Journal of Retailing and Consumer Services 71 (2023) 103211

Contents lists available at ScienceDirect

Journal of Retailing and Consumer Services

journal homepage: www.elsevier.com/locate/jretconser

Understanding the user satisfaction and loyalty of customer service chatbots

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ARTICLE INFO

Keywords:
AI chatbot
Service quality
Customer service
Satisfaction
Loyalty

ABSTRACT

The artificial intelligence (AI) chatbot is emerging as a significant corporate customer-facing application, potentially increasin customer service efficiency while reducing costs. However, little work has sought to assess the quality of service they provide consumers. This study applies the e-service quality by incorporating conversational AI quality to predict users' satisfaction and loyalty to customer service chatbots. The proposed model was empirically evaluated using survey data collected from 219 users responding about their perceptions of customer service chatbots. The findings indicate that AI chatbot service recovery quality and AI chatbot conversational quality significantly influence user satisfaction. On the other hand, core AI chatbot service quality and satisfaction significantly influenced chatbot user loyalty. This study contributes to researchers and practitioners by proposing and evaluating a more comprehensive chatbot e-service quality that combines both fundamental (core service and service recovery qualities) and human-like (conversational quality) aspects of e-service. The results are of value in devising future AI chatbot services and related strategies.

1. Introduction

AI-driven chatbots have emerged as a potential customer service application attempting to provide economical and round-the-clock customer service. Statistics show that nearly one out of four customer service organizations employ AI-driven chatbots to serve their customers (Gartner, 2019). It is no wonder that the related market is expected to grow to more than USD 142 billion by 2024 (Yuen, 2022).

Chatbots are especially useful for retail and eCommerce industries. By serving and responding to customers appropriately, chatbots help increase sales and conversion rates, enhance the shopping experience, gather customer data and among others. For example, Lego announced its chatbot, Ralph, to support Christmas sales. Ralph had his own personality and was fun to engage with. As a result, Ralph helped drive 25% of sales from social media, and most importantly, with Ralph's help, Lego successfully reduced the cost per each conversion by more than 70% (Davies, 2022).

As promising as it may seem, the efficacy of such applications compared to human customer service agents remains in question (Janssen et al., 2021). One recent investigation (Chatbots, 2018) found that 53% of users felt customer service chatbots are "not effective" or only "somewhat effective." Particularly, 59% of respondents felt frustrated at repeatedly providing the same information more than once when chatbots cannot effectively serve their needs and have to transfer the task in question to a human agent. Therefore, to evaluate the effectiveness of chatbot applications, one not only needs to assess the human make-believe quality of such chatbots (i.e., AI technologies) but also how seamlessness chatbot applications fit into the entire customer service teams. Together, they represent the overall quality of conversational interaction between customers and companies.

Previous studies have mainly focused on issues such as system architecture (Ngai et al., 2021), human-chatbot interaction and satisfaction (Eren, B.A., 2021; Chen et al., 2021), and acceptance (Rese et al., 2020). While these studies provide a better understanding of the use of chatbots in customer service, they largely overlook interaction-related service quality measurement (i.e., conversational quality). The existing information system and marketing literature have empirically verified that service quality shapes user satisfaction and behavior (Cristobal et al., 2007; Bressolles et al., 2014; Ngo and Nguyen, 2016; Akıl and Ungan, 2022). In the context of chatbots, it is imperative to investigate the effect of interaction-related service quality since chatbots are created to mimic human interaction. Therefore, including interaction-related

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https://doi.org/10.1016/j.jretconser.2022.103211
Received 9 August 2022; Received in revised form 22 October 2022; Accepted 20 November 2022
Available online 24 November 2022
0969-6989/

assessment when evaluating the overall service quality of chatbots is crucial for companies seeking to improve customer experience via AI-enabled chatbots.

This study extends the past e-service quality literature (e.g., Loonam and O'Loughlin, 2008; Ladhari, 2010; Mathew et al., 2020; Gutierrez et al., 2020), which emphasizes the importance of core service quality and service recovery quality, and extends it to include AI conversational quality in developing chatbot customer service quality. The importance of AI conversational quality can be explained in the existing human-like user interface literature (e.g., Sundar, 2008; Lee and Oh, 2015; Chattaraman et al., 2019; Califf et al., 2020). This study proposes the AI conversational quality variable for two reasons. First, AI chatbots are used to imitate humans. It is vital to understand how its human-like characteristics, such as conversational ability, affect customers. Second, customer-chatbot interaction includes inputs, processing, and outputs. The overall process, including asking questions, searching and retrieving information, as well as obtaining answers, plays a role in the customer's evaluation of chatbot service quality.

Moreover, the business value of chatbots lies in customers' loyalty. Therefore, this study uses the service quality literature and incorporates conversational service quality as belief-related constructs to predict user satisfaction and loyalty to customer service chatbots. From a theoretical perspective, this study proposes a new construct of conversational service quality based on the Input-Process-Output (IPO) model and identifies antecedents of chatbot user satisfaction and loyalty. From a practical standpoint, findings may help chatbot service providers plan more effective customer relationship management (CRM) strategies.

2. Literature review

2.1. Customer service chatbots

A chatbot is a computer program that can communicate with humans through synthesized audio or text, simulating human interlocutors for entertainment or information retrieval purposes (Dahiya, 2017). The first chatbots were developed as early as 1966 (Güzeldere and Franchi, 1995), but hardware limitations and lack of network access limited their applications. In recent years, the development of AI technologies has enabled chatbots to use natural language processing (NLP) to engage in increasingly sophisticated dialogue with human interlocutors, opening the door to the extensive use of e-commerce applications such as financial consultations and customer service (Heo and Lee, 2018). At present, chatbot apps are usually integrated into e-commerce websites as online or mobile applications to provide online customer service. Successful adoptions can be seen in well-known brands such as Lego, Michael Kors, and Domino's Pizza (Srivastava,2019). Though chatbots come in different forms (e.g., bot platforms such as Alexa, messaging apps such as social media embedded messenger bots, etc.), the one that e-commerce companies mainly provide would be bots on the landing webpages. This kind of service chatbots acts as human employees to interact with customers and offer possible solutions to customers' problems (Doorn et al., 2017; Sheehan et al., 2020). Therefore, its ability to converse with customers naturally becomes a very important characteristic.

Currently, enterprise-level customer service chatbots are mostly procured using existing applications through cloud service platforms (such as Google's Dialogflow and LINE bot) or through developing custom solutions either internally or through outsourcing. Regardless of the development method, chatbot design must consider the nature of the customer problems it will attempt to address. Simple, established processes, such as handling reservations or product returns, can be accomplished by relatively unsophisticated chatbots, but more difficult interactions which require the chatbot to understand customers' inquiries expressed in natural language and to analyze the conversational context require the use of AI. Such chatbots can engage in appropriate small talk and colloquial speech, thus enhancing user comfort. In addition, if unable to solve the customer's problem, chatbots can rescue a failed service encounter by forwarding the issue to a human agent.

2.2. AI bot service quality

Service quality has been traditionally defined as the consumer's assessment of the overall excellence or superiority of the service experienced (Zeithaml, 1988). With rapid changes in technology and social structures, companies increasingly seek to establish competitive advantages through enhanced service quality, which is a key factor affecting users' satisfaction and behavior.

Previous studies have proposed that service quality is also an essential factor for successful information system (IS) adoptions (DeLone and McLean, 2003; Hsu and Lin, 2010; Aldholay et al., 2018; Jeyaraj, 2020). This research trend has extended to e-services, with many studies exploring the relationships between e-service quality (e.g., consumer-facing websites) and customer behavior (Blut, 2016; Rita et al., 2019; Kalia and Paul, 2021). To further investigate the effect of e-service quality on the entire transaction process, subsequent studies have examined the impact of transaction failures on service recovery quality. For example, based on SERVQUAL, Parasuraman et al. (2005) developed a scale to measure the quality of internet services, including E-S-QUAL (electronic-core service quality scale) and E-RecS-QUAL (electronic-recovery service quality scale). E-S-QUAL measures efficiency, fulfillment, privacy and system availability, while E-RecS-QUAL measures compensation, responsiveness and contact.

However, the above-mentioned qualities do not examine the interaction quality between customers and the website. In response to these limitations, Zemblyte (2015) added WS-QUAL (Website quality scale) in addition to E-S-QUAL and E-RecS-QUAL and proposed a service quality framework for e-services that comprehensively measures overall e-service quality.

In the context of AI applications, the present study suggests that AI customer service chatbots use technologies that differ from website services in that their primary purpose is to provide customer service in the form of simulated humans. Therefore, the current study proposes three AI bot service quality constructs, including core AI Bot service quality, AI Bot service recovery quality and AI Bot conversational quality. Notably, the present study uses E-S-QUAL to measure core AI Bot service quality and E-RecS-QUAL to measure AI Bot service recovery quality. The following section describes the proposed measurement of AI Bot conversational quality.

2.3. AI bot conversational quality

With the fast advancement of machine learning and natural language processing (NLP) technologies, several studies have explored issues related to conversational AI chatbots and their impact on user attitudes and behavior (Edwards et al., 2019; Pereira and Díaz, 2019; Rese et al., 2020; Fernandes and Oliveira, 2020). Conversational AI bots are digital bots that use natural language, in the form of voice or text, to communicate with users (Khatri et al., 2018). Research on conversational AI bots with human-like attributes has focused on identifying characteristics that make AI bots seem more similar to humans. Giving a chatbot a human name, image and personality/emotion, for example, will enhance user perceptions of human likeness (Følstad et al., 2018; Hu et al., 2021). Mimicking human-like attributes such as visual and verbal cues would also enhance the user's sense of rapport with bots (Go and Sundar, 2019).

For effective bidirectional interaction, a bot must understand the user's natural language input and respond with a human-like response either by voice or text (Foehr and Germelmann, 2020). Therefore, to measure interactive quality, the current study applies the Input–Process–Output (IPO) model and proposes a second-order formative construct called AI bot conversational quality, which is formed by the following three factors: understanding humanness (input), perceived contingency (process) and response humanness (output). Of which, understanding humanness refers to the degree to which a chatbot can accurately comprehend the user's input. Good quality speech recognition (or text analysis) on the part of the chatbot will ensure an accurate understanding of user commands. Hsu and Lin (2021) empirically verified that speech recognition accuracy (through devices such as smart speakers) is a key determinant of user stickiness. That is, if users feel frustrated making themselves understood by a smart speaker, they will give up using it.

Perceived contingency is defined as the message interactivity in the dialogue between chatbots and humans. Past researchers have noted that the human-like aspect of communication between humans is determined by response contingency, where the content and presentation of each response depend on the content and presentation of the previous message, collectively creating a coherent conversation thread (Sundar et al., 2016). Compared to the 'functional view' of simple questions and answers (i.e., FAQ), the 'contingency view' of interactivity stresses the increased interdependency of message exchanges (Sundar et al., 2003). For example, when instant message (IM) users talk with their friends, they perceive a higher degree of contingency since the messages are interdependent.

Finally, response humanness refers to the degree to which chatbot responses feel natural and similar to a genuine human response. Response humanness is determined partly by the user's perception of the chatbot's ability to respond to user inputs with a human-like voice or text messages, where greater humanness increases the user's sense of intimacy (Schuetzler et al., 2020; Westerman et al., 2020).

3. Research model and hypotheses

Fig. 1 illustrates the research model based on the literature review. The formative higher-order (second-order) constructs include core AI Bot service quality, AI Bot service recovery quality and AI Bot conversational quality. Core AI Bot service quality contains four first-order constructs which reflectively measure the higher-order constructs including efficiency, fulfillment, security/privacy and system availability. Similarly, AI Bot service recovery quality measures compensation, responsiveness and contact. AI Bot conversational quality measures understanding humanness, perceived contingency and response humanness. The model asserts that user loyalty is determined by core AI Bot service quality, AI Bot service recovery quality, AI Bot conversational quality and satisfaction. Furthermore, satisfaction mediates the impact of user perceptions about three second-order constructs on loyalty. The service qualities of AI bots, satisfaction and loyalty are defined in Table 1.

3.1. Core AI bot service quality and AI bot service recovery quality

With the rapid proliferation of e-services, past studies have demonstrated that e-service quality has a significant impact on user satisfaction (Jun et al., 2004; Rafiq et al., 2012; Jiang and Ji, 2014; Yang and Tsai, 2022). Moreover, Zehir and Baykal (2016) found that e-service quality and recovery have direct and significant effects on loyalty intention in the context of Turkish e-business. Theodosiou et al. (2019) also found that e-service quality has a significant influence on customer satisfaction and loyalty. Accordingly, we hypothesize:

H1a. An individual's perception of core AI bot service quality has a positive effect on his/her satisfaction.

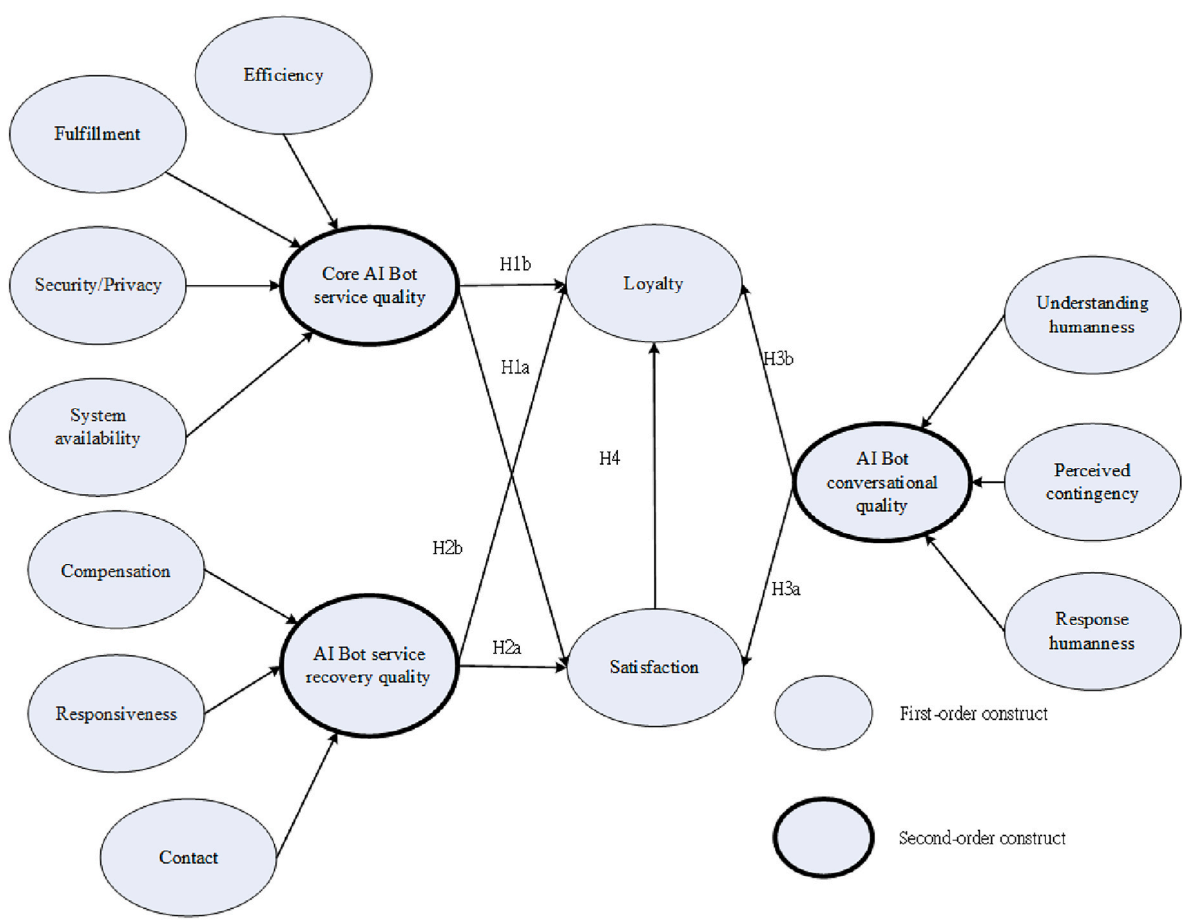

Fig. 1. Research model.

Table 1
Construct definition.

Construct	Definition
Efficiency	The ease and speed of accessing and using the AI bot.
Fulfillment	The extent to which the AI bot's promises about services and item availability are fulfilled.
Security/Privacy	The degree to which the AI bot is safe and protects customer information.
System availability	The correct technical functioning of the AI bot.
Compensation	The extent to which the AI bot assists in compensating for customer loss in response to transaction/operation failure.
Responsiveness	The extent to which the AI bot effectively handles customer issues.
Contact	The AI bot can refer problems beyond its functional scope to phone-based or online live customer service.
Understanding humanness	The AI bot can accurately comprehend the user's questions or commands.
Perceived contingency	The AI bot's responses are relevant to the user's input.
Response humanness	The AI bot response is natural and human-like.
Satisfaction	The extent to which the user perceives his or her needs are met by the AI bot's performance.
Loyalty	The degree to which the user intends to continue using AI bot and recommend it to others.

H1b. An individual's perception of core AI bot service quality has a positive effect on his/her loyalty.

H2a. An individual's perception of AI bot service recovery quality has a positive effect on his/her satisfaction.

H2b. An individual's perception of AI bot service recovery quality has a positive effect on his/her loyalty.

3.2. AI bot conversational quality

This study proposes that if AI bots have good conversational quality, including understanding humanness, perceived contingency, and response humanness, it will increase user satisfaction and loyalty. For example, Chung et al. (2020) empirically verified that those AI agents (e.g., chatbots) presenting human-like perceived credibility such as honesty, trustworthiness, honorable, and morals in the conversation process have a strong positive influence on customer satisfaction regarding luxury brands. Conversational quality reflects a human-like interaction between humans and machines. De Visser et al. (2017) stated that chatbots and users interact more efficiently when they are anthropomorphized, in which users see human-like attributes in a service agent. Sheehan et al. (2020) found that users with a high need for human interaction are more likely to accept anthropomorphized chatbots.

Similarly, perceived anthropomorphic psychological characteristics of AI significantly affect acceptance and trust. (Pelau et al., 2021). Hsiao and Chen (2021) revealed that anthropomorphism and service quality in food-ordering chatbots are antecedents for trust and satisfaction-showe021) revealed that consumers' perception of chatbot anthropomorphism influences the purchase intention in chatbot commerce. Jenneboer et al. (2022) demonstrated that human-like chatbots promote customer satisfaction and trust, leading to enhanced consumer adoption of chatbot applications. Perceived anthropomorphism significantly affected voice assistant continued usage intention (Maroufkhani et al., 2022). Accordingly, we hypothesize:

H3a. An individual's perception of AI bot's conversational quality has a positive effect on his/her satisfaction.

H3b. An individual's perception of AI bot's conversational quality has a positive effect on his/her loyalty.

3.3. Satisfaction to loyalty

The present study proposes that satisfaction has a positive effect on loyalty in the context of human-chatbot interaction. Previous information system studies have found loyalty to be an outcome of satisfaction (Limayem and Cheung, 2008; Lee and Kwon, 2011; Lu et al., 2019). Specifically, the expectation confirmation model (ECM) proposes that user satisfaction influences post-acceptance (i.e., continued use) of information technologies (IT). Subsequent ECM studies revealed that satisfaction plays an important role in shaping users' continued usage of IT (Kim, 2010; Lin, 2012; Hew et al., 2016; Chiu et al., 2021). Moreover, many studies have indicated that the loyalty of chatbots is influenced by satisfaction (Araujo, 2018; Johari et al., 2019; Rossmann et al., 2020). Accordingly, we propose the following hypothesis:

H4. An individual's sense of satisfaction has a positive effect on his/her loyalty.

3.4. Satisfaction as a mediating variable

Baron and Kenny (1986) stated that mediation is the mechanism where 'an activated organism intervenes between stimulus and response.' To better understand the relationship between three types of chatbot service quality and loyalty, this study view satisfaction as a mediator and perform the mediation analysis. Past studies related to customer services also examined similar relations (Caruana, 2002; Mosahab et al., 2010; Yunus et al., 2018; Satti et al., 2020). Therefore, we hypothesize that satisfaction is a mediating variable, mediating the effect of core AI Bot service quality, AI Bot service recovery quality, and AI Bot conversational quality on loyalty as follows:

H5a. Satisfaction mediates the influence of core AI Bot service quality on loyalty.

H5b. Satisfaction mediates the influence of AI Bot service recovery quality on loyalty.

H5c. Satisfaction mediates the influence of AI Bot conversational quality on loyalty.

4. Research methodology

4.1. Sample and procedure

Empirical data were collected through a field survey of Taiwan customer service chatbot users. According to Tawain Internet Taiwan Internet Report (2022), Taiwan users' Internet access rate reaches 84.3%. 56.14% of them access the Internet several times a day. Moreover, Taiwan was ranked 8th in the world in digital competitiveness. The citizens in Taiwan have high acceptability of innovative technology applications. In fact, more than 60% (60.96%) of Taiwanese people view the advantages of AI very positively (IMD, 2022). As AI-related applications (e.g., AI chatbots) become available in the service and retail industries, the adoption behavior of Taiwanese users would shed light on the understanding of such applications. Therefore, this study uses Taiwan users as the target.

Survey messages explaining the goal of this study and a hyperlink to the survey form (https://docs.google.com/forms) were posted on relevant Facebook groups and local bulletin boards (https://www.ptt.cc/bb) for four weeks (from July 06, 2021 to July 07, 2021). These groups were chosen because of their broad outreach and popularity in Taiwan. Participants participated in this survey voluntarily. Participants were asked to answer the questionnaire concerning the chatbot they used most frequently. This method is intended to allow the respondents to answer based on their own experiences with the customer service chatbot. Respondents were entered into a raffle to win 30 NT$300 (US $10) convenience store gift certificates to maximize the response rate.

A total of 219 valid responses were returned, with a gender ratio of

34% male and 66% female. Nearly two-thirds of respondents were below the age of 29, and 58% had a bachelor's degree. Nearly half (46%) of respondents indicated 1–3 years' experience using chatbots, while 32% had under one year. Most of their chatbot service encounters are from service/retail industries. The composition of our sample was similar to the investigation result of the survey on the profile of populations of Internet users as conducted by TWNIC (2022), a famous official research center in Taiwan. Table 2 summarizes the respondent profiles.

4.2. Measurement of variables

We modified previously validated scales to fit the context of core AI bot service quality, AI bot service recovery quality and AI bot conversational quality. Specifically, the contexts of the original scales mainly investigated website services (Zehir et al., 2014; Theodosiou et al., 2019; Parasuraman et al., 2005), organization (Zemblyte, 2015), and voice assistant (Hu et al., 2021; Sundar et al., 2016). Core AI bot service quality dimensions such as efficiency, fulfillment, security/privacy and system availability, and AI bot service recovery quality dimensions such as compensation, responsiveness and contact, were adapted from previous work (Wolfinbarger and Gilly, 2003; Zehir et al., 2014; Blut, 2016; Zemblyte, 2015). AI bot conversational quality dimensions, such as understanding humanness, perceived contingency and response humanness, were measured using the scales designed by Hu et al. (2021) and Sundar et al. (2016). To measure constructs such as satisfaction and loyalty, we used scales from Hsu and Lin (2015). Each item was measured on a five-point Likert scale from "strongly disagree'' (1) to "strongly agree'' (5).

5. Data analysis and results

Partial least squares (PLS-SEM) are applied to assess the empirical strength of the relationships in the proposed model for the following reasons. First, the proposed model is a reflective-formative second-order model, and PLS is a better-suited tool to analyze such complex models (Hair et al., 2011). Secondly, PLS can perform efficiently with a much wider range of sample sizes (Henseler et al., 2009; Hair et al., 2011). Table 3 summarizes measurement model test results, indicating that the factor loading ranged from 0.623 to 0.968, exceeding the acceptable value of 0.50 (Hair et al., 1995). We computed composite reliability (CR) to assess the model's internal consistency. Consistent with the recommendations of Fornell (1982), all composite reliability values exceeded the benchmark of 0.60 (see Table 4). The average variance extracted (AVE) for all constructs exceeded the threshold value of 0.5 recommended by Fornell and Larcker (1981). As the three reliability values (i.e., factor loading, CR, and AVE) all exceeded the recommended

Table 2
Demographic profile.

Measure	Items	Frequency	Percent
Gender	Male	74	34
	Female	145	66
Age	Under 20	34	16
	20–29	103	47
	30–39	18	8
	40–49	37	17
	Over 50	27	12
Education	Senior high school or below	48	22
	Bachelor's degree	126	58
	Graduate degree	45	21
Experience in using customer service chatbot	Under 1 year	69	32
	1–3 years	101	46
	Over 3 years	49	22
Chatbot service most frequently used	Hospital, health, healthcare	23	11
	Finance, Banking, Insurance	88	40
	Retail and online shopping	88	40
	Other (i.e., telecommunications, library, order, entertainment, etc.)	20	9

Table 3
Scale items of constructs and factor loading weight values.

Construct	Item	Factor loading (weight)	t-statistics
Efficiency (Zehir et al., 2014)	1. This AI bot makes it easy to find the information I need.	0.774	20.434
	2. The information provided by this AI bot is well organized.	0.855	39.819
	3. This AI bot is simple to use.	0.807	22.877
	4. This AI bot provides well-organized information.	0.873	42.808
	5. This AI bot enables me to get information quickly.	0.735	17.284
Fulfillment (Zehir et al., 2014)	1. This AI bot can help me reserve a service or buy a product.	0.749	13.503
	2. This AI bot makes services available within a suitable time frame.	0.851	39.808
	3. This AI bot can accurately satisfy my needs.	0.890	55.906
	4. This AI bot can accomplish what it promises (such as answering my inquiries).	0.803	24.258
Security/Privacy (Theodosiou et al., 2019)	1. I feel safe in my interaction with this AI bot.	0.872	43.355
	2. I feel my privacy is protected by this AI bot.	0.898	51.295
	3. I trust this AI bot will not misuse my personal information.	0.892	48.450
	4. I feel I can trust this AI bot.	0.918	74.463
	5. This AI bot instills confidence in me.	0.815	28.907
System availability (Zehir et al., 2014)	1. This AI bot does not crash.	0.927	.96.725
	2. This AI bot does not freeze after I enter my information.	0.930	76.442
	3. This AI bot responds quickly to my inputs.	0.887	44.939
	4. I can quickly download information when using this AI bot.	0.901	45.358
Compensation (Zemblyte, 2015)	1. This AI bot compensates me when order errors or transaction failures occur.	0.939	85.176
	2. If the transaction or operation fails, the AI bot will provide me with useful information for compensation.	0.934	62.725
Responsiveness (Zemblyte, 2015)	1. This AI bot processes services accurately.	0.896	51.099
	2. This AI bot answers quickly when I ask a question.	0.871	34.974
	3. This AI bot delivers orders or transactions as promised.	0.889	39.747
Contact (Parasuraman et al., 2005)	1. When this AI bot cannot handle my problems, it will provide ways to contact human agents.	0.905	40.684
	2. When this AI bot cannot solve the problem, it will transfer me to online customer service or provide other contact methods such as hyperlinks.	0.922	68.240
	3. When a problem occurs, this AI bot can connect users to a human customer service staff.	0.870	38.668
Understanding humanness (Hu et al., 2021)	1. This AI bot can accurately comprehend what I mean.	0.840	36.917
	2. This AI bot is smart in understanding my intentions.	0.874	41.102
	3. The understanding ability of this AI bot is similar to that of a human being.	0.882	49.858
		0.823	29.633

(continued on next page)

Table 3 (*continued*)

Construct	Item	Factor loading (weight)	t-statistics
	4. This AI bot always understands what I mean.		
	5. I consider the AI bot's comprehending ability to be human-like.	0.866	39.429
Perceived contingency (Sundar et al., 2016)	1. The AI bot's responses are relevant to my previous input in threaded conversations.	0.888	50.318
	2. The response from the AI bot is contingent upon my preceding inputs.	0.885	40.878
	3. This AI bot will consider my previous series of inquiries and respond to them.	0.880	41.527
	4. The responses of the AI bot seem to be interconnected.	0.911	69.500
Response humanness (Hu et al., 2021)	1. The AI bot's responses feel natural.	0.845	37.132
	2. The AI bot has a human-like response.	0.892	40.227
	3. The AI bot's responses do not feel machine-like.	0.904	62.608
	4. The AI bot reacts in a very human way.	0.891	56.157
	5. The AI bot's responses seem human to me.	0.898	40.886
Satisfaction (Hsu and Lin, 2015)	1. Using the AI bot makes me feel very satisfied.	0.922	65.610
	2. Using the AI bot gives me a sense of enjoyment.	0.959	45.362
	3. Using the AI bot makes me feel very contented.	0.934	67.157
	4. Using the AI bot makes me feel very delighted.	0.944	88.343
Loyalty (Hsu and Lin, 2015)	1. I intend to keep using this AI bot in the future.	0.956	95.771
	2. I would like to continue using this AI bot.	0.968	157.187
	3. I would recommend this AI bot to friends.	0.908	47.341

thresholds, the scales for evaluating these constructs were deemed to exhibit adequate convergence reliability. Furthermore, Table 4 also shows that the square root of AVE for all constructs exceeds any correlation among the constructs, indicating that the constructs are empirically distinct. Thus, the test of discriminant validity measures of the measurement model is satisfactory.

In addition, to assess the degree of multicollinearity, the variance inflation factor (VIF) for each construct was assessed. All VIF values are well below 10, ranging from 2.459 to 3.109 (Hair et al., 1995), and thus the data exhibit no significant multicollinearity problem. Moreover, the standardized root mean square residual (SRMR) can be used as a model fit measure for PLS-SEM (Henseler et al., 2014). The data show that the SRMR value is 0.096, below the threshold value of 0.10 recommended by Henseler et al. (2014). Consequently, the proposed model provides a suitable fit.

5.1. Structural model

To estimate the second-order formative indicator weights, we conducted bootstrapping with 5000 subsamples, and the path coefficients were re-estimated using each of these samples. Results are presented in Fig. 2. All second-ordered formative indicators have strong and high loading on the first-order constructs, including core AI bot service quality, AI bot service recovery quality, and AI bot conversational quality.

Core AI bot service quality is not found to influence satisfaction significantly; thus, H1a is not supported. AI bot service recovery quality and AI bot conversational quality significantly affected satisfaction (β = 0.37, t-value = 4.73, $p < 0.001$; β = 0.48, t-value = 7.06, $p < 0.001$), thereby supporting H2a and H3a. Together, these two paths accounted for 64% of the satisfaction variance. Consistent with our expectations, core AI bot service quality and satisfaction had a significant effect on loyalty, as shown by respective path coefficients of 0.44 (t-value = 8.41, $p < 0.001$) and 0.35 (t-value = 4.63, $p < 0.001$), thus supporting H1b and H4. The model accounted for 72% of the variance for loyalty. Unexpectedly, AI bot service recovery quality and AI bot conversational quality had no direct influence on loyalty; therefore, H2b and H3b are not supported.

Notably, AI Bot service recovery quality and AI Bot conversational quality has indirect effects, mainly through satisfaction, on loyalty toward the chatbot, as shown in Table 5; therefore, H5b and H5c are supported. However, core AI Bot service quality had no indirect effect on loyalty. Thus, H5a is not supported. Two paths were significant, leading to the support of the hypothesis that satisfaction is a partial mediator. A summary of research hypotheses and findings had shown in Table 6.

6. Discussion and conclusions

6.1. Discussion

The proposed model is found to predict user loyalty to AI chatbots (R^2 = 72%). Core AI Bot service quality and satisfaction significantly and directly influence loyalty. Core AI Bot service quality, as the fundamental e-service quality, plays a crucial role in explaining user loyalty. This finding emphasizes that users will abandon using chatbots that fail to provide essential service quality such as efficiency, fulfillment, security/privacy, system availability, and satisfaction. This finding is consistent with previous studies (Amin, 2016; Al-dweeri et al., 2017; Anser et al., 2021) that found a positive relationship between e-service

Table 4
Reliability and discriminant validity.

	CR	AVE	EF	FF	SP	SA	CP	RP	CT	UH	CN	RH	SA	LY
EF	0.91	0.66	**0.81**											
FF	0.90	0.68	0.76	**0.94**										
SP	0.95	0.83	0.63	0.56	**0.91**									
SA	0.95	0.77	0.62	0.51	0.67	**0.88**								
CP	0.93	0.88	0.34	0.41	0.43	0.41	**0.94**							
RP	0.92	0.78	0.74	0.72	0.61	0.62	0.58	**0.88**						
CT	0.93	0.81	0.41	0.34	0.28	0.32	0.47	0.56	**0.9**					
UH	0.93	0.74	0.55	0.57	0.45	0.39	0.53	0.63	0.49	**0.86**				
CN	0.94	0.79	0.63	0.61	0.51	0.47	0.36	0.6	0.35	0.64	**0.88**			
RH	0.95	0.79	0.48	0.57	0.47	0.34	0.5	0.56	0.4	0.78	0.56	**0.88**		
SA	0.97	0.88	0.6	0.61	0.39	0.3	0.48	0.65	0.6	0.68	0.53	0.71	**0.94**	
LY	0.96	0.89	0.72	0.73	0.55	0.49	0.45	0.71	0.5	0.64	0.62	0.6	0.75	**0.94**

Notes: EF, Efficiency; FF, Fulfillment; SP, Security/Privacy; SA, System availability; CP, Compensation; RP, Responsiveness; CT, Contact; UH, Understanding humanness; CN, Contingency; RH, Response humanness; SA, Satisfaction; LY, Loyalty.

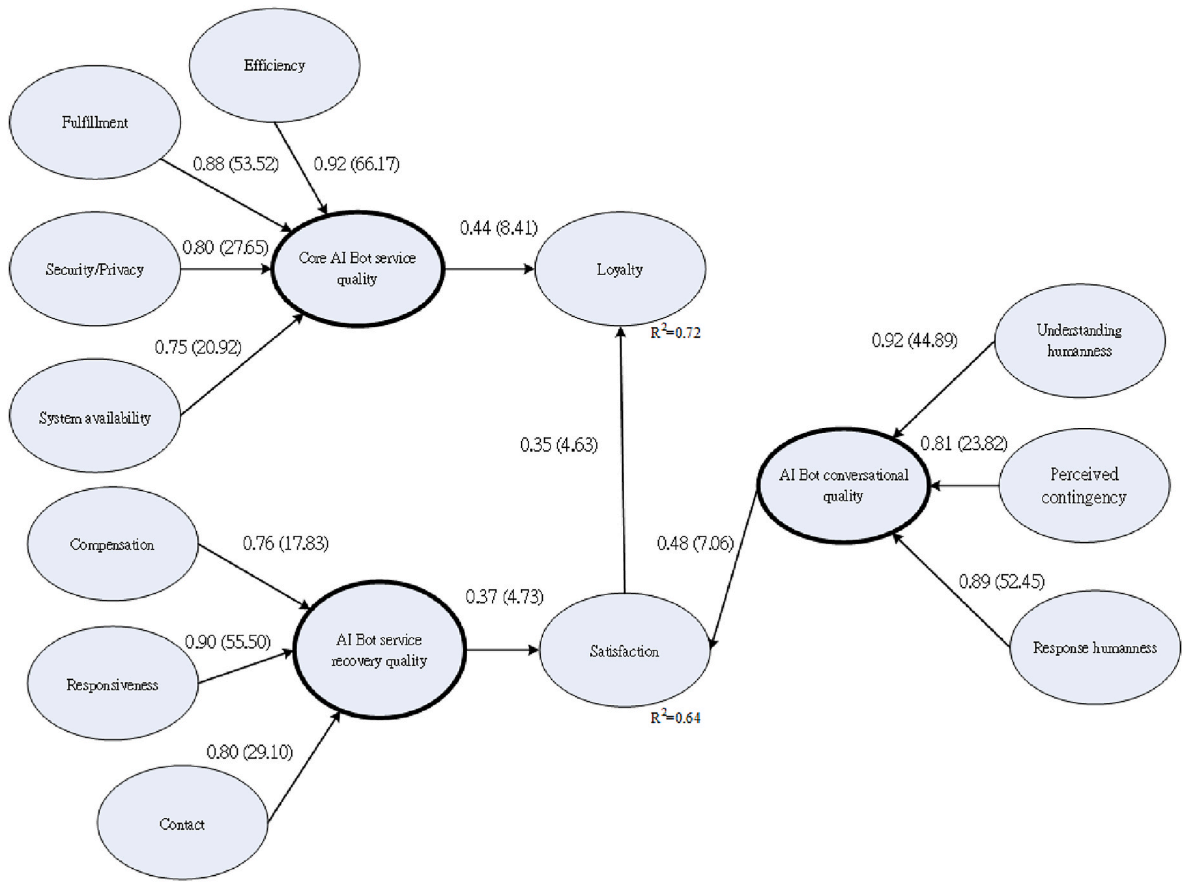

Fig. 2. Results of structural modeling analysis.

Table 5
Effects on loyalty: satisfaction as a mediator.

Construct	Direct effects	Indirect effects	Total effects
Core AI Bot service quality	0.440***	0.002	0.442***
AI Bot service recovery quality	0.066	0.130**	0.196**
AI Bot conversational quality	0.094	0.168***	0.262***

, * Significance at the $p < 0.01$ and $p < 0.001$ levels, respectively.

quality and loyalty. However, AI Bot service recovery quality and AI bot conversational quality had no direct effect on loyalty. This implies that aspects of service recovery quality (i.e., compensation, responsiveness, and contact), as well as human-like interaction, do not drive user loyalty. Furthermore, we tested the mediating role of satisfaction in the relationship between service quality (including core AI bot service quality, AI bot service recovery quality, and AI bot conversational quality) and loyalty. The findings indicate that AI bot service recovery quality and AI bot conversational quality significantly affected satisfaction. Nevertheless, core AI bot service quality has no significant effect on satisfaction.

These findings are understandable since customer satisfaction generally measures how happy the customers are with a particular service. Core AI bot service quality measures the AI bot's fundamental business functions such as efficiency, fulfillment, security/privacy, and system availability. It can be considered a hygiene factor. To continue using the AI bot service (i.e., loyalty), customers need to be sure that such bots will accurately and efficiently deliver the required service. Without a good perception of core AI bot service quality, a customer may never return, not to mention to be happy (i.e., satisfaction). Similar findings indicating hedonic motivations directly affect satisfaction but not loyalty in task-oriented applications (e.g., Hsu and Lin, 2019).

Table 6
Summary of research hypotheses.

Hypotheses		Path coefficients	Supported
H1a	An individual's perception of core AI bot service quality has a positive effect on his/her satisfaction.	–	No
H1b	An individual's perception of core AI bot service quality has a positive effect on his/her loyalty.	0.440***	Yes
H2a	An individual's perception of AI bot service recovery quality has a positive effect on his/her satisfaction.	0.370***	Yes
H2b	An individual's perception of AI bot service recovery quality has a positive effect on his/her loyalty.	–	No
H3a	An individual's perception of an AI bot's conversational quality has a positive effect on his/her satisfaction.	0.484***	Yes
H3b	An individual's perception of an AI bot's conversational quality has a positive effect on his/her loyalty.	–	No
H4	An individual's sense of satisfaction has a positive effect on his/her loyalty.	0.354***	Yes
H5a	Satisfaction mediates the influence of core AI Bot service quality on loyalty.	–	No
H5b	Satisfaction mediates the influence of AI Bot service recovery quality on loyalty.	0.130***	Yes
H5c	Satisfaction mediates the influence of AI Bot conversational quality on loyalty.	0.168***	Yes

On the other hand, a good service recovery experience as well as human-like interaction with an AI Bot will enhance the "wow factor" of the overall experience. Thus, the core AI bot service quality is the only quality among the three proposed factors affecting loyalty. Service recovery quality and conversational quality, however, indirectly affect loyalty through satisfaction.

6.2. Implications for research

For academic researchers, the presented findings contribute the following theoretical implications. First and foremost, this study contributes to the chatbot usage behavior literature by developing and validating an instrument for measuring a multidimensional chatbot service quality (i.e., core AI bot service quality, AI bot service recovery quality, and AI bot conversational quality) and examining its effect on user satisfaction and loyalty. Specifically, this study proposes a new second-order construct, AI bot conversational quality, which consists of three components: understanding humanness, perceived contingency, and response humanness, based on the IPO model. The empirical findings highlight that core AI bot service quality plays an important role in influencing user loyalty, while the other aspects indirectly but significantly improve loyalty through user satisfaction. Furthermore, efficiency is found to be the key factor in determining core AI bot service quality, suggesting that a critical strategy to enhance user loyalty is to increase bot interaction efficiency by ensuring users can quickly access the desired information or service outcome. Moreover, AI bot conversational quality was found to have the strongest impact on satisfaction, with a coefficient much higher than service recovery quality. This result highlights the importance of providing human-like conversation for user satisfaction.

6.3. Implications for practice

Our results provide important implications for managers. First, to improve customer service quality, companies that use chatbots as a CRM strategy should emphasize core service quality. Many companies rely on operational, analytical, and collaborative CRM applications. Operational CRM streamlines business processes, including sales, marketing and service automation. Chatbots with strong core AI service quality can play an important role in improving service automation, thus increasing user loyalty. Second, the recoverability of chatbots reflects the nature of collaborative CRM by which companies share customer information among various business departments for service and technical support. When a chatbot fails to provide the desired service outcome, it can transfer the user to human customer service agents, or share service information with other customer service departments, and provide adequate remediation information. Finally, chatbots can also be viewed as an analytical CRM tool because they can be used to collect and analyze customer data, which can then be used to improve the company's understanding of customer behavior and, thus, conversational quality.

6.4. Limitations and future research

The results of the present study need to be interpreted with caution for several reasons. First, the self-selected sample may produce bias. However, some confidence can be taken from the consistency of our results with those from previous studies (Amin, 2016; Al-dweeri et al., 2017; Hsu and Lin, 2019; Anser et al., 2021). Second, subjects were recruited in Taiwan, where the mobile penetration rate is over 120% (Kemp, 2022), and possess a culture to embrace innovative technology applications readily. Thus, the results may be affected by country-specific demographic, cultural factors, and lifestyle. Therefore, caution should be taken when generalizing the results. Third, this study only investigates user behavior in interaction with customer service chatbots. Future studies may examine differences in user behavior with different types of chatbots to provide additional practical value.

In addition, future research may investigate the effect of other AI-related issues, such as trust, risk and legal or ethical problems on service quality. Finally, attention needs also be given to studying the impact of cultural differences in adopting AI-related applications (e.g., chatbot usage). Understanding the challenges black-box AI systems pose may enable organizations to successfully develop and deploy AI systems (Asatiani et al., 2020).

Funding

This study was supported in part by grants from the National Science and Technology Council of the Republic of China under Contract Number MOST 109-2410-H-141-008.

Data availability

The data that has been used is confidential.

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