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RESEARCH ARTICLE

Exploring the Impact of Emotional Awareness, Anthropomorphism, Technology Trust and Familiarity on Adoption of AI-Enabled Customer Service

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ABSTRACT

The adoption of AI-enabled customer service is taking the service industry toward efficiency and personalization, with human-like behavior. However, the factors influencing customer acceptance of these systems in relation to emotional awareness, anthropomorphism, and technology trust remain less explored. This study investigates the role of these factors in entailing consumer attitudes and behaviors toward AI-driven customer service-development proposed an integrative adoption model. Emotional awareness, where being AI enables an interaction to detect and hence respond to human emotion, is supposed to improve customer satisfaction and loyalty by contributing to empathetic and personalized experiences. Anthropomorphism is considered an avenue that attributes human-like traits to AI agents in order to create emotional bridging and help eliminate user resistance. The moderating effects of trust in technologies and familiarity on perception of technology and adoption are also investigated. The findings advance the knowledge on cognitive and emotional processes that influence engagement with AI service agents. This research addresses the plan for AI systems that satisfy operational demands and will not only serve, but also address the emotional and psychological needs of the customers-or, ultimately, that support advancing the human-centered AI within customer service contexts.

1. Introduction

The burgeoning demand for personalized, hassle-free experiences has prompted consumers to express a desire for concierge-level service experiences that sometimes hover within the luxury spectrum. AI technologies such as natural language processing (NLP) and conversational AI have a cardinal role in facilitating this transition in creating dialogs on behalf of their businesses with customers (Sharma et al., 2021). Chatbots and virtual assistants powered by AI, to help customers solve simple queries or do complicated requests related to service, are taking a hold of the market and improving convenience and satisfaction all around (Nguyen, 2024). They propel personalized, emotionally intelligent experiences that adapt to the unfolding needs of today's consumers beyond efficient operationality. Increasing competition in customer service results in AI becoming indispensable for service tomorrow, where AI applications are forecasted to grow from roughly USD 1.55 billion in 2019 to 8.12 billion by the year 2033.

Recent studies have listed emotional awareness as a significant input in AI systems, where AI has to move beyond its limitations of recognizing and responding to emotional promptings from customer queries (Sesha Bhargavi Velagaleti, 2024; Singh et al., 2024). From the customer's perspective, the customer experience improves enormously owing to emotion recognition in addition to query handling. For example, recognizing voice tone or facial expressions can allow an AI system to gauge whether a customer is frustrated or satisfied and customize service accordingly (Bromuri et al., 2021). The good face of AI in the customer service sector seems to be bright, but certain challenges remain, such as sympathy, emotional connection, and trust in communication led by AI. A large degree of difficulty still exists to use technology to deliver an emotionally resonant connection akin to humans for another client. While Chandra et al., (2022) put great emphasis on how the AI has transformed the working style of customer services, they still argue that in some instances, and particularly those instances that require empathy and emotional sensitivity, the human presence cannot be totally replaced.

Some of the methods to ameliorate user engagement and user trust in AI service agents include anthropomorphism that can possibly help foster trust and enhance customer engagement (Cheng et al., 2022; Golossenko et al., 2020). AI service agents' anthropomorphism adds a human touch to the technology and makes its interaction more relatable while minimizing the degree of cognitive dissonance for customers using nonhuman agents. Service robots or AI chatbots with human-like personas forge an emotional bond with users, increasing their willingness to interact with the technology and resulting in higher overall satisfaction with the service provided ((Khan et al., 2025). While anthropomorphism is often accepted as promoting user interaction, the effects of anthropomorphism on the performance and acceptance of AI entities are contentious. The effet of anthropomorphism is moderated by customer control orientations in addition to service encounter types (Blut et al., 2021; Yang et al., 2022).

Simultaneously, emotional awareness (EA) has been recognized for the remarkable potential to change perceptions and how customers behave toward AI service agents. EA can be described as the ability of an AI system to recognize and respond to human emotions during the course of the interaction. This, in turn, engenders a more personalized and empathetic encounter for the customer (Lv et al., 2022). An emotional-aware AI will enable the emotional states of customers to gauge and, thereby, the possibility to customize interactions in congruence; this, in turn, improves service levels and creates loyalty (Liu-Thompkins et al., 2022). Yet the chances still pose challenges to such integration into AI systems, especially with regards to accuracy and not falsely attributing meanings to emotional cues.

The study aims to explore the different factors that affect the adoption of AI in customer service, mainly anthropomorphism, emotional awareness, and technology trust. This research shall build on Lazarus's cognitive-motivation-emotion framework (Mutlu, 2024) and develop a model depicting the stages through which customers engage in an evaluation of and subsequently adopt artificial intelligence technology in customer service settings.

2. Literature Review

2.1 AI Customer service

The design of customer service solutions is always evolving with the advancement of technology. With recent breakthroughs in AI technology, connecting with clients using AI has become a preferred method for many businesses to deliver real-time customer care (Adam et al., 2021). AI Customer Service is an AI information system that automatically interacts with its users to offer operational assistance, accept complaints, and provide consulting services (Cheng et al., 2024). This shift to technology is likely to change human roles and empower the customer service workers of tomorrow. Such technology aids organizations in creating custom, real-time engagements for customers, automating repeat tasks, anticipating customer needs, and thereby improving customer journeys. Natural language constitutes an appealing trait of customer service chatbots, embodying the humanized testament that chatbots are designed to replicate human interactions (Sheehan et al., 2020). Roesler et al., (2021) argues that some anthropomorphic traits in either the appearance or the behavior of the robot are essential in making perception and interaction meaningful between a robot and a human being. An AI chatbot, designed with emotional intelligence, will socially engage the client with even greater proficiency than its cognitively intelligent counterpart, because it can make estimates about intrinsic features from the analysis of emotional data (Zhang et al., 2024). A sympathetic chatbot should grasp situations and relate them empathically enough that it can feel the customer's emotions and offer emotional support, just like a good human employee would (Fan et al., 2024).

Another feature is user contact, which needs AI customer service to reliably recognize user inquiries and deliver replies, as well as conduct very complicated rounds of discussion (Hsu & Lin, 2023). AI systems provide scalability and continuous availability, allowing them to manage large volumes of client contacts while working around the clock. This allows continual customer assistance, enhancing reliability and satisfaction within their service. AI-based chatbots can respond to customers around the clock, which guarantees a rapid response in the case of a need for client assistance. The capacity to give ongoing help increases customer trust and engagement, especially in businesses with large customer interaction volumes. Implementing AI technology, such as chatbots and process automation, has been shown to greatly improve customer service productivity by handling routine questions and duties (Spring et al., 2022). All these ultimately help human agents to devote resources on more complex challenges which boosts overall productivity while shortens the time response (Raisch & Krakowski, 2021).

2.2 Emotional Awareness and Technology Trust

People in an AI service setting with social interactions must perceive the emotion of AI service agents. Social and emotional experiences are of critical importance to the whole consumer experience (Manthiou et al., 2020). In the context of human-chatbot interactions, they capture the subjective sensations generated in the service-related interactive process between people and chatbots and contribute toward consumer acceptability (Kuuru et al., 2020). Conversational signals, such as interactivity and emotional expressions, are positively linked with perceived social presence, as shown in studies on human encounters with chatbots (Li et al., 2023; Tsai et al., 2021).

Lee et al. (2023) found that human-like linguistic signals result in increased social presence, which leads to favorable interaction outcomes such as more homophily, emotional intimacy, connectivity, and, ultimately, higher positive user ratings of a chatbot. Song and Kim (2022) found that a robot's higher social competence (i.e., more natural and human-like speech) resulted in stronger social presence, which was also connected to subjective happiness in interacting with the robot. AI assistant personification characteristics reduce the psychological barrier between users and AI helpers during engagement and encourage participants to evaluate themselves positively (Lv et al., 2022). Following the literature, this study posits that:

H1. Emotional Awareness is significantly related with technology trust

2.3 Anthropomorphism and technology trust

Face-to-face interaction is the most natural and popular form of communication for humans (Chandra et al., 2022). However, interacting with technology makes it impossible to apply the same social cues as in face-to-face encounters, lowering the quality of customer engagement experiences. Mimicking face-to-face conversation appears to be an effective technique to improve the naturalness of online service interactions. Furthermore, when people communicate with computers, they instinctively apply some of the social norms they use to connect with humans and elicit social reactions, considering computers as social actors (Xu et al., 2022). This social reaction is heightened when the technology under discussion exhibits human features or social signs (Lv et al., 2022). Accordingly, we propose that:

H2: Anthropomorphism is significantly related with technology trust

2.4 Technology Trust and Technology Adoption

Technology adoption is a process that begins with user knowledge of the technology and ends with embracement and full usage of the technology (Saghafian et al., 2021). Human behavior research online has emphasized the need of including trust in adoption models to better understand the success elements that drive customer acceptance and uptake of IoT devices and services (Abushakra et al., 2022). In uncertain situations, trust helps the individual grasp the social context of the technology and reduces susceptibility. It is found that trust confidence in conversational AI is the primary facilitator of consumers' desire to interact with such digital agents (Becker & Fischer, 2024). Thus, trust is seen as a significant feature in studies involving online services. Arfi et al. (2021) concluded that trust has a substantial impact on behavioral intentions to use IoT goods and services. Bedué & Fritzsche (2022) agreed that trust is an important aspect in the adoption of third-party apps. Therefore, we propose the following hypothesis:

H3. Technology trust is positively related with technology adoption.

2.5 Technology Familiarity as a Moderating Variable

Familiarity is a perception generated from top-down processing that visual perception is an associative process involving not only memory and cognition but also past experience and familiarity (Montaldi & Kafkas, 2022). Familiarity not only provides a solid structure or framework for future expectations of the systems but also allows end-users to establish concrete solutions of what to expect based on their previous experience of the system (F. Zhao & Nakatani, 2023). According to Luhmann (2018), end-users are likely to perceive less complexity and uncertainty if they are familiar with a system (Joslyn & Savelli, 2021). In contrast, people are more likely to resist or be reluctant to use the technology when overwhelmed by the complexity of an interface and navigation (Salimzadeh et al., 2024). Therefore, Sutherland et al. (2022) argues that familiarity increases knowledge, understanding, comprehension; and thus, reduces risk. Accordingly, we propose the that:

H4. Technology familiarity moderates the influence of technology trust on technology adoption

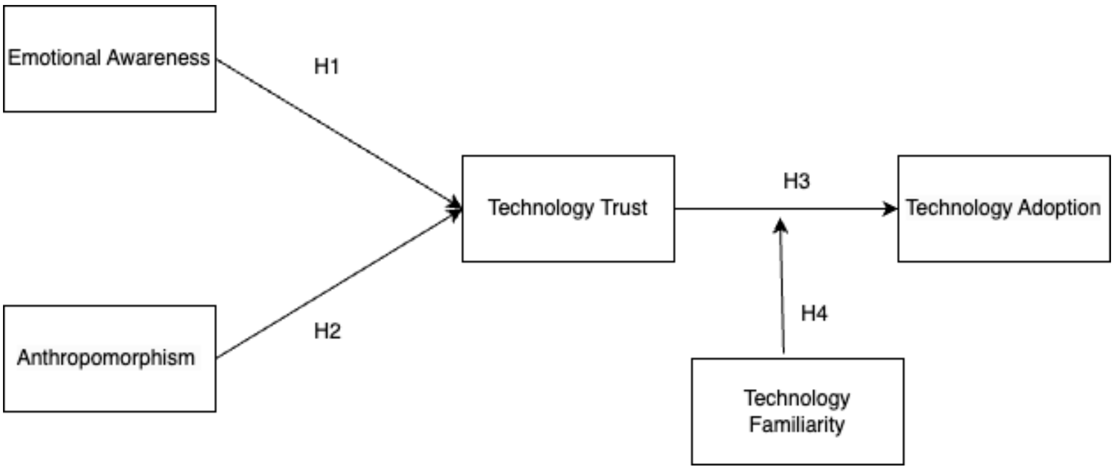

Figure 1: Research model.

3. Methodology and Procedures

3.1 Sample and procedure

A field survey of Chinese customer service consumers provided empirical data. China is ranked highly in worldwide AI capabilities for customer service. In 2022, the whole AI customer service market in China was worth 6.68 billion yuan. According to the prediction, the market would be worth around 18.13 billion yuan by 2027 (Slotta, 2024). More than 63% of retail organizations employ AI to improve customer experience (Fokina, 2024) and over half (56.2%) of consumers have used AI services while making purchases (Arcibal, 2023). As AI-related customer services become available in various industries including banking, insurance, healthcare, software，and telecommunications, the adoption patterns of Chinese users would provide insight into the comprehension of such programs. For two weeks, survey messages detailing the purpose of this study, along with a hyperlink to the survey form, were posted to relevant WeChat groups (from Nov 21, 2024, to Dec 05, 2024). WeChat is the most widely and frequently used social networking platform in China, with approximately 1.38 billion active users (Thomala, 2024). It allows convenient and comfortable contact with potential AI customer service users.

3.2 Measures

The current study's research instrument and items were based on previous research, with slight alterations to fit the current setting. The questions were assessed using a 5-point Likert scale and a rating scale ranging from strongly disagree (1 to strongly agree = 5). To measure emotional awareness (EA), three items were adapted from Del Prete (2021). The two scales, anthropomorphism (AP) are adapted from existing literature (Sun et al., 2024) and slightly modified from the virtual live shopping experience to the AI customer service context. Technology trust (TT) was measured using a four-item scale adapted from Shareef et al. (2021). To assess technology familiarity (TF), a set of three items was adapted from the studies conducted by Wirani et al. (2021). We revised the "smartphone" context to "I customer service," removed the item "company/brand familiarity ," as it was irrelevant to this study, and assessed it using a three-item scale. Finally, purchase intention (PI) was evaluated using a 2-item scale adapted from Khaksar et al. (2021) and Kumar et al. (2021) and slightly changed from contexts of the blockchain-enabled system and robot to the AI customer service system.

3.3 Data collection

Wenjuanxing, an online platform, collects data through self-administered surveys. Wenjuanxing is a popular platform among researchers (Guo et al., 2021; Zhao et al., 2020), because to its high-quality data and outcomes. In addition, it allows scholars to extract information from various points in China. The survey had three sections: First, we stated the purpose of the study. Second, detailed demographic data were collected from respondents, inclusive of a question regarding their frequency of using AI customer support. The third part incorporated the factors in question. The researchers used convenience sampling and a cross-sectional study approach to collect data. Convenience sampling is an example of a non-probability sampling method in which the researcher chooses individuals or subjects that are easiest for him/her to reach (Golzar et al., 2022). This research design tapped into simple sampling method-mode due to the challenge of contacting every participant in a large population (Mweshi & Sakyi, 2020). Henceforth convenience sampling is most often used in online cases as it becomes easy to reach respondents through emails, social networks, or other online ways. Participants of convenience sampling are chosen on the basis of their availability and willingness to participate.

The questionnaire consisted of three parts. First, we stated the goal of the study. Second, we gathered demographic information from respondents, including a query regarding their frequency of using AI customer support. The final part contained the variables of interest. We conducted data collecting using a purposive sampling approach and a cross-sectional survey. We deliberately targeted respondents who have used AI customer service by including a screening question asking if they had used AI customer service in the previous three months. Those who responded "No" were sent to the end of the survey. According to Majeed et al. (2021), a sample size of fewer than 500 but larger than 30 is ideal for marketing and behavioral science research. To assure the validity of the current investigation, we set a sample size of 30-500. Of these replies, 294 had been declared valid, comprising 45.2% males and 54.8% females. Nearly three-quarters of the respondents are aged below 40 years old, and over half hold a bachelor's degree. More over half (62.4%) of respondents reported having 1-3 years of experience with AI customer service, while 37.6% had less than a year. Table 1 shows the demographic parameters in detail.

Table 1: Demographic characteristics of the respondents

Measure	Items	Frequency	Percentage
Gender	Male	133	45.2
	Female	161	54.8
Age	18-25	67	22.7
	26-30	46	15.6
	31-35	51	17.3
	36-40	54	18.3
	＞40	76	26.1
Highest Education	Senior High school and below	52	17.7
Level	Graduate school/ Professional training	93	31.6
	Bachelor’s degree anda above	149	50.7
AI customer	Less than one month	23	7.8
service	One to six months	31	10.5
experience	Seven months to 1 year	57	19.3
	1–2 years	62	21.1
	More than 2 years	121	41.3

4. Results and Discussion

The researchers employed IBM SPSS 29.0 to examine common method bias (CMB) and demographics, as well as Smart PLS 4 software to evaluate measurement and structural modeling methodologies. The data was assessed in two steps: (1) model fit, reliability, and validity, and (2) hypothesis testing.

4.1 Common method bias

Common method bias (CMB) can be used in behavioral research. The results obtained from this type of research are likely to be compromised by the noise of biased instruments (Vomberg & Klarmann, 2022). To address CMB, the questionnaire included instructions on the strict anonymity protocol of the study. Respondents were told to be neutral and honest and were informed that there were no right or wrong answers. We also performed Harman’s single-factor approach, and the total variance for a single factor was 18.6%, which met the cut-off criteria. Ideally, a single factor should have a variance of less than 50%. Thus, CMB is not of concern in this study.

4.2 Measurement model assessment

In the measuring model, we looked at construct reliability, discrimination, and convergent validity. Cronbach's alpha (α), composite reliability (CR), and average variance extracted (AVE) are used to evaluate the reliability of any concept. All of the variables have explained why Cronbach's Alpha (0.76-0.95) and composite reliability (0.86-0.96) values are beyond the acceptable range of 0.70. Similarly, the values of AVE are above the indicated acceptable range of 0.50, indicating that the supplied construct is reliable. In PLS SEM, we first examined convergent validity, which is assessed by factor loadings for each construct under consideration (Cheung et al., 2024).

As a consequence, Table 2's findings demonstrate that the factor loadings for each construct are more than the proposed threshold of 0.70, indicating good convergent validity (Henseler et al., 2015). Following the examination of convergent validity in PLS-SEM, discriminant validity was examined, which specifies that it occurs when the correlations between components are smaller than the square root of the constructs' AVE, according to the criterion. According to Table 3, all of the constructs in the study fulfill the criteria for excellent discriminant validity. Discriminant validity was assessed using the Fornell and Larcker criteria. The square roots of AVE outperformed their corresponding correlations, suggesting discriminant validity. The current study employed the HTMT ratio, which is a regularly used method for evaluating discriminant validity. Roemer et al. (2021) recommended a threshold of 0.90 for HTMT readings, although all values in Table 3 were lower. Thus, discriminant validity was demonstrated.

4.3 Structural model assessment

To estimate the second-order formative indicator weights, we used bootstrapping with 5000 subsamples, and the route coefficients were re-estimated for each of these samples. The results are shown in Figure 2. All second-order formative indicators have a strong and high loading on the first-order constructs, including core Emotional Awareness, Anthropomorphism, Social Presence, Psychological Distance, Technology Trust, Technology Adoption, and Technology Familiarity.

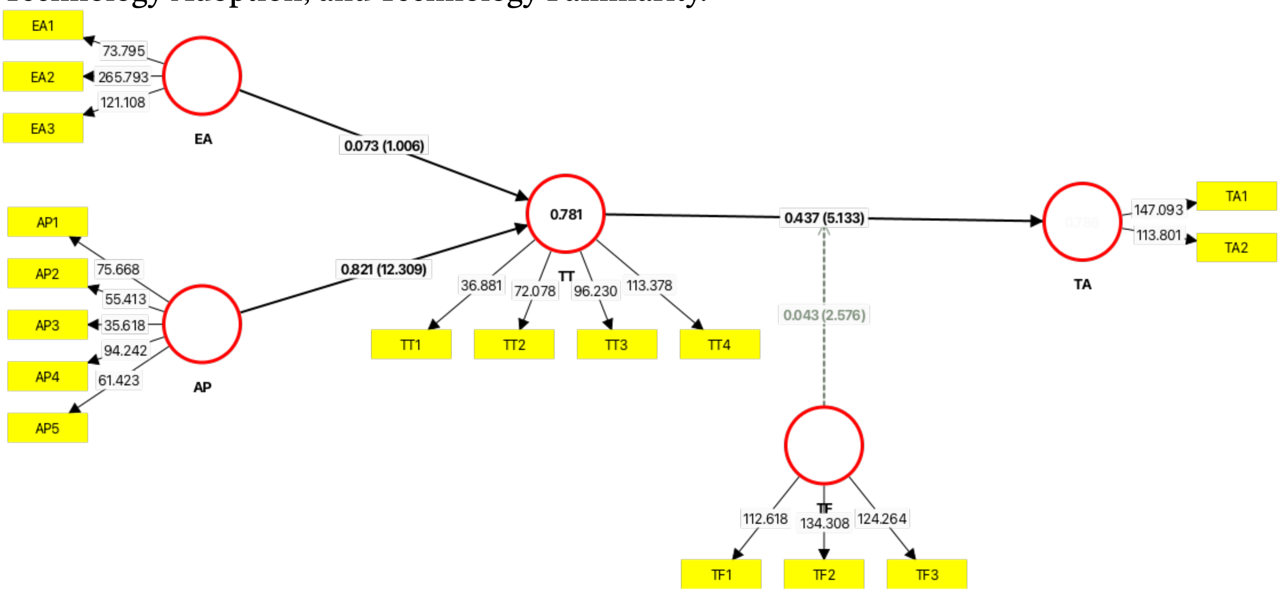

Figure 2: Results of structural modeling analysis.

Consistent with our expectations, anthropomorphism significantly affected technology trust (β = 0.821, t-value = 12.309, $p < 0.001$;) , thereby supporting H2. Technology trust is found to have direct influence on technology adoption with the path coefficients of 0.437 (t-value = 5.133, $p < 0.001$) ; therefore, H3 is supported. Notably, emotional awareness is not found to influence technology trust; thus, H1 is not supported. Technology familiarity (β = 0.043, t-value = 2.576, $p < 0.001$) has a positive moderating effect, therefore, H4 is supported. Table 4 provide the results of the proposed hypotheses.

Table 2:Factor loadings

Contrast	Items		FL	Alpha	CR	AVE	Source
EA				0.956	0.971	0.919	
	EA1	AI customer service appeares aware of my emotional state.	0.939				
	EA2	AI customer service seems to understand my feelings during the interaction.	0.977				(Del Prete, 2021).
	EA3	AI customer service demonstrates empathy toward my situation.	0.960				
AP				0.949	0.961	0.831	
	AP1	AI customer service acted intentionally.	0.918				
	AP2	AI customer service displayed emotions relevant to the context.	0.905				
	AP3	AI customer service seemed to make decisions autonomously.	0.877				(Sun et al., 2024)
	AP4	AI customer service felt sentient in its responses.	0.940				
	AP5	AI customer servic behaved as though it had a mind of its own.	0.917				
TT				0.954	0.967	0.879	
	TT1	AI customer service system demonstrated honesty in its responses.	0.915				
	TT2	AI customer service demonstrated care for my needs.	0.937				(Zhang et al. 2021)
	TT3	AI customer service consistently provided reliable assistance.	0.946				
	TT4	AI customer service proved to be trustworthy.	0.952				
TA				0.950	0.976	0.952	Wirani et al. (2022), and Idemudia and Raisinghani (2014).
	TA1		0.977				
	TA2		0.975				
TF				0.960	0.974	0.927	
	TF1		0.962				
	TF2		0.967				
	TF3		0.96				

Table 3: Validity test

Constructs	AP	EA	TA	TF	TT
AP	0.912				
EA	0.845	0.959			
TA	0.822	0.761	0.976		
TF	0.803	0.708	0.855	0.963	
TT	0.883	0.766	0.851	0.866	0.938
AP					
EA	0.886				
PD	0.746	0.849			
SP	0.748	0.891			
TA	0.864	0.798			
TF	0.841	0.738	0.895		
TT	0.727	0.801	0.893	0.804	

Table 4: Results of hypothesis testing.

Hypotheses		SD	T-statistics	P-values	Supported
Direct effect					
H1	EA -> TT	0.072	1.006	0.314	No
H2	AP -> TT	0.067	12.309	0	Yes
H3	TT -> TA	0.085	5.135	0	Yes
Moderation effect					
H4	TF x TT -> TA	0.017	2.576	0.010	Yes

5. Conclusion and Suggestion

This study investigates the factors influencing the adoption of AI-driven customer service focusing on the roles of anthropomorphism, emotional awareness, technology trust, and technology familiarity. The results provide meaningful insights into the appraisal process customers undergo when interacting with AI-driven customer services.

Findings from our research highlighted the key importance of anthropomorphism, trust in the technology, and familiarity with the technology in shaping customers' appraisal toward AI interactions. When building interaction quality, emotional connection, and trust, customers feel that anthropomorphic characteristics were noted as important (Chi & Hoang Vu, 2023; Khan et al., 2025); they are liable to apply the rules and expectations of sociability toward AI agents (Yuan et al., 2022) and are seen as social entities despite an understanding of their artificiality. This will further enhance the notion of trust and relational bonding. The application of anthropomorphism in cues such as avatars, personalized messages, and human-like verbal communication heightened social warmth and sociability (Verhagen et al., 2014; Yuan et al., 2022). Humanizing AI entities will trigger social behavior and perceptions as in human-to-human interaction. The results are informative when using the construal level theory of Trope and Liberman since the more human-like AI appears to be, the easier the psychological distance will be closed, thus enhancing the trust and closeness feeling (Kim et al., 2022; Pentina et al., 2023).

Moreover, these results also support that technology trust leads to the outcome phase in customer adoption, where choices regarding continued use intentions were strongly affected by trust in AI system. Trust is a basis for forming expectations about the behavior of some technology or service, as suggested by Bodó (2021). When users know that the AI will work as expected, fulfilling their needs without compromising security or performance, they will be perhaps inclined to maintain its continued usage. Trust is based on the belief by the users of the AI of its reliability and ability to perform under their expectation, even under unpredictable conditions (Choung et al., 2023). The incorporation of supportive messages from the AI, such as empathic responses or human-like conversations, creates an emotional linkage whereby trust is built and the psychological distance between the user and the technologies is decreased (Kim, 2024; Liu, 2024).

While the moderation effect of technology familiarity revealed that greater familiarity with technology generally results in a more positive attitude toward adoption- a reality that was in line with findings from Horowitz et al. (2024). When technology becomes somewhat familiar, users also become more comfortable and confident in using it. And various literatures report that as users become more familiar with AI systems, they are less likely to regard these technologies as overwhelming or unreliable which reduced psychological distance. Familiarity encourages consumers to rely on their own judgment rather than external sources, further driving adoption decisions (Liu et al., 2021). The more people interact with technology like AI, it is not intimidating to them; lowering perceived risks improves attitudes toward adoption (Zhan et al., 2024). In many applications: Such as smart speakers, where AI addresses practical needs while providing companionship, increased exposure increases users' willingness to adopt and continue using such systems. Furthermore, as consumers see the utility and ease of use increase alongside familiarity, they also begin to trust that AI can fulfill their needs, resulting in increased adoption.

Nonetheless, our research could not find significant evidence in support of the premise that emotional awareness has a direct effect on the relation between technological trust and technology acceptance. This contrasts with previous studies that suggest emotional awareness might be of utmost importance in determining one's perception of technology (e.g. Mantello et al., 2023, 2023; Zhi et al., 2024). One potential explanation for this diverging pattern is the contextual differences between the present study and the previous literature. Earlier studies tended to examine specific technological innovations or applications and were usually conducted within controlled environments; ours focused on a variety of technologies in more naturalistic contexts, which may have diluted the potential influence of emotional awareness on trust and adoption.

5.1 Theoretical Implications

The current study has significant theoretical implications for the existing body of literature. First, it contributes to understanding the influence that AI-driven customer service technologies have on consumer perceptions, emotional reactions, and behaviors in the service context. More specifically, it contributes to the literature on AI adoption by exploring the role of anthropomorphism and emotional awareness in influencing trust and adoption of a technology. Earlier studies generally placed the focus of discussion regarding customer satisfaction and technology acceptance in AI settings, while few attempted to broadly tackle the influence that these AI characteristics have on emotional and cognitive mechanisms during different stages of customers' journeys. In addition, this work adds to the emerging field of technology adoption research using the lens of technology familiarity as it shapes consumer attitudes and intentions toward AI-based services. Technology adoption models extend from an ease of use and usefulness technology standpoint; this study widens their scope by placing technology familiarity as another relevant factor included with regard to adopting AI. Our results suggest a daily interaction with AI technologies will provide that much less perceived risk, greater trust and confidence, and a more optimistic attitude toward future use of AI. Such theoretical contribution extends the previous work on technology acceptance by looking into familiarity as another critical dimension influencing AI technology adoption.

5.2 Practical implications

These findings have several implications for organizations using AI-enabled customer service technologies and other digital marketing avenues. First, organizations must note that the success of AI service adoption hinges on the technology itself and on emotional and psychological parameters influencing customer engagement. The findings suggest products or services offered with an emotional intelligence and aspects of anthropomorphism will build consumer trust and enhance purchase intention. Thus, organizations should invest in systems of AI that decipher human emotions and respond in real-time. Secondly, seamless integration of AI technologies and the current service framework emerged as a focal point for this research. Organizations will need to align their AI systems to be sophisticated but deliver what's best for their consumers. AI must be careful not to disrupt, but supplement or improve the flow of the customer journey. For example, the more personalized the recommendations provided by AI, or the more effectively it can predict what customers want, the better the user experience becomes. However, continuous monitoring of AI touchpoints by businesses is imperative as this makes certain the AI interactions create the desired customer experience and emotional connection.

5.3 Limitations and future research directions

This study had several limitations, which future research should take into consideration. First, the limited sample was restricted to a single location; this may not be strictly typical of the general population. Hence, the findings could be limited by regional culture-specific variables and particular characteristics of the participants. Future research could increase the sample size and use a more varied sample from different countries and cultures to shed meaningful light on how consumers in various regions perceive and adopt AI-driven customer service. Second, the current study was cross-sectional; thus, it was limited to the "snapshot" of the customer journey rather than following through any long-term effects or changes in consumer behavior across time. A longitudinal approach would better narrate continual perception and intent changes through time as AI technology further penetrates customer interactions in future studies since this would afford an opportunity towards more nuanced insights into the longer-term effects of AI on customer trust, engagement, and purchase intentions.

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