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"I Am Here to Assist Your Tourism": Predicting Continuance Intention to Use AI-based Chatbots for Tourism. Does Gender Really Matter?

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ABSTRACT

AI-based chatbot, a typical product of human–computer interaction (HCI), is widely employed by tourism service providers. However, there is a lack of research on the determinants that explain why customers continuously use chatbots for tourism. Based on the Unified Theory of Adoption and Use of Technology 2 (UTAUT2), the Theory of Perceived Risk (TPR), anthropomorphism, and personalization, this research developed an integrated model to investigate the determinants behind customers' continuance intention to use chatbots for tourism. In addition, the moderating role of gender differences in the relationships between determinants and continuance intention was tested. The analysis based on a sample of 613 users highlighted the positive effects of performance expectancy, social influence, habit, anthropomorphism, and personalization. However, the findings showed that time risk and privacy risk have negative influences. Although the moderating test did find two differences due to gender, many other relationships showed no differences between male and female.

1. Introduction

Conversational user interface (CUI), an alternative form of human–computer interaction (HCI), has rapidly become a key user interface across many products, such as automobiles, home devices, and computers (McDonnell & Baxter, 2019). As a type of CUI, AI-based chatbot plays increasingly important role in human-centered AI technology (W. Xu et al., 2022). Commonly, AI-based chatbot is defined as a computer program that interacts with users using voice methods or natural language text (Pillai & Sivathanu, 2020). An AI-based chatbot is designed to offer services or service-related information through the interaction with users (Aoki, 2020). The earlier versions of chatbots were simple response robots, whereas the development of machine learning and intelligent algorithms make the current chatbots more sophisticated and capable, improving the user experience of HCI (Rajan & Saffiotti, 2017).

AI-based chatbots become a game-changer for tourism industry due to their competitive advantages, such as 24/7 customer support, automatic services, and cost reduction (Sheehan, 2018; Van Doorn et al., 2017). Currently, AI-based chatbots are increasingly used by travel agencies, airline companies, and hotels for interaction with people in various frontline services, such as bookings, customer support, and recommendations (Li et al., 2021). According to Ghosh and Chakravarty (2018), over 42% airports are deciding to use AI-based chatbots to provide services. In China, one of the leading countries of chatbot-enabled applications, major travel agencies have widely utilized AI-based chatbots to better meet customers' demands (Li et al., 2021).

Although AI-based chatbots are increasingly implemented in tourism industry, there are two obvious research gaps in existing studies concerning the usage of these chatbots. First, the existing studies on the adoption of chatbots for tourism have predominantly relied on technology acceptance theories, such as the Technology Acceptance Model (TAM) and the Unified Theory of Adoption and Use of Technology 2 (UTAUT2). However, technology acceptance theories cannot comprehensively explain the use of chatbots because these theories only focus on the technological features but ignore other determinants (Zhu, Wang, & Pu, 2022). In most cases, chatbots for tourism are implemented to achieve business goals. Thus, it is necessary to employ a research theory in the business or psychological field to deeply explore the determinants behind users' continuance intention.

Second, to date, there is a paucity of work testing the moderating role of gender in the adoption of chatbots for tourism. Such a research gap may become an obstacle to system design and personalized marketing strategies. According to McDonnell and Baxter (2019), the awareness of gender dimension in AI-based service delivery is rising. Thus, it is necessary to test whether users' perceptions of chatbots for tourism are homogenous across genders.

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Moreover, research findings of gender effect on HCI technology acceptance are inconsistent. Some studies suggested the significance of gender differences (Lin & Yeh, 2019; McDonnell & Baxter, 2019; Nguyen et al., 2019), whereas others found little or no gender differences (Long & Tefertiller, 2020; Zhu, Wang, Zeng, et al., 2022). Thus, theoretically speaking, this research on chatbots for tourism can enhance the existing literature regarding the role of gender difference in HCI technology acceptance.

To fill in the research gaps above, this research developed two objectives. First, the Theory of Perceived Risk (TPR) was employed in this study. This theory has been extensively used in the business and psychological field (Choe et al., 2021; Zhu, Wang, Zeng, et al., 2022), but has rarely been used to predict continuance intention to adopt chatbots. This study constructed a new integrated model in the context of chatbot use via contextualization and integration of UTAUT2, TPR, and additional antecedents (anthropomorphism and personalization). Based on this integrated model, we seek to identify the potential predictors for the use of chatbots for tourism. Second, this research attempts to examine the moderating role of gender differences in the integrated model.

2. Theoretical background

2.1. Gender differences in HCI

In the field of gender studies, many theories emphasize the differences between men and women when deciding to use a service. For example, the Selectivity Hypothesis Theory (SHT) focuses on gender differences in information processing strategies (Meyers-Levy & Maheswaran, 1991). This theory states that there are biological differences between men and women, in turn leading to different information processing strategies when evaluating a service (Kim et al., 2007). According to SHT, men prefer to concentrate on overall message schemas, while women tend to engage in comprehensive and itemized assessment of all available information (Zhu, Wang, Zeng, et al., 2022). Meanwhile, women are more visually oriented than men when analyzing data about a product or service (Meyers-Levy, 1988). In addition, women tend to collect more data before making a plan, whereas men do not assimilate all available information (Ramkissoon & Nunkoo, 2012).

The Gender Motivational Theory (GMT) is another influential theory in the area of gender studies. It is founded on the Sexual Selection Theory and the Social Role Theory (Winstok & Weinberg, 2018). According to GMT, two basic social motives are grounded in gender: status enhancement characterizes male and risk reduction characterizes female (Winstok & Straus, 2011). These social motives promote different behaviors when male and female choose a service (Winstok et al., 2017). Compared to childhood and adolescence, GMT is more significant for adult age (Winstok & Weinberg, 2018).

Recently, gender has received a considerable amount of interest in HCI literature, especially those research on HCI technology acceptance. It is believed that HCI information management, HCI system design, and personalized marketing strategies can benefit greatly from a perspective of gender differences (Lin & Yeh, 2019). Thus, a growing number of studies tested the moderating role of gender differences in HCI technology acceptance. To list a few, Nguyen et al. (2019) investigated the differences across genders when using voice-user interface. The findings showed that perceived ease of use has greater impact on behavioral intention of men. According to the research by Lin and Yeh (2019), the effect of perceived playfulness on behavioral intention was only found in women when people interact with virtual reality (VR)-supported technology for mental rotation learning. In addition, the research by McDonnell and Baxter (2019) revealed that men tend to feel higher level of satisfaction when interacting with chatbots. However, there is a lack of research on the effect of gender differences when people interact with chatbots for tourism.

2.2. HCI and AI-based chatbots for tourism

AI will be at the heart of HCI technology and industry in the near future (Harper, 2019). Recently, an alternative form of HCI has gained traction known as CUI. It allows users to interact with computer systems via spoken dialogue or text for information access (McDonnell & Baxter, 2019). Along with the emergence of CUI, considerable attention has been given to making HCI more natural and humanlike (Lee et al., 2020). As a type of CUI, AI-based chatbots become increasingly popular in a variety of domains, such as task management (Aoki, 2020), mental healthcare (Zhu, Janssen, et al., 2022), and banking (Hari et al., 2022). An AI-based chatbot usually uses natural language processing, machine learning, and other AI technologies. Commonly, the interaction between users and chatbots is triggered by users' inputs, such as wake-up call and inquiry (McTear et al., 2016). The contextual awareness technologies allow chatbots to wait until the systems receive a message before taking the turn (Pearl, 2016).

Chatbots' growing popularity has changed the patterns of HCI and transformed how business is conducted (Chaves & Gerosa, 2021; Hari et al., 2022). Tourism industry the one that benefits greatly from the implementation of AI-based chatbots (FlowXO, 2020; Li et al., 2021). These chatbots are employed for travel planning, ticket booking, emergency support, and travel recommendations (Pillai & Sivathanu, 2020). They help services providers in tourism industry for 24/7 customer support, efficiency improvement, cost reduction, more revenue chances, and time saving (Sheehan, 2018). Over 80% customers in tourism industry use web services for their demands, while there are around 70% of web service users in finance and retail industries (Dubrova, 2020; Milenkovic, 2020). Thus, compared to finance and retail industries, customers in tourism industry have more opportunities to interact with AI-based chatbots.

With the development of chatbot services in tourism industry, a growing number of research has focused on this field. To list a few, based on TAM, Pillai and Sivathanu (2020) found that people's intention to use chatbots for tourism are positively influenced by perceived usefulness. Li et al. (2021) demonstrated that user satisfaction is greatly related to customers' continuance intention to use chatbots for tourism in China. Although more and more academicians have concentrated on AI-based chatbots for tourism, the empirical-based conceptual research on users' continuance intention to use these chatbots has rarely been made.

2.3. Unified theory of adoption and use of technology 2

On the basis of review of earlier technology acceptance research, Venkatesh et al. (2003) introduced UTAUT. This model was formulated by evaluating eight competing models: TAM, the Theory of Reasoned Action, the Theory of Planned Behavior (TPB), the Combined model of TAM and TPB, the Motivational Model, the Model of Personal Computer Utilization, the Social Cognitive Theory, and the Innovation Diffusion Theory (Baptista & Oliveira, 2017). According to UTAUT, four constructs directly drive technology acceptance behavior: performance expectancy, effort expectancy, social influence, and facilitating condition (Raman & Don, 2013). Moreover, age, gender, experience, and voluntariness are the moderators identified in UTAUT to make this model different from the other acceptance models (Goh et al., 2016). The explanatory power of UTAUT can explain around 70% of the variance in behavioral intention, exceeding many other research models (Ramírez-Correa et al., 2019).

Since its inception, UTAUT has been widely used to explain the use of technology in organizational context (Herrero et al., 2017). However, this model has to be revised and expanded to explain the adoption of technology in individual context (Cabrera-Sánchez et al., 2021). Thus, UTAUT2 was formulated by Venkatesh et al. (2012). The new model evolved to seven constructs, the new factors include hedonic motivation, price value, and habit.

According to UTAUT2, performance expectancy and effort expectancy are two determinants factors behind users' behavioral intention (Tak & Panwar, 2017).

Influenced by TAM, Venkatesh et al. (2012) included performance expectancy in place of perceived usefulness and effort expectancy in place of perceived ease of use. Specifically, performance expectancy refers to the degree to which adopting a technology will help people in performing activities (X. Xu, 2014). Effort expectancy describes the degree of ease connected with the adoption of technology (Arenas Gaitán et al., 2015).

Social influence is defined as the degree to which a person perceives that others believe they need use a technology (Ramírez-Correa et al., 2019). This construct is composed of three factors: subjective norm, social factors, and image (Akinnuwesi et al., 2022). The effect of social influence on technology acceptance is moderated by gender, age, experience, and voluntariness (Cabrera-Sánchez et al., 2021). Facilitating condition describes the degree to which a person believes that the existence of technical facilitates can support the adoption of technology (Raman & Don, 2013). The variables defined to moderate the influence of facilitating condition are age and experience (Venkatesh et al., 2003).

Hedonic motivation is defined as the degree to which a person feels pleasure when this person adopts a technology (Baptista & Oliveira, 2017). According to Cabrera-Sánchez et al. (2021), pleasure-oriented features are often embedded into a technology to increase user engagement and usage. Habit is another factor that is considered important to the adoption of technology. It refers to the degree to which a person tends to use a technology automatically and repeatedly (Kwateng et al., 2019). Price value is defined as a person's cognitive trade-off between the perceived benefits and the monetary cost for using it (Melián-González et al., 2021). The perceived benefits that promote price value include quality, ubiquity, and convenience (Cabrera-Sánchez et al., 2021).

This research employed UTAUT2 to examine the adoption of AI-based chatbots for tourism. Following the research on chatbot usage by Melián-González et al. (2021), this study excluded facilitating conditions and price value. Because this study focuses on customers' continuance intention, the target respondents should be those who with user experience of chatbot services and without difficulty of facilitating conditions. Thus, facilitating conditions were excluded. Meanwhile, the factor of price value assumes that customers must pay for the technology (Melián-González et al., 2021). However, this is not the case for chatbots in tourism industry because most of chatbot services are free of charge. Therefore, price value was excluded.

2.4. Theory of perceived risk

Perceived risk refers to the feeling of uncertainty about the possible loss when people use a product or service (Featherman & Pavlou, 2003). According to TPR, perceived risk often makes individuals less likely to use a product or service (Choe et al., 2021). Thus, this concept can be considered as an important element in predicting customer decision behavior (Choi et al., 2013). As many studies have suggested, perceived risk is multidimensional and situation specific, which means perceived risk consists of different facets and each facet is formed based on the particular usage situation (Choe et al., 2021; Zhu, Wang, Zeng, et al., 2022).

Although tourism industry can benefit greatly from the use of AI-based chatbots (Li et al., 2021), there is a growing concern and anxiety among customers about this new technology of HCI (Pillai & Sivathanu, 2020). First, customers may worry about the possibility of time loss when they interact with chatbots for tourism. According to Aldás-Manzano et al. (2009), when using a new technology, customers must invest time and effort into obtaining information. Also, they have to spend time in learning the new operating methods. Some customers may consider these processes to be too time wasting, and thus continue to use traditional services to save time. Second, customers may perceive privacy concerns around chatbots for tourism. Privacy has become one of most important factors in HCI technology (Ravich, 2015). In tourism industry, customers may suspect that chatbots are used by tourism companies and hotels for illegal purposes, which in return makes them anxious that their private information might be exposed to others. Thus, in this research, perceived risk is comprised of time risk and privacy risk.

2.5. Anthropomorphism and personalization

Anthropomorphism, which refers to the perceived level of humanlike characteristics for non-human objects (Liu & Tao, 2022), is employed in various areas, such as healthcare, business, and computer science (Cheng et al., 2022). Recently, anthropomorphism has become a key feature of HCI technology, especially AI-based technology. According to Cowan et al. (2015), anthropomorphism is a process of giving humanity to a non-human objects. In order to develop an efficient system that is more easily adapted to social interaction, more and more AI-based products are equipped with anthropomorphism (Huang et al., 2021).

Owing to the fundamental role of anthropomorphism in HCI, there is growing number of research concentrating on the relationship between anthropomorphism and acceptance intention. However, previous studies have yielded mixed results. Some have found positive association (Melián-González et al., 2021; Pillai & Sivathanu, 2020; Roy & Naidoo, 2021), while others have not (Lu et al., 2019; Pelau et al., 2021). The well-known Uncanny Valley Theory (UVT) explains the relationship between the human likeness of non-human objects and the corresponding affinity of humans toward them (Mori et al., 2012). According to UVT, robots with anthropomorphic features can elicit a feeling of sympathy, in turn increasing users' positive attitudes (Mori et al., 2012). However, when the appearance of a robot almost perfectly resembles that of a human, people's emotional response to the robot immediately becomes negative (Liu & Tao, 2022). This may be because robots with perfect humanlike features can pose a threat to users' human identity (Lu et al., 2019). Thus, UVT offers support to the concept of attitudinal ambivalence to some extent. Accordingly, those non-human objects with high level of anthropomorphism may attract negative assessment from people, in turn causing the rejection of non-human objects (Huang et al., 2021).

Personalization refers to the delivery of products or services according to a customer's characteristics and needs (Xiao & Benbasat, 2007). In today's market, customers have become more sophisticated than ever before, they look for personalized experiences rather than "one-sizes-fits-all" services (Lim et al., 2021). Thus, personalization becomes a significant function of AI-based chatbots. Based on data mining technologies, personalization allows AI-based chatbots to accurately identify users' demands and provide services accordingly. As a result, customers may consider chatbots as useful and thus have greater motivation to continuously use them. Thus, personalization is considered in this research to understand customers' continuous intention while interacting with chatbots for tourism.

3. Hypotheses development and research model

Generally, customers have greater motivation to accept and adopt a technology if they perceive that this technology is beneficial (Cabrera-Sánchez et al., 2021). According to previous studies, performance expectancy was one of the predictors of behavioral intention to adopt a HCI technology (Trapero et al., 2020). In particular, in their research to investigate the acceptance of chatbots for tourism, Melián-González et al. (2021) found that performance expectancy has great impact on customers' continuance intention. Therefore, the following hypothesis is formulated:

Hypothesis 1 (H1): Performance expectancy is positively related to customers' continuance intention to use chatbots for tourism.

It is believed that a person's intention to use a HCI technology is not only influenced by how much this technology is beneficial but also by how much this technology is ease to use (Cabrera-Sánchez et al., 2021; Casey & Wilson-Evered, 2012). The relationship between effort expectancy and continuance intention is well established in many fields, such as online banking (Alalwan et al., 2017), digital learning (Ho et al., 2010), and mobile services (E. Park & Kim, 2014). In the context of chatbots for tourism, prior studies found that customers tend to use chatbots less if they think chatbots are complex (Melián-González et al., 2021). Based on the above arguments, we hypothesize that:

Hypothesis 2 (H2): Effort expectancy is positively related to customers' continuance intention to use chatbots for tourism.

In modern society, the interactions both between and among individuals and communities have increased tremendously, which in return creates a social atmosphere that influences behavioral intention to use a HCI technology (Cabrera-Sánchez et al., 2021). This social atmosphere is always created by those people surrounding a person, including family, friends, colleagues, etc. In other words, the recommendations and information offered by people surrounding a person could play a significant role in this person's behavioral intention (Alalwan et al., 2016). The selection of social influence as a predictor of the continuance intention was built on many previous studies (Kol et al., 2021; Wang et al., 2020). In the context of chatbots for tourism, Trapero et al. (2020) found that the relationship between social influence and the use of chatbots is positive. Hence, this research postulates the following hypothesis:

Hypothesis 3 (H3): Social influence is positively related to customers' continuance intention to use chatbots for tourism.

According to Venkatesh et al. (2012), the concept of hedonic motivation contains different hedonic features, such as fun, happiness, playfulness, enjoyment, and joy. Cabrera-Sánchez et al. (2021) believe that the purpose of embedding hedonic features into HCI products is to encourage people's continuance intention. Prior studies in the fields of online games (X. Xu, 2014) and touristic geolocation (Gupta et al., 2018) have proved that hedonic motivation is a key antecedent of the continuance intention to use a technology. Thus, the following hypothesis is formulated:

Hypothesis 4 (H4): Hedonic motivation is positively related to customers' continuance intention to use chatbots for tourism.

Venkatesh et al. (2012) believed that habit results from previous experiences and can influence people's continuance intention to use a technology. Over the HCI literature, it has been argued that that habit could play a significant role in encouraging people's intention to adopt a technology (Merhi et al., 2019; Morosan & DeFranco, 2016). Melián-González et al. (2021) found that habit has positive impact on customers' intention to use chatbots in tourism industry. Thus, we hypothesize that:

Hypothesis 5 (H5): Habit is positively related to customers' continuance intention to use chatbots for tourism.

Trying a technology involves risks, as all behaviors have uncertain consequences (Yang et al., 2016). Time risk refers to the risk that a person will waste time and efforts when using a technology (S. Park & Tussyadiah, 2017). Previous studies in the areas of drone delivery services (Choe et al., 2021) and ride-hailing services (Ma et al., 2019) have demonstrated a negative relationship between time risk and customers' continuance intention. As to tourism industry, the research by S. Park and Tussyadiah (2017) found that the more time risk people perceive in mobile travel booking, the less likely they will book. Privacy risk refers to the potential loss of control over one's privacy information (Chiu et al., 2014). As mentioned by prior studies (Siau & Shen, 2003; Thakur & Srivastava, 2014), privacy risk is the key factor devoting to customers' continuance intention. In the context of chatbots for tourism, customers may believe that their personal information is exposed to others when they interact with chatbots. As a result, they may refuse to continuously adopt chatbots. Based on the arguments above, we hypothesize that:

Hypothesis 6 (H6): Time risk is negatively related to customers' continuance intention to use chatbots for tourism.

Hypothesis 7 (H7): Privacy risk is negatively related to customers' continuance intention to use chatbots for tourism.

Anthropomorphism has been debated and discussed throughout the history of the field of HCI. Previous research on the relationship between anthropomorphism and acceptance intention has yielded mixed findings. For example, Roy and Naidoo (2021) found that growing perceived humanness of chatbots lead to more effective human–chatbot interaction. Pillai and Sivathanu (2020) revealed that higher level of anthropomorphism is positively related to people's continuance intention to use chatbots. A recent study by Melián-González et al. (2021) indicated that anthropomorphic features significantly influence consumers' acceptance of chatbots for tourism. However, Lu et al. (2019) found that people's intention to use AI-based robot in a hotel is negatively influenced by anthropomorphic characteristics. Moreover, Pelau et al. (2021) indicated that humanlike characteristics exert insignificant effect on users' acceptance of AI-based devices. According to Liu and Tao (2022), although prior research has reported mix results, anthropomorphism has largely been found to positively influence acceptance intention. When people interact with chatbots for tourism, anthropomorphic features of chatbots may elicit more significant feelings of sympathy and ultimately increase continuance intention. Thus, we expect a positive anthropomorphism-behavioral intention relationship in this research.

The development of machine learning, data mining, and other AI-based technologies make personalization become a significant advantage of chatbots. Based on the analysis of customers' characteristics and interests, personalization allows chatbots to more accurately provide services for customers (Shi et al., 2020). According to previous studies, users tend to use a personalized HCI service because it can meet their individualized demands (Komiak & Benbasat, 2006; Liu & Tao, 2022; Zhu, Janssen, et al., 2022). For example, Zhu, Janssen, et al. (2022) reported that people's perceived personalization has positive impact on their adoption intention of mental health chatbots. The research by Liu and Tao (2022) found that users' perceived personalization is greatly related to their behavioral intention of smart health services. Thus, we hypothesize that:

Hypothesis 8 (H8): Anthropomorphism is positively related to customers' continuance intention to use chatbots for tourism.

Hypothesis 9 (H9): Personalization is positively related to customers' continuance intention to use chatbots for tourism.

A large body of literature in HCI technology acceptance, such as VR-supported learning systems (Lin & Yeh, 2019) and voice-user interface (Nguyen et al., 2019), has taken into account the role of gender differences. However, explicit research that addresses gender differences in the context of chatbots for tourism remains underexplored. According to previous studies, men tend to more care about their privacy when they use HCI services (Nguyen et al., 2019). Women are willing to spend more time in learning a new technology (Arroyo et al., 2013). In addition, the study by Kwateng et al. (2019) found that men tend to be influenced by performance expectancy, whereas women tend to be stimulated by effort expectancy when they decide to use HCI service. Moreover, it can be suggested that when customers use HCI services, men tend to be greater influenced by hedonic motivation (McDonnell & Baxter, 2019), while women tend to be more motivated by social influence (Zhu, Wang, Zeng, et al., 2022). Shao et al. (2021) found that compared to male, female will have stronger adoption intention when a service is anthropomorphized. Additionally, women will be more sensitive to cue changes in the environment and pay attention to such changes that in return weaken the influence of habit on their intention to use HCI services (Kwateng et al., 2019). Furthermore, a personalized HCI service can greater influence women's attitudes

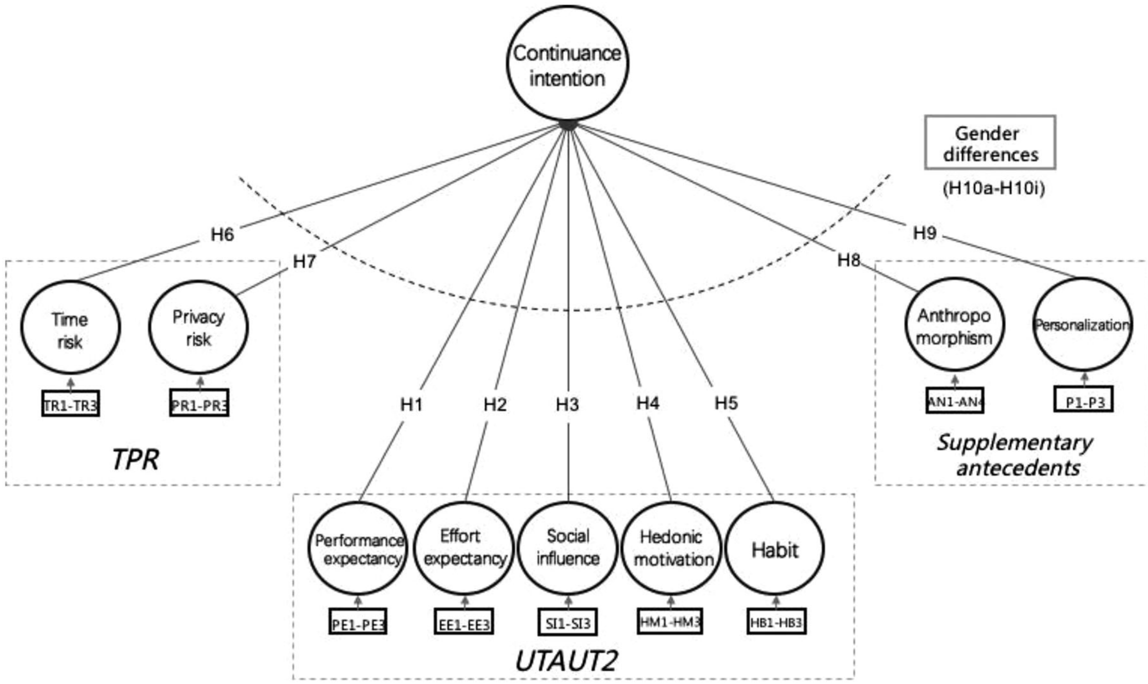

Figure 1. Research model.

(Rodríguez-Ardura & Meseguer-Artola, 2021). Therefore, we hypothesize that:

Hypothesis 10a (H10a): The relationship between performance expectancy and continuance intention is stronger among male.

Hypothesis 10b (H10b): The relationship between effort expectancy and continuance intention is stronger among female.

Hypothesis 10c (H10c): The relationship between social influence and continuance intention is stronger among female.

Hypothesis 10d (H10d): The relationship between hedonic motivation and continuance intention is stronger among male.

Hypothesis 10e (H10e): The relationship between habit and continuance intention is stronger among male.

Hypothesis 10f (H10f): The relationship between time risk and continuance intention is stronger among male.

Hypothesis 10g (H10g): The relationship between privacy risk and continuance intention is stronger among male.

Hypothesis 10h (H10h): The relationship between anthropomorphism and continuance intention is stronger among female.

Hypothesis 10i (H10i): The relationship between personalization and continuance intention is stronger among female.

The research model is shown in Figure 1.

4. Research method

4.1. Data collection

In this research, the tourism industry in China was selected. According to Li et al. (2021), the annual growth rate of the market in China is 27%, much more than the US's growth rate over 2017. Two online tourism platforms in China were chosen as our research sites: Ctrip.com and Qunar.com. These platforms dominate the online tourism market in China. Moreover, these platforms are major chatbot service providers in the Chinese tourism market, a large number of customers have user experiences with their chatbot services (Li et al., 2021). Therefore, the reliability and relevancy of this research can be ensured.

Ctrip.com and Qunar.com provide their chatbot services through both websites and mobile apps. When customers log on to these tourism platforms, they can clearly see the option of chatbot services in the homepage. If customers click the icon of chatbot services, the system will jump to another page and begin the chatbot services by using a chatbot profile image. Figure 2 illustrates the typical conversation between a customer and a chatbot. Specifically, a chatbot system starts the services by sending a welcome message and offering different kinds of options to a customer. After customer inputs questions via voice, more detailed information about these questions are provided by chatbot to guide the customer, such as how to get refund a ticket and how to purchase a student ticket. In order to better guide customers, chatbots usually use both letters and pictures.

Research data was collected online from June to August 2021. The So Jump survey platform (http://www.sojump.com) was chosen to distribute online questionnaires. This platform is one of the largest professional questionnaire

Figure 2. A typical conversation between a customer and a chatbot.

platforms in China and it has been employed by previous research to investigate customers' continuance intention to use chatbots for tourism (Li et al., 2021). The target respondents were those who have user experiences with online chatbots for tourism. We posted the link to our self-report research questionnaire on Weibo, one of the most popular and influential social media platforms in China (Zhu & Kou, 2019). To attract people who may have user experiences with chatbots for tourism, we used tourism-related hashtags on Weibo (eg, #tourism, #flight ticket, #train ticket, #airbnb, #travel tips, #self-driving, #hotels, #trip, #booking, #Ctrip, and #tourism discount). Moreover, we cooperated with seven tourism agencies in three cities of China: Chengdu, Chongqing, and Wuhan. These tourism agencies helped us send the online questionnaires to their customers.

The pilot test was conducted with 30 undergraduate students who have used chatbots for tourism before. Meanwhile, two professors and two industry practitioners gave their suggestions. After the pilot test, we modified the measurement items to ensure the appropriateness and representativeness of the questionnaire. In the first part of the questionnaire, we introduced the objectives of our work. Then, we identified those respondents who have user experiences with chatbots by asking "have you used chatbots for tourism in Ctrip, Qunar, or Fliggy within the last 12 months?" Only those who selected "Yes" can move to next section. In the second section, respondents' demographic information was collected, following by the third part on potential determinant factors. The final part evaluated respondents' continuance intention to use chatbots for tourism.

A total of 783 respondents were surveyed, after deleting those who without user experiences and removing those incomplete data, finally 613 questionnaires were considered as valid. The final sample was balanced by gender (48.1% males and 51.9% females). Melián-González et al. (2021) found that most of chatbot users in tourism industry are young people. The data in this research are consistent with their findings; 55.31% of respondents were between 18 and 30, and 26.75% were between 31 and 40. Regarding education, most of respondents had bachelor degree (68.84%) or above (11.75%). Meanwhile, 72.59% earned less than 100,000 CNY each year. Table 1 presents the demographic information of samples.

4.2. Measures

All measurement items were adapted from the existing studies. Specifically, items measuring performance expectancy were modified from the study by Venkatesh et al. (2012).

The construct of effort expectancy was modified from Muhammad et al. (2018). Items for social influence were adapted from Alalwan et al. (2016) and items for hedonic motivation were modified according to Gupta et al. (2018). The construct of habit was modified according to Cabrera-Sánchez et al. (2021). Items for privacy risk were modified from Choe et al. (2021). Measurement items for time risk were adapted from S. Park and Tussyadiah (2017). Items developed by Pillai and Sivathanu (2020) were used to measure anthropomorphism. The construct of personalization was modified according to Chen et al. (2021). Finally, items for continuance intention were adapted from Li et al. (2021). Each measurement was assessed by a five-point Likert scale, from 1 (strongly disagree) to 5 (strongly agree). The measurement items and their source were shown in Table 2.

Table 1. The demographic information.

Variables	Number	Percentage
Gender		
Male	295	48.12%
Female	318	51.88%
Age		
18–30	339	55.31%
31–40	164	26.75%
41–50	83	13.53%
Over 50	27	4.41%
Education		
Under high school	9	1.47%
High school	27	4.41%
Polytechnic college	83	13.53%
Bachelor degree	422	68.84%
Postgraduate degree	72	11.75%
Annual income		
50,000 CNY or below	231	37.68%
50,001–100,000 CNY	214	34.91%
100,001–300,000 CNY	104	16.97%
300,001–500,000 CNY	43	7.01%
Over 500,000 CNY	21	3.43%

Note. 1 CNY≈ 0.155 USD.

5. Results

5.1. Measurement model assessment

In this research, the Structural Equation Modeling (SEM) using AMOS22.0 was employed to test the measurement model. First, the measurement model was run to test the validity, reliability, and goodness of fit. Then, the proposed research hypotheses were tested.

In this research, confirmatory factor analysis (CFA) was selected to test the validity and reliability. According to Table 3, Cronbach's α of each construct was over the recommended level of 0.7 (B. Zhang & Zhu, 2021). Thus, the reliability of the measurement model was confirmed. Furthermore, composite reliability (CR) value of each construct was more than 0.7 (Nunnally, 1978), factor loading for each item was over 0.6 (Kaur et al., 2018), and average variance extracted (AVE) value for each construct was higher than 0.5 (Leong et al., 2013), establishing the convergent validity. Discriminant validity was next assessed through Fornell–Larcker criterion. As shown in Table 4, the square root of AVE for each construct was greater than the correlation values between any two constructs (Yang et al., 2016). Meanwhile, each pair of independent variables in the correlation was less than the 0.9 criterion (Hair et al., 2010), establishing the discriminant validity.

Table 2. Measures and sources.

Construct	Measurement	References
PE	PE1: Using chatbots improves information search	Venkatesh et al. (2012)
	PE2: Chatbots for tourism can help to book tickets and hotels more quickly	
	PE3: Chatbots for tourism are useful	
EE	EE1: Chatbots for tourism are easy to use	Muhammad et al. (2018)
	EE2: It is easy for me to become skillful at using chatbots for tourism	
	EE3: Learning how to use chatbots for tourism is easy	
SI	SI1: My families influence my decision to use chatbots for tourism	Alalwan et al. (2016)
	SI2: My friends influence my decision to use chatbots for tourism	
	SI3: My classmates/colleagues influence my decision to use chatbots for tourism	
HM	HM1: Using chatbots for tourism is entertaining	Gupta and Dogra (2017)
	HM2: Using chatbots for tourism is fun	
	HM3: Using chatbots for tourism is enjoyable	
HB	HB1: The use of chatbots for tourism becomes my habit	Cabrera-Sánchez et al. (2021)
	HB2: The use of chatbots for tourism becomes natural to me	
	HB3: I tend to use chatbots when I prepare my next trip	
PR	PR1: Using chatbots for tourism may not protect my personal information	Choe et al. (2021)
	PR2: When I use chatbots for tourism, my personal information may be stolen	
	PR3: My personal information could be exposed when using chatbots for tourism	
TR	TR1: Learning how to use chatbots for tourism may cause time loss	S. Park and Tussyadiah (2017)
	TR2: If I use chatbots for tourism, I am more likely to lose time by switching to a different service	
	TR3: The possible time loss from the use of chatbots is high	
AN	AN1: I feel chatbots for tourism are computer-animated: real	Pillai and Sivathanu (2020)
	AN2: I feel chatbots for tourism have their own mind	
	AN3: I feel chatbots for tourism have their emotions	
	AN4: The interaction with chatbots for tourism is natural	
P	P1: Chatbots for tourism understand my specific moods	Chen et al. (2021)
	P2: Chatbots for tourism know what I really need	
	P3: The services provided by chatbots for tourism are customized to my demands	
CI	CI1: I will continue to use chatbots for tourism	Li et al. (2021)
	CI2: I intend to use chatbots for tourism in the future	
	CI3: When required, I will use chatbots for tourism	

Table 3. Assessment results of the measurement model.

Construct and items	Factor loading	Mean	Standard deviation	Alpha	CR	AVE
Performance expectancy (PE)				0.843	0.845	0.645
PE1	0.800	4.12	0.726			
PE2	0.793	3.89	0.802			
PE3	0.816	3.88	0.811			
Effort expectancy (EE)				0.833	0.835	0.628
EE1	0.764	4.49	0.843			
EE2	0.777	4.31	0.786			
EE3	0.834	4.37	0.839			
Social influence (SI)				0.749	0.758	0.515
SI1	0.612	3.69	0.779			
SI2	0.727	3.72	0.845			
SI3	0.789	3.66	0.835			
Hedonic motivation (HM)				0.855	0.856	0.665
HM1	0.818	3.20	0.988			
HM2	0.871	2.88	0.970			
HM3	0.755	2.50	0.981			
Habit (HB)				0.764	0.762	0.517
HB1	0.759	3.96	0.714			
HB2	0.713	3.77	0.765			
HB3	0.688	3.65	0.767			
Privacy risk (PR)				0.852	0.856	0.667
PR1	0.687	3.79	1.244			
PR2	0.868	3.68	1.193			
PR3	0.880	3.62	1.282			
Time risk (TR)				0.899	0.901	0.752
TR1	0.873	3.16	1.149			
TR2	0.885	2.89	1.251			
TR3	0.848	2.82	1.366			
Anthropomorphism (AN)				0.867	0.869	0.625
AN1	0.737	3.29	0.976			
AN2	0.824	2.79	0.892			
AN3	0.821	2.80	0.963			
AN4	0.782	2.79	0.897			
Personalization (P)				0.828	0.834	0.626
P1	0.809	3.25	0.810			
P2	0.734	3.05	0.797			
P3	0.826	3.33	0.803			
Continuance intention				0.888	0.891	0.732
CI1	0.823	3.93	0.816			
CI2	0.846	3.91	0.867			
CI3	0.895	3.84	0.844			

Table 4. Discriminant validity.

	PE	EE	SI	HM	HB	PR	TR	AN	P	CI
PE	0.803									
EE	0.155	0.793								
SI	0.241	0.478	0.718							
HM	0.244	0.144	0.159	0.816						
HB	0.415	0.365	0.396	0.263	0.719					
PR	−0.083	−0.239	−0.158	−0.095	−0.110	0.817				
TR	−0.070	−0.375	−0.279	−0.063	−0.122	0.523	0.867			
AN	0.149	0.401	0.349	0.250	0.143	−0.289	−0.323	0.790		
P	0.195	0.469	0.391	0.233	0.209	−0.281	−0.347	0.624	0.791	
CI	0.380	0.517	0.517	0.267	0.507	−0.392	−0.460	0.536	0.634	0.855

Table 5. Measures of the model fit.

Goodness-of-fit measures	CMIN/df	CFI	GFI	RMSEA	RMR	SRMR	IFI	NFI
Recommended value	≤3.00	≥0.90	≥0.90	≤0.08	≤0.05	≤0.05	≥0.90	≥0.90
This model	2.601	0.942	0.903	0.051	0.036	0.042	0.942	0.910

Moreover, the goodness of fit was examined based on the following statistical recommendations: x^2 statistics/degree of freedom (df) should be no more than 3 (Bagozzi & Yi, 1988), goodness-of-fit index (GFI) should be higher than 0.9 (Hair et al., 2010), comparative fit index (CFI) should be greater than 0.9 (Browne & Cudeck, 1992), root mean squared residual (RMR) should be less than 0.05 (Byrne, 2001), standardized root mean squared residual (SRMR) should be less than 0.1 (Leong et al., 2013), root mean square error of approximation (RMSEA) should not exceed 0.08 (Alalwan et al., 2017), incremental fit index (IFI) should be greater than 0.9 (Anderson & Gerbing, 1988), and normed fit index (NFI) should be higher than 0.9 (Hong et al., 2006). According to Table 5, all fit indices satisfied these requirements. Therefore, the measurement model returned a good model fit.

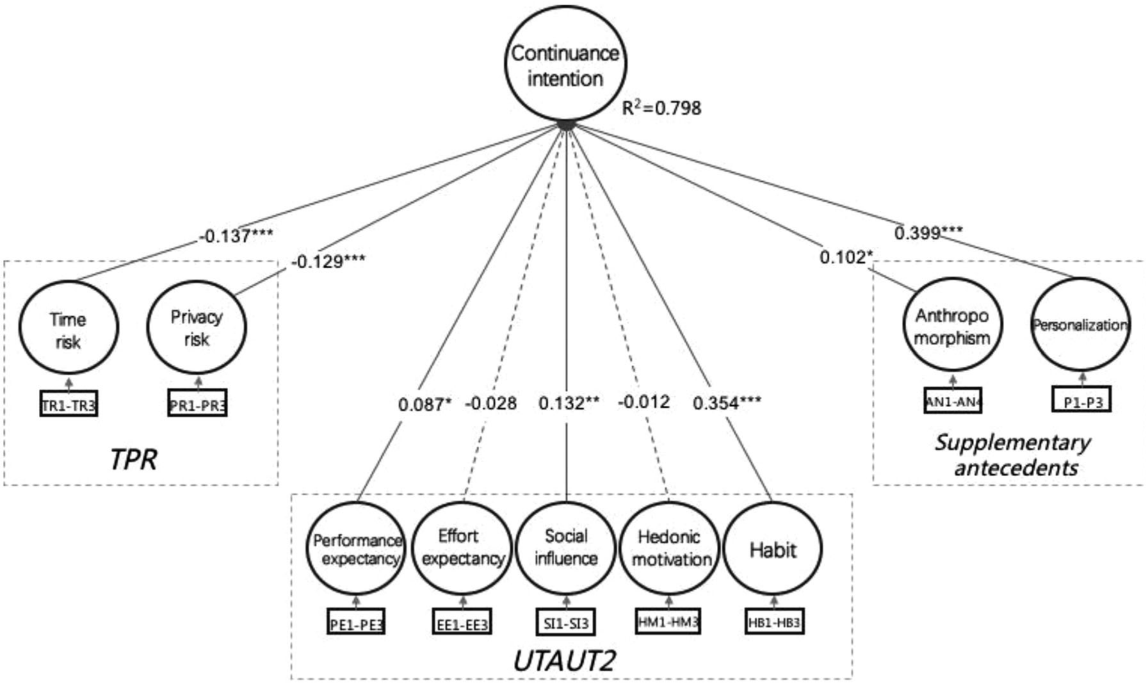

Figure 3. Hypothesis testing. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Table 6. Results of multiple group analysis.

	Path	Male	Female	Chi-square difference	*p* Value	Significance
H10a	PE→CI	0.531***	0.286***	11.329***	0.001	Yes
H10b	EE→CI	0.475***	0.533***	2.093	0.148	No
H10c	SI→CI	0.457***	0.551***	1.281	0.258	No
H10d	HM→CI	0.323***	0.214***	0.687	0.407	No
H10e	HB→CI	0.662***	0.401***	12.099***	0.001	Yes
H10f	PR→CI	−0.351***	−0.400***	0.444	0.505	No
H10g	TR→CI	−0.477***	−0.402***	2.522	0.112	No
H10h	AN→CI	0.523***	0.531***	1.920	0.166	No
H10i	P→CI	0.640***	0.607***	1.183	0.178	No

***$p < 0.001$.

5.2. Hypothesis testing

Figure 3 shows the results of hypothesis testing. Performance expectancy was positively associated with customers' continuance intention ($\beta = 0.087$, $p < 0.05$), while effort expectancy had insignificant impact on continuance intention ($\beta = -0.028$, $p > 0.05$). Thus, H1 should be supported but H2 should be rejected. In addition, social influence showed a significant and positive influence on continuance intention ($\beta = 0.132$, $p < 0.01$), supporting H3. However, hedonic motivation was insignificantly correlated with customers' continuance intention ($\beta = -0.012$, $p > 0.05$). Therefore, H4 should be rejected. Meanwhile, habit ($\beta = 0.354$, $p < 0.001$) and personalization ($\beta = 0.399$, $p < 0.001$) had great influences on continuance intention to use chatbots, offering supports to H5 and H8. Moreover, the relationship between anthropomorphism ($\beta = 0.102$, $p < 0.05$) and continuance intention was positive, supporting H9. Time risk ($\beta = -0.137$, $p < 0.001$) and Privacy risk ($\beta = -0.129$, $p < 0.001$) exerted negative effects on customers' continuance intention. Therefore, H6 and H7 should be supported. Totally, seven out of the nine hypotheses are supported.

The model explained 79.8% of the variance (R^2) for continuance intention. According to previous studies (Chin, 1998; Seo & Bernsen, 2016), when R^2 value is above 0.67, the predictive power is substantial. Thus, the research model is considered to have substantial predictive power.

5.3. The moderating effects of gender differences

In this research, multiple group analysis (Table 6) and pairwise parameter comparisons (Table 7) were performed to examine the moderating effects of gender differences. According to Choe et al. (2021), there is a significant moderating effect when the chi-square difference is greater than 3.841 at the 5% level. Also, the moderating role is significant when the critical ratio for differences between parameters is above 1.960 at 5% level (Leong et al., 2013). As shown in Table 6 and Table 7, the moderating effect was significant in the relationship between performance expectancy and continuance intention, and the path coefficient for men ($\beta = 0.531$, $p < 0.001$) was higher than women ($\beta = 0.286$, $p < 0.001$), offering support to H10a. Similarly, the relationship between habit and continuance intention was

Table 7. Critical ratios for differences between parameters.

Path	Parameters for male								
	PE→CI	EE→CI	SI→CI	HM→CI	HB→CI	PR→CI	TR→CI	AN→CI	P→CI
Parameters for female									
PE→CI	−3.382								
EE→CI		1.448							
SI→CI			1.132						
HM→CI				−0.829					
HB→CI					−3.496				
PR→CI						0.667			
TR→CI							1.590		
AN→CI								−1.387	
P→CI									−1.347

significantly moderated by gender differences (male, $\beta = 0.662$, $p < 0.001$; female, $\beta = 0.401$, $p < 0.001$), supporting H10e. However, H10b, H10c, H10d, H10f, H10g, H10h, and H10i should be rejected because the moderating effects of gender differences were nonsignificant. Thus, only two out of the nine hypotheses are supported.

6. Discussion and implications

The findings in this research demonstrated a positive relationship between performance expectancy and continuance intention to use chatbots for tourism. This coincides with prior studies which showed that performance expectancy and usefulness are key predictors of continuance intention of chatbots (Ashfaq et al., 2020; Trapero et al., 2020). In tourism industry, tourists use chatbots to book tickets, search information, arrange travel plans, and obtain other services (Melián-González et al., 2021). Thus, it is logical that customers continue to adopt chatbots because these AI-based agents can help their tourism. Moreover, social influence also greatly explains customers' continuance intention to use chatbots. As many previous research has suggested (Alalwan et al., 2017; Seo & Bernsen, 2016), a person's social environment, consisting of family, friends, colleagues, and neighbors, can commonly exert a great influence on continuance intention. With the development of social media, the impact of social influence will become stronger in the near future.

As expected, habit was empirically evidenced to be a key factor affecting continuance intention to use chatbots for tourism. This result is in line with many previous literature (Melián-González et al., 2021; Venkatesh et al., 2012), revealing that the likelihood of using chatbots could reach a high level among customers who get used to them. In addition, this research approved the considerable impact of personalization on continuance intention. It is no surprise that today's customers have become and will continue to become more sophisticated. The demands for personalized experiences will rapidly grow in the market of HCI. Meanwhile, the findings in this research affirmed a positive relationship between anthropomorphism and continuance intention. an explanation for this might be that chatbots for tourism are low-threat robots. According to UVT, anthropomorphism of a robot can increase people's closeness to it (Mori et al., 2012). However, when a robot has many humanlike characteristics and looks very similar to a human, this robot becomes a high-threat robot (Huang et al., 2021). A high-threat robot will pose a realistic threat to humans' routine work and human identity, in turn leading to the rejection of the robot (Liu & Tao, 2022). Compared with those high-threat robots, chatbots for tourism do not have many humanlike features or behaviors. Therefore, they engender less alertness and anxiety.

In addition, the findings in this study proved that privacy risk and time risk have negative influences on continuance intention. As expected, customers worry that their personal information is exposed to others when they interact with chatbots. Also, customers feel anxious that the use of chatbots for tourism is inefficient and time wasting. Thus, privacy protection and efficiency improvement are important factors which should be considered by tourism service providers and chatbot developers in the future.

The relationship between effort expectancy and continuance intention was not confirmed in this research. This result coincides with some previous studies (Cabrera-Sánchez et al., 2021; Melián-González et al., 2021). A potential explanation for this is that the concept of effort expectancy is commonly examined with technologies that have a certain learning curve. However, an AI-based chatbot is not the case because the use of a chatbot is simple (eg, opening chatbots, typing questions, and conversing with the systems) and does not require any specific skills (Melián-González et al., 2021).

A surprising result was that hedonic motivation showed insignificant impact on customers' continuance intention. According to previous studies (Alalwan et al., 2017; Gupta et al., 2018), hedonic motivation becomes effective in technology acceptance, especially in the case of hedonic technologies. When users adopt a technology, they also expect to enjoy the usage. However, this research found that the use of chatbots for tourism cannot be influenced by hedonic motivation. A possible explanation for this is that many customers in China still ignore the hedonic functions of chatbots in tourism industry. People who use chatbots for tourism may much more care about how chatbots can help them arrange the trips rather than how chatbots can make a feeling of fun.

With regard to gender differences, it only showed great moderating effects on two relationships. First, performance expectancy was found to have greater impact on male, as compared to female. This is in line with the arguments proposed by some existing studies (Venkatesh & Morris, 2000; Venkatesh et al., 2000), men generally more focus on usefulness when they decide to use a technology. Second, our findings indicated that the relationship between habit and continuance intention has a stronger relevance for male than for female.

However, the findings in this research indicated insufficient evidence to prove the existence of gender differences in the adoption of chatbots among other relationships.

SHT and GMT suggest the existence of gender differences when people decide to use a service (Meyers-Levy, 1988; Winstok et al., 2017). Many earlier studies found significant differences between male and female when choosing a technology (Lim et al., 2021; Shao et al., 2021; Sobieraj & Kramer, 2020; Venkatesh et al., 2012), therefore offering support to SHT and GMT. However, this research might provide a special case to challenge these traditional gender theories because it showed that men and women tend to perceive similarly when making continuance intention to use chatbots for tourism.

With the development of AI-based chatbots in tourism industry, an increasing number of studies have focused on the use of chatbots for tourism. For example, Melián-González et al. (2021) investigated the determinants behind customers' continuance intention based on UTAUT2. Compared with the research by Melián-González et al. (2021), this study provided new knowledge about the use of chatbots for tourism. First, Melián-González et al. (2021) only employed one theory (UTAUT2) to construct the research model. However, this study used two theories (UTAUT2 and TPR) to build an integrated research model. The explanatory power of this study is higher than the research by Melián-González et al. (2021). More importantly, the moderating role of gender differences was not tested by Melián-González et al. (2021). This study filled in this research gap, it employed multiple group analysis and pairwise parameter comparisons to test the moderating effect of gender differences. Third, the supplementary antecedents between this research and the study by Melián-González et al. (2021) are different. While this research considered anthropomorphism and personalization as the supplementary factors, Melián-González et al. (2021) employed perceived innovativeness, inconveniences, anthropomorphism, and automation.

6.1. Theoretical implications

This research added salient contributions to the existing HCI literature in following ways. First, to the best of our knowledge, this research is the first to construct an integrated model in the context of chatbot use through integration of UTAUT2 and TPR. Previous studies on the use of chatbots in tourism have only constructed theoretical framework according to technology acceptance theories, such as UTAUT2 (Melián-González et al., 2021). However, this study employed TPR, a theory has been rarely used in the context of chatbot adoption. The research model benefits greatly from TPR because this theory helps to more comprehensively understand how customers evaluate chatbots when interacting with them. Technology acceptance theories, which usually concentrate on technological aspects of a HCI product (Zhu, Janssen, et al., 2022), cannot fully explain customers' continuance intention to use a chatbot for tourism. Making a decision to use chatbots for tourism is an economic behavior, and thus it contains risks. TPR contributes to identifying the potential risks in the interaction between customers and chatbots for tourism, which in return helps to more comprehensively understand customers' behavioral intention. The integration of UTAUT2 and TPR in this study made the explanatory power of the research model become substantial ($R^2 = 79.8\%$), higher than prior studies which only depended on UTAUT2, such as the research by Melián-González et al. (2021; $R^2 = 49.5\%$).

Second, this research also offered new knowledge about UTAUT2 in the context of chatbots for tourism. This research demonstrated that the outcome based on UTAUT2 by Melián-González et al. (2021) cannot be generalized in a different cultural context. Specifically, the influences of hedonic motivation in this research was insignificant. However, according to the findings by Melián-González et al. (2021), hedonic motivation was significantly and positively associated with customers' continuance intention to use chatbots for tourism. Moreover, while Melián-González et al. (2021) found performance expectance ($\beta = 0.326$, $p < 0.001$) was the most influential factor, this research revealed that the effect of habit ($\beta = 0.354$, $p < 0.001$) was more powerful than other factors of UTAUT2. The research by Melián-González et al. (2021) collected data in Spain and employed Smart PLS as statistical tool. However, this research collected data in China and used Amos as statistical tool. These might lead to the differences between two studies. Although the findings of this research are different to previous literature, these findings prove that UTAUT2 can be used to explain customers' continuance intention to use chatbots for tourism. Thus, this study contributes to the use of UTAUT2 in the context of HCI.

Third, to the best of our knowledge, this study is one of the earliest attempts to explore the moderating role of gender differences in continuance intention of chatbots for tourism. Traditional gender theories, such as SHT and GMT, stated that both men and women tend to perceive differently when selecting a technology (Winstok et al., 2017; Zhu, Wang, Zeng, et al., 2022). However, this research only found two significant differences between male and female. The findings in this study may offer a special case to challenge SHT and GMT. According to Winstok and Weinberg (2018), SHT and GMT are not without limitations because these theories fail to consider gender as a flexible continuum. Due to the development of society, both men and women may change their psychological features when selecting a service. Accordingly, it is possible that male and female tend to have similar information processing strategies and social motivates when they evaluate a new emerging technology, such as chatbots for tourism. Thus, the findings of this research suggested a possibility that SHT and GMT may cannot explain the role of gender differences in people's behavioral intention when selecting new HCI technology, such as AI-based chatbots for tourism. Therefore, this study enhances the existing literature regarding the role of gender differences in HCI technology acceptance.

Finally, this research responds to the call for empirical studies that need investigate continuance intention of chabots by using personalization (Pillai & Sivathanu, 2020). With the development of AI-based technologies, personalization becomes a key predictor of acceptance intention in this field because it can improve user experiences of HCI (Chen et al., 2021). However, it is difficult to find a research that empirically tests the role of personalization in influencing customers' continuance intention to use chatbots for tourism. This research demonstrated a strong relationship between personalization and continuance intention. This predictor can be used in future studies regarding the adoption of AI-based chatbots in tourism industry.

6.2. Practical implications

According to the findings in this research, some practical suggestions can be offered to promote the successful adoption of chatbots in tourism industry. First, the findings revealed that privacy risk is a major concern that decrease continuance intention to use chatbots for tourism. Therefore, chatbot developers need consider more to reduce consumer privacy concerns. For example, chatbots should improve the ability to identify consumer privacy concerns during conversation. When a person only discloses limited privacy information and has worries about privacy leakage, then the chatbot should conduct routine conversations and avoid asking many personal information (Fan et al., 2022). Meanwhile, chatbots for tourism might advise customers about the firm's comprehensive privacy policy. Offering such assurance can reduce the perceived risk of information disclosure.

Time risk also showed negative impact on customers' behavioral intention. Thus, chatbots for tourism should provide services more efficiently and save people's time. For instance, chatbots for tourism can be manipulated to offer more introverted chatbot responses when interacting with people. Introverted chatbot responses use language that is effective and goal oriented (Hirsh et al., 2012). Thus, more introverted chatbot responses can improve the efficiency of chatbots and reduce the perceived risk of time wasting. In addition, because social influence plays important role in predicting customers' continuance intention, tourism service providers should partner with communities, social media platforms, interest groups, and civil society organizations to create a social atmosphere that can stimulate individuals' motivation to use chatbots for tourism.

Moreover, personalization plays a key role in customers' behavioral intention. Thus, it is necessary to improve the level of personalization. The emerging research by Shumanov and Johnson (2021) suggested that human–chatbot interaction can be more personalized by matching consumer personality with congruent chatbot personality using language. According to Shumanov and Johnson (2021), consumer personality can be learned and predicted during contextual interactions. Then, chatbots can be manipulated to assume a congruent personality via response language. The human-chatbot personality congruence can offer more personalized experiences to consumers. Thus, psycholinguistic models can be used to improve the emotional intelligence of chatbots for tourism. A chatbot with higher level of emotional intelligence can better capture and analyze customers' personality traits during contextual interaction, and ultimately provide adapted responses (Jiménez-Barreto et al., 2021).

In addition, improving the level of anthropomorphism is important strategy to create a natural human–chatbot interaction. Chatbot developers should concentrate on intangible emotion contact between human and chatbot, especially eye contact and voice interaction. Currently, many service robots in other business fields are equipped with "dead eyes" and "mechanical voice" (Huang et al., 2021; Nguyen et al., 2019). Excellent eye contact and voice interaction send a message of welcome and friendliness (Huang et al., 2021). Thus, it is necessary to employ advanced 3 D computer model and voice system (eg, multidialectal system) to make eye contact and voice interaction become more humanlike when developing chatbots for tourism. However, the anthropomorphic appearance of chatbots also should be carefully considered to ensure that these robots for tourism will not blur the line between human and AI. According to Huang et al. (2021), one design principle is that design elements of chatbots should be in line with human realism.

7. Conclusion and limitations

AI-based chatbots become game-changer for tourism industry. These AI-driven agents are expected to be integrated into many aspects of tourism in the near future (Bowen & Morosan, 2018; Pillai & Sivathanu, 2020; Tussyadiah, 2020), an increasing number of tourism service providers begin to massively employ them to offer services. The purpose of this research is to understand the determinants that influence the continuance intention of chatbots for tourism based on UTAUT2, TPR, and supplementary antecedents. The findings highlighted the significances of performance expectancy, social influence, habit, time risk, privacy risk, anthropomorphism, and personalization. Moreover, this research also attempts to examine whether customers' perceptions of chatbots are homogeneous across genders. According to the findings, performance expectancy and habit had stronger influences on male. This research devotes to strengthening theoretical framework regarding the use of chatbots for tourism. In addition, it reconsiders the generalizability of SHT and GMT in the context of AI-based chatbot use.

Meanwhile, future studies should address some limitations related to this research. First, this study has geographic limitations: only Chinese tourism market was investigated. Thus, the findings in this research cannot be generalized to other countries. Future studies should examine the research model in this study across a variety of countries to improve the generalization. Second, the cultural differences with regard to users' perceptions on HCI are not fully taken into account. Thus, it might be problematic to generalize the findings in this research over the context of Chinese users. Third, there were biases of age (mostly young users) and educational level (mostly bachelor degree or above) in this research. Fourth, this study only tested the moderating effect of gender differences on nine factors. Some other factors, such as technological anxiety, may show different impact between male and female. Therefore, future studies should be extended to include more antecedents and understand the moderating effect of gender differences on them.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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