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Overcoming customer innovation resistance to the sustainable adoption of chatbot services: A community-enterprise perspective in Thailand

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A B S T R A C T

The primary goal of utilizing chatbots for customer service is to fulfill customer requests without requiring a conversation. However, the challenge to the sustainable adoption of innovations is overcoming the obstacles that prevent the innovation's spread. The current study examined factors including consumers' perceptions, barriers and perceived risks that influence consumers' intentions to continue utilizing chatbot services in community enterprise. Modeling integrates the innovation-decision process in Phase 1 (knowledge, persuasion, and decision) with the technology acceptance model (TAM), perceived convenience and information quality. We also consider technological anxiety and openness to experience as potential barriers to individual innovation. The research model was tested using partial least squares structural equation modeling (PLS-SEM) from 401 users with no more than 6 months of community-enterprise chatbot experience. Key findings that perceived privacy and time risk directly affected attitudes and intentions toward using chatbots. Moreover, technological anxiety is a barrier that affects attitudes toward chatbot usage, while perceived information quality indirectly influences users to use chatbots continually. However, there was no correlation between openness to experience and attitudes toward the continued use of chatbots. The finding indicates that experienced chatbot users are concerned with privacy and time constraints. This study contributes significantly to knowledge of the impediments to the diffusion of sustainable innovations among community-enterprise entrepreneurs.

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Introduction

Advances in information and communication technology have significantly affected lifestyles and business practices. In addition, consumer behaviors and expectations regarding goods and services are constantly changing. As a result, businesses must improve their services and communication to be more convenient and always available to the customer (Calvaresi et al., 2021; Popesku, 2019). Therefore, researchers and businesses have applied information and communication technology to facilitate online services and mobile applications in contexts such as hotel reservations, air ticket bookings, ordering food, product and service inquiries, travel advice, and other customer inquiries (Følstad & Taylor, 2021; Leung & Wen, 2020; Ukpabi et al., 2019; Um et al., 2020). Furthermore, these online services reduce the time required for customers to access services and increase the efficiency of organizations' resource management, thus enabling employees to do more work in other areas (Ceccarini & Prandi, 2019).

One of the most popular online services for doing business in the digital age is chatbots. Chatbots are computer programs that simulate human conversations using natural language to communicate and improve human-technology interactions (Behera et al., 2021; Calvaresi et al., 2021). Chatbots that communicate with users to facilitate real-time inquiries about products and services are gaining popularity Luo et al., 2019). Moreover, chatbots' simplicity and versatility mean that they can be used to support both end-users and businesses (Przegalinska et al., 2019). In addition, as a consequence of the COVID-19 epidemic, companies have been impacted by social isolation measures that limit their in-store services. In response, chatbots have been deployed to meet the needs of such businesses (McLean & Osei-Frimpong, 2019). Chatbots are being implemented in the hospitality and tourism sectors to assist in travel planning and customer support and provide advice to customers 24 h a day; these applications increase revenue opportunities and create a competitive advantage (Bowen & Morosan, 2018).

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As chatbots become more widespread, there has been a growing interest in user satisfaction and acceptability of chatbot usage and communication. Rese et al. (2020) explored the effects of retailers' adoption of chatbots on customer satisfaction. They found that factors related to the authenticity of the conversations and perceived usefulness (PU), as well as hedonic factors related to enjoyment, affected the adoption of chatbots. According to Pillai and Sivathanu (2020) and Behera et al. (2021)), perceived ease of use (PEOU), perceived usefulness (PU), perceived trust (PTRU), perceived intelligence, and anthropomorphism predict users' intentions to use chatbots for travel planning.

Factors affecting sustained intentions to use chatbots for customer service include satisfaction, perceived enjoyment, and perceived benefit. PEOU also predicts users' continued intentions to use chatbots. In a study applying the perspective of information system success to the use of chatbots, Ashfaq et al. (2020) found that information quality (IQ) and service quality (SQ) positively affect consumer satisfaction. This finding suggests that businesses interested in utilizing chatbots to support customer service should concentrate on improving their chatbots' PEOU, PU, and PTRU relative to team member communication. Indeed, these factors may increase user satisfaction and support the continued use of chatbots.

Although chatbots' capabilities are widely recognized in the business sector, there are concerns regarding their ability to solve specific problems compared to humans. Most studies have focused on designing effective chatbots, building trust, and creating positive user experiences (Følstad et al., 2018). However, few studies have examined the barriers to and limitations of chatbot acceptance. Rese et al. (2020) studied the adoption and use of "Emma" chatbots in Germany's online fashion retail sector and found that users were concerned about privacy and the technology's immaturity, which negatively affected their intentions and frequency of chatbot usage. Luo et al. (2019)reported that chatbots result in lower purchasing decisions and a perception of inattention to care for business owners' customers.

Additional limitations of chatbots have also been observed, such as their response times, lack of privacy, and customers' preference for human interaction over chatbots (Pillai & Sivathanu, 2020). Problematically, these restrictions may affect the future acceptance of chatbots. Especially for small and medium-sized enterprises to bring innovation to enhance customer service. This result could affect the sustainability of the customer's use of chatbots or other technologies.

However, describing user behavior toward and relationships with new technologies requires understanding the factors associated with adopting or rejecting technology. An individual's decision to accept a technology occurs through a process involving several steps: 1) knowledge, 2) persuasion, 3) decision, 4) implementation, and 5) confirmation (Rogers, 2010). The present study examines user perspectives to overcome innovation resistance to the sustainable adoption of chatbots for customer service in community enterprises. Previous research has not adequately explained the resistance of users to the use of chatbots in community-enterprise customer service. This study describes the factors that negatively affect the decision-making process regarding the continued adoption and use of chatbots following technological innovation. We intend to address the following research questions:

1) What factors in the knowledge process influence persuasion and individuals' attitudes toward accepting the continued use of chatbots for community-enterprise customer service?
2) What knowledge process factors influence individuals' acceptance of the continued use of chatbots for community-enterprise customer service?
3) Do individuals' attitudes from the persuasion process influence their acceptance of the continued use of chatbots?

In this article, Part 2 presents the literature review and theoretical background, and Part 3 presents the research model and hypotheses before the research methodology is presented in Part 4. The results of the study are described in Part 5, and Part 6 details the discussion and implications of the results. Finally, part 7 summarizes the conclusions of this research.

Theoretical background

Community enterprise

Sustainability in the agricultural sector has attracted significant attention because it is recognized that farmers will experience the impact of future economic changes; in particular, production costs are likely to increase, and urbanization will lead to changes in consumer behavior (Mojo et al., 2017; Petcho et al., 2019; Pingali et al., 2005). These developments profoundly impact farmers, especially smallholders in communities with limited funding. Therefore, various community members have formed to generate income and sustainable dependence among local communities. These groups are referred to as community enterprises (Peredo & Chrisman, 2006).

Community enterprises engage in various activities, such as manufacturing, the provision of services (e.g., community shops and tourism), and natural resource management. These activities aim to increase the value of locally available raw materials (for products) and inputs (for services) to meet consumer needs and add value to products (Petcho et al., 2019). In addition, these efforts generate a competitive advantage and new revenue streams from existing community resources.

In Thailand, the 1997 financial crisis led the Thai government to establish the concepts of a sufficiency economy and self-reliance as solutions to economic problems (Petcho et al., 2019). Community enterprises reflect these concepts by developing a grassroots economy that focuses on building community entrepreneurship while maximizing the community's capacity and role using existing local resources. This grassroots economy generates income in the community, increases employment rates, and enhances skill transfer and the production and sale of various products (Dzingirai, 2021; Tracey et al., 2005; Valeepitakdej & Wongsurawat, 2015). However, previous research has suggested that the development of effective agricultural enterprises requires a supportive environment, an entrepreneurial orientation, and agricultural sustainability to improve entrepreneurial performance (Bignotti et al., 2021).

However, concerns remain about the barriers to establishing community enterprises. These include a lack of organizational management experience, funding problems, inefficient packaging design, and low levels of entrepreneurial skill among farmers (Buratti et al., 2021; Sakolnakorn & Naipinit, 2013). Significantly, these obstacles may affect the long-term survival of community enterprises. In addition to entrepreneurs' knowledge of the natural and social environments, innovation capability is crucial to the development of sustainable products and services, according to previous research. (Aksoy, 2017; Patzelt & Shepherd, 2011; Senge et al., 2007). Therefore, the adoption of innovation to enhance the sustainable service efficiency of a business requires an understanding of the initial factors influencing users' acceptance decisions and the identification of obstacles that may cause users to resist innovation.

Diffusion of innovation theory (DOI)

As a result of increasing competition in the global market, businesses have begun to focus on preserving the value of their products and services to thrive in this highly competitive environment. Innovation has been confirmed as a key tool in companies' success and sustainable development (Sulistyo & Ayuni, 2020; Tóth et al., 2020).

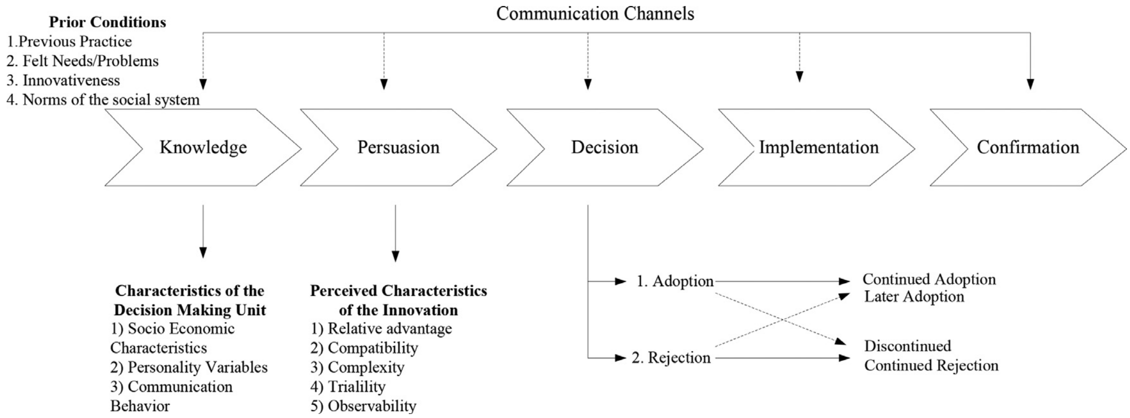

Fig. 1. The Innovation-Decision Process (Rogers, 2010).

Innovation can be defined as a product (method or device), process (adoption of new ideas, discoveries, and inventions), or result (significant measurable change)(Benson, 2019) .

Rogers (2010) explains that diffusion of innovation theory (DOI) consists of five steps in an innovative decision-making process (Fig. 1). 1) Knowledge involves personal understanding. The characteristics of the decision-making unit include socioeconomic characteristics, personality variables, and communication behavior. 2) Persuasion is when individuals display a favorable or unfavorable opinion toward innovation based on their own emotions and sentiments. 3) Decision is the step when a person must choose whether to reject or accept an innovation by considering the pros and cons before making a decision. 4) A person puts the innovation into practice during the implementation step. However, issues with innovation's usability or unique value can lead to resistance to innovation. 5) Finally, the user confirms that the innovation is a good choice during confirmation.

As illustrated in Fig. 1, Rogers (2010) explains that the perceived characteristics of innovation that affect implementation include 1) relative advantage, which is the extent to which the innovation is perceived as better than traditional methods; 2) compatibility, which is how consistent the innovation is perceived to be compared with past experiences (improving acceptance); 3) complexity, which refers to whether the innovation is perceived as easy to understand and use; 4) trialability, which refers to whether innovation can be tried on a limited basis; and 5) observability, which is the amount of benefit that users can gain from the innovation.

DOI has been widely used in medicine and business (Table 1). For example, previous research has applied the innovation-decision model to describe the process of disseminating innovative therapies for outpatients with alcohol-related disorders (Walitzer et al., 2015). The authors conducted three stages of research on the model: phase 1 measured knowledge, persuasion, and the decision-making process immediately after the publication of the invention. Phase 2 evaluated the progress of implementation one month following publication. Finally, Phase 3 assessed the confirmation process six months after publication. The results showed that clinicians' baseline characteristics (i.e., gender, education, caseload, beliefs, and behavioral therapeutic style) predicted variables related to the knowledge, persuasion, and implementation stages (Walitzer et al., 2015). In another study, DOI was used to examine the perceptions of individuals who accepted or rejected a patient portal. The portal was viewed as having a relative advantage compared to traditional methods for accessing health information (Emani et al., 2018).

With regard to business applications, DOI was used to determine the characteristics related to innovation adoption and its impact on the efficiency of Malaysian manufacturing in small and medium-sized enterprises (SMEs); the authors of this study found that persuasion, strategic orientation, and firm antecedents had significant effects on innovation adoption and SME performance (Al Mamun, 2018). Nikou (2019) also adopted DOI as a conceptual framework to explain individuals' intentions toward using innovative home technologies. The results showed that compatibility, PU, and PEOU affected smart-home technology adoption. In addition, innovation characteristics affect innovative products' perceived trustworthiness and benefit (Ju & Lee, 2020).

Table 1 provides an overview of previous studies of the factors that affect the decision to adopt innovative applications in many businesses, such as the automotive industry (Chu et al., 2019; Yuen et al., 2021), renewable energy industry, retail sector (Roy et al., 2018; Tabrizian, 2019), and information technology sector (Al-Rahmi et al., 2021; Min et al., 2019; Nguyen et al., 2021). Most studies have applied DOI and TAM to assess innovation acceptance; these frameworks will advance the understanding of user behavior and lead to future improvements and innovations. However, previous studies have focused solely on explaining consumer behavior toward technology adoption among innovators.

Moreover, most studies on chatbot innovation have focused on banking, tourism and hospitality, e-retailing, and the workplace Lei et al., 2021; Meyer von Wolff et al., 2021). In contrast, chatbots are not extensively utilized in community enterprises. Additionally, previous studies have focused solely on the factors that affect the process of chatbot adoption, while no studies have examined the factors that contribute to the sustainability of continued chatbot use. This research addresses a gap in the literature by concentrating on the obstacles and hazards associated with chatbot usage. Furthermore, it examines the factors' correlation through a decision-making process by which a user decides whether to accept an innovation based on the user's experience.

Research model and hypotheses

Rogers (2010) presented an innovative decision-making process that involves five steps before individuals accept or reject innovation: 1) knowledge, 2) persuasion, 3) decision, 4) implementation, and 5) confirmation. Steps 1–3 involve personal thoughts and feelings. In steps 4 and 5, the individual accepts and adheres to an innovative approach or method, confirming that the innovation is a good choice for the individual. In addition, Rogers (2010) categorizes people according to their openness to innovations or new technologies: 1) innovators, 2) early adopters, 3) early majority, 4) late majority, and 5) laggards.

This study aims to consider the innovation decision-making process in Phase 1, during which users' perspectives immediately after the innovation's publication are evaluated based on their understanding and perception (Walitzer et al., 2015). This study differs from

Table 1
Overview of studies on the decision to adopt new innovations.

Authors, Year	Innovation	Sample	Theories	Input Factors	Output Factors	Barriers Factor
Min et al. (2019)	Uber mobile application	220 college students	Diffusion of Innovation Theory (DOI) and technology acceptance model (TAM)	Relative advantage, compatibility, complexity, observability, social influence, perceived usefulness, and perceived ease of use	Consumer attitudes and adoption intentions	–
Yuen et al. (2021)	Autonomous vehicles (AVs)	274 users in the Midwest of the United States	DOI and TAM	Perceived usefulness (PU), perceived ease of use (PEOU), and perceived characteristics of innovation (PCIS)	Users' behavioral intention to use AVs	–
Chu et al. (2019)	Electric vehicle (EV)	204 Chinese EV users and 177 Korean EV users	Psychological factors and usage satisfaction	Psychological (functional, symbolic, and experiential motives) and behavioral factors	EV adoption and satisfaction	Environmental concern
Al-Rahmi et al. (2021)	Massive open online courses (MOOCs) system	148 students using the MOOCs system in Malaysia	DOI and TAM	Relative advantages, complexity, trialability, observability, compatibility, and perceived enjoyment	Students' behavioral intentions to use MOOCs	–
Gruenhagen and Parker (2020)	Mining industry	27 articles (systematic literature review)	DOI	Drivers, barriers, and stakeholders involved	Mapping the evidence base, synthesizing knowledge, and providing guidance	Investment costs and lack of financial resources
Tabrizian (2019)	Renewable energy industry	Review of electricity market literature	Economic theory perspective	Renewable energy development and slow diffusion	Market failure	Lack of infrastructures
Roy et al. (2018)	Retail sector	361 consumers in Australia	TAM, system characteristics, technology readiness, and store reputation	Perceived technology readiness, perceived ease of use, perceived usefulness, superior functionality, perceived adaptiveness, and store reputation	Customer acceptance of and resistance to smart technologies	Absence of technology readiness, system characteristics of superior functionality and adaptiveness
Nguyen et al. (2021)	Banks' chatbot services	359 users of real banks' chatbot services in Vietnam	Information systems success (ISS) model and the expectation confirmation model (ECM)	Satisfaction, trust, and perceived usefulness, information quality, system quality, service quality, and confirmation of expectations	Users' continuance intentions toward chatbot services	–
(Li et al., 2021)	Online travel agencies	295 users of Chinese online travel agencies (OTAs)	Extended post-acceptance model	Understandability, reliability, assurance, interactivity, technology anxiety, chatbot quality dimensions, and satisfaction	Continuously use chatbot services	–

previous research in that we present our opinions from the perspective of innovators who are likely to develop into early adopters to understand consumers' behavior better. The result of this study will lead to the adoption of sustainable innovations. Below, we describe three decision-making processes utilized by innovators.

Process 1, knowledge: The analysis focuses on personality variables related to the user's knowledge and cognitive response to the chatbot after it has been used. It is divided into two main sections. Part 1 includes the barriers of individual innovation due to technological anxiety and openness to experience. Part 2 covers perceived risk, which is the personal belief and understanding of uncertainty in a situation and its effect on behavioral decisions (Kim et al., 2008). The study will focus on perceived privacy and time risks as common concerns in adopting new technologies (Ischen et al., 2019; Rese et al., 2020). The difference between the present study and previous research is that we present users' opinions from the perspective of individuals with actual chatbot experience.

Process 2, persuasion: The analysis focuses on the perceived characteristics of the chatbots after implementation, which is related to personal attitudes and feelings. Rogers (2010) describes the influence of innovation characteristics on adoption, including 1) relative advantage, 2) compatibility, 3) complexity, 4) trialability, and 5) observability. Therefore, this study focused on attitudes toward the continued use of chatbots, perceived usefulness, perceived ease of use, perceived convenience, and perceived information quality.

Process 3, decision: The analysis focuses on explaining factors that affect the intent to continue using chatbots. We present the perspectives of community-enterprise customer service chatbot users with previous experience; the proposed conceptual model is presented in Fig. 2.

Consumers' perceptions of chatbot adoption

Chatbots are a technology used to facilitate the connection between customers and businesses, and they are currently used to support services in various fields (Ashfaq et al., 2020). TAM has been widely used to describe user behavior and better understand users' perceptions and acceptance of chatbots. TAM relates to technologies' PEOU and PU, which influence the attitudes and actions of technology adopters (Davis, 1989). Previous research has applied TAM to describe user adoption behavior for new technologies, and recently, TAM has been used to describe chatbot behavior (Nikou, 2019; Sharma, 2019). Past studies have found that PEOU and PU can predict intentions regarding the continued future use of chatbots in the tourism industry. This result indicates that users decide to accept new technologies after realizing that they are easy to use, effortless to learn, and beneficial. However, most previous studies have focused on using chatbots in the tourism industry (Behera et al., 2021; Pillai & Sivathanu, 2020; Rese et al., 2020). Therefore, to understand the continued adoption of chatbots for community-enterprise customer service, we use TAM to formulate the following hypotheses:

H1: PU positively influences the attitude toward the continued (ATT) use of chatbots for community-enterprise customer service.
H2: PEOU positively influences ATT use of chatbots for community-enterprise customer service.

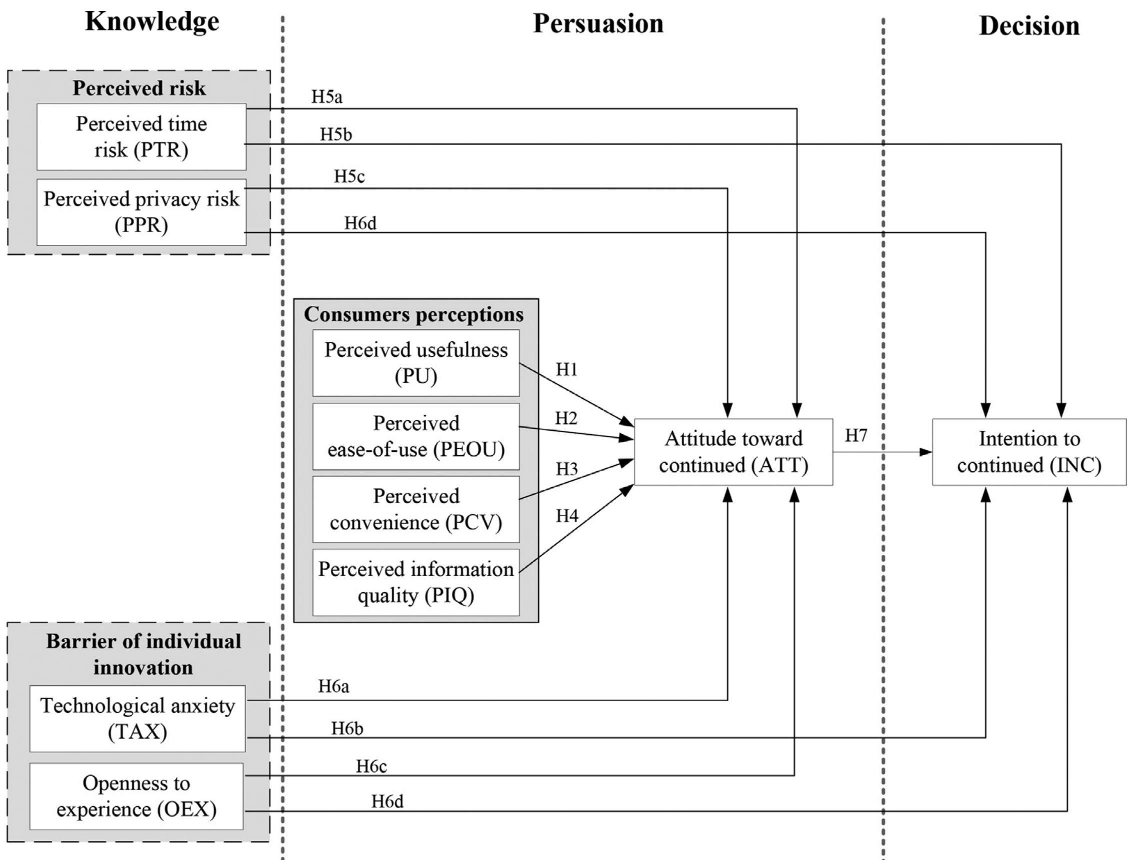

Fig. 2. Proposed conceptual model for deciding on continued adoption of chatbots.

The ongoing COVID-19 pandemic has significantly impacted the global economy because consumers have had to change their behavior to avoid in-person services (Noy & Shields, 2019). Consumers are now less likely to visit supermarkets and more likely to shop in stores close to their homes (Szymkowiak et al., 2021). Therefore, retail stores must implement marketing strategies to target and support consumer behavior in the current situation. Digital content marketing (DCM) is one of the most common marketing tactics for influencing customer behavior (Castro et al., 2017). In the case of using DCM to purchase travel products or services, consumer intentions and behaviors are strongly influenced by their perceptions of enjoyment and convenience (Mathew & Soliman, 2021). Similarly, the present study examines the association between perceived convenience (PCV) and attitudes toward the continued adoption of chatbots for community-enterprise customer service. We propose the following hypothesis:

H3: PCV positively influences ATT use of chatbots for community-enterprise customer service.

Customers can use chatbots to receive information from service providers 24 h a day, improving the service quality. Consumers have a better customer experience when they perceive high-quality information (Behera et al., 2021). However, if a chatbot fails to provide the correct information at the right time, this can lead to bad user experiences that result in downtime (Trivedi, 2019). These findings suggest that service providers should prioritize data quality, as creating higher-quality data provides users with better customer-service experiences with chatbots. Therefore, we examine the relationship between perceived information quality (PIQ) and attitudes toward continued use in customers who previously received data from community-enterprise customer-service chatbots. We present the following hypothesis:

H4: PIQ positively influences ATT use of chatbots for community-enterprise customer service.

Technology risk perceptions

Consumer resistance to digital innovations is an issue of concern for companies, as consumer reluctance to use innovative technologies can cause such innovations to fail (Ju & Lee, 2020; Talwar et al., 2020). Indeed, consumer resistance has led to many innovation failures (Heidenreich & Kraemer, 2016). Therefore, consumer resistance is an important issue that organizations must address. In particular, organizations should increase consumer confidence by reducing barriers to resistance innovation. Examining the reasons for consumers' reluctance is one method of achieving this objective.

In the early stages of technology adoption, users may be concerned about the integrity of the technology. This concern may negatively affect their attitudes toward technology. Perceived risk refers to an individual's beliefs about the insecurity of a situation, which can negatively affect the individual's behavioral decisions (Kim et al., 2008). In a study of mobile travel bookings, Park and Tussyadiah (2017) divided risk perception into seven categories: time risk, financial risk, performance risk, privacy and security risk, psychological risk, physical risk, and device risk. The concept of perceived risk has been applied to describe consumer behavior concerning community enterprises using e-commerce websites, and it has been observed that perceived security risk plays a key role in building customer trust in using these websites (Jattamart et al., 2019).

As for the chatbot platform, users are exposed to increased privacy concerns from product or service advisory activities that require personal data collection (Ischen et al., 2019). A study of the perceived risks associated with chatbots and applications found that perceived privacy risk (PPR) negatively affects the intention and frequency of chatbot use; this data privacy concern arises because some platforms and applications collect and access users' personal information, such as personal data and geolocations (Aloudat et al., 2014; Rese et al., 2020). In addition, chatbot latency was found to be another limitation affecting chatbot adoption (Pillai & Sivathanu, 2020). As a result, users may consider chatbots more time-consuming than human conversations.

In light of these studies, we hypothesize that after a customer has used a chatbot for customer service, they may become aware of the risks that chatbots pose. In particular, PPR and perceived time risks (PTR) are predominant concerns about adopting new technologies. Therefore, attitudes and intentions toward the continued use of chatbots for customer service in community enterprises may be related to the levels of perceived privacy and time risks. Accordingly, we formulated the following hypotheses:

H5a: PTR positively influences ATT use of chatbots for community-enterprise customer service.
H5b: PTR positively influences the intention to continue (INC) using chatbots for community-enterprise customer service.
H5c: PPR positively influences ATT use of chatbots for community-enterprise customer service.
H5d: PPR positively influences INC using chatbots for community-enterprise customer service.

Barriers related to individual innovation characteristics

Technological anxiety (TAX) is a personal trait of fear and anxiety regarding new technologies being discovered to influence the adoption of new technologies (Lam et al., 2008; Mani & Chouk, 2018; Venkatesh, 2000). A previous study examined TAX with self-service technology (SST) and identified a direct negative effect of TAX on intentions to use SST (Gelbrich & Sattler, 2014). This result contradicts previous studies on user acceptance of mobile-based money, which argued that TAX played no role in acceptance in this case. In contrast, the authors argued that users might view mobile-based money as easy to use, thus reducing TAX (Gbongli et al., 2019).

From the health perspective, some studies have examined the relationship between TAX and intentions toward telehealth and mobile health (mHealth). Indeed, studies have found that technological concerns represent a significant obstacle that deters users from using new technologies. However, raising awareness of new technologies' benefits can mitigate this barrier (Hoque & Sorwar, 2017; Tsai et al., 2019). Therefore, we aim to explain the relationship between TAX and acceptance of the continued use of chatbots for community-enterprise customer service with users who have experience with chatbots.

H6a: TAX positively influences ATT use of chatbots for community-enterprise customer service.
H6b: TAX positively influences INC using chatbots for community-enterprise customer service.

Previous studies have suggested that consumers prefer human conversations over chatbots (Pillai & Sivathanu, 2020). However, some studies argue that consumers prefer chatbots with conversational styles that possess human-like characteristics (Araujo, 2018). Furthermore, anthropomorphizing chatbots enhances interaction efficiency with consumers because human-like chatbots show warmth and competence, improving consumers' experiences and influencing their decisions toward products and their intentions to engage in chatbot commerce (Han, 2021; Roy & Naidoo, 2021).

In addition to the nature of technology, personality traits are important factors that affect human behavior in different situations. Famously, the Five-Factor Model ("Big Five") describes a person's personality traits, including extraversion (e.g., experiencing enthusiasm and other positive emotions), agreeableness (e.g., honesty, decency, and trustworthiness), conscientiousness (e.g., planning and persistence), neuroticism (e.g., experiencing negative feelings) and openness to experience (OEX) (e.g., self-awareness and individualism/nonconformity) (McCrae & Costa Jr, 2008). Furthermore, previous research has found that OEX influences innovation at the individual level (Ali, 2019), especially in the cases of innovation capability (Hsieh et al., 2011) and innovation performance (Weele, 2013). However, these results were reported in studies conducted when innovations were first introduced. Therefore, further investigation is necessary to understand the continued adoption of chatbots for community-enterprise customer service. Based on this, the following hypothesis is proposed:

H6c: OEX positively influences ATT use of chatbots for community-enterprise customer service.
H6d: OEX positively influences INC using chatbots for community-enterprise customer service.

Attitude is a concept that describes a person's intentions to behave in specific ways in various contexts (Davis, 1989; Fishbein, 1967; Jattamart & Leelasantitham, 2019). Previous studies have examined intentions related to technology adoption, such as their relationship with user attitudes toward e-banking and attitudes toward using a smartphone chatbot for shopping. It was found that users' attitudes play an essential role in their satisfaction with chatbots (Ahmad et al., 2020; Kasilingam, 2020). Indeed, when a chatbot can meet the customer's basic needs, this condition leads the customer to have a positive attitude, increased satisfaction, and increased intention to use the chatbot. However, if users are dissatisfied with chatbot conversations or using the technology, this can significantly reduce their intentions to use chatbots. Therefore, we propose the following hypothesis:

H7: ATT chatbots positively influence INC using chatbots for community-enterprise customer service.

Methodology

Sampling and data collection

The study design conducted a cross-sectional survey between August and October of 2021. Using a purposive sampling method, we recruited customers with no more than 6 months of experience using chatbots for community-enterprise customer service in Prachuap Khiri Khan Province, Thailand. In accordance with the human research ethics procedure, we selected the research participants and conducted the online questionnaire. Data collection began with submitting an online questionnaire after the customer had used the customer-service chatbot. Next, the research objectives and measures were explained to the participants. We maintained the participants' information confidentiality and provided online contact information for the researcher and research assistant in case respondents had any questions, thereby reducing bias and building trust in the researchers (Ball, 2019; Evans & Mathur, 2018). The respondents voluntarily decided whether to participate, and they could confirm their participation and answer the online questionnaire in the following menu. The respondents could withdraw their participation in the study at any time. Furthermore, the data from the questionnaire were destroyed after the results had been analyzed.

Table 2
Measurement items of the questionnaire.

Construct	Items	Survey Item	References
Perceived usefulness (PU)	PU1	Using chatbots improves the shopping experience of community enterprises.	Adapted from Mathew and Soliman (2021); Phaosathianphan and Leelasantitham (2021)
	PU2	Using chatbots saves time in inquiries into community enterprises' product information.	
	PU3	Using chatbots increases the channels to connect with community enterprises.	
	PU4	Overall, the use of chatbots benefits the customer service of community enterprises.	
Perceived ease of use (PEOU)	PEOU1	Using chatbots makes it easy to get information about community-enterprise products and services.	Adapted from Mathew and Soliman (2021); Petcharat and Leelasantitham (2021)
	PEOU2	Using chatbots makes it easy to decide to buy products from community enterprises.	
	PEOU3	Using chatbots to inquire about the products and services of community enterprises does not require much mental effort.	
	PEOU4	Overall, using chatbots connects me with community enterprises.	
Perceived convenience (PCV)	PCV1	I can inquire about community-enterprise products and services at any time via chatbot.	Adapted from Pillai and Sivathanu (2020); Rese et al. (2020)
	PCV2	I can inquire about the products and services of community enterprises anywhere via chatbot.	
	PCV3	Using chatbots is a convenient way for me to inquire about the products and services of community enterprises.	
Perceived information quality (PIQ)	PIQ1	The information obtained from the chatbot is reliable.	Adapted from Ashfaq et al. (2020))
	PIQ2	The information obtained from the chatbot is up-to-date.	
	PIQ3	The information obtained from the chatbot is accurate.	
	PIQ4	I get information from chatbots on time.	
Perceived time risk (PTR)	PTR1	I acknowledge that chatbot conversations take more time to make inquiries than conversations with humans.	Adapted from Jattamart and Leelasantitham (2020); Pillai and Sivathanu (2020)
	PTR2	I acknowledge that chatbot conversations are more time-consuming than conversations with humans.	
	PTR3	Time risks are an essential part of my next chatbot decision.	
Perceived privacy risk (PPR)	PPR1	I think chatbot conversations can cause personal information to be published.	Adapted from Jattamart and Leelasantitham (2020); Rese et al. (2020)
	PPR2	I think chatbot conversations may have collected my personal information.	
	PPR3	I recognize that disclosing personal information through chatbots is a risk.	
	PPR4	I recognize that disclosing personal information through chatbots can have a negative impact on me.	
	PPR5	Privacy risks are an essential part of my next chatbot decision.	
Technological anxiety (TAX)	TAX1	I may encounter problems when using a chatbot to ask questions about community-enterprise products and services in the future.	Adapted from Pillai and Sivathanu (2020)
	TAX2	I am afraid to use chatbots because I feel like I will make mistakes and will not be able to fix them.	
Openness to experience (OEX)	OEX1	I do not frequently scan the environment for new technologies.	Adapted from Mazzucchelli et al., and Fontana (2019)
	OEX2	I do not like thoroughly observing technological trends.	
	OEX 3	I do not like regularly approaching external institutions to acquire technological knowledge.	
Attitude toward continued (ATT)	ATT1	It is good to continue using chatbots to inquire about community-enterprise products and services.	Adapted from Mathew and Soliman (2021)
	ATT2	Chatbots are essential for me to inquire about future community-enterprise products and services.	
	ATT3	Getting information about community products and services through chatbots is a good idea for buying products from community enterprises.	
	ATT4	Overall, I like to use chatbots for customer service.	
Intention concerning continued use (INC)	INC1	I intend to continue using chatbots for inquiries about the products and services of community enterprises.	Adapted from Mathew and Soliman (2021)
	INC2	I intend to continue to use chatbots as a way to connect with community enterprises.	
	INC3	I intend to advise friends to use chatbots for inquiries about community-enterprise products and services.	
	INC4	Overall, I intend to continue using chatbots.	

Measurement instrument

The questionnaire was designed according to the innovation-decision process and TAM concepts. Questions were divided into two sections: general information about the respondents (e.g., gender, age) and factors related to their perceptions of chatbots. These chatbot-related factors were 1) user perception factors, including perceived usefulness, perceived ease of use, perceived convenience, and perceived information quality; 2) perceived risk factors, including perceived time privacy risk; 3) barrier factors, including technological anxiety and openness to experience; 4) attitude toward the continuous use of chatbots; and 5) intentions to accept the continued use of chatbots. The responses to the questionnaire were evaluated using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), as shown in Table 2.

Data analysis

We assessed the causal relationships of the relevant factors using a partial least squares structural equation model (PLS-SEM), which is conducted through a variance-based SEM test. SmartPLS 3.3.3 was used to assess both measurement and structural model (Ringle et al., 2015). PLS-SEM has been confirmed to predict factors related to individuals' behavior toward technology effectively. For example, this method was used in a study of online customer behavior in response to the use of artificial intelligence (AI) chatbots in e-retailing (Chen et al., 2021), a study of customer behavior related to AI chatbots in hospitality and tourism (Pillai & Sivathanu, 2020), a study of customer intentions toward electronic word-of-mouth (e-WOM) communication on e-commerce websites, and a study investigating victimization from social media use and its effect on health behaviors (Jattamart & Kwangsawad, 2021). In addition, PLS-SEM can analyze the results of measurement and structural models simultaneously, and it can provide results regarding content and classification accuracy using composite reliability statistics (CR) and average variance extracted (AVE) (Puengwattanapong & Leelasantitham, 2022) (Sukma & Leelasantitham, 2022). Based on these capabilities, PLS-SEM was the most appropriate model for this study.

Results

Descriptive statistics

We received 407 survey responses; 401 surveys were fully completed. Table 3 shows the demographic characteristics of the sample. Most of the respondents were female (54.6%), aged 20–25 (57.4%), preferred using facebook messenger as a messaging platform (66.6%),

Table 3
Demographic characteristics of the participants.

Characteristics	Number (*N* = 401)	Percentage
Gender		
Female	182	45.4
Male	219	54.6
Age		
Less than 20 olds or less	55	13.7
20–25	230	57.4
26–30	59	14.7
31–35	24	6.0
36–40	15	3.7
41–45	12	3.0
46–50	6	1.5
Average amount of time per day spent communicating through facebook messenger.		
Less than 1 h	57	14.2
1–2 h	100	24.9
3–4 h	80	20.0
More than 4 h	164	40.9

and spent more than 4 h per day communicating through the facebook messenger (40.9%).

Measurement model

To evaluate the measurement model, Convergent Validity was calculated in accordance with the criteria of Hair Hair et al., and Sarstedt (2021) using CR, cronbach's α, and AVE. The CR, Cronbach's α, and AVE were all higher than the threshold values, indicating the reliability of the questionnaire items. Discriminant validity was tested using cross-loading measurements to determine the question items' reliability; the results determining the weight value of all variables were above the thresholds (Table 4). Moreover, we examined the relationship between the variables in a diagonal matrix (Fornell & Larcker, 1981), which identifies the square roots of AVE for each construct (bold letters were greater than the values in the corresponding horizontal and vertical rows). This method showed that the tool has a reasonable level of discriminant validity, as demonstrated in Table 5.

Structural model

We validated the model's conformance to the data before assessing the significance of the structural model's path coefficients. (Hair et al., 2021; Henseler et al., 2016). To confirm the reliability and correctness of the measurement of the (outer) model, we conducted a goodness-of-fit (GOF) assessment to lead to a valid assessment of the structural (inner) model (Soh et al., 2017).

Table 6 shows that the GOF for the Henseler et al. (2016) acceptable-criterion model is the root mean square residual (SRMR) of the acceptance criterion, which must be less than 0.08; our result was 0.045. This result conforms to the findings of Hu and Bentler (1999), who suggested that the cut-off value of 0.08 is suitable for PLS path modeling for new-technology research. Therefore, the HI95 SRMR value of 0.045 corresponds to the suitability criteria of the goodness of model. Additionally, we used the blindfolding method to evaluate the Stone–Geisser Q^2, which indicated the results that passed the threshold of values greater than 0 (Q^2 of Attitude toward continued use = 0.590; Q^2 of Intention concerning continued use = 0.687). This shows that these constructs have predictive relevance in the model and were evaluated as standardized. Taken together, the results of this analysis demonstrate a good model fit.

Table 4
Internal consistency, reliability and convergent validity of the measurement model.

Construct	Items	Loading(> 0.70)	CR(> 0.70)	Cronbach's α (> 0.70)	AVE(> 0.50)
Perceived usefulness (PU)	PU1	0.903	0.947	0.925	0.816
	PU2	0.904			
	PU3	0.906			
	PU4	0.900			
Perceived ease-of-use (PEOU)	PEOU1	0.916	0.941	0.917	0.801
	PEOU2	0.872			
	PEOU3	0.931			
	PEOU4	0.858			
Perceived convenience (PCV)	PCV1	0.842	0.890	0.816	0.730
	PCV2	0.865			
	PCV3	0.857			
Perceived information quality (PIQ)	PIQ1	0.923	0.951	0.931	0.828
	PIQ2	0.900			
	PIQ3	0.908			
	PIQ4	0.908			
Perceived time risk (PTR)	PTR1	0.947	0.967	0.949	0.907
	PTR2	0.953			
	PTR3	0.957			
Perceived privacy risk (PPR)	PPR1	0.800	0.900	0.861	0.643
	PPR2	0.750			
	PPR3	0.791			
	PPR4	0.842			
	PPR5	0.823			
Technological anxiety (TAX)	TAX1	0.957	0.953	0.901	0.910
	TAX2	0.951			
Openness to Experience (OEX)	OEX1	0.868	0.906	0.847	0.762
	OEX2	0.875			
	OEX3	0.876			
Attitude toward continued (ATT)	ATT1	0.913	0.954	0.936	0.839
	ATT2	0.907			
	ATT3	0.932			
	ATT4	0.913			
Intention to continued (INC)	INC1	0.918	0.961	0.946	0.861
	INC2	0.933			
	INC3	0.933			
	INC4	0.927			

Table 5
Fornell–Larcker criterion analysis.

Construct	PU	PEOU	PCV	PIQ	PTR	PPR	TAX	OEX	AT	INT
PU	**0.903**									
PEOU	0.866	**0.895**								
PCV	0.588	0.647	**0.855**							
PIQ	0.779	0.852	0.653	**0.910**						
PTR	0.676	0.684	0.538	0.757	**0.952**					
PPR	0.618	0.635	0.514	0.707	0.775	**0.802**				
TAX	0.643	0.665	0.486	0.682	0.853	0.699	**0.954**			
OEX	0.257	0.259	0.266	0.236	0.259	0.216	0.179	**0.873**		
AT	0.708	0.751	0.558	0.782	0.693	0.690	0.735	0.211	**0.916**	
INT	0.699	0.765	0.576	0.788	0.683	0.691	0.725	0.191	0.890	**0.928**

Note: PU = Perceived usefulness, PEOU = Perceived ease-of-use, PCV = Perceived convenience, PIQ = Perceived information quality, PTR = Perceived time risk, PPR = Perceived privacy risk, TAX = Technological anxiety, OEX = Openness to Experience, ATT = Attitude toward continued, INC = Intention to continued.

Table 6
Goodness of model fit (saturated model).

PLS goodness-of-fit indices	Value	HI95
SRMR	0.045	0.047
dULS	1.351	1.502
dG	1.193	1.211

After checking for conformity, the structural model was tested. We randomly resampled the data with the bootstrap method with 5000 entries to increase confidence in the correlation analysis between the constructs (Hair et al., 2021). Moreover, we assessed multicollinearity with the variance inflation factor (VIF), which showed that the causal variables were not correlated beyond the threshold of 5.0 (Grewal et al., 2004). In the next step, we identified the path coefficients with p-values and t-values meeting the following criteria: t-value higher than 1.96 (significance level = 5%), 2.58 (significance level = 1%), and 3.29 (significance level = 0.1%). The results indicate that H4 should be accepted, as PIQ significantly influenced ATT (β = 0.355, t = 4.461, p < .001). H5a should be accepted because PTR significantly influenced ATT (β = 0.209, t = 2.267, p < .05). For H5c, PPR significantly influenced ATT (β = 0.179, t = 3.186, p < .01); for H5d, PPR significantly influenced INC (β = 0.110, t = 2.333, p < .05); and for H6a, TAX significantly influenced ATT (β = 0.399, t = 4.573 p < .001). Finally, for H7, ATT significantly influenced INC (β = 0.770, t = 16.333, p < .001). The results are presented in Table 7 and Fig. 3.

Discussion and implications

This is the first study to investigate overcoming consumer innovation resistance in accepting the continued use of chatbots for community-enterprise customer service. The model was developed using diffusion innovation theory, which explains the decision-making process for accepting innovations in terms of three processes: 1) knowledge, 2) persuasion, and 3) decision. Additionally, we adopted the innovation-decision process as a conceptual framework describing education to assess the perspectives of users who have previous experience using chatbots for customer service.

The results will improve the operations of community enterprises by implementing innovative technology for sustainable services. Individuals in communities have collectively established community enterprises. However, these enterprises may lack experienced managers (Buratti et al., 2021). Problematically, these issues can cause operational barriers that affect the sustainability of community enterprises. Therefore, adopting innovative technologies may reduce organizational management constraints, thus allowing community enterprises to operate sustainably in highly competitive environments.

Theoretical implications

Knowledge process: The first objective of this study is to explicate the influence of factors involved in the knowledge process on attitudes toward continued acceptance of chatbots for community-enterprise customer service. We found that PTR and PPR negatively

Table 7
Hypothesis testing.

Hypotheses	Relationship	β	p-value	t- value	VIF	Supported
H1	PU -> ATT	0.085	0.214	1.243	4.271	Not supported
H2	PEOU -> ATT	0.124	0.139	1.478	4.197	Not supported
H3	PCV -> ATT	0.021	0.655	0.448	1.883	Not supported
H4	PIQ -> ATT	0.355	0.000***	4.461	4.000	Supported
H5a	PTR -> ATT	0.209	0.023*	2.267	3.389	Supported
H5b	PTR -> INC	0.065	0.209	1.257	2.807	Not supported
H5c	PPR -> ATT	0.179	0.001**	3.186	2.772	Supported
H5d	PPR -> INC	0.110	0.020*	2.333	2.823	Supported
H6a	TAX -> ATT	0.399	0.000***	4.573	1.920	Supported
H6b	TAX -> INC	0.115	0.122	1.548	2.333	Not supported
H6c	OEX -> ATT	0.005	0.869	0.164	1.102	Not supported
H6d	OEX -> INC	−0.007	0.775	0.286	1.066	Not supported
H7	ATT -> INC	0.770	0.000***	16.333	2.524	Supported

Note: * = p < .05, ** = p < .01, *** = p < .001, β = Path Coefficients, PU = Perceived usefulness, PEOU = Perceived ease-of-use, PCV = Perceived convenience, PIQ = Perceived information quality, PTR = Perceived time risk, PPR = Perceived privacy risk, TAX = Technological anxiety, OEX = Openness to Experience, ATT = Attitude toward continued and INC = Intention to continued.

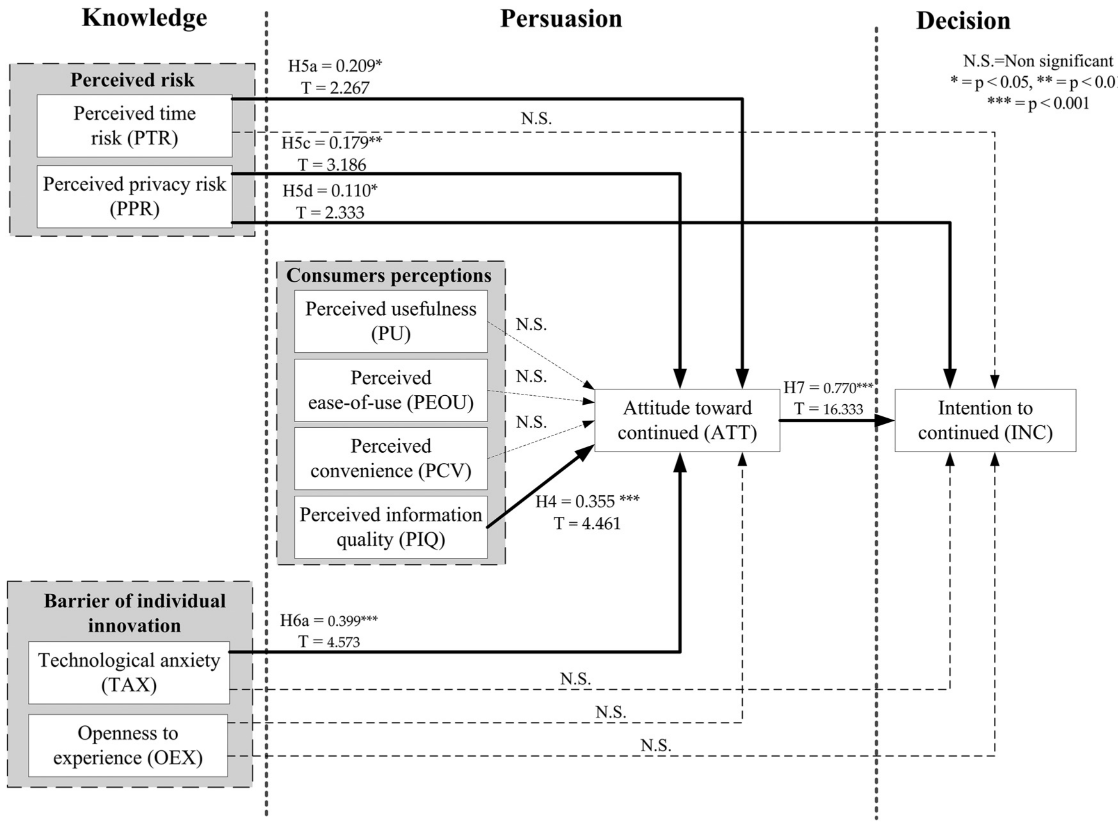

Fig. 3. Results of hypothesis testing.

ATT use of chatbots, consistent with past studies (Aloudat et al., 2014; Pillai & Sivathanu, 2020; Rese et al., 2020). Based on these results, we argue that users of community-enterprise customer-service chatbots remain concerned that their data may be collected and accessed during the conversation. Furthermore, as they may also be unconvinced that chatbots can meet their needs more quickly than human conversations, concerns about the timing can also affect their attitudes. These issues could lead users to discontinue chatbot service usage.

We also found that a significant barrier to the continued adoption of chatbots was TAX, which is known to be a key psychological factor influencing the adoption of new technologies (Mani & Chouk, 2018). However, technologies' ease of use and benefit to users can reduce TAX (Gbongli et al., 2019; Tsai et al., 2019). Therefore, enterprises should raise awareness that chatbots can provide information and services at any time of day, and developers should design chatbots with user-friendly interfaces to encourage users to continue using chatbots. In addition, the results of this study found no relationship between OEX and attitudes and willingness to accept the continued use of chatbots. While OEX positively influences the adoption of innovations, it may not affect users who have experience in innovation.

Persuasion process: The second objective of this study focuses on the influence of knowledge-process factors on the decision to accept the continued use of chatbots for community-enterprise customer service. We identified a novel correlation: PPR directly influenced decisions to accept the continued use of chatbots. As a result of using chatbots, some platforms have access to users' data (Aloudat et al., 2014). As users become aware that chatbots are collecting their personal information based on their past experiences, the effect of PPR on their decisions to accept chatbots will grow.

The relationship analysis indicated that PIQ positively affected ATT chatbot adoption. This result is consistent with previous studies reporting that perceptions of the quality of data from chatbots play a key role in creating positive customer experiences (Behera et al., 2021). It has been shown that the high perceived information quality increases the positivity of customers' perceptions of chatbot conversations. Therefore, to encourage the continued use of chatbots, it is necessary to ensure that the information received from chatbots and human conversations is of the same perceived quality. In addition, the PU, PEOU, and PCV factors conflict with past studies, which have reported that these are important factors for predicting intentions regarding continued chatbot use for service employees and banks (Ashfaq et al., 2020; Nguyen et al., 2021).

However, we suggest that because the participants had previous experience using chatbots for customer service, they may have been aware of the processes and benefits of chatbot conversations. Since it takes time to understand and learn new things, these factors may not be significant once customers have already used chatbots. Conversely, attention should be given to PU, PEOU, and PCV when customers have not yet experienced the chatbot service.

Decision process: The third objective of this study focuses on the attitudes from the persuasion process that acceptance of the continued use of chatbots. We found that persuasion attitudes were the strongest predictor of the continued acceptance of chatbot use. Therefore, users' positive attitudes toward chatbots affect their intentions to continue using chatbots. However, if users believe chatbots are incapable of meeting their service requirements, this perception could significantly reduce their future intent to use chatbots. This finding is consistent with previous research, which suggests that understanding user attitudes toward using technology is necessary to increase consumer confidence and reduce barriers to innovation (Ahmad et al., 2020; Kasilingam, 2020).

Practical implications

A key strength of this study is that it describes the factors that affect the decision-making process regarding the continued use of chatbots for community-enterprise customer service. The practical implications of this study's results will greatly benefit organizations seeking to adopt innovative chatbots for customer service. First, in terms of knowledge, customers should be assured that the information obtained from chatbots is the same quality as information obtained from conversations with humans. Indeed, information quality contributes to positive attitudes toward the continued use of chatbots. Additionally, service providers should clarify their data storage procedures during conversations to ensure that users can access their data. Developers should also design chatbots to have user-friendly interfaces to alleviate customers' technology concerns, thus reducing their avoidance of the technology.

In terms of persuasion, chatbots should provide timely, human-like interactions and create new experiences using community-enterprise services beyond in-store purchases. Moreover, customers' positive attitudes and confidence in using chatbots can support continued adoption in terms of decisions. In turn, this may allow the management of community enterprises to solve the issue of insufficient personnel in customer service. Nevertheless, the problem of the lack of technological expertise in community enterprises should not be ignored. Therefore, we suggest that local government agencies and educational institutions initiate innovation or technology development academic service projects. These projects could increase the value of community enterprises' products and services and provide them with knowledge about marketing and customer service techniques. This will increase the sustainability of the community enterprises' operations, allowing them to survive despite increasing competition.

Second, in addition to presenting the factors that play an essential role in the sustainable use of chatbots, we present a different user perspective on how to overcome resistance to chatbots among innovators. This approach allows us to understand users' behaviors who are likely to become early adopters. Moreover, it presents a different perspective from previous research since groups socially accept early adopters for innovation adoption. Early adopters seek advantages and are a group of people whose opinions influence the opinions of others. However, the ultimate decision to adopt a new technology rests on carefully considering the data and the benefits of using that innovation (Rogers, 2010).

The study found that overcoming the first innovators' resistance to chatbots to become early adopters requires a focus on promoting positive attitudes among those using a chatbot service. This is because users expect the best and most beneficial customer-service experience. For example, Chatbots can provide real-time information in response to inquiries outside regular business hours and display frequently asked questions (FAQs) (Behera et al., 2021). We also discovered that chatbots could reduce the likelihood of service provider-customer conflicts. Likewise, the chatbot will always inquire and react respectfully even if the client uses unpleasant language and will be able to provide answers in a language that the user can readily comprehend. Therefore, service providers should focus on designing chatbots' commands and learning rules to provide users with excellent service.

We also suggest that service providers continue to develop chatbots that can answer very complex questions. This is important because users expect to receive high-quality information from chatbots even when they ask complex questions. However, if a chatbot presents low-quality information and does not meet users' needs, it can cause users to waste time reading unnecessary and unhelpful messages. This will leave a more negative impression about using chatbots and cause users to avoid using them, possibly affecting the sustainability of the business and brand when the customer engages in word-of-mouth communication online.

Finally, the study examines groups of innovator users who have accepted and used chatbots in the past. These groups continue to express concerns regarding the continued use of chatbots in the future. We found that, of the personal barriers, technological anxiety remains an important psychological factor in the development of early adopters. Previous research has shown that technological anxiety is a key psychological factor affecting new technologies' adoption (Mani & Chouk, 2018). Nevertheless, our research demonstrates that TAX also affects attitudes and willingness to adopt sustainable innovations, even if they are not new technologies, as evidenced by a sample of users with chatbot experience. This finding may suggest that users remain concerned about using chatbots when service providers constantly modify the chat design to suit the situation. Sometimes, service providers may be overly focused on reducing customer service work and forget to create a good experience for users; providers must also consider that PEOU will reduce technological anxiety (Gbongli et al., 2019).

Therefore, to reduce the TAX that chatbots cause, service providers should ensure that chatbot conversations are as succinct and straightforward to comprehend as possible. Moreover, providers should avoid including suboptimal and complex options. Providers will promote a positive attitude toward sustainable use by making users aware of the ease and utility of interacting with chatbots.

Concerns about the privacy and timing risks associated with chatbots also arise for experienced chatbot users. Users are aware that using a chatbot service creates a high risk that chat data and other personal details may be collected and stored to improve the service in accordance with the behavior of the chatbot. Users can become dissatisfied as a result of these concerns. After careful consideration, users may perceive more disadvantages than advantages of using a chatbot leading to a negative attitude. This dynamic is an obstacle to the development of early adopters of innovations because such users influence others' thoughts, which may have a widespread impact on the continued use of chatbot services.

Therefore, service providers must clarify data storage procedures during the conversation to ensure access to personal data, explaining the benefits that users will receive from analyzing the data following the behavior of individual users. To address this issue, chatbot operators should continue to focus on developing requirements and giving users confidence. The results of a sample trial may be presented to show users the back-end process of collecting data for behavioral analysis. This presentation could also explain service options, such as the benefits users will receive from granting access to their data while utilizing the chatbot service.

Limitations and future research

There were some limitations of this study that should be mentioned. First, the sample comprised only customers who had used community-enterprise chatbot services in Prachuap Khiri Khan province, Thailand. As a result, the sample lacked demographic and geographical diversity. Second, cross-sectional studies only provide explanations of behavior over the short term. Third, the survey was conducted using a self-assessment questionnaire that measured the participants' experience using chatbots. However, some of the information collected by this survey method may be inaccurate because some subjects may be confused about past situations or unable to recall the information accurately.

Finally, as this study only examines the facebook chatbot platform, the results cannot explain user behavior on other chatbot platforms. Therefore, future research should evaluate chatbot use across each chatbot platform and utilize diverse samples from other geographic regions to comprehend user behavior variation better. Moreover, future research should explore technological anxiety in more detail. This is because chatbot-induced technological anxiety is a complex psychological factor that can be interpreted in various ways, including dialog design (e.g., complex choices, difficult-to-understand dialog, and excessively long sentences for display), conversation screen design (e.g., using the keypad instead of typing, choosing the keypad to suit the content, or enter typing). The results will help operators better understand users' concerns about various issues.

Conclusion

This research has presented an in-depth study of the innovation-decision process for overcoming innovation resistance to the sustainable adoption of chatbots for community-enterprise customer service. This study proposes a model that integrates the conceptual framework of the innovation-decision process, TAM, and perceived risk theory (PPR and PTR). Our findings indicate that PIQ positively affected ATT use of chatbots, while PPR and PTR negatively affected ATT chatbot acceptance. Furthermore, TAX is a barrier that consistently affects attitudes toward accepting chatbots. Finally, the PPR and ATT acceptance directly affect the INC utilizing chatbots.

Declaration of Competing Interest

The authors declare no conflicts of interest.

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