies like chatbot AI. Regarded as the most influential model in adoption technologies, TAM has been validated by its strong predictive power in predicting users' intention to accept novel technology (Ashfaq et al., 2020).

The model identifies two core factors of behavioral intention: perceived usefulness (PU) and perceived ease of use (PEOU). (PU) refers to a belief that using an IT product or system will enhance their work efficiency, whereas (PEOU) denotes the degree to which the system is perceived as requiring minimal effort (Qatawneh et al, 2024).

Conversational agents offer deeper insights into how ease of use impacts the acceptance of AI-driven tools (Choe et al., 2024; Hanji et al., 2024). If users perceive chatbots as effortless to use, their willingness to adopt them increases, reinforcing their role in service engagement (Chen & Tsai, 2019). By improving usability, chatbot developers can facilitate broader acceptance and adoption of these AI-driven systems. In the context of chatbots, Ayanwale and Molefi (Ayanwale et al., 2024) found that (PEOU) does not significantly influence behavioral intention. However, Chi et al. (2023) on AI-service robots found that (PEOU) can significantly influence intention. It is also worthwhile for researchers to explore further the relationship between (PEOU) and behavioral intention.

Perceived usefulness has the most significant effect on intention to use technology, as users tend to evaluate a chatbot based on its ability to offer meaningful and efficient assistance (Davis, 1989). Consequently, when users believe that a system, device, or application can effectively assist them in completing a task, they are more likely to adopt it again (Muslichah, 2018; Gümüş & Çark, 2021). Numerous AI technology studies have confirmed that perceived usefulness (PU) can significantly affect users' intention, including E-commerce (Wang et al., 2023), ChatGPT (Liu & Ma, 2024), and chatbots (Sfar et al., 2024).

Besides that, most TAM studies have confirmed that PEOU can significantly impact users' PU of AI products, including metaverse platforms (Al-Adwan et al., 2023) and AI robots (Chen et al., 2023). Specifically, Chatbots that are easy to use are more likely to be perceived as useful. Therefore, this paper posits the following hypotheses.

H1: Perceived ease of use (PEOU) positively impacts the intention to use chatbots.

H2: Perceived usefulness (PU) positively impacts the intention to use a chatbot

H3: Perceived ease of use (PEOU) has a significant impact on perceived usefulness (PU)

Technology anxiety and the Technology Acceptance Model (TAM)

AI anxiety refers to a psychological state of discomfort, hesitation, and cognitive strain arising from unfamiliarity, loss of control, and uncertainty in AI interactions (Li & Huang, 2020). Prior research has shown that computer anxiety has been associated with negative perceptions of technology, usage difficulties, and technology resistance (Igbaria & Iivari, 1995). When interaction with information technologies elicits feelings of discomfort, users are more likely to perceive these systems as complex and cognitively demanding (Van Raaij & Schepers, 2008). Within the TAM3 framework, computer anxiety is conceptualized as an emotional response to technology exposure and is identified as a crucial determinant of perceived ease of use (PEOU) (Venkatesh, 2000; Venkatesh & Bala, 2008). This concept has been expanded to AI-enabled technologies (Clarke, 2019; Li & Huang, 2020; Wang & Wang, 2022). In this study, AI chatbot anxiety is defined as a generalized affective state of fear or apprehension that discourages users from engaging with AI chatbots (Wang & Wang, 2022). Drawing on cognitive load theory, anxiety elevates arousal and consumes cognitive resources, thereby compromising cognitive processing and increasing perceived complexity (Eysenck et al., 2007). In the context of AI chatbots, heightened anxiety is therefore likely to lower users' perceived ease of use, as interactions are experienced as less intuitive and more mentally effortful.

In addition, insights from learned helplessness theory suggest that anxiety can erode users' sense of control, limiting their perceived capacity to effectively interact with new technologies (Maier & Seligman, 1976; Fincham et al., 1989). When applied to AI chatbots, elevated anxiety may intensify feelings of helplessness, further reducing perceived ease of use (Venkatesh & Bala, 2008 ; Kleine et al, 2025). Empirical studies support this view, proved that AI anxiety negatively predicts positive attitudes toward AI (Cho & Seo, 2024; Schiavo et al., 2024).

Beyond usability, technological anxiety may further impair perceived usefulness. Anxious users are more likely to question a chatbot's reliability, accuracy, and ability to support task completion, leading to an underestimation of its functional benefits. This reasoning aligns with previous studies showing that negative affective states bias evaluations of technological performance and outcomes (Meuter et al., 2003; Li & Huang, 2020; Li et al., 2024; Kleine et al, 2025). Therefore, the following hypotheses are proposed in this study.

H4: Technology anxiety negatively affects the perceived ease of use (PEOU) of AI chatbots.

H5: Technology anxiety negatively affects the perceived usefulness (PU) of AI chatbots.

Anthropomorphism and Technology Anxiety

Anthropomorphism refers to "the tendency to imbue the real or imagined behavior of non-human agents with human-like characteristics, motivations, intentions, or emotions." Epley et al. (2007). This process improves the novelty and appeal of conversational agent technologies, making it a crucial determinant in their adoption (Pizzi et al., 2023). Anthropomorphism is a central concept in research on human-chatbot interactions (Rapp et al., 2021). This study focuses on the conversational style and anthropomorphic language of chatbots, although users prefer text messaging interaction to chatbots with human characteristics (Ciechanowski et al., 2019)

Technology anxiety reflects deeper apprehensions related to AI autonomy, human-likeness, and its potential to challenge fundamental conceptions of human identity, agency, and social norms. In addition, AI anxiety reveals concerns regarding ethical implications, technological dependency, and the erosion of boundaries between

humans and intelligent machines (Li & Huang, 2020).

AI anxiety offers a more nuanced understanding of users' complex and ambivalent responses to anthropomorphic AI chatbots. This perspective aligns with the Media Evocation Paradigm's (Van Der Goot & Etzrod, 2023), which conceptualizes anxiety as a manifestation of the tension and uncertainty inherent in the interaction with anthropomorphic AI.

Research suggests that when AI systems exhibit human-like characteristics, they can influence users' emotional and cognitive responses (Epley et al., 2007; Li & Huang, 2020; Yao & Xi, 2025). More specifically, chatbots with human-like characteristics can reduce AI anxiety by fostering a sense of familiarity and improving users' feelings of control. When a chatbot exhibits empathy, uses natural language, or displays friendliness, the interaction appears more intuitive and socially consistent, thus reducing cognitive load and alleviating user anxiety (Li & Sung, 2021; Lee et al., 2020). Furthermore, anthropomorphism makes the system's behavior more predictable and transforms users' view of AI chatbots from a potentially disruptive to a cooperative partner, thereby reducing feelings of uncertainty or discomfort. In other words, the more human traits users perceive in a chatbot, the less anxious or uncomfortable they feel during the interaction with the chatbot. Consequently, we propose the following hypothesis:

H6: The perceived anthropomorphism of a chatbot is negatively associated with AI anxiety.

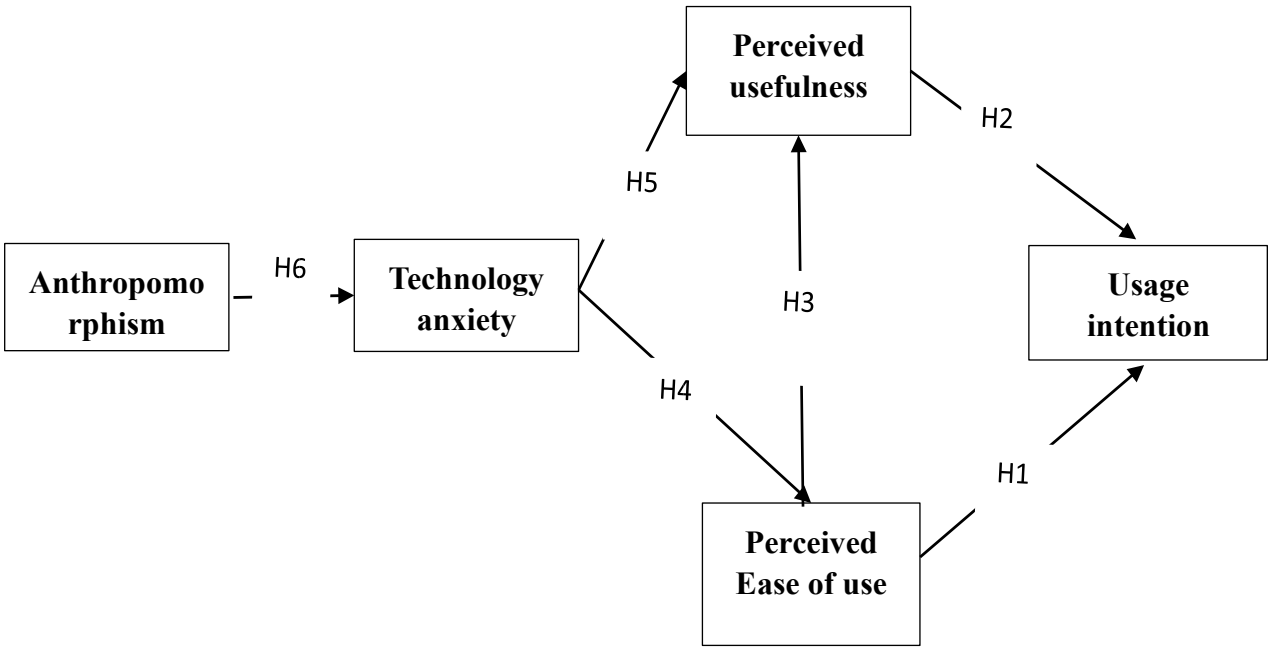

Figure 1. Conceptual Framework

Source(s): The authors' own work

METHODOLOGY

Data Collection and Sample

A convenience sample of Tunisian students was recruited for this study, as they represent one of the most technologically savvy age groups and are highly familiar with digital technologies. The study adopted a survey-based methodology using an online questionnaire distributed via email. After receiving an invitation outlining the purpose of the research and the conditions of participation, respondents voluntarily took part in the study. Firstly, they were instructed to interact with a telecommunication services chatbot using any language, including the Tunisian dialect. Then, they were redirected to complete the questionnaire. The final sample is composed of 380 respondents.

Measures

All the variables used in the survey are adapted from previous research using seven-point Likert scales Varying from 1 "strongly disagree" to 7 "strongly agree" (Table 1). Anthropomorphism was measured from the study of Melián-González et al. (2021). Ease of use and perceived usefulness were adapted from Davis's study (1989). Technology anxiety was assessed by four items taken from the study of Meuter et al. (2005). Finally, the measure of usage intention is taken from the study by Venkatesh et al. (2003)

Table 1. Variables measures

Constructs	Items	Sources
Anthropomorphism	ANTH1. The conversations I have with chatbots provided are as if I have a dialogue with a real human being	Melián-González et al. (2021)
	ANTH2. My interaction with the chatbot I use feels natural	
	ANTH3. The chatbot I use is like understanding who the chatbot is interacting with	
	ANTH4. Conversations with chatbot that I use don't seem artificial (natural)	
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	
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.	
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

Measurement Model

Data were analyzed by the PLS-SEM estimation method (Smart PLS4).The results presented in Table 2 confirm the robustness of the measurement model. Indeed, all Cronbach's α values are above 0.7, indicating strong

internal consistency. Similarly, CR values exceed 0.7, validating the internal consistency of each construct (Hair et al., 2019). Additionally, 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)
ANTH	0.858	0.958	0.900	0.693
CUI	0.955	0.957	0.971	0.917
PEU	0.825	0.853	0.893	0.736
PU	0.934	0.937	0.953	0.837
TA	0.823	0.986	0.864	0.619

Table 3. Discriminant Validity (HTMT Criterion)

	ANTH	CUI	PEU	PU	TA
ANTH					
CUI	0.463				
PEU	0.464	0.272			
PU	0.446	0.549	0.395		
TA	0.094	0.041	0.099	0.121	

Structural Model

First, we assessed the multicollinearity issues. Following the recommendations of MacKenzie et al. (2012), the item PU4 is eliminated since its variance inflation factor value is above 10 (VIF= 14.017). The structural Model is shown in Figure 2.

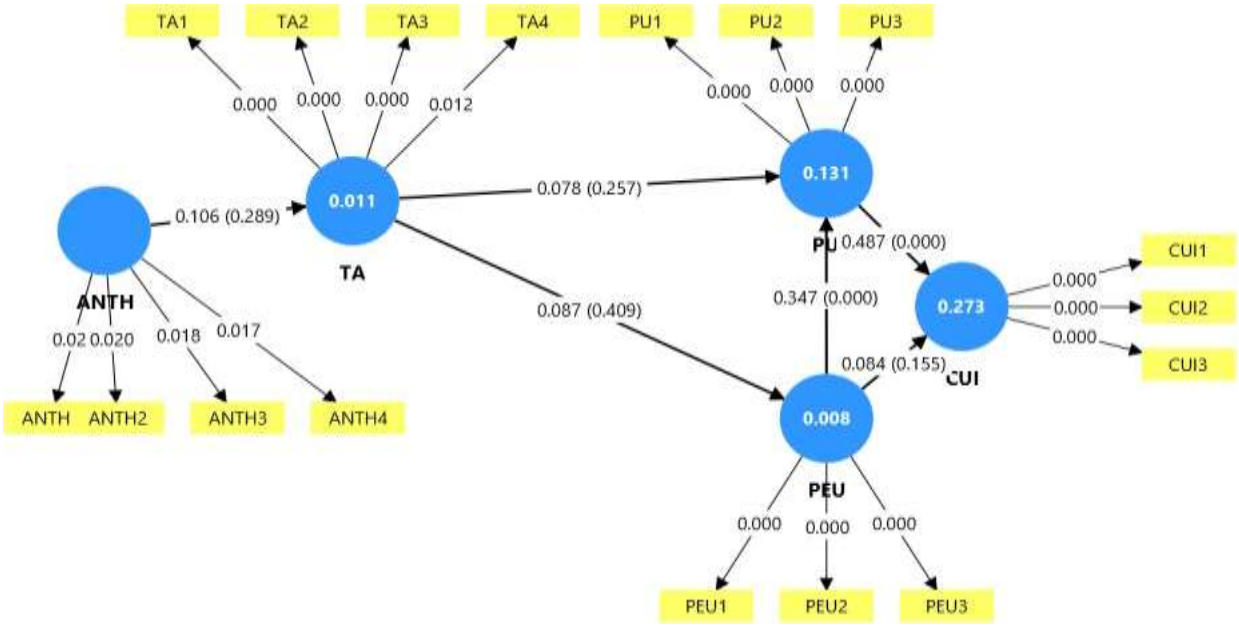

Figure 2: Structural Model

Source: PLS4 Software Output

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, H4, H5, and H6 are rejected. Among the variables that influence chatbot usage intention, perceived usefulness turned out to be the most significant predictor (β= 0.487, t= 8.567).

Table 4. Results

	Original sample (O)	T statistics (|O/STDEV|)	P values	Supported?
H1 : PEU -> CUI	0.084	1.422	0.155	Not supported
H2 : PU -> CUI	0.487	8.567	0.000	Supported
H3 : PEU -> PU	0.347	5.848	0.000	Supported
H4 : TA -> PEU	0.087	0.825	0.409	Not supported
H5 : TA -> PU	0.078	1.134	0.257	Not supported
H6 : ANTH -> TA	0.106	1.060	0.289	Not supported

CONCLUSION

Discussion And Implications

The findings of this study reveal a differentiated pattern in the relationships among anthropomorphism, technology anxiety, perceived ease of use, perceived usefulness, and intention to use chatbots.

First, perceived usefulness (PU) has consistently been a reliable predictor of behavioral intention in Technology Acceptance Model (TAM) studies. This study also demonstrated that the perceived usefulness and benefits of AI chatbots can significantly influence the intention to adopt them, consistent with the findings of numerous previous studies (An et al, 2024; Ismatullaev and Kim, 2024; Rafique et al., 2020; Sfar et al, 2025). AI developers should constantly work on improving the core functionality of these tools, such as algorithmic improvements or updates to advanced natural language processing techniques.

It has been found that perceived ease of use (PEOU) has a significant impact on perceived usefulness (PU), consistent with the findings of numerous previous studies (Chen et al, 2023; Al-Adwan et al, 2023; Xiao et al, 2025). When the chatbot has a user-friendly interface and operational process, users perceive it as efficient and useful. In this case, students perceive the chatbot tool as easy and intuitive, which will increase its perceived usefulness. Therefore, designers of AI chatbot tools should prioritize simplifying the interaction between users and these tools as much as possible.

Additionally, PEOU has no significant effect on users' intention. This result contradicts the framework of the technology acceptance model (TAM). Our findings are in line with (Gopinath and Kasilingam, 2023; Sboui et al, 2024; Topsakal, 2024), suggesting that simplicity and facility are not important in the adoption of chatbot AI. Although perceived ease of use (PEOU) does not significantly influence the intention to use chatbots, it can indirectly influence it significantly through perceived usefulness (PU), which is consistent with the results of some previous studies (Almusharraf et al, 2025; Zhang et al, 2023).

In an environment where users have limited exposure to AI chatbots, ease of use may be less important than perceived usefulness, as users focus more on the functional advantage of the technology rather than its interface. Specifically for digital native users, PEOU alone is not sufficient to adopt chatbots; they need to ensure that these AI tools offer them sufficient potential added value before adopting them. AI developers must understand that while PEOU is important, they must focus more on enhancing the benefits that AI tools can bring to users.

Second, the findings indicate that technology anxiety has no significant effect on perceived ease of use. This suggests that anxiety toward chatbot AI does not affect perception of complexity when using this system (Venkatesh & Bala, 2008; Kleine et al, 2025). Similarly, the relationship between technology anxiety and

perceived usefulness is not significant. This implies that negative emotions do not directly affect the perception of the functional benefits of chatbots (Li et al., 2024). Anxiety might influence adoption indirectly, but the perceived functional value remains robust in the face of users' emotional reactions.

The non-significant effect of technology anxiety may reflect a normalization of digital technologies across different user segments. The widespread diffusion of AI-based services in developing countries has likely attenuated technology-related fears, particularly among younger and digitally active generations (Dakduk et al., 2023; Sboui et al, 2024). Youth in these regions tend to have higher access rates, especially in emerging technologies (Afzal et al., 2023). This generational exposure may reduce the explanatory power of technology anxiety in predicting chatbot adoption, suggesting that its relevance may be context and cohort-dependent rather than universal.

Anxiety does not directly influence users' fundamental cognitive evaluation of the chatbot. Therefore, it may indirectly impact adoption through other mechanisms, such as trust or social influence (Sboui et al, 2024), rather than through perceived usability or usefulness. Telecom service operators should prioritize an intuitive design for chatbots and clearly communicate their functional benefits, as technology anxiety does not directly compromise users' perception of ease of use or usefulness, but can influence adoption through other factors such as trust.

Finally, the relationship between anthropomorphism and technology anxiety is not significant. This indicates that integrating human characteristics into AI chatbots does not impact technology anxiety. Our results, in line with previous research, proved that users are now familiar with humanized AI chatbots, which reduces any direct emotional reaction ((Li & Sung, 2021; Lee et al., 2020). Anthropomorphism could, however, indirectly influence the perception of anxiety, for example, through perceived usefulness or trustworthiness. Furthermore, collectivist consumers show a marked preference for anthropomorphic chatbots (Yanxia et al., 2024). This preference can be attributed to their willingness to value anthropomorphic objects as social substitutes, which mitigates their anxiety about AI technologies.

This study provides a context-specific validation of TAM in an emerging market characterized by differences in users' digital skills, varying levels of AI chatbot familiarity, and ongoing concerns about trust (Sboui et al, 2024; Mostafa and Kasamani, 2022). By empirically testing TAM relationships in this specific context, the study identifies boundary conditions under which the model holds. For instance, our results indicate that perceived usefulness is a strong predictor of chatbot adoption. This finding indicates that the "tech-savvy sailors in emergent markets prioritize the efficacy and utility of chatbot AI rather than their usefulness.

From a managerial perspective, the results of this study suggest that firms operating in emerging markets should prioritize the functional performance of chatbots over purely anthropomorphic enhancements. Investments should focus on improving response accuracy, task completion, and service reliability, as these elements directly reinforce perceived usefulness. Anthropomorphic features may still play a complementary role, particularly in improving usability, but should not be considered a substitute for functional value creation.

Limitations and future research

This research has some limitations that should be considered in future studies. First, we focused on the direct relationships between perceived ease of use, expected performance, anthropomorphism, and anxiety about the intention to use the chatbot. However, future research could explore other variables from broader theories of technology acceptance to enrich the model. Furthermore, incorporating moderating variables, such as social influence or demographic factors, could strengthen the predictive power of the research model (Iancu & Iancu, 2023). Another limitation is the use of cross-sectional data. Future studies could adopt a longitudinal approach to capture changes in customer experiences with chatbots over time. Furthermore, the observed gender imbalance in the sample may have influenced the results. Future research should adopt more balanced and representative sampling strategies and extend the analysis to multiple emerging market contexts to strengthen external validity. Finally, the study focuses on limiting the generalizability of the findings. Future research should consider extending the sample beyond students to include diverse age groups and professional backgrounds to improve external validity.

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