

RESEARCH ARTICLE

The Impacts of Experiences with Chatbots on Customer Satisfaction: The Role of Trust in Chatbots

Cheng-hsin Chiang¹, Ting Wu², Ananaya Leesirisuk³

Received: 30 June 2025 Accepted: 22 July 2025 Published: 25 July 2025

Corresponding Author: Ting Wu, School of Business, Macau University of Science and Technology, Avenida Wai Long, Taipa, Macau, China.

Abstract

With the integration of chatbot technology in contemporary e-commerce, growing attention has been paid to chatbot-user relationships and customer service improvement in Thailand. Nevertheless, limited research delved into factors influencing customer satisfaction with chatbot usage experiences. This study focuses on the impact of chatbot applications on Thai users' online experiences and further investigates information quality, system quality, and emotional experiences of chatbots on customer satisfaction. Questionnaires were received from 354 valid online users, and the results indicate that information quality, system quality, and emotional experiences positively influence these chatbot service users' satisfaction. This research further highlights the importance of trust in chatbots in examining customer online experiences on their satisfaction. The study underscores the need for online businesses to personalize chatbot communication strategies according to demographic preferences. Future research may include other potential influences from chatbot usage and contextual factors, such as personality traits and cultural differences.

Keywords: Information Quality, System Quality, Emotional Experience, Customer Satisfaction, Trust in Chatbot.

1. Introduction

Electronic commerce (e-commerce) thrives rapidly in Thailand due to governmental and active consumer participation. Research indicates that Thai companies are assertively adopting artificial intelligence (AI) accompanied chatbot technologies in predictive analytics and personalized process to improve customer satisfaction with better service (Kamkankaew et al., 2024).

Chatbots, as machine agents, are software applications that communicate with conversational natural language and make human-machine interactive service systems possible (Weizenbaum, 1966). Like humans, chatbots play a pivotal role in improving customer experiences by accurately and efficiently identifying natural language and offering personalized recommendations

to meet customers' needs and wants. Chatbots use voice, text messages, and graphics, which gradually replaced services previously accountable by humans since they can concurrently and timely respond to multiple requests (Tezcan & Zhang, 2014). Businesses have increasingly applied AI and chatbots in sales and marketing fields due to the huge breakthroughs in 2022 (Nordheim et al., 2019). Unlike traditional technologies (e.g., self-service), chatbot provides services through automatically sensing, learning, and responding to customers that directly or indirectly engage in customers with various functional and emotional benefits (Huang et al., 2021).

The investment in chatbots has revolutionized the landscape of customer service since chatbots improve operational efficiency in analysing data, supporting

Citation: Cheng-hsin Chiang, Ting Wu, Ananaya Leesirisuk. The Impacts of Experiences with Chatbots on Customer Satisfaction: The Role of Trust in Chatbots. Open Journal of Human Resource Management. 2025;6(1):16-25.

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¹Department of International Business, Feng Chia University, Taiwan.

²School of Business, Macau University of Science and Technology, Avenida Wai Long, Taipa, Macau, China.

³Department of International Business, Feng Chia University, Taiwan.

systems and upscaling personalized experiencing processes (Huang et al., 2021; Jaichobdeeyingsakul et al., 2023; Kamkankaew et al., 2024). The success of chatbots results from their timely response that improves customer satisfaction and strengthens customer relationship (Tezcan & Zhang, 2014; Tussyadiah & Park, 2018).

Concerns about the potential risks of data misuse in customer-robot interaction recently has received attention due to broadly adopting chatbots across industries (e.g., Huang et al., 2021; Mouakket & Bettayeb, 2015). Building trust in chatbots as a determinant helps attract, satisfy and retain customers to continuously use service applications in e-commerce (Alagarsamy & Mehrolia, 2023; Belanche et al., 2020; Hariguna et al., 2020). As a result, this study focuses on Thai users' online experiences interacting with chatbots and investigates trust in chatbots to improve their satisfaction. Based on the Consumer Acceptance of Technology (CAT; Kulviwat et al., 2007) model from Technology Acceptance Model (TAM; Davis, 1989), this study mainly proposes three features of chatbots, representing respectively the functional and hedonic dimensions, including information quality, system quality and emotional experiences to examine the impacts on customer satisfaction. Subsequently, this study examines the role of trust in chatbots in human-robot interaction since few studies have dedicated trust in chatbots and its influence on customer satisfaction. Further, implications for future research are suggested.

2. Literature Review

2.1 Customer Experiences with Chatbot Service

Though customer service has been transformed into more automated and self-service oriented thanks to the advances in computer science and mechanical engineering, it has always been taken as the core issue especially in service industry. Interactive channels, such as company websites, social media platforms, email, and online-forum are considered as effective mechanisms to provide detailed instructions and instant response to users and customers (Følstad et al., 2018). The prevalence and rapid development of artificial intelligence (AI) and machine learning from 2022 further promote chatbots as machine agents to offer services and access via natural language interactions to facilitate convenient and responsive interaction (Følstad et al., 2018; Huang et al., 2021).

Nevertheless, complicated and diverse needs and wants customers may not be fully satisfied by simply including assistance in the service-proving process. The DeLone and McLean Information Systems Success Model (D&M ISS model; 1992) explains that system usage and user satisfaction may closely interact with information quality, system quality, and service quality. During the process interacting with e-commerce platforms, users value system quality attributes, such as usability, availability, reliability, adaptability, and response time (e.g., download time) may influence consumer perceptions of system quality (DeLone & McLean, 1992; Trivedi, 2019). Therefore, optimizing the system quality from support functions throughout online activities becomes a key that may directly contribute to customer satisfaction and purchasing decision in the following process (Trivedi, 2019).

The presence of inaccurate or outdated information in the information systems may damage user trust, particularly in mobile commerce (m-commerce) (Gao et al., 2015). Information quality encompasses the notion that web contents should be comprehensive, relevant, personalized, and secure (Delone & Mclean, 2003). This is essential to ensure users' recurrent patronage, foster their confidence and motivate those prospective buyers' participation in continuously use e-commerce platforms via internet-based transactions (Chet et al., 2021; Handarkho, 2020). Despite the perceived usefulness, it won't significantly affect consumer attitudes and intentions to adopt without considering the emotional responses (Kulviwat et al., 2007). Extended from the Technology Acceptance Model (TAM) focusing on the perceived simplicity and usefulness in cognitive aspects (Davis, 1989), Consumer Acceptance of Technology (CAT) model involves a more comprehensive framework by including both cognitive and affective components to understand technology adoption (Kulviwat et al., 2007). Based on CAT, customers' intention to use a new technology not only depends on the cognitive evaluation of its perceived usefulness and ease of use but emotional and social elements of the service (Wirtz et al., 2018). Chatbot services may generate hedonic experiences including fun, enjoyment, and excitement through interactions in mentally stimulating conversations (Ashfaq et al., 2020). In addition to usability and perceived ease of use, studies showed that processing emotional experiences during service contacts has emerged as a significant factor to influence customer attitudes in the uses of chatbot (Alagarsamy & Mehrolia, 2023). The interactions between human and chatbot together impact both customer functional and emotional perceptions regarding the services provided.

2.2 Customer Satisfaction

The journey of understanding consumer satisfaction in academic literature has been underscored in capturing the essence of user experiences (e.g., Handarkho, 2020). Customer satisfaction is defined as a comprehensive reaction and feeling related to user experiences with a product or service (e.g., e-commerce). Previous studies regarding online shopping experiences suggest that interactions with chatbots act as the determinant in customer satisfaction on their capacity to search for information, collect data, provide specific and personalized recommendation in decisions (Chen et al., 2021). Customer satisfaction on chatbots, therefore, mainly depends on the aspects of systems, such as ease of use, reliability, emotional responses, expectations, usefulness, and reliability (Alagarsamy & Mehrolia, 2023; Chen et al., 2021). Thus, it is critical to understand how consumers perceive and evaluate their interactions with chatbots (Trivedi, 2019).

2.3 Customer Trust in Chatbots

Trust is seen as the social adhesive in interpersonal relationships that binds organizations and societies together. The success of any information system (IS) is significantly depend on user trust (Lee & Park, 2019; Mostafa & Kasamani, 2022; Kasilingam, 2020). Rousseau et al. (1998) define trust as a psychological condition in which an individual chooses to be vulnerable because they have good expectations of others' intentions or behaviours. With the volatile changes in a dynamic and uncertain context, it's challenging for customers to develop trust and alleviate doubt in chatbots without fully comprehending due to the complexity and unpredictability. Chatbots characteristics, such as natural language interaction and other human-like aspects (e.g., amiability) may increase more enjoyable and satisfying service contact and further develop a sense of trust in service providers (Mostafa & Kasamani, 2022). Building trust in chatbots when interacting may help customer reduce perceived risks, anxiety, and discomfort (Følstad et al., 2018; McLean et al., 2020; Mostafa & Kasamani, 2022).

2.4 Hypothesis Development

2.4.1 The Impact of Customer Experiences on Customer Satisfaction

Research on consumer technology interaction focuses on utilitarian and hedonic views (Jo, 2022). Utilitarian perspectives prioritize practicality, instrumentality and goal achievement while hedonic

views emphasize aesthetic, pleasure and enjoyment (Dhar and Wertenbroch 2000). According to the consumer adoption theory (CAT) model (Kulviwat et al., 2007), this study discusses the features of chatbots on customer experiences by integrating both utilitarian (i.e., information and system quality) and hedonic (i.e. emotional experiences) factors to investigate the relationship of a given chatbots service and customer's psychological reactions throughout the human-chatbot interaction. Consumer acceptance of chatbots depends on how well chatbots can meet with customer functional and instrumental needs (i.e., system and information quality) as well as the emotional and relational needs (i.e., emotional experience) to achieve congruency (Wirtz et al., 2018). Chatbots' capacity to search for information and identify products, including functionality, usability, and reliability (i.e., system and information quality of chatbot) that meet customers' expectations may influence customer satisfaction (Chen et al., 2021). In addition, feeling of confidence, novelty, along with fun and enjoyment may increase the likelihood of feeling valued and comfortable through chatbot Subsequently, enjoyment, pleasure, interaction. anxiety representing hedonic value from experiences with chatbots predict customer satisfaction, a key indicator of the success of the information systems (Alagarsamy & Mehrolia, 2023; D&M ISS model; 1992). Thus,

H1: Chatbot system quality has a positive effect on customer satisfaction.

H2: Chatbot information quality has a positive effect on customer satisfaction.

H3: Emotional experiences with chatbot has a positive effect on customer satisfaction

2.4.2 The Impact of Customer Experiences on Trust in Chatbot

Superior technological performance can improve the credibility of chatbots. Searched information and collected data from chatbots regarding their accuracy, relevance, and timeliness result in chatbot trust, highlighting the importance of high-quality data in building chatbot trustworthiness. Maintain accurate and updated information is highlighted in developing and preserving trust in information systems, with implications in volatile areas of e-commerce and digital services. Similarly, emotional experiences (e.g., joys, pleasure) resulting from chatbot interaction (e.g., verbal communication) help generate values and trustworthiness (Alagarsamy & Mehrolia, 2023).

Therefore,

H4: Chatbot system quality has a positive effect on trust in chatbot.

H5: Chatbot information quality has a positive effect on trust in chatbot

H6: Customer emotional experiences toward chatbot has a positive effect on trust in chatbot.

2.4.3 The Impact of Trust in Chatbot on Customer Satisfaction

The importance of trust in chatbot may be considered as the fundamental factor that shape customers' further attitudes and intentions to use (e.g., Kasilingam, 2020). Based on previous discussion, trust in chatbot is defined as customers' perceptions about the trustworthiness and reliability of the chatbot system (Nikou & Economides, 2017). Customers' trust in chatbot grows with constant and continuous use over a period of time (Alagarsamy & Mehrolia, 2023). Empirical research has identified a positive correlation between trust and customer satisfaction; that is, trust in chatbot based on the stability, creditability, security and fun of chatbot systems positively related to customers' attitudes toward chatbots, and behavioural intention to use service later (Alagarsamy & Mehrolia, 2023; Delone & Mclean, 2003). That is, the higher the trust, the more satisfied chatbot experiences customers hold. Therefore.

Hypothesis 7: Trust in chatbot has a positive effect on customer satisfaction.

Table 1. The list of measures and the corresponding items

3. Method

3.1 Participants and Procedure

As an emerging country, Thailand is quickly catching on to new technology. Knowing people's thoughts about the chatbot service will be crucial for developing new technologies. This study applied an online survey to collect data. The questionnaire items were adapted from existing literature. We have modified some items into a chatbot condition to make the questions more specific for our research proposes. For information quality, we adopted the items from Roca et al., (2006) and Trivedi (2019); for system quality, the items were adopted from Nikou and Economides (2017) and Trivedi (2019). Besides information quality and system quality, we also considered users' emotional experience with chatbot service. The questionnaire items came from Jo (2022) and Lee and Choi (2017). In this study, we proposed that trust in chatbot is the mediator between chatbot quality, user experience, and customer satisfaction. The questionnaire items came from Wang, Ngamsiriudom and Hsieh (2015). The customer satisfaction was measured from the questions adapted from Trivedi (2019) and Algarsamy and Mehrolia (2023). The questionnaire questions are listed in Table 1. The questionnaire consisted of closed-ended questions, incorporating measures using a seven-point Likert scale item from 1 = totally disagree to 7 = totally agree. Using a Google Form, a widely accessible and user-friendly platform, participants could provide their responses conveniently and securely.

Factors	Items	Source	
	Information provided by chatbot service is in a useful format	D 1 (2006 (01)	
Information quality	Information provided by chatbot service is up-to-date	Roca et al. (2006; p.691)	
	Information provided by chatbot service is reliable	Trivedi (2019; p.102).	
System quality	I find it easy to become skilful at using chatbot service	Nikou & Economides (2017)	
	I believe that chatbot services are easy to use		
	Using chatbot service requires very little mental effort	Trivedi (2019; p.102)	
Emotional experience	It is fun and <i>pleasant</i> to share a conversation with the <i>chatbot service</i>	Jo (2022; p.12) Lee & Choi (2017; p.102)	
	The conversation with the <i>chatbot</i> service is exciting		
	I enjoy <i>choosing products</i> more if the chatbot service recommends them than if I choose them myself.		
Trust in chatbot	I believe the chatbot is trustworthy	Wang et al. (2015; 564)	
	I believe the chatbot keeps its promises and commitments		
	I believe the chatbot considers customers' profit as top priority		
Customer satisfaction	I am happy with the experiences I have had with chatbot service	Trivedi (2019; p.102)	
	I think that I did the right thing when I chose chatbot instead of traditional services	Alagarsamy & Mehrolia (2023)	

We have conducted a pilot test of our questionnaire, which collected 33 responses. We collected the respondents' opinions and did the statistical analysis. We modified the questionnaire based on the respondents' opinions for formal data collection. We have collected a total of 356 respondents; the collected period was from Mar. 11- April 11, 2024. 2 of the respondents did not have experience using chatbot service, so we dropped those responses. The validated responses were 354.

Most respondents were female, 243 (68.6%), while males had 110 respondents (31.2%). 246 respondents between 28-43 represent the most (69.7%), followed by 18-27, 60 responses (17%); the 44-59 group collected 44 responses (12.5%). Most respondents hold a Bachelor's degree (318, 90.1%), while 33 hold a Master's degree (9.3%). The monthly income of the respondents between 30,001-100,000 THB was around 77%. Most respondents were not students; they worked in different industries and had chatting experience with a chatbot service.

This study applied SmartPLS 4.0 to conduct data analysis to test the proposed hypotheses. We used SmartPLS as our analytical tool because the proposed model considered all the relationships simultaneously. It is suitable for using SmartPLS to conduct the analysis. Our model focused on explaining the variance in the dependent variables (Chin et al., 2020) and testing the causal-predictive relationships between all variables (Jöreskog and Wold, 1982).

The common method variance (CMV) was tested before we conducted further analysis. We applied Harman's single factor to test the CMV problem (Podsakoff et al., 2003). The largest factor explains the 40.27 % variance, which is lower than the suggested value of 50%. The result shows that the data did not have serious CMV problems.

 Table 2. HTMT table

CT CS EE IO SO CS CT 0.648EE 0.618 0.604 0.578 0.487 ΙQ 0.426 0.505 0.444 SQ 0.504 0.391

Table 3. Reliability and convergent validity

Construct	Measurement items	Factor loading/ coefficient (t-value)	Composite reliability	AVE	Cronbach's alpha
Information quality (IQ)	IQ1	0.879	0.886	0.722	0.808
	IQ2	0.810			
	IQ3	0.859			

4. Results

4.1 Model Estimation and Assessment

The PLS-SEM approach was used to examine the measurement model and the hypothesis testing. This study applied SmartPLS 4.0 to conduct the analysis. We have set the iteration time as 300 and a stop criterion of 107 and use the bootstrapping method to obtain the significant level of each relationship. We set a two-tailed test with a significance level of 0.05. For all p-value and confidence intervals with 5,000 subsamples to do the calculation (Ringle et al., 2024).

The proposed measurement model in this study needs to pass the criteria of convergent and discriminant validities and reliabilities. We followed the steps proposed by Hair et al., (2017).

Convergent validity items are examined on average variance extracted (AVE) and outer loading. As suggested, all values of AVE in our model are larger than 0.5, which was the minimum value suggested by Fornell and Larcker (1981). The AVE values support convergent validity (Hair et al., 2014), ranging from 0.722 to 0.862. The outer loadings of each item are above 0.6, which was the threshold value suggested by Bagozzi and Yi (1998). For the Heterotrait-monotrait ratio (HTMT), the quality criteria of discriminant validity, which threshold values should be below 0.85 or 0.9. As the data shown in Table 1, all the values in the HTMT table are below 0.85, which means that all constructs were fit to do further analysis. Composite reliability measurements can be tested by Cronbach's alpha, in our model, all constructs are above the 0.7 threshold (Chin, 2010). Table 3 shows the validity and reliability results of our data.

System Quality (SQ)	SQ1	0.908	0.914	0.779	0.858
	SQ2	0.863			
	SQ3	0.877			
Emotional Experience (EE)	EE1	0.842	0.917	0.786	0.864
	EE2	0.917			
	EE3	0.899			
Trust in Chatbot (CT)	CT1	0.894	0.910	0.771	0.852
	CT2	0.872			
	CT3	0.869			
Customer satisfaction (CS)	CS1	0.916	0.926	0.862	0.841
	CS2	0.940			

4.2 Structural Model

In this study, we also tested for the collinearity of each construct; the results represent no variance inflation factor (VIF) value larger than 5, which indicates our

data did not have a severe collinearity problem (Petter et al., 2007). We then conducted the significance of the path coefficients, explanatory (R2), and predictive power. The results are shown in Table 4.

Table 4. *Structural model estimates*

Relationships	Std. Beta	P-value	95% Confidence Interval		VIF
			2.5%	97.5%	VIF
EE -> CS	0.253	0.000	0.145	0.358	1.468
EE -> CT	0.362	0.000	0.262	0.455	1.260
IQ -> CS	0.235	0.000	0.133	0.332	1.267
IQ -> CT	0.200	0.000	0.092	0.300	1.204
SQ -> CS	0.139	0.004	0.048	0.239	1.317
SQ -> CT	0.230	0.000	0.131	0.323	1.233
EE -> CS	0.253	0.000	0.145	0.358	1.468
CT -> CS	0.263	0.000	0.146	0.387	1.585

In Table 4, we can see the path coefficients and the significance levels, R2 values. The structural model was assessed to examine the relationships between the latent variables. Figure 1 represents the PLS results of the hypotheses.

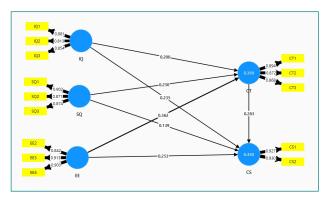


Figure 1. The PLS results of the hypotheses.

The results indicate that information quality (β =0.235, p < 0.001), system quality (β = 0.139, p < 0.01), and emotional experience (β =0.253, p < 0.001) had a significant positive influence on customer satisfaction of chatbot services. Hypotheses 1, 2, and 3 were supported. Information quality (β =0.200, p < 0.001), system quality (β = 0.230, p < 0.001), and emotional experience (β =0.362, p < 0.001) had a

significant positive influence on consumer trust in chatbots. Hypotheses 4, 5, and 6 were supported. Furthermore, trust in chatbot service had a positive statistically significant relationship ($\beta = 0.263$, p < 0.001), thus supporting H7. The model explained 36.9% of the variance in consumer trust; the model also explained 45.0% of the variance in trust in chatbots. Emotional experience demonstrated the

largest effect size ($f^2 = 0.165$), indicating that it is a strong predictor of trust. The PLS results indicate that all the hypotheses we raised in this study have positive significant relationships between the constructs. This study shows that information quality, system quality, and emotional experience can positively influence customers' trust in chatbots and customer satisfaction. Moreover, customers' trust in chatbots also influences their satisfaction.

5. Discussion and Implications

Chatbots, as virtual human interaction mechanisms, have been broadly applied to customer relationship management, navigation and searching, investment analysis, recommendation, and decision assistance (Alagarsamy & Mehrolia, 2023; Ashfaq et al., 2020). Managed 85% of customer service jobs, chatbots save business annual costs and have been intertwined with service-providing processes for companies such as Facebook, Skype, WeChat, and Amazon (Ashfaq et al., 2020). By focusing on the application of chatbots in e-retailing in Thailand, this study examines the features of chatbots on customer satisfaction and trust in chatbots in between these two variables. The findings are as follows.

First, our result shows that chatbots provide customers with reliable information, quick response, and individualised experiences may lead to higher customer satisfaction (Hypothesis 1-3). Chatbots in different contexts serve multiple roles, such as personal assistant, decision-making support, and companion (Ashfaq et al., 2020; Chen et al., 2021). The interactive process makes customers feel more enjoyable and satisfied since solid and up-to-date information in e-commerce is provided (Chung et al., 2018). The higher the customer satisfaction, the better organizational performance and competitiveness.

The research on customer satisfaction in chatbots gradually grows its importance in e-commerce (e.g., Ashfaq et al., 2020; Chung et al., 2018). On the basis of the ISS Model and CAM, this study not only helps understand the factors of chatbots (i.e., practical and hedonic aspects) but also includes trust in chatbots built through this interactive process to strengthen the customer relationships in the long run (H4-6, 7). Trust as the subjective attitude supports individuals to make vulnerable decisions (Kelly et al., 2023). Trust in chatbots can save costs in making decisions and decrease risks and uncertainties seen in the context of e-commerce. Trust in chatbots allows customers to believe that their purposes can be attained by using these devices. Serving as one of the significant

predictors of customer satisfaction through shopping and relevant processes, trust in chatbots maintains and increases customers positive experiences and further behavioral intentions for continuous use (Kelly et al., 2023). Our study reflects that perceived usefulness, enjoyment, information performance expectancy, and trust significantly and positively predicted customer satisfaction in the e-commerce process (e.g., Ashfaq et al., 2020; Chung et al., 2018; Kelly et al., 2023).

5.1 Theoretical Implications

This study brings theoretical implications as follows. First, this study develops a framework based on IS success model (Delone & Mclean, 2003) and Customer Acceptance Model (CAM; Kulviwat et al., 2007) to analyse the relationship between customer experiences with chatbots, the trust developed and customer satisfaction.

Customer emotional experiences as a critical factor in the process signifies a paradigm shift from mainly cognitive evaluations to a more holistic understanding out of hedonic perspectives (Huang et al., 2021). Incorporating emotional dimensions in addition to perceived usefulness and ease of use, this study provides a more comprehensive model that better captures the complexities of user interactions with chatbots. This further acknowledges that customer satisfaction from chatbot interactions surpass utilitarian benefits, encompassing the joy, disappointment, and excitement experienced during the process (e.g., Wirtz et al., 2018).

Furthermore, trust in chatbots may be influenced throughout the interaction by focusing on stability, creditability, reliability and security (Nikou et al., 2017). Though existing knowledge of user trust receives a degree of attention (e.g., Følstad et al., 2018), relatively less insight is emphasised on the factors leading to trust in chatbots. Therefore, the current research specifically includes both explicit (i.e., system quality, information quality) and intrinsic (i.e., emotional experience) characteristics of chatbots in examining the sources of user trust in chatbots that again stresses the critical role of robust and reflective chatbot design.

5.2 Practical Implications

There are practical implications to be addressed regarding this current study. First, collaboration among different department should be facilitated since when designing chatbot e-service systems. There are factors to be specifically noted, including relevant, credible, precise, personalized, and latest information

in a practical and easy-to-use format. Chatbot service systems should not only deliver up-to-date information but also be closely related to chatbot users' needs based on current trends. If chatbot users cannot get the information that they actually want from the chatbot e-service systems, they could consider such systems as useless. In such a case, the chatbot e-service leaves a negative impact on users' satisfaction, which, in turn, discourages to continue using it.

Second, this study shows that trust in chatbots serves as another important factor of customer satisfaction; the trust and trustworthiness toward chatbot-based service can be built by sharing information, intentionally intensive and interactive building relationships, such as lively game and competition, simulations, and the like to support the long-term relationship with customers. Also, it is suggested that the online service business should make sure their chatbot provides timely, easy-to-use, trouble-free, and enjoyable experiences when communicating with text or chat exchange with chatbots since previous research also proposed that user continuous intention to chatbot service largely depends on 24/7, enjoyable, simple, useful functions in day-to-day life (Ashfaq et al., 2020).

5.3 Limitations and Directions for Future Research

Exploring the impact of chatbots on customer satisfaction contributes to current digital communication research. This study also has some limitations that may direct further research.

First, applying quantitative metrics, the crosssectional design collected and analysed structured and generalizable data that may overlook the nuanced transformation in user trust and attitudes in chatbot with prolonged exposure and interaction. The dynamic process of technology adoption suggests that increasing familiarity potentially fosters greater trust and satisfaction over time. A longitudinal research approach would offer invaluable insight into these temporal shifts, elucidating the trajectory of user satisfaction and trust in chatbot technologies over time. Moreover, by adopting qualitative methods, such as in-depth interviews and focus groups, these narratives may uncover customer emotional responses that quantitative surveys fail to capture. For example, trust in chatbots may be observed through user interactions in the personalized communication process, highlighting the value that chatbots are capable of recording, recalling, and cooperating user interactions into ongoing dialogues.

Next, the samples were limited to those who had previously interacted with chatbots, which could generate a relatively homogenized view of chatbot efficacy and acceptance. Relatively narrow samples may capture specific groups of people with features such as age cohort. For instance, a younger and more tech-savvy cohort may have different expectations and perceptions due to their digital literacy and interactive experiences (Ashfaq et al., 2020). Also, user habits may determine their trust in the chatbot, attitudes, and behavior intentions. People who intensively use chatbots may be too familiar to be aware of the process. Also, the preferences and values people hold may exert influence on the experiences of using chatbots. For example, some participants may prioritize speed and efficiency in timely responses while others may place value on the clarity and thoroughness of information provided to enhance comprehension.

Consequently, future research may embrace a broader and more inclusive research sample, ensuring the representation of diverse demographics across industries and other demographic spectrums. Such inclusiveness may not only enhance the external validity of the findings but also provide a more comprehensive understanding of chatbot interactions across different social groups. Comparative studies aiming at user perceptions among age groups, organizations, and even industries, such as healthcare, finance, and retail, may yield further unique insights into customer experiences with chatbots and satisfaction, guiding the development of more universally accessible and effective chatbot interfaces. The finding suggests that future studies may enclose other dimensions in identifying general and prevalent qualities in chatbot usage (e.g., predictive accuracy or personalization capabilities). Previous research also included factors from the environment, such as uncertainty and risks, which may limit chatbot trust in customer satisfaction (Trivedi, 2019). This further underscores the complexity of digital services, where perceived risk may significantly influence the chatbot's performance and effectiveness. In exception for the three different features of chatbots, individual dispositions, and contextual elements are suggested to more comprehensively address the nuances of interactions in digital and AI-induced environments, potentially guiding businesses in creating safer and more trustworthy digital service platforms.

Acknowledgement

We gratefully acknowledge the financial support provided by Faculty Research Grant (FRG-25-017-MSB), Macau University of Science and Technology for this research.

6. References

- 1. Alagarsamy, S., & Mehrolia, S. (2023). Exploring chatbot trust: Antecedents and behavioural outcomes. *Heliyon*, *9*(5): e16074.
- Ashfaq, M., Yun, J., Yu, S., & Loureiro, S. M. C. (2020). I, Chatbot: Modeling the determinants of users' satisfaction and continuance intention of AIpowered service agents. *Telematics and Informatics*, 54, 101473.
- 3. Belanche, D., Casaló, L. V., Flavián, C., & Schepers, J. (2020). Robots or frontline employees? Exploring customers' attributions of responsibility and stability after service failure or success. *Journal of Service Management*, 31(2), 267-289.
- 4. Bagozzi, R. P., & Yi, Y. (1998). On the Evaluation of Structure Equation Models. *Journal of the Academy of Marketing Science*, *16*, 76-94.
- 5. Chen, J. S., Le, T. T. Y., & Florence, D. (2021). Usability and responsiveness of artificial intelligence chatbot on online customer experience in e-retailing. *International Journal of Retail & Distribution Management*, 49(11), 1512-1531.
- 6. Chin, W. W. (2009). How to write up and report PLS analyses. In *Handbook of partial least squares: Concepts, methods and applications* (pp. 655-690). Berlin, Heidelberg: Springer Berlin Heidelberg.
- 7. Chin, W., Cheah, J. H., Liu, Y., Ting, H., Lim, X. J., & Cham, T. H. (2020). Demystifying the role of causal-predictive modeling using partial least squares structural equation modeling in information systems research. *Industrial Management & Data Systems*, 120(12), 2161-2209.
- 8. Chung, M., Ko, E., Joung, H., & Kim, S. J. (2020). Chatbot e-service and customer satisfaction regarding luxury brands. *Journal of business research*, *117*, 587-595.
- 9. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, *13*(3), 319-340.
- 10. DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: a ten-year update. *Journal of Management Information Systems*, 19(4), 9-30.
- 11. Dhar, R., & Wertenbroch, K. (2000). Consumer choice between hedonic and utilitarian goods. *Journal of Marketing Research*, *37*(1), 60-71.
- 12. Følstad, A., Nordheim, C. B., & Bjørkli, C. A. (2018). What makes users trust a chatbot for customer service? An exploratory interview study. In Proceedings of *the Internet Science: 5th International Conference, INSCI 2018*, St. Petersburg, Russia, October 24-26, 2018, ed. 194-208. Springer International Publishing.

- 13. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39-50.
- 14. Gao, L., Waechter, K. A., & Bai, X. (2015). Understanding consumers' continuance intention towards mobile purchase: A theoretical framework and empirical study-A case of China. *Computers in Human Behaviour*, 53, 249-262.
- 15. Hair Jr, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. 2017. PLS-SEM or CB-SEM: updated guidelines on which method to use. *International* Journal of Multivariate Data Analysis, 1(2), 107-123.
- 16. Hair Jr, J. F., Sarstedt, M., Hopkins, L., & G. Kuppelwieser, V. (2014). Partial least squares structural equation modeling (PLS-SEM) An emerging tool in business research. *European Business Review*, 26(2), 106-121.
- 17. Handarkho, Y. D. (2020). The factors influencing customer loyalty in social commerce platform: variety-seeking and social impact perspective. *International Journal of Web Information Systems*, 16(4), 369-386.
- 18. Hariguna, T., Adiandari, A. M., & Ruangkanjanases, A. (2020). Assessing customer intention use of mobile money application and the antecedent of perceived value, economic trust and service trust. *International Journal of Web Information Systems*, 16(3), 331-345.
- 19. Huang, D., Chen, Q., Huang, J., Kong, S., and Li, Z. 2021. Customer-robot interactions: Understanding customer experience with service robots. *International Journal of Hospitality Management* 99: 103078.
- 20. Jaichobdeeyingsakul, J., Phon-ngam, P., & Roeksabutr, A. 2023. การ พัฒนา นวัตกรรม ส่งเสริม ศักยภาพ ใน การ แข่งขัน ของ ธุรกิจ สาย เคเบิล เส้นใย นำ แสง ใน ประเทศไทย. Journal of Social Science and Cultural, 7(7), 144-154.
- 21. Jo, H. (2022). Continuance intention to use artificial intelligence personal assistant: type, gender, and use experience. *Heliyon*, 8(9), e10662.
- 22. Jöreskog, K.G., & Wold, H.O.A. (1982). The ML and PLS techniques for modeling with latent variables: historical and comparative aspects. In *Systems under Indirect Observation Part I*, eds., Wold, H.O.A. and Jöreskog, K.G., 263-270. Amsterdam: North-Holland.
- 23. Kamkankaew, P., Thanitbenjasith, P., Sribenjachot, S., Sanpatanon, N., Phattarowas, V., & Thanin, P. (2024). How Artificial Intelligence is Helping Businesses Grow and Thrive: The Transformative Role of Artificial Intelligence in Thai B2C Digital Marketing. International Journal of Sociologies and Anthropologies Science Reviews, 4 (1), 137-164.

- 24. Kasilingam, D. L. (2020). Understanding the attitude and intention to use smartphone chatbots for shopping. *Technology in Society, 62*, 101280.
- 25. 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.
- Kulviwat, S., Bruner II, G. C., Kumar, A., Nasco, S. A., & Clark, T. (2007). Toward a unified theory of consumer acceptance technology. *Psychology & Marketing*, 24(12), 1059-1084.
- 27. Lee, J., & Choi, H. (2017). What affects learner's higher-order thinking in technology-enhanced learning environments? The effects of learner factors. *Computers & Education*, 115, 143-152.
- 28. McLean, G., Osei-Frimpong, K., Wilson, A., & Pitardi, V. (2020). How live chat assistants drive travel consumers' attitudes, trust and purchase intentions: the role of human touch. *International Journal of Contemporary Hospitality Management*, 32(5), 1795-1812.
- 29. Mostafa, R. B., & Kasamani, T. (2022). Antecedents and consequences of chatbot initial trust. *European Journal of Marketing*, 56(6), 1748-1771.
- 30. Mouakket, S., & Bettayeb, A.M. (2015). Investigating the factors influencing continuance usage intention of learningmanagementsystems by university instructors: The Blackboard system case. *International Journal of Web Information Systems*, *11*(4), 491-509. https://doi.org/10.1108/IJWIS-03-2015-0008
- 31. Nikou, S. A., and Economides, A. A. (2017). Mobile-based assessment: Investigating the factors that influence behavioural intention to use. *Computers & Education*, 109, 56-73.
- 32. Nordheim, C. B., Følstad, A., and Bjørkli, C. A. (2019). An initial model of trust in chatbots for customer service-findings from a questionnaire study. *Interacting with Computers*, 31(3), 317-335.

- 33. Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioural research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879-903.
- 34. Ringle, C. M., Wende, S., & Becker, J.-M. (2024). "SmartPLS 4." Bönningstedt: SmartPLS, https://www.smartpls.com.
- 35. Roca, J. C., Chiu, C. M., & Martínez, F. J. (2006). Understanding e-learning continuance intention: An extension of the Technology Acceptance Model. *International Journal of Human-Computer Studies*, 64 (8), 683-696.
- 36. Rousseau, D. M., Sitkin, S. B., Burt, R. S., & Camerer, C. (1998). Not so different after all: A cross-discipline view of trust. *Academy of Management Review*, *23*(3), 393-404.
- 37. Tezcan, T., & Zhang, J. (2014). Routing and staffing in customer service chat systems with impatient customers. *Operations Research*, 62(4), 943-956.
- 38. Trivedi, J. (2019). Examining the customer experience of using banking chatbots and its impact on brand love: The moderating role of perceived risk. *Journal of Internet Commerce*, 18(1), 91-111.
- 39. Tussyadiah, I. P., & Park, S. (2018). Consumer evaluation of hotel service robots, In *Information and Communication Technologies in Tourism 2018: Proceedings of the International Conference in Jönköping, Sweden, January 24-26, 2018* (pp. 308-320). Springer International Publishing.
- 40. Wang, S. W., Ngamsiriudom, W. & Hsieh, C. H. (2015). Trust disposition, trust antecedents, trust, and behavioral intention. *The Service Industries Journal*, 35(10), 555-572.
- 41. Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., & Martins, A. (2018). Brave new world: service robots in the frontline. *Journal of Service Management*, 5, 907-931.