Understanding the Continuance Intention to Use Chatbot Services☆

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Abstract

Chatbot services have become an essential communication tool for interacting with consumers in e-commerce. To understand consumer behavior in the context of chatbot services, we apply the Theory of Planned Behavior (TPB) to analyze continuance intention to use and additional predictors to explain behavioral intention. An analysis of data collected from 300 digital shopping users who had experienced chatbot services revealed that an extended TPB model holds for the continuous use of chatbot services, driven by both interaction and information quality. Accordingly, these findings provide a better understanding of consumer behavior toward chatbot services and valuable insights into digital customer relationship management.

Keywords: Chatbot services, Theory of planned behavior, Interaction quality, Information quality, Continuance intention to use

1. Introduction

Chatbots have become popular tools for businesses in the marketing industry because of their ability to engage with customers and provide personalized experiences. Given the accelerating digital transformation since the Covid-19 pandemic, consumers have frequent opportunities to use chatbot services in their daily lives. For example, chatbots have replaced human service agents on social media platforms like Facebook and WeChat (Luo et al. 2019). Accordingly, more businesses have replaced service providers and used chatbots instead of human service agents. Approximately 80% of organizations currently use chatbot services or want to do so soon to interact with customers and address their issues (Ramasamy 2019). Moreover, chatbots have generally shown significant promise in enhancing long-term relationships and increasing loyalty (Huang and Lee 2022).

With the widespread adoption of chatbots for services, diverse interactions and engagement between customers and chatbots have surged. Specifically, chatbots are increasingly used in various services, such as digital shopping, O2O services (e.g., real-time meal ordering), and fintech. For instance, chatbot services on digital shopping platforms can provide customers with customized recommendations, help with information searches and product selection, and offer support for transactions (Wien and Peluso 2021). In banking services, chatbots enhance customer service by providing personalized financial advice and answering customer queries about products and services (Huang and Lee 2022). Studies in healthcare have explored how chatbots can help patients and provide health education (Hsu, Chih-Hsi, and Hsu 2019). Despite a growing body of literature on chatbots, little attention has been paid to understanding the customer perception-related antecedents and behavioral constructs that influence customers' continued usage.

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Hence, this study seeks to address this gap by applying a behavioral perspective to understand chatbot service continuance usage behavior. Specifically, this study addresses consumers' perceived quality of chatbot services and considers continuance of use as planned behavior. This is achieved by studying the extent to which the Theory of Planned Behavior (TPB) (Ajzen 1991) can be used to capture and predict human behavior and its antecedents according to attitudes, subjective norms, and perceived behavioral control. Therefore, we delve into its effect on the continuance intention to use chatbot services and aim to answer the following research questions:

- How does the interaction quality of chatbot services impact TPB behavioral constructs?
- How does the information quality of chatbot services impact TPB behavioral constructs?
- How do TPB behavioral constructs impact continuance intention to use chatbot services?

Therefore, this study addresses a gap in existing research on chatbot service contexts by understanding the antecedent relationships driven by the TPB beyond general relationships. This study contributes to prior research by applying the concept of quality perception, which is crucial for understanding the continuance intention to use chatbot services. It also extends the literature on AI-powered service marketing by applying TPB, which has rarely been studied in the context of chatbot service platforms. Additionally, we offer practical implications for chatbot service providers regarding the beneficial effects of enhancing relationships.

The remainder of this paper is organized as follows. Section 2 reviews the literature on service quality perceptions and behavioral constructs (i.e., the TPB) in chatbot services. Subsequently, Section 3 provides a list of hypotheses to test the relevance of an extended TPB framework in the context of the continuance intention to use chatbot services. Section 4 presents and discusses the findings in light of previous research. Finally, Section 5 concludes the paper by highlighting the key contributions, limitations, as well as theoretical and practical implications of this study.

2. Theoretical background

2.1. Chatbot services in e-commerce

Chatbot services are becoming increasingly popular in the e-commerce industry as they offer a convenient and efficient way for businesses to engage with customers and enhance their overall experience (Roy and Naidoo 2021; Whang et al. 2022). A chatbot is defined as an automated conversation system that uses machine learning and AI technology to interact with human users via voice-driven digital assistants (e.g., Alexa, Google Duplex, and Siri) (Luo et al. 2019; Moriuchi 2021) or text-based messaging systems (e.g., digital retailers and social media platforms) (Ashfaq et al. 2020; Sheehan, Jin, and Gottlieb 2020). Chatbot services are human-like agents that assist consumers with multiple purposes, such as searching for and finding information, personalizing recommendations, building social relationships, and tracking orders (Chung et al. 2020; Xu et al. 2020; Zhu et al. 2022). For example, consumers can use chatbots to inquire about product availability, receive personalized product recommendations based on their browsing histories, or track their order status.

The benefits of chatbot services in e-commerce include their ability to improve customer satisfaction and retention (Chung et al. 2020; Li and Wang 2023; Park, Choi, and Shin 2021). Chatbots can provide quick and reliable customer support, reduce wait times, and ensure customer queries are promptly resolved (Rese, Ganster, and Baier 2020). Like human service agents, chatbots offer personalized and conversational experiences that make customers feel valued and engaged (Luo et al. 2019). Earlier studies on e-commerce examined how the efficiency, trust, quality, and characteristics of chatbot services impact the intention and satisfaction of using chatbot services (Park, Tung, and Lee 2021; Xu et al. 2020; Zhu et al. 2022). For example, Chung et al. (2020) measured marketing activities in five dimensions: interaction, entertainment, trendiness, customization, and problem-solving of chatbot services in the context of luxury fashion brand shopping; these activities determine communication quality (i.e., accuracy, credibility, competence). However, despite various research aspects, there is a paucity of research on understanding consumers' behavioral constructs on e-commerce platforms.

2.2. Quality perceptions

Chatbots are crucial for enhancing customer-brand relationships, much like customer service representatives (Chung et al. 2020). Particularly, communication between customers and service representatives must be easy, gratifying, prompt, efficient, and accurate for customers to regard them as having received excellent communication (Whang et al. 2022). However, unlike traditional service agents, chatbot interactions do not involve direct face-to-face interactions, thus it lacks personal touch in their services. For instance, according to Press (2019), 87% of consumers still favor talking to real agents over chatbots. Respondents also concurred that humans outperform chatbots in several areas, particularly in their comprehension of complex scenarios; in other words, they believe that human agents comprehend complex situations better. This indicates that much more reliable and human-like technology is critical to continue using services.

Interaction quality

In the digital shopping realm, the key to effective interaction and engagement in cultivating positive relationships with customers is providing timely and attentive services that meet customers' needs and preferences (Teo, Srivastava, and Jiang 2008). Earlier studies have shown the importance of interaction quality in the context of human service agents based on the reciprocity theory (Çelen, Schotter, and Blanco 2017). Moreover, interaction quality leads to positive spending in stores (Haas and Kenning 2014) and positive purchase intentions (Fassnacht, Beatty, and Szajna 2019). Like human service agents, high-quality interactions with chatbots can help build trust and loyalty between customers and brands, ultimately leading to higher sales and customer retention.

Furthermore, customers are more likely to engage with chatbots that offer friendly conversational interactions that mimic human-like conversations (Lou, Kang, and Tse 2022; Roy and Naidoo 2021). This indicates that chatbots with natural language processing and machine learning algorithms can simulate the conversational flow of customer interactions, leading to greater engagement and satisfaction (Go and Shyam Sundar 2019; Park, Choi, and Shin 2021). Moreover, customers are more likely to engage with chatbots that offer intimate and helpful interactions, particularly when they encounter problems or have questions (Li and Wang 2023; Xu et al. 2020). This indicates that chatbots are more likely to be viewed as valuable and helpful in detecting customer frustration and providing prompt solutions.

Information quality

The quality of information is critical in digital shopping because of the uncertainty regarding product assessment (Jiang et al. 2020). Consumers generally expect accurate and relevant information about products, promotions, and services among various information. Consumers are more likely to trust and engage in complete and accurate information relevant to their needs and preferences (Chung et al. 2020; Rese, Ganster, and Baier 2020). Previous research has insisted that the success of services or digital platforms is determined by information quality (DeLone and McLean 2003; Gao, Waechter, and Bai 2015; Teo, Srivastava, and Jiang 2008).

The quality of information provided by chatbot services can vary widely and significantly impact customer satisfaction and loyalty (DeLone and McLean 2003). Several studies have presented perspectives on information-quality issues in the context of chatbot services. For example, customers are more likely to trust and engage with chatbots that provide accurate, relevant, and timely information (Ashfaq et al. 2020). The factors contributing to the quality of information provided by chatbots include the accuracy and completeness of the data on which they are trained, the sophistication of their natural language processing algorithms, and the ability of their designers to anticipate and address common customer queries and concerns (Zhu et al. 2022). Ultimately, the success of chatbot services depends on their ability to provide high-quality information and effectively meet customer needs (Ashfaq et al. 2020).

2.3. *Theory of planned behavior (TPB)*

The theory of planned behavior is a fundamental theoretical framework for understanding or forecasting human behavior (Sheppard, Hartwick, and Warshaw 1988). In 1991, Ajzen proposed that behavior is a product of intention. The central tenet of the TPB is that an individual's intention to engage in a certain behavior impacts how likely they are to do so (Mathieson 1991). Specifically, behavioral intention indicates the patterns and motivations to behave in a particular circumstance. An individual's positive or negative attitude toward a particular conduct is called their attitude (Ajzen 1991). A subjective norm is a societal pressure to engage in or refrain from a particular behavior (Ajzen 1991). The term "perceived behavioral control" describes how people perceive whether they have the knowledge, opportunities, and resources necessary to engage in a particular behavior (Ajzen 1991).

TPB has already been used to advance research in several different areas because it can forecast how people will learn to use various forms of contemporary technology. For instance, Shneor and Munim (2019) used TPB to analyze contribution intentions and behavior and their antecedents in the context of reward crowdfunding, a prominent channel for entrepreneur fundraising. They demonstrated the validity of an extended TPB model for reward-based crowdfunding and the predictive power of both information-sharing and monetary contribution intentions. Furthermore, Arpaci, Kilicer, and Bardakci (2015) conducted a study examining the behavioral intention to utilize a cloud service utilizing an attitude toward behavior. TPB explains how students accept mobile learning in their education.

The TPB has been widely used to examine user motivations for interacting with chatbot services (Brachten, Kissmer, and Stieglitz 2021; Ciechanowski et al. 2019; Hsu, Chih-Hsi, and Hsu 2019). For instance, numerous e-commerce businesses use chatbots to deliver relevant information to customers who consult for product information, make purchases, or address problems on digital platforms during the pre and post-purchase stages (Chung et al. 2020; Wien and Peluso 2021; Zhu et al. 2022). Attitude is defined as a customer's favorable or unfavorable response to an interaction with a chatbot. Social pressures influence subjective norms, such as whether others believe a person should utilize chatbots when shopping. Perceived behavioral control refers to the capacity to complete a task; in other words, it alludes to the belief that a consumer can interact with a chatbot for digital shopping.

2.4. Continuance intention to use

Previous research has examined the context of chatbots in terms of their intentions to use (Rese, Ganster, and Baier 2020; Sheehan, Jin, and Gottlieb 2020; Zhu et al. 2022), satisfaction (Chung et al. 2020; Park, Choi, and Shin 2021), and purchase intention (Roy and Naidoo 2021; Wien and Peluso 2021). Specifically, the behavioral intention to use chatbot services is influenced by technology, hedonic factors, and risks (Rese, Ganster, and Baier 2020). Zhu et al. (2022) showed that chatbot adoption is determined by the certainty of needs, mediated by perceived effectiveness, and moderated by product type (search vs. experience goods). Chung et al. (2020) demonstrated that the communication quality of chatbots leads to higher satisfaction. In summary, consumers tend to demonstrate a considerable willingness to engage in chatbot services when they perceive that such technologies provide benefits (e.g., Hsu, Chih-Hsi, and Hsu 2019; Roca, Chiu, and Martínez 2006).

Despite the growing body of research on chatbots that examines the first adoption of chatbots and satisfaction, little is known about how to use social cues to increase the intention to repeat the use of chatbot services in e-commerce contexts, even if chatbots are widely used in e-commerce. Continuance intention is a widely researched topic and a critical factor in the success of digital marketing and information system management (Yan, Filieri, and Gorton 2021). Moreover, given the prevalence of chatbot services, consumers probably come across chatbots when shopping digitally and have general opinions based on that experience. In this situation, it would make more sense to gauge customers' intention to continue using a chatbot they had previously been using rather than their desire to use it for the first time (Lee and Kwon 2011; Li and Wang 2023).

Several studies have highlighted the continued intention to use chatbot services (Moriuchi 2021). For example, Ashfaq et al. (2020) exhibited that users are more likely to continue using chatbot services when they perceive them as useful, easy to use, and reliable. Li and Wang (2023) found that language style (formal versus informal) has different effects on the continuance intention to use and the mediating role of parasocial interaction. Huang and Lee (2022) investigated the effects of social capital and attitudes on the continuous intention to use fintech chatbots based on social response theory. Similarly, this research highlights the continuance intention to use chatbot services in e-commerce, which is the context most confronted by consumers' daily lives and digital retail businesses.

3. Hypotheses development and conceptual model

This study focuses on two critical constructs in chatbot services and crucial behavioral constructs from the TPB to drive continued intention to use chatbot services. Specifically, the current research employs the TPB against the background of chatbot services. It proposes a specific model that includes its antecedents (i.e., interaction and information quality), behavioral constructs (i.e., attitudes, subjective norms, and perceived behavioral control), and outcomes (continuance intention to use). Fig. 1 illustrates this conceptual framework.

Given the benefits of chatbot services, the quality of interaction offered by chatbot services can be a significant antecedent of belief constructs such as attitude, subjective norms, and perceived behavioral control. High-quality chatbot services can create a positive perception of quality, such as perceived ease of use, leading to a positive attitude toward the technology and its use (Brachten, Kissmer, and Stieglitz 2021; Park, Tung, and Lee 2021). Moreover, chatbots that offer personalized attention and guidance can create a sense of social and personal norms that supports their use, thereby influencing consumers' subjective norms toward chatbot services. Additionally, the quality of interaction with chatbots can affect consumers' perceived ease of use and control over the technology, leading to greater perceived behavioral control of chatbot services. Accordingly, we propose the following hypotheses:

H1. *The interaction quality of chatbot services has a positive influence on (a) attitude, (b) subjective norm, and (c) perceived behavioral control.*

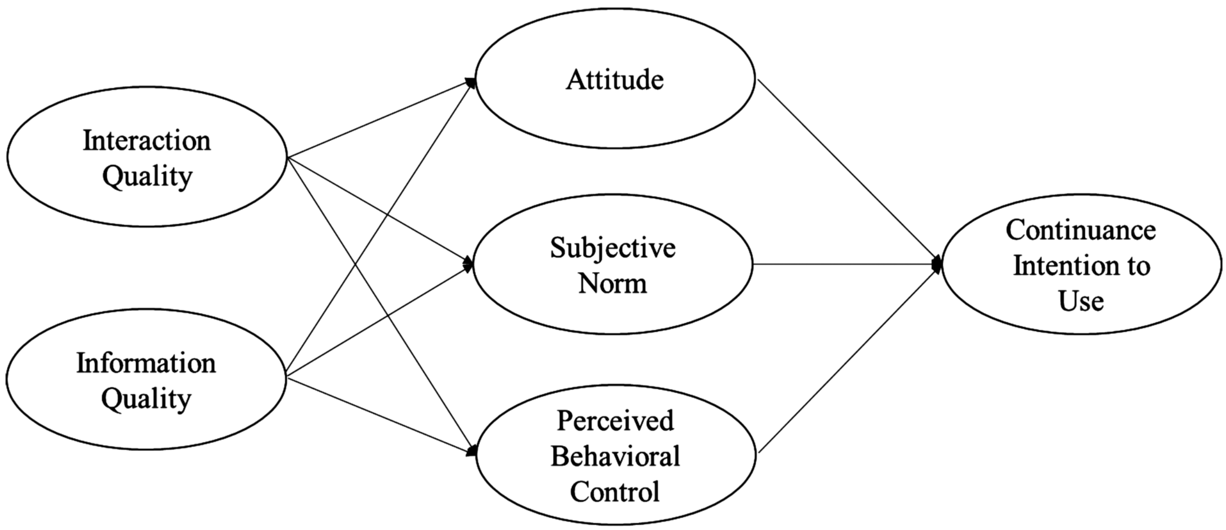

Fig. 1. The conceptual framework.

Similarly, the information quality of chatbot services positively influences attitudes, subjective norms, and perceived behavioral control for several reasons. According to Teo, Srivastava, and Jiang (2008), access to sufficient, precise, accurate, updated, and reliable information is crucial for consumer satisfaction. This indicates that accurate and relevant information provided by chatbots can create a positive perception of quality, leading to a positive attitude toward the technology and its use. Moreover, chatbots that offer sufficient information and timely responses can create a sense of social and personal norms that support their use, thereby influencing consumers' subjective norms regarding chatbot services. We thus postulate:

H2. *The information quality of chatbot services has a positive influence on (a) attitude, (b) subjective norm, and (c) perceived behavioral control.*

According to Park, Choi, and Shin (2021), perceived usefulness and ease of use derive consumers' positive opinions of chatbot services. In particular, chatbots that are viewed as user-friendly and offer value-added services can foster favorable attitudes toward chatbot services and encourage customers to use them repeatedly. This indicates that attitude has the potential to be a key determinant of actual usage intention for chatbot services. Therefore, we assume that the construct of attitude toward intention to repeat use plays a significant role in our approach. Chatbots that are perceived as easy to use and provide value-added services can help promote positive attitudes toward chatbot services and encourage continuous usage among customers. Therefore, a strong positive correlation exists between how consumers perceive chatbot services and their conduct (Ashfaq et al. 2020; Brachten, Kissmer, and Stieglitz 2021; Huang and Lee 2022). Accordingly, we propose the following hypothesis:

H3. *Attitude toward chatbots positively affect continuance intention to use.*

Subjective norms are expectations or perceived societal pressures to utilize chatbot services and reflect how people see their surroundings. The subjective perception of whether an individual's surroundings will accept the related activity (e.g., using a new technology) might affect the chance of adopting the technology (Brachten, Kissmer, and Stieglitz 2021; Mathieson 1991). Note that the normative impact is expected to be significant in every decision-making process and has a favorable influence on the desire to utilize a system (Hsu, Chih-Hsi, and Hsu 2019; Yan, Filieri, and Gorton 2021). Specifically, social norms affect online purchase behavior (Kim et al. 2019), and subjective norms positively affect the acceptance of smart home devices (Yang, Lee, and Zo 2017). In other words, subjective norms are key determinants in the choice process toward intended behavior (Brachten, Kissmer, and Stieglitz 2021). Hence, customers are more likely to utilize chatbot services in the future if they believe that their friends and social networks will support them and use them. This indicates that social influence may be a significant factor in determining whether chatbot services are continuously used. Consequently, we propose the following hypotheses:

H4. *Subjective norm toward chatbots positively affects continuance intention to use.*

Perceived behavioral control represents users' opinions about external and internal forces over which they have no control (Brachten, Kissmer, and Stieglitz 2021). These influences may operate as restrictions that prevent someone from doing something or as prerequisites that make a given activity possible (Taylor and Todd 1995). Customers are more prone to repeatedly using chatbot services when they feel in charge of a conversation, such as when they have the option to ask questions or comment. Moreover, perceived behavioral control has been found to be the deciding factor for behavioral intention in virtual communities (Yang, Lee, and Zo 2017). In other words, customers may feel more responsible for conversations with responsive and supportive chatbots, which may increase customer satisfaction and encourage repeat usage. Thus, we propose the following hypotheses:

H5. *Perceived behavioral control toward chatbots positively affects continuance intention to use.*

4. Methods

4.1. Survey instrument

To understand consumer behavior toward chatbot services using the extended TPB model, we conducted a survey to measure six key constructs of our conceptual framework (i.e., interaction quality, information quality, attitude, subjective norm, perceived behavioral control, and continuance intention to use). The interaction quality measurement items capture the extent to which chatbot services offer attentive and helpful interactions. A five-item measure extracted from previous studies (Fassnacht, Beatty, and Szajna 2019; Roca, Chiu, and Martínez 2006) was used to assess the interaction quality. Information quality measurement items determine how much chatbot services provide information relevant to customer requirements and preferences. A six-item measure developed in previous studies (Teo, Srivastava, and Jiang 2008) was used to assess information quality. Among the three constructs related to TPB, seven items are used to measure attitudes toward chatbot services (Hsu and Lin 2008; Hsu, Ke, and Yang 2006), six items are used to measure subjective norms toward chatbot services (Hsu and Lin 2008; Hsu, Ke, and Yang 2006; Hung, Chang, and Ma 2021; Saleem et al. 2021; Venkatesh et al. 2003), and four items are used to measure perceived behavioral control toward chatbot services (Hsu, Ke, and Yang 2006; Hung, Chang, and Ma 2021; Saleem et al. 2021). Finally, the continuance intention to use chatbot services was assessed using a six-item scale derived from previous studies (Algesheimer, Dholakia, and Herrmann 2005; Gao, Waechter, and Bai 2015; Hung, Chang, and Ma 2021). We slightly modified all the survey items to fit the context of our study and assessed them on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). Table 1 lists the measurement parameters.

4.2. Participants and data collection

We collected the data using Prolific, a small-reward online research platform. Prolific is used by academics from various fields, e.g., social science, psychology, and marketing, to acquire data from participants (Moriuchi 2021; Zhang, Pentina, and Fan 2021). In this study, we focus on text-based customer service chatbots because they are the most prevalent type. Participants regularly engaged in digital shopping (i.e., online or mobile shopping) and used chatbot services on e-commerce platforms at least once. A text-based customer service chatbot was defined as an introductory text that participants were required to read. Subsequently, we instructed them to recall the most recent time they had a text-based chatbot communicating with them for customer service and to complete the survey on a 7-point scale. Questions on the characteristics and chatbot usage patterns of the respondents were asked in the last section of the survey concluded (Huang and Lee 2022; Li and Wang 2023). The participants were asked how frequently they used chatbot services. The findings were interpreted using the data.

A total of 300 valid participants answered "yes" to the screening questions (i.e., "Do you usually shop using a smartphone or computer?" and "Have you ever interacted with a chatbot before?") were included in the analysis ($M_{age} = 32.17$, $SD = 9.86$; $N_{female} = 141$, $N_{male} = 157$, $N_{other} = 2$). Table 2 lists the frequencies and percentages of the sample characteristics. Regarding the frequency of using chatbot services, 71.6% of the participants used chatbot services 1–3 times per month, and the remaining 28.4% used chatbot services at least 4–6 times per month.

4.3. Results

Assessment of measurement model

The reliability and validity of the measurement models were assessed. First, we conducted reliability tests to check the consistency among the items that measured the constructs. As shown in Table 3, the values of Cronbach's alpha for all variables,

Table 1. Measurement items of key constructs.

Construct	Items		References
Interaction quality	IntQ_1	The chatbot is friendly.	Fassnacht, Beatty, and Szajna (2019), Roca, Chiu, and Martínez (2006)
	IntQ_2	The chatbot gives me individual attention.	
	IntQ_3	The chatbot has an attentive interaction to communicate my needs.	
	IntQ_4	The chatbot is very engaged in order to address my needs.	
	IntQ_5	Overall, I would say that the quality of my interaction with the chatbot is excellent.	
Information quality	InfQ_1	The chatbot provides sufficient information.	Teo, Srivastava, and Jiang (2008)
	InfQ_2	The chatbot provides information in a useful format.	
	InfQ_3	The chatbot provides clear information.	
	InfQ_4	The chatbot provides accurate information.	
	InfQ_5	The chatbot provides up-to-date information.	
	InfQ_6	The chatbot provides truthful Information.	
Attitude	ATT_1	I enjoy a conversation with the chatbot.	Hsu and Lin (2008), Hsu, Ke, and Yang (2006)
	ATT_2	It is helpful to share a conversation with the chatbot.	
	ATT_3	I think using the chatbot is appropriate for me.	
	ATT_4	I think using the chatbot is beneficial for me.	
	ATT_5	I am likely to feel good about using chatbots.	
	ATT_6	I have a positive opinion about using chatbots.	
	ATT_7	I think that chatbots are likable.	
Subjective norm	SN_1	People surrounding me use chatbots.	Hsu, Ke, and Yang (2006), Hsu and Lin (2008), Hung, Chang, and Ma (2021), Saleem et al. (2021), Venkatesh et al. (2003)
	SN_2	People surrounding me would support me in using any chatbot.	
	SN_3	People who are important to me think that I would use chatbots.	
	SN_4	People who influence my behavior encourage me to use chatbots.	
	SN_5	My colleagues think that I would use chatbots.	
	SN_6	My friends think that I would use chatbots.	
Perceived behavioral control	PBC_1	I can access and use the chatbot service.	Hsu, Ke, and Yang (2006), Hung, Chang, and Ma (2021), Saleem et al. (2021)
	PBC_2	I can access and receive related information through the chatbot service.	
	PBC_3	My engagement in using chatbots is within my control.	
	PBC_4	I would be able to use chatbots if I wanted to.	
Continuance intention to use	CU_1	Given the chance, I intend to continue using chatbots.	Algesheimer, Dholakia, and Herrmann (2005), Hung, Chang, and Ma (2021)
	CU_2	Given the chance, I predict that I will continue using chatbots in the future.	
	CU_3	I will likely continue using chatbots in the near future.	
	CU_4	I have the intention to use chatbots continuously.	
	CU_5	I intend to actively use chatbots continuously.	
	CU_6	I will continue to use the chatbot to get information or shopping.	

interaction quality (Cronbach's alpha = 0.880), information quality (Cronbach's alpha = 0.906), attitude (Cronbach's alpha = 0.957), subjective norm (Cronbach's alpha = 0.926), perceived behavioral control (Cronbach's alpha = 0.776), and continuance intention to use (Cronbach's alpha = 0.965), are higher than the minimum threshold of 0.70, proving the high reliability of the constructs. Next, we assessed the validity of the items and constructs. The factor loading values of all items ranged from 0.626 to 0.934, above the suggested minimum threshold of 0.60 (Hair et al. 2019). In addition, we employed average variance extracted (AVE) and composite reliability (CR) to measure the convergent validity and confirmed that the AVE of nearly all constructs was higher than the suggested threshold of 0.50, and the composite reliability ranged from 0.785 to 0.964, which are greater than the suggested threshold of 0.70 (Fornell and Larcker 1981; Hair et al. 2019). Finally, we employed the Fornell and Larcker criterion (1981)to evaluate the discriminant validity of the measurement model. According to this criterion, the square root of the AVE for each construct should be greater than the correlations between that construct and all other constructs in the structural model. As shown in Table 4, most of the diagonal values (square root of AVE) are greater than off-diagonal values (correlations with other constructs), indicating adequate discriminant validity among the latent constructs. The above results provide evidence of the reliability and validity of the measures for the items and constructs.

Assessment of structural model

We test the hypotheses using structural equation modeling (SEM). As shown in Table 5, the various model fit indices indicated that the configural model had adequate goodness of fit ($\chi^2 = 1540.5$; df = 517, $p < 0.001$; $\chi^2/\mathrm{df} = 2.980$; IFI = 0.898; TLI = 0.882;

Table 2. Sample characteristics.

Variable	Attribute	N	%
Gender	Male	157	52.3%
	Female	141	47.0%
	Non-binary/third gender	2	0.7%
Age	<20	4	1.3%
	20–30	163	54.3%
	31–40	72	24.0%
	41–50	36	12.0%
	>50	25	8.3%
Education level	Less than high school	5	1.7%
	High school graduate	74	24.7%
	Undergraduate	111	37.0%
	Postgraduate and beyond	110	36.7%
Income level	Less than $1,000	87	29.0%
	$1,001–$3,000	140	46.7%
	$3,001–$5,000	45	15.0%
	$5,001–$7,000	22	7.3%
	$7,001–$9,000	2	0.7%
	More than $9,001	4	1.3%
Frequency of using chatbot services	1–3 times per month	215	71.7%
	4–6 times per month	60	20.0%
	7–9 times per month	15	5.0%
	10–15 times per month	5	1.7%
	Almost every day	5	1.7%

CFI = 0.892; RMSEA = 0.081), and all hypotheses, apart from H1(c), were supported. Specifically, interaction quality has a significant positive effect on attitude (H1(a): $\beta = 0.924$, t = 6.665, $p < 0.001$) and subjective norm (H1(b): $\beta = 0.661$, t = 4.617, $p < 0.001$), but has no significant effect on perceived behavioral control (H1(c): $\beta = 0.138$, t = 1.438, $p = 0.151$). Therefore, H1(a) and H1(b) are supported, and H1(c) is rejected. The hypotheses related to information quality demonstrate a significant positive effect on attitude (H2(a): $\beta = 0.407$, t = 4.588, $p < 0.001$), a marginally significant positive effect on subjective norm (H2(b): $\beta = 0.171$, t = 1.803, $p = 0.071$), and a significant positive effect on perceived behavioral control (H2(c): $\beta = 0.300$, t = 4.018, $p < 0.001$). Thus, H2(a), H2(b), and H2(c) are supported. It suggests that when users perceive the information provided by the chatbot as accurate, sufficient, and helpful, they are more likely to develop a positive attitude toward the technology, form social and personal norms, and feel confident in their ability to successfully complete tasks with the chatbots. However, while interaction quality is indeed important for user satisfaction and overall chatbot performance, it may not directly impact users' confidence in effectively completing tasks with the chatbots. Finally, attitude (H3: $\beta = 0.796$, t = 13.319, $p < 0.001$), subjective norm (H4: $\beta = 0.357$, t = 6.028, $p < 0.001$), and perceived behavioral control (H5: $\beta = 0.377$, t = 3.954, $p < 0.001$) has positive effects on continuance intention to use, suggesting that H3, H4, and H5 are supported.

5. Conclusion

Chatbots have radically changed the customer service sector to include advantages for both businesses and consumers (Sheehan, Jin, and Gottlieb 2020). By identifying the antecedent ties generated by the TPB beyond general relationships, this study intends to close the gap in the corpus of research on the chatbot service context. Given the expansion of chatbot services across all industries, it is essential to understand the nuanced and complex roles of quality and its antecedent factors. The results of this study support all the anticipated assumptions across the studies.

This study revealed a favorable direct relationship between interaction quality and TPB items, i.e., attitudes and subjective norms, the first research topic related to H1. This suggests that consumers are more likely to have favorable views and are positively affected by those around them if they experience high-quality interaction and engagement value from chatbots. Second, we found a positive relationship between information quality and TPB items with respect to the second question related to H2. According to these findings, the quality of information significantly impacts TPB items. This indicates that chatbots are more likely to be perceived as important and effective if they provide great information quality, such as accurate, relevant, sufficient, and timely information; personalized recommendations; and tailored offers based on consumers' behavior and preferences. Third, regarding the third research issue related to H3, H4, and H5, this study supports the notion that attitudes, subjective norms, and perceived behavioral control are crucial variables for predicting behavior in the context of chatbot services. In particular, these TPB items can contribute to favorable and significant variables in the comprehension of and continuance intention to use chatbot services during digital shopping.

5.1. Theoretical implications

This study contributes to the literature on chatbot services in the following ways. First, our results deepen our understanding of the importance of the continued intention to use chatbot services. Earlier research on chatbot services or AI-powered service agents has been focused on anthropomorphism (Moriuchi 2021; Roy and Naidoo 2021; Sheehan, Jin, and Gottlieb 2020), adoption (Rese, Ganster, and Baier 2020; Zhu et al. 2022), comparison between human and chatbot agents, (Lou, Kang, and Tse 2022; Luo et al. 2019; Wien and Peluso 2021; Zhang, Pentina, and Fan 2021) and message type (Li and Wang 2023; Whang et al. 2022). Unlike previous marketing

Table 3. Results of reliability and validity.

Construct	Items	Mean	SD	Factor loadings	CR	AVE	Cronbach's alpha
Interaction quality	IntQ_1	5.557	1.291	0.626	0.881	0.599	0.880
	IntQ_2	4.757	1.623	0.750			
	IntQ_3	5.090	1.359	0.805			
	IntQ_4	5.080	1.438	0.833			
	IntQ_5	4.603	1.640	0.836			
Information quality	InfQ_1	4.520	1.496	0.732	0.910	0.628	0.906
	InfQ_2	5.263	1.280	0.870			
	InfQ_3	5.223	1.259	0.826			
	InfQ_4	5.163	1.315	0.811			
	InfQ_5	5.410	1.194	0.785			
	InfQ_6	5.490	1.132	0.719			
Attitude	ATT_1	3.826	1.601	0.820	0.957	0.760	0.957
	ATT_2	4.430	1.516	0.852			
	ATT_3	4.544	1.629	0.883			
	ATT_4	4.513	1.609	0.897			
	ATT_5	4.336	1.664	0.899			
	ATT_6	4.651	1.647	0.921			
	ATT_7	4.564	1.638	0.826			
Subjective norm	SN_1	4.527	1.566	0.674	0.926	0.679	0.926
	SN_2	4.708	1.499	0.739			
	SN_3	4.466	1.629	0.848			
	SN_4	3.946	1.630	0.781			
	SN_5	4.403	1.606	0.930			
	SN_6	4.413	1.629	0.938			
Perceived behavioral control	PBC_1	6.220	1.053	0.642	0.785	0.480	0.776
	PBC_2	5.923	1.099	0.813			
	PBC_3	5.507	1.441	0.654			
	PBC_4	6.180	1.028	0.646			
Continuance intention to use	CU_1	4.970	1.729	0.934	0.964	0.819	0.965
	CU_2	5.205	1.640	0.910			
	CU_3	5.377	1.538	0.870			
	CU_4	4.599	1.772	0.916			
	CU_5	4.532	1.778	0.902			
	CU_6	5.047	1.606	0.896			

Note: CR = Composite Reliability, AVE = Average Variance Extracted.

Table 4. Discriminant validity.

Construct	Interaction quality	Information quality	Attitude	Subjective norm	Perceived behavioral control	Continuance intention to use
Interaction quality	**0.760**	0.810	0.828	0.622	0.546	0.757
Information quality		**0.772**	0.796	0.574	0.614	0.745
Attitude			**0.860**	0.679	0.548	0.887
Subjective norm				**0.806**	0.469	0.731
Perceived behavioral control					**0.669**	0.617
Continuance intention to use						**0.900**

Note: The off-diagonal values in the above matrix are the square correlations between the latent constructs and diagonal are square root of AVE.

research on chatbot services, this study shed light on the continuance intention to use, a key success indicator for adopting and managing new technology services.

Second, the results of the present study theoretically close gaps in the literature on chatbot services by emphasizing two crucial performance criteria of chatbot services (interaction quality and information quality) in the context of digital commerce. In particular, this research shows the role of interaction quality and information quality given by chatbot services in influencing the users' behavioral response from the perspective of the TPB. The two antecedents that reflect communication quality are crucial for enhancing long-term customer-brand relationships (Chung et al. 2020). As a result, this broadens our understanding of how different types of quality perception continually influence consumers' intentions to use such services.

Table 5. Structural parameter estimates.

Hypothesis	Parameter estimate	Estimate	SE	t-value	*p*-value	Inference
H1(a) (+)	Interaction Quality→Attitude	0.924	0.139	6.665	***	Supported
H1(b) (+)	Interaction Quality→Subjective Norm	0.661	0.143	4.617	***	Supported
H1(c) (+)	Interaction Quality→Perceived Behavioral Control	0.138	0.096	1.438	0.151	Rejected
H2(a) (+)	Information Quality→Attitude	0.407	0.089	4.588	***	Supported
H2(b) (+)	Information Quality→Subjective Norm	0.171	0.095	1.803	*	Supported
H2(a) (+)	Information Quality→Perceived Behavioral Control	0.300	0.075	4.018	***	Supported
H3 (+)	Attitude→Continuance Intention to Use	0.796	0.060	13.319	***	Supported
H4 (+)	Subjective Norm→Continuance Intention to Use	0.357	0.059	6.028	***	Supported
H5 (+)	Perceived Behavioral Control→Continuance Intention to Use	0.377	0.095	3.954	***	Supported

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.
Model Fit: Chi-square = 1540.5, df = 517, $p < 0.001$, Chi-square/df = 2.980, IFI = 0.898, TLI = 0.882, CFI = 0.892, RMSEA = 0.081.

Third, this study explicitly examines the literature on the continued use of chatbot services in light of TPB and provides strengthen insights. Previous studies largely used Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) as their theoretical frameworks and looked into how instrumental beliefs like perceived usefulness and performance expectancy affected chatbot service adoption. However, this study demonstrates how favorable views of chatbot services, subjective norms that encourage chatbot usage, and perceived behavioral control over chatbot usage encourage consumers to continue. Applying TPB, which has not been extensively utilized in the context of chatbot service platforms, adds to the body of knowledge on AI-powered service marketing and supports the claims made by Ajzen (1991).

5.2. Managerial implications

This study's findings have managerial implications for chatbot service providers to better understand digital consumers. First, chatbot service providers can successfully manage their clients with a high level of attentive and responsive contact. In particular, managers and service providers ought to be familiar with the fundamental mechanisms of personalized chatbot service. Our study specifically adds useful knowledge to the understanding of the human-like touch in a chatbot service setting. For example, chatbots deliver high-quality communication, including courtesy, thoughtfulness, and individualized attention, and can help foster consumer fulfillment and assurance. This could encourage the continued use of chatbot services and foster favorable sentiments toward them, thereby strengthening customer relationships.

Second, another insight is the chatbot-based solution should provide prompt, high-quality help in its entirety. The continuous intention to use a chatbot service may reduce if it offers delayed or insufficient information, ignores users' inquiries, or interrupts the flow. In other words, businesses can positively influence customer perceptions of chatbot services in a good way and promote their ongoing use through information quality control. Our results may be useful in motivating consumers who are hesitant to utilize chatbot services due to discomfort and annoyance. Accordingly, service providers should exercise caution when creating chatbot systems.

Third, this study also offers insightful guidelines for managers who control the creation and marketing of chatbot services. Service providers should concentrate on using behavioral mechanism-related services that let customers access chatbot services while shopping rather than human agents based on control and monitoring functions in order to boost continuous usage. Additionally, service providers should collaborate with those who create operating systems and policymakers in order to create innovative and appealing services or to improve the simplicity of customer communications. For instance, providing systematic services given by behavioral bigdata-driven solutions when new e-commerce platforms are opened should also be examined.

5.3. Limitations and future research

Although the results of the current study have theoretical and practical implications, there are some limitations. First, the research model developed in this study relies on the classic theory, TPB which is a very powerful theory aggregated in a simplified manner for anticipating the continuous behavioral intentions of potential chatbot service users. The future research can the TBP and other antecedent elements can be combined to produce an insightful structure with a theoretical foundation for explaining chatbot services to explore additional consumer perceptions. This can open new future research on the adoption of new convergence services that look at users' intentions to use.

Second, participants may be biased considering the results and setting of our research. For instance, some participants may experience the case of choosing the service agents between chatbots and humans. This indicates that chatbots would not work as an only option but as a consumer's service choice. Moreover, there are various experiences of participants interacting with chatbots, such as asking simple inquiries, quickly reacting to customer complaints, making recommendations, and acknowledging them. Future studies should examine whether specific interactions and engagement styles are more successful in boosting consumer retention and satisfaction.

Lastly, the survey data included self-reports, susceptible to recall bias. This research mainly focuses on text-based chatbot services and recalling their previous experience. In the survey, a well-defined and detailed explanation of what text-based customer service chatbots are on e-commerce platforms, nevertheless, participants' experience in chatbot services might be different. Further investigations based on log, text, and voice data gathered from different types of behavioral information would offer insightful idea on content creation for chatbot services and customer relationship management.

Conflict of interest

The authors declare that there is no conflict of interest.

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