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Abstract:

Drawing on the extended Unified Theory of Acceptance and Use of Technology (UTAUT2) and Task-Technology Fit (TTF) theory, we developed a unique research model to explore the factors affecting ChatGPT use and the main activities individuals do while using ChatGPT, and determine whether they continue using ChatGPT and recommend it to others. The moderating role of curiosity in the relationships between various influencing factors and ChatGPT use was also examined. We conducted a quantitative research with the data collected from 671 users in Vietnam. The results indicated that (1) the majority of the dimensions of UTAUT2 and TTF affect ChatGPT use. However, interestingly, contrary to our expectation, effort expectancy, social influence, and trust have no effect on ChatGPT use, (2) ChatGPT use directly influences intention to continue using ChatGPT and word-of-mouth (WOM), (3) intention to continue using ChatGPT has a significant effect on WOM, and (4) curiosity acts as a moderator on only three paths from hedonic motivation, facilitating conditions, and performance expectancy to ChatGPT use. The originality of this study lies in (1) a unique research model by combining the UTAUT 2 and the TTF inclusive of trust and curiosity, and (2) enriching understanding of the users' behavioral process in technology adoption by examining a comprehensive process, namely actual usage–continuance intention to use–recommending. Practical implications for ChatGPT providers, policymakers, and business marketers are also discussed.

Keywords: Generative AI, ChatGPT, UTAUT2, TTF, Continuance Intention to Use, Word of Mouth

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1 Introduction

Artificial intelligence (AI), which is machines exhibiting facets of human intelligence (Flavián et al., 2022; Mariani et al., 2022), has been used in various fields because it provides enormous possibilities for improving people's lives (Berente et al., 2021: Mariani et al., 2022). AI has made significant impacts on different aspects of human beings such as human decision accuracy or unique human knowledge (Fügener et al., 2021). The recent launch of ChatGPT (Generative Pre-trained Transformer), a generative (conversational) AI (Dwivedi et al., 2023) on November 30, 2022, shocked the world. Indeed, ChatGPT is an extremely powerful technology that can understand varied and complex human languages and generate structured and rich human-like responses (Lim et al., 2023). The ChatGPT's functions are vast and unique in comparison with other modern AI technologies (Dwivedi et al., 2023). Despite their popularity, there is much we do not know with regard to their adoption.

The current literature has attempted to (1) explain the application of generative AI, such as ChatGPT in various fields, such as education (e.g., Gilson et al., 2023; Rospigliosi, 2023; Rudolph et al., 2023), healthcare (e.g., Hirosawa et al., 2023), finance (e.g., Dowling & Lucey, 2023), or medical research (e.g., Dahmen et al., 2023), (2) discuss challenges, opportunities, and implications of ChatGPT for practice, research, and policy from multidisciplinary perspectives (Dwivedi et al., 2023), or (3) review the ChatGPT's major functions (e.g., Aljanabi et al., 2023). So far, to the best of our knowledge, there has been no research on mass adaptation of ChatGPT. As underlined by Mariani et al. (2023) in their very recent systematic literature review paper on AI, consumer research on AI in general and on conversational agents in particular has been growing, but remains under-explored. Nah et al. (2023) have also called for further investigation on how generative AI can work together with humans effectively. Rather than replace humans, AI should enhance humans (Paul et al., 2022; Zhou et al., 2021). In addition, like product consumption, using technology is also a process of consuming the product; thus, researching user behavior toward technology, like ChatGPT, is critical. Accordingly, a key question is whether ChatGPT is actually becoming a meaningful tool as AI technologies like ChatGPT have raised concerns related to fairness, trust, and ethics (Robert et al., 2020).

Existing research has developed several models to explain technology acceptance and use, such as the theory of reasoned action (TRA) (Ajzen & Fishbein, 2000), the theory of planned behavior (TPB) (Ajzen, 1991), the technology acceptance model (TAM) (Davis, 1989), the Unified Theory of Technology Acceptance and Use (UTAUT) (Venkatesh et al., 2003) or the extended UTAUT2 as a fundamental theoretical framework (e.g., Ateş & Garzón, 2023; Farzin et al., 2021; Gupta et al., 2018). These studies identified a number of common factors affecting users' acceptance or use of technology, including perceived privacy risks, performance expectancy, facilitating conditions, social influence, and perceived ease of use. However, very few studies have used these theories to investigate behavioral intention to use products that explicitly incorporate AI (Gansser & Reich, 2021).

Furthermore, these existing models have been shown to have the potential in explaining users' acceptance of technology, they mainly reflect users' perceptions about the technology (e.g., performance expectancy and effort expectancy) as well as the consumption context (e.g., facilitating conditions, social influence, and hedonic motivation). However, users are more likely to renounce a technology when they think that its characteristics (e.g., ChatGPT's functionalities) cannot fit task requirements, and vice versa, which is the key point of Task-Technology Fit (TTF) theory (Goodhue & Thompson, 1995; Huy et al., 2019; Kang et al., 2022; Lu & Yang, 2014; Oliveira et al., 2014). Hence, we argue that using or not a technology like ChatGPT may not only be shaped by users' perceptions of that technology but also by a fair task-technology fit. As highlighted by Berente et al. (2021) and Nah et al. (2023), a socio-technical thinking is necessary to effectively manage AI.

Our study, therefore, aims to fill the above research gaps by investigating users' behavior towards using ChatGPT with the following research questions.

1. What are the factors affecting the use of ChatGPT?

2. What specific tasks do people use ChatGPT for?

3. Do users intend to continue using and recommending ChatGPT?

4. Does users' curiosity towards ChatGPT moderate the relationships between various influencing factors and ChatGPT use?

We developed an integrated research model based on the UTAUT2 and TTF to address the above research questions. We intentionally combined both models (i.e., UTAUT2 and TTF) for two main reasons. First, UTAUT2 is recognized as one of the most complete models explaining technology acceptance and use (Goodhue & Thompson, 1995), which reflects how users perceive the technology and consumption context. Second, TTF allows us to assess the match between technology and task. Therefore, combining UTAUT2 with TTF has the potential to better explain users' behavioral intention towards ChatGPT than employing them separately. The study was conducted in Vietnam, a developing country where ChatGPT is still in the early adoption stage and users' behavior toward ChatGPT unquestionably requires further research. We believe that investing consumer behaviors towards a chatbot, in particular, ChatGPT, from a user perspective is critical as this will inform businesses of the factors influencing ChatGPT use, how individuals use it, and their behavioral intentions after use, helping improve their technological ecosystem (Mariani et al., 2022; Pizzi et al., 2023).

Our study makes several significant contributions to the literature on technology adoption. First, we are among the first to examine whether this emerging technology (i.e., ChatGPT) is a meaningful tool from a user perspective by mobilizing both UTAUT2 and TTF. This paper has the potential to provide a novel theoretical combination that helps explain in a comprehensive manner users' behavior of ChatGPT from both theoretical perspectives, including technology perceptions and task-technology fit, which is critical for extensively understanding individuals' behavioral intention towards an emerging technology like ChatGPT. With this contribution, our study also responded to the call that future research needs to investigate AI technology acceptance and adoption (Mariani et al., 2022). Second, our study is the first to shed light on the moderating effect of user curiosity towards an emerging technology, which allows us to gain a deeper understanding of the relationships between users' perceptions and trust and users' behavior regarding a technology like ChatGPT. Third, with various functions of ChatGPT, this study demonstrated the crucial role of ChatGPT use in shaping users' intention to continue using and recommending it, thus, enriching understanding of the users' behavioral process in technology adoption by examining a comprehensive process, namely actual usage–continuance intention to use–recommending. Finally, we also provided ChatGPT developers, policymakers, and businesses with practical implications to reach more users.

2 Background

Generative AI, such as ChatGPT, utilizes deep learning models to create content similar to human-made content in response to varying and complicated prompts (Lim et al., 2023). Furthermore, ChatGPT goes beyond the human-like interactions in conversational AI by not only providing a response but also generating the content in that response (Lim et al., 2022; Mariani et al., 2023). This emerging technology has been considered the most advanced chatbot in the world (Rudolph et al., 2023). ChatGPT is an intelligent chatting machine trained to follow instructions in a prompt and provide a detailed response (Ouyang et al., 2022). More specifically, this chatbot is known as a large language model, a machine-learning system that learns autonomously from data, and can create sophisticated and seemingly intelligent writing after training on a mammoth data set of text (Van Dis et al., 2023). ChatGPT integrates various abilities including academic writing, a search engine, coding, detecting security vulnerabilities, or machine translation (Aljanabi et al., 2023). After launching, this immersive technology has created a global wave.

According to Statista (2023a), ChatGPT gained one million users just five days after launching. It was downloaded 3,771 times from global users in the first ten days of January 2023 (Statista, 2023b). This signal shows that ChatGPT has great potential in the future. However, there is still a lot of controversy surrounding the benefits and drawbacks this emerging technology has brought to the consumers (i.e., users) of ChatGPT. Generative AI creates challenges for educators (Stokel-Walker, 2022), which may destroy the education system (Lim et al., 2023). Nevertheless, Pavlik (2023) argued that generative AI is ushering in an era of the potential transformation of journalism and media content, bringing a new dawn of accessible information and automation.

Furthermore, although the future of ChatGPT stays unknown, opportunities and challenges take shape for businesses. Like Google, ChatGPT can be regarded as an effective content curation tool (Dwivedi et al., 2023). The generative responses delivered by this emerging tool are subject to the users' query. An unspecific inquiry may engender inaccurate results, thus leading to the degradation of brand value. Thus, marketers need to develop an ecosystem to precisely answer customer requests (Dwivedi et al., 2023). With this in mind, there is a need for research on identifying specific tasks that users do while using ChatGPT, which helps businesses better respond to their expectations. Unfortunately, the use of ChatGPT remains, so far, overlooked (Dwivedi et al., 2023). In the same vein, Mariani et al. (2022), through a systematic literature review on AI in marketing, consumer research, and psychology, identified technology acceptance and adoption, social media and text mining, big data and robots, and social media content analysis as one of the three macro clusters that need further research. According to these authors, future research should essentially cover AI technologies acceptance and adoption as they evolve further.

Moreover, ChatGPT is undoubtedly the focus of many continuous discussions about how generative AI can impact our lives in the years to come. This is indisputably true for business, education, government, and many other domains. As a new phenomenon, ChatGPT has sparked mixed opinions (refer to Lim et al., 2023 and Pavlik, 2023, for example) and a lot of debate, which may lead to one's certain curiosity toward this technological tool. Thus, we suggest that users' curiosity towards ChatGPT may play a moderating role in the relationships between various factors affecting ChatGPT use.

3 Theoretical framework and research hypotheses

3.1 Theoretical framework

3.1.1 The extended Unified Theory of Acceptance and Use of Technology (UTAUT2)

Venkatesh et al. (2003) have integrated eight common theories into a comprehensive model named "Unified Theory of Acceptance and Use of Technology (UTAUT)". UTAUT identifies four key constructs, including performance expectancy, effort expectancy, social influence, and facilitating conditions to predict users' behavioral intention towards a technology or an innovation (Mariani et al., 2022; Williams et al., 2015). However, it has some limitations when being used in different technological contexts. One of the prominent limitations is that UTAUT was formulated to explain the acceptance and use of technology within an organizational setting where technology use is mandated (Shaw & Sergueeva, 2019). Therefore, Venkatesh et al. (2012) extended UTAUT to UTAUT2 by adding hedonic motivation, price value, and habit. UTAUT2 also addressed the user context where individuals use a technology on a voluntary basis by including privacy concerns (Oliveira et al., 2014). UTAUT2 has been used by researchers as a powerful framework that effectively explains and analyzes an individual's technology acceptance and use (Venkatesh et al., 2012; Gupta et al., 2018; Ateş & Garzón, 2023).

3.1.2 The Task-Technology Fit theory (TTF)

Goodhue and Thompson (1995) proposed the TTF model, which suggests that the user will use a new technology if it is good enough to execute the daily task efficiently (Oliveira et al., 2014). Also, a technology will be adopted by individuals if it has the fit between the technology characteristics and task requirements (Goodhue & Thompson, 1995). Therefore, according to Goodhue and Thompson (1995), the TTF includes some main constructs to explain users' adoption of a new technology, including task characteristics, technology characteristics, task - technology fit, and use. Specifically, the TTF is determined by the match between task characteristics and technology characteristics, which leads to the adoption and use of a technology. The fit between tasks and technology is the degree to which the technology features match the task requirements (Lu & Yang, 2014). A user is likely to use a technology when it fits their tasks and improves their performance (Goodhue & Thompson, 1995).

The TTF model has mainly been applied at the organizational level rather than at the user level, while researchers indicate the potential application of TTF at the individual level (Aljukhadar et al., 2014). Furthermore, so far, it is still unclear if a good TTF will impact ChatGPT use and how well it will influence its users. Therefore, to obtain more insights into TTF's validation, the model still needs further studies across different contexts (Lu & Yang, 2014). Related to ChatGPT, given the various functions of ChatGPT and its advantages and disadvantages, recent studies have paid increasing attention to exploring the application of this technology in different contexts (refer to Rudolph et al., 2023, Gilson et al., 2023, and Rospigliosi, 2023 for education; Hirosawa et al., 2023 for healthcare; Dowling & Lucey, 2023 for finance; or Dahmen et al., 2023 for medical setting). Therefore, to pinpoint the factors that facilitate individual users' successful completion of tasks and show the relative importance of these factors in predicting task completion, the TTF model appears very appropriate.

3.2 Hypothesis development

3.2.1 Performance expectancy

Performance expectancy is a concept that explains how using technology can be beneficial when completing certain activities (Venkatesh et al., 2012). In this study, this concept refers to the degree to which users believe that using ChatGPT may help them attain increased opportunities and productivity in their job or reflects users' perceptions of their performance improvement by using ChatGPT. Many previous studies have shown that performance expectancy is one of the main determinants of users' behavioral intention toward a technology (Chua et al., 2018; Hsu et al., 2017; Jain et al., 2022). Thus, the following hypothesis is proposed:

Hypothesis 1: Performance expectancy positively affects ChatGPT use.

3.2.2 Effort expectancy

Effort expectancy is a term used to describe how simple or hard it is to use a technology (Venkatesh et al., 2012). Herein, in this study, the effort expectancy refers to how easy it is for users to utilize ChatGPT in their job. Indeed, the more users find ChatGPT easy to use, the more they use it. Users expect that ChatGPT can bring convenience and speed in performing tasks. Empirical studies showed that effort expectancy positively affected individuals' use of new technology (Hsu et al., 2017; Yueh et al., 2015). Additionally, the positive relationship between effort expectancy and AI-enabled tools adoption was tested and validated in a recent study related to AI (Jain et al., 2022). Therefore, we hypothesize that:

Hypothesis 2: Effort expectancy positively affects ChatGPT use.

3.2.3 Facilitating conditions

Facilitating conditions are described as users' awareness of the availability of facilities and support systems to perform a behavior (Venkatesh et al., 2003). In the information systems context, facilitating conditions include both technological and organizational elements planned to eliminate barriers to using the IS, such as financial resources, time, necessary knowledge, and government policies. These elements help to increase user's behavioral intention to use technologies (Hu et al., 2020; Thompson et al., 1991; Venkatesh et al., 2003). Extant research showed a positive association between facilitating conditions and technology use (Oliveira et al., 2014; Hsu et al., 2017; Haller et al., 2021; Jain et al., 2022). We thus posit the following hypothesis:

Hypothesis 3: Facilitating conditions positively affect ChatGPT use.

3.2.4 Hedonic motivation

Hedonic motivation refers to the fun or pleasure individuals derive from using a technology (Venkatesh et al., 2012). An individual performs certain activities to experience the pleasure and satisfaction inherent to these activities (Farzin et al., 2021). UTAUT2 has been improved by the addition of hedonic motivation, which brings the affective dimension into the mainly cognition-based UTAUT (Tamilmani et al., 2019). A hedonic information system is ubiquitous in the information technology market, and hedonic motivation plays an important role in predicting intentions for a hedonic information system (Van der Heijden, 2004; Venkatesh et al., 2012). Tamilmani et al. (2019) also proved that hedonic motivation served as an antecedent in understanding individual adoption of various technologies. Mishra et al. (2022) confirmed that hedonic motivation is positively related to using Smart Voice Assistants. Based on these arguments, the following hypothesis is suggested:

Hypothesis 4: Hedonic motivation positively affects ChatGPT use.

3.2.5 Social influence

Social influence is defined as the degree to which an individual perceives that important people (e.g., family and friends) believe they should use a specific technology because individuals' intention to use a technology is informed by the opinions of others (Venkatesh et al., 2003). Previous studies demonstrated that social influence is a significant antecedent of technology use (Hsu et al., 2017; Jain et al., 2022). Thus, we argue that users are willing to use ChatGPT if others approve its use. Accordingly, we suggest that:

Hypothesis 5: Social influence positively affects ChatGPT use.

3.2.6 Trust

Trust is defined as “a willingness to rely on an exchange partner in whom one has confidence” (Moorman et al., 1992, p. 83). In this study, based on Afshan and Sharif (2016), we describe trust in a technology (i.e., ChatGPT) as the confidence users place in that technology, which is regarded as dependable, secure, reliable, and helpful to users. Users’ trust in AI and conversational agents has gained growing attention from researchers (Mariani et al., 2023). Trust is essential for the advancement of online technology and for lowering the fear of damage in a technological setting (Afshan & Sharif, 2016). Trust is one of the most critical factors affecting a user’s intention to utilize an innovative technology when they have not much experience towards that technology (Mariani et al., 2023; Oliveira et al., 2014). Concretely, with the other four factors, namely usage convenience, perceived usefulness, enjoyment, and attitude towards technology, trust is among the five main factors that have been found to boost conversational agent adoption (Mariani et al., 2023). In mobile health (mHealth) app research, Alam et al. (2020) asserted that trust significantly influences using mHealth apps. In the same vein, Hsu et al. (2017) revealed that trust positively affects users’ adoption of e-books. Thus, under the setting of ChatGPT, we develop the following hypothesis:

Hypothesis 6: Trust positively affects ChatGPT use.

3.2.7 Technology characteristics, task characteristics, and task-technology fit

TTF is predicted by two technological aspects, which are technology characteristics and task characteristics (Goodhue & Thompson, 1995). In this study, based on Lu and Yang (2014) and Zhou et al. (2010), we define task characteristics as the users’ needs, while technology characteristics essentially refer to users’ appreciation of the capacity of a technology (i.e., ChatGPT) to provide them with ubiquitous, real-time, and reliable data. Task-technology fit reflects how a technology’s functions match the tasks that individuals perform and their needs (Goodhue & Thompson, 1995).

Empirical evidence in the e-books’ context showed that technology and task characteristics significantly positively affect TTF (D’Ambra et al., 2013). Furthermore, previous studies demonstrated a positive relationship between technology characteristics and TTF (Kang et al., 2022; Lin & Huang, 2008; Oliveira et al., 2014; Paulo et al., 2018). In addition, researchers generally agree that task characteristics are positively associated with task-technology fit (Oliveira et al., 2014; Paulo et al., 2018). Following these findings, we postulate that:

Hypothesis 7: Technology characteristics positively affect TTF.

Hypothesis 8: Task characteristics positively affect TTF.

The research by Lin and Huang (2008) revealed that perceived TTF had a substantial influence on knowledge management system usage and that knowledge management system self-efficacy was found to be positively associated with perceived TTF. Users will not use a technology if TTF is not satisfied (Goodhue & Thompson, 1995). In other words, a good TTF will promote users’ adoption of a technology, whereas a poor TTF will decrease users’ technology adoption (Lee et al., 2007; Lin & Huang, 2008). Individuals are not willing to adopt a technology if they find it unfit for their daily tasks and that technology brings no improvement in their tasks’ execution (Oliveira et al., 2014; Sharif et al., 2019). Previous studies on information systems also suggest the influence of TTF on user adoption (Alam et al., 2020; Faqih & Jaradat, 2021; Paulo et al., 2018; Sharif et al., 2019) as TTF positively affects using technology (Lin & Huang, 2008; Oliveira et al., 2014; Paulo et al., 2018). Thus, we argue that if ChatGPT cannot meet the requirements of users in achieving their tasks (e.g., using search functions, creating helpful content, performing data analysis and management, creating works of art, programming and fixing errors in programming, performing multilingual translation), they may not want to use ChatGPT. Thus, the following hypothesis is formulated:

Hypothesis 9: TTF positively affects ChatGPT use.

3.2.8 Continuance intention to use and word of mouth

Continuance intention to use is defined as users’ intention to continue using a technology until an alternative is presented, either with the introduction of a replacement or an improved version (Mathieson, 1991; Bhattacherjee, 2001). In this study, continuance intention to use ChatGPT is described as users’ intention to continue using ChatGPT for their daily and professional activities.

Word of mouth (WOM) on technology acceptance or use is defined as the level of exchange of information in relation to using technology among users and potential users (Parry et al., 2012). WOM on technology acceptance or use is the starting point for spreading good (or bad) words about a particular technology. In addition, continuance is the outcome of acceptance behaviour as both acceptance and continuance decisions are made when users employ the same set of pre-acceptance variables (Bhattacherjee, 2001). Kim and Malhotra (2005) found that past behavior can be a predictor of a future information systems use. Empirical evidence showed that actual usage of the Wiki system positively affects continuance intention to use that system (Yueh et al., 2015). Bhattacherjee (2001) stated that information systems users' continuance decision is influenced by the initial use (of an IS or a product) experience. In the same vein, Kang et al. (2022) also acknowledged that using smart home healthcare services has a positive effect on the intention to continue using those services. Based on these findings, we conjecture that:

Hypothesis 10: ChatGPT use positively affects intention to continue using ChatGPT.

Hypothesis 11: ChatGPT use positively affects WOM.

Hypothesis 12: Intention to continue using ChatGPT positively affects WOM.

3.2.9 Curiosity

Curiosity is an essential element in online activities since it drives people to explore the Internet environment in search of knowledge and perhaps in order to gain and integrate new ideas and experiences (Fang et al., 2018). Curiosity refers to the extent the experience arouses sensory and cognitive curiosity in individuals during the interaction with technologies (Webster et al., 1993). There is a heightened arousal of sensory and cognitive curiosity during a flow experience (Agarwal & Karahanna, 2000). Curiosity suggests that interacting with the software invokes excitement about available possibilities through such technology characteristics as color and sound (Webster et al., 1993). Most studies adopting UTAUT2 have often tested the moderating role of variables such as socio-demographic ones. However, few studies have attempted to extend the model to improve its explanatory power (Farzin et al., 2021). Therefore, in this study, to gain a deep understanding of the role curiosity may play in the relationship between various constructs of UTAUT2 (i.e., performance expectancy, effort expectancy, facilitating conditions, hedonic motivation, social influence), and trust and ChatGPT use, we propose the following hypotheses:

Hypothesis 13a: Curiosity moderates the path between trust and ChatGPT use.

Hypothesis 13b: Curiosity moderates the path between social influence and ChatGPT use.

Hypothesis 13c: Curiosity moderates the path between hedonic motivation and ChatGPT use.

Hypothesis 13d: Curiosity moderates the path between facilitating conditions and ChatGPT use.

Hypothesis 13e: Curiosity moderates the path between effort expectancy and ChatGPT use.

Hypothesis 13f: Curiosity moderates the path between performance expectancy and ChatGPT use.

Figure 1 summarizes our research model.

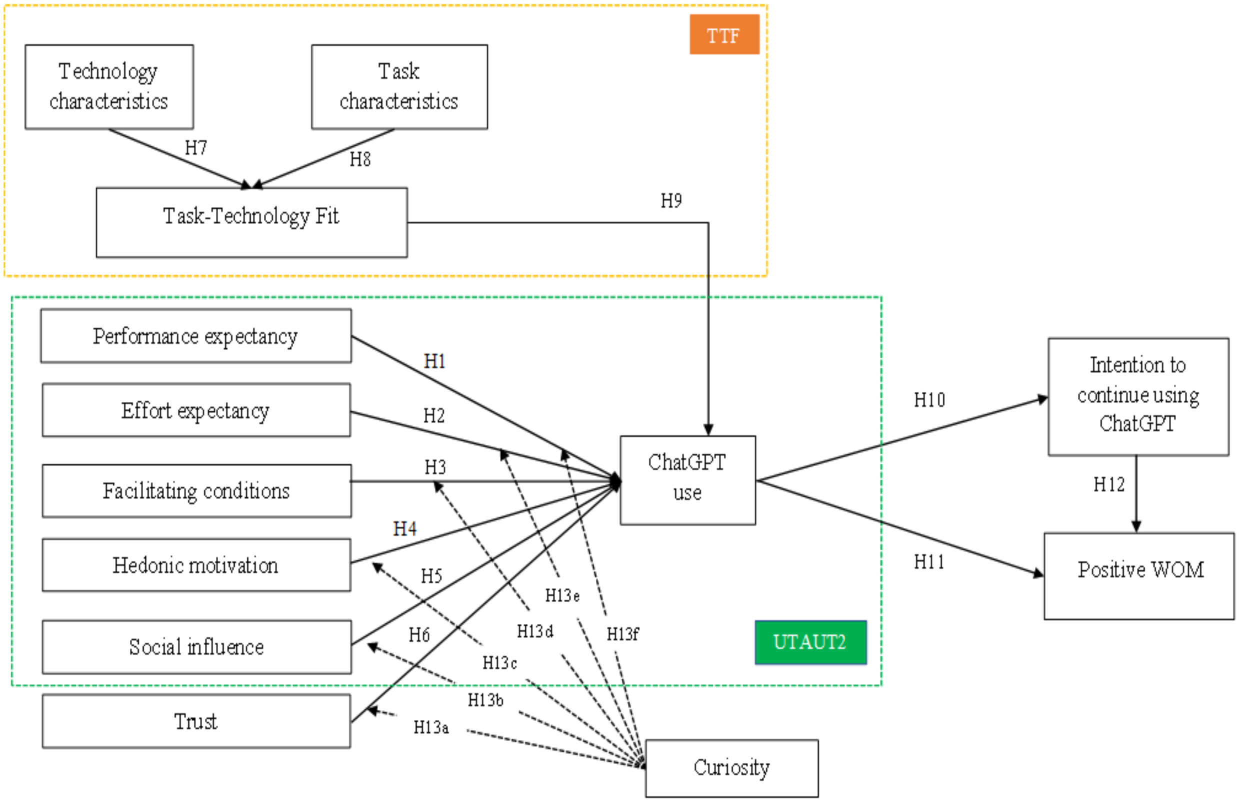

Figure 1. Research model

4 Methodology

4.1 Research design and measurements

In this study, a quantitative approach was adopted to understand how various constructs of UTAUT2 and TTF influence the use of ChatGPT, and how ChatGPT use informs continuance intention to use ChatGPT and WOM. A questionnaire was developed to obtain insights from users. Measurement scales were extracted from previous studies and adjusted to be suitable for the ChatGPT setting. On a five-point Likert scale, ranging from (1) “strongly disagree” to (5) “strongly agree”, except for ChatGPT use construct, the items of all the remaining constructs in the research model were rated. ChatGPT use was assessed employing respondents’ usage frequency, from (1) “never” to (5) “many times per month” (Appendix A). As the ChatGPT use scale has not been existing and our study in the field of ChatGPT must have a holistic view on the various ChatGPT uses, on the basis of Venkatesh et al.’s (2012) scale, using the convenience sampling and semantic saturation, we conducted 20 individual in-depth interviews with ChatGPT users to fully capture the various ChatGPT uses. The items were considered for removal when 25% or more of respondents did not consider them appropriate. Accordingly, six items for measuring ChatGPT use construct were suggested by the participants. Additionally, following Hardesty and Bearden (2004), five artificial intelligence professors were invited to evaluate the face and content validity of these six items. As a result, some items were modified linguistically, but no items were dropped. The ChatGPT use construct includes 6 items, as shown in Appendix A.

4.2 Sampling and data collection

The population of the study includes Vietnamese aged from 18 years old who have already used ChatGPT. A convenience sampling technique was employed. The questionnaire was administered both face-to-face and online through popular media channels in Vietnam such as Zalo, FB Messenger, and e-mail. To reduce common method bias, in the introduction section of the questionnaire, we explicitly mentioned that we strictly keep the anonymity of respondents, that respondents need to choose the options that best describe their experience, and that there are no right or wrong answers. A filter question at the beginning of the questionnaire helped us select people who have already experienced ChatGPT only. Regarding the face-to-face data collection, it was conducted from late December 2022 to mid-February 2023 in the four biggest cities, including Ha Noi, Da Nang, Nha Trang, and Ho Chi Minh City. These are major cities located in both the North, Central and South of Vietnam. Therefore, the sample is somewhat representative of the urban population that is prone to new technologies use. Moreover, we purposely administrated the survey in a way that helped us obtain a sample with a more or less equal proportion of men/women and varied categories in terms of age, occupation, and education (Table1). The questionnaire built in English was translated into Vietnamese and translated back into English to avoid any inconsistencies. The translation process was controlled by two experts in information systems and two experts in marketing who are perfectly bilingual. The questionnaire was then tested with ten Vietnamese ChatGPT users. According to the test results, no changes were formulated by these ten participants. This study was based on the sample size calculation method suggested by Bollen (1989). As the total measurement parameters in the model were 48, following a 5:1 ratio, the minimum sample size should be 240. However, we aimed for a larger sample size to increase the reliability of our research. Moreover, analyzing data using CB-SEM requires a large sample size because this technique is based on the large sample distribution theory (Raykov & Widaman, 1995). Thus, we targeted a sample larger than 240. Accordingly, we received 750 questionnaires in total; however, only 671 questionnaires were included in the analysis after the incomplete questionnaires were eliminated. The socio-demographic data of respondents were presented in Table 1.

Table 1. Respondents' socio-demographic characteristics

Socio-demographic variables		**Frequency (N=671)**	**St.dev**
1. Gender	Male	330	49.20
	Female	341	50.80
2. Age	18 - < 25 years old	186	27.70
	25 - < 35 years old	200	29.80
	35 - < 45 years old	232	34.60
	45 – < 55 years old	45	6.70
	= > 55 years old	8	1.20
3. Occupation	Student	177	26.40
	Businessman	95	14.20
	Governmental officer	190	28.30
	Office staff	102	15.20
	Others	107	15.90
4. Education	Secondary school	19	2.80
	High school	46	6.90
	College	122	18.20
	Bachelor	332	49.50
	Master	131	19.50
	Doctoral	21	3.10

4.3 Data analysis

SPSS 25.0 and AMOS 24.0 were used for statistical analyses. Testing the measurement model and the structural model are two stages in the procedure. In the first stage, Cronbach's alphas were used to evaluate the internal consistency reliability of the constructs. Then, exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were also used to confirm the reliability, convergent validity, and discriminant validity of the scales. In the second stage, the structural equation modelling (SEM) method was used to test the hypotheses.

5 Results

5.1 Measurement model

First, exploratory factor analysis (EFA) was performed. Principal Axis Factoring and Promax Rotation were applied. The results showed that the KMO value was 0.92 and the Bartlett's Test was significant at the 0.00 level. These findings supported the factorial ability of the data. Moreover, about 66.23% of the total explained variation was explained by the 13 components that were retrieved. As shown in Appendix A, the lowest outer loading was 0.54, while the maximum was 0.91, above the 0.50 criterion. Therefore, all 48 items were retained for further analysis. Moreover, Appendix A indicates the means, standard deviations, and modes of 48 items used to assess 13 variables in the research model.

Second, in addition to the outer loadings being above 0.50, the Cronbach's alphas of 13 constructs were largely greater than 0.70 (Appendix A) and their CRs obtained from the confirmatory factor analysis (CFA) ranged from 0.80 to 0.92 (Table 2), confirming a satisfactory internal consistency reliability of the constructs (Hair et al., 2010).

In the next step, to examine the level of model fit, the measurement model was established. The indicators, which were the ratio Chi-square/degree of freedom ($\chi 2/df \leq 3$), goodness-of-fit index (GFI≥0.80), adjusted goodness-of-fit index (GFI≥0.90), comparative fit index (CFI≥0.90), Tucker–Lewis index (TLI≥0.90), and root mean square error of approximation (RMSEA≤0.08)were used for assessing the measurement model. The results indicated that the measurement model exhibited a good level of model fit ($\chi 2/df=2.63$, GFI=0.85, CFI=0.92, TLI=0.91, RMSEA=0.05) (Doll et al., 1994; Hair et al., 2010). Through the use of average variance extracted (AVE), CRs, and outer loadings, the constructs' convergent validity was evaluated. Appendix A demonstrates that outer loadings varied from 0.54 to 0.91, higher than the recommended threshold of 0.5. Besides, all estimated path coefficients were statistically significant ($p < 0.00$). All of the CR values were more than 0.70, and the lowest AVE value was 0.57 (Table 2). All these results indicated a high level of convergent validity (Hair et al., 2010; Steenkamp & van Trijp, 1991). Additionally, Table 2 shows that AVE was higher than the Maximum Shared Variance (MSV) and that AVE square roots were higher than correlation coefficients, indicating that all of the components had discriminant validity (Fornell & Larcker, 1981).

5.2 Common method bias

Despite applying procedural remedies (such as questionnaire construction and validation, closed-ended questions, and respondents' anonymity), common method bias (CMB) can be an issue that distorts the research results (Podsakoff et al., 2003). Furthermore, although sources of measurement error can be both random and systematic, the systematic component often has a more negative impact on the study's findings (Jakobsen & Jensen, 2015). Thus, the Harman single factor was utilized to evaluate the CMB statistically (Podsakoff et al., 2003). An unrotated factor solution of the principal component analysis revealed that no single factor explained the majority of the variance (the first factor merely accounted for 13.36% of the total variance, which is less than the threshold value of 50%). Hence, there was no CMB in this study (Podsakoff et al., 2012).

Table 2. Correlation coefficients and discriminant validity analysis

	CR	AVE	MSV	1	2	3	4	5	6	7	8	9	10	11	12	13
CHUSE	0.92	0.64	0.24	**0.80**												
EFOEX	0.90	0.67	0.39	0.27***	**0.82**											
PEREX	0.88	0.65	0.26	0.36***	0.44***	**0.81**										
TRUST	0.87	0.63	0.26	0.29***	0.41***	0.50***	**0.80**									
WOM	0.88	0.64	0.34	0.36***	0.35***	0.51***	0.47***	**0.80**								
SOINF	0.87	0.62	0.34	0.31***	0.29***	0.48***	0.49***	0.59***	**0.79**							
FACON	0.84	0.57	0.26	0.32***	0.45***	0.41***	0.51***	0.39***	0.46***	**0.75**						
CURIS	0.89	0.72	0.24	0.49***	0.38***	0.34***	0.27***	0.34***	0.32***	0.32***	**0.85**					
HEMOT	0.83	0.64	0.39	0.31***	0.63***	0.36***	0.31***	0.39***	0.31***	0.28***	0.39***	**0.80**				
INCUS	0.86	0.67	0.24	0.30***	0.37***	0.44***	0.41***	0.49***	0.41***	0.38***	0.30***	0.35***	**0.82**			
TTF	0.85	0.66	0.22	0.47***	0.41***	0.43***	0.45***	0.41***	0.36***	0.37***	0.36***	0.35***	0.40***	**0.81**		
TACHA	0.86	0.67	0.38	0.31***	0.62***	0.44***	0.43***	0.40***	0.32***	0.36***	0.37***	0.57***	0.42***	0.47***	**0.82**	
TECHA	0.80	0.58	0.20	0.22***	0.41***	0.35***	0.40***	0.44***	0.44***	0.43***	0.34***	0.27***	0.36***	0.45***	0.42***	**0.76**

CR = Composite Reliability; AVE = Average Variance Extracted; MSV = Maximum Shared Variance; On the major diagonal, the square root of AVE is shown in bold; CHUSE = ChatGPT use ; EFOEX = Effort expectancy; PEREX = Performance expectancy; TRUST = Trust; WOM = Word-of-mouth; SOINF =Social influence; FACON = Facilitating conditions; CURIS = Curiosity; HEMOT = Hedonic motivation; INCUS = Intention to continue using ChatGPT; TTF = Task-Technology Fit; TACHA = Task characteristics; TECHA = Technology characteristics

Significance of correlations: †: $p < 0.10$; *: $p < 0.05$; **: $p < 0.01$, ***: $p < 0.00$

5.3 Structural model and hypothesis testing

The Structural Equation Modelling (SEM) technique was applied to estimate multiple and interrelated dependence relationships (Hair et al., 2010), which can be considered an ideal technique to test the hypotheses given the complex relationships among the constructs. So, an SEM was conducted to assess how each of the constructs of TTF and UTAUT2 affects ChatGPT use and whether the latter is related to the intention to continue using ChatGPT and WOM. The SEM results suggested a good-fitting model ($\chi 2/df=2.67$, GFI=0.86, CFI=0.92, TLI=0.91, RMSEA=0.05) (Doll et al., 1994; Hair et al., 2010).

Regarding ChatGPT use, the findings showed that performance expectancy, facilitating conditions, hedonic motivation, TTF had a positive effect on ChatGPT use, supporting H1, H3, H4, and H9. Specifically, the factor that had the strongest effect on ChatGPT use was TTF ($\beta=0.34$). However, contrary to what we have imagined, H2, H5, and H6 were not supported ($p>0.10$) (Table 3).

In terms of users' WOM, both ChatGPT use and intention to continue using ChatGPT had a significant effect on WOM, confirming H11 and H12. Furthermore, the intention to continue using ChatGPT had a stronger effect ($\beta=0.40$) than ChatGPT use ($\beta=0.26$) on WOM (Table 3). The results also indicated that technology characteristics ($\beta=0.36$, $p=0.00$) and task characteristics ($\beta=0.31$, $p=0.00$) were related to TTF, supporting H7 and H8 (Table 3).

About the intention to continue using ChatGPT, the relationship between ChatGPT use and continuance intention to use ChatGPT was significant and positive ($\beta=0.32$, $p=0.00$) (Table 3), validating H10.

With regard to the moderating effect of curiosity, the paths from hedonic motivation, facilitating conditions, and performance expectancy to ChatGPT use were significantly and negatively moderated by curiosity, verifying H13c, H13d, and H13f (Table 3). However, the moderating effect of curiosity on the relationships between trust, social influence, effort expectancy, and ChatGPT use was not significant, rejecting H13a, H13b, and H13e (Table 3).

Table 3. Structural relationships

Hypothesis	Relationship	β coefficient		p-value	Result
		Unstandardized	Standardized		
H1	Performance expectancy → ChatGPT use	0.16	0.14	0.01	Supported
H2	Effort expectancy → ChatGPT use	-0.10	-0.07	0.18	Not supported
H3	Facilitating conditions → ChatGPT use	0.16	0.15	0.01	Supported
H4	Hedonic motivation → ChatGPT use	0.16	0.14	0.01	Supported
H5	Social influence → ChatGPT use	0.09	0.08	0.11	Not supported
H6	Trust → ChatGPT use	-0.04	-0.03	0.56	Not supported
H7	Technology characteristics → TTF	0.30	0.36	***	Supported
H8	Task characteristics → TTF	0.39	0.31	***	Supported
H9	TTF → ChatGPT use	0.41	0.34	***	Supported
H10	ChatGPT use → Intention to continue using ChatGPT	0.29	0.32	***	Supported
H11	ChatGPT use → WOM	0.22	0.26	***	Supported
H12	Intention to continue using ChatGPT → WOM	0.37	0.40	***	Supported
H13a	Moderating role of curiosity on the path from trust to ChatGPT use	-0.03	-0.04	0.34	Not supported
H13b	Moderating role of curiosity on the path from social influence to ChatGPT use	-0.05	-0.06	0.10	Not supported
H13c	Moderating role of curiosity on the path from hedonic motivation to ChatGPT use	-0.08	-0.11	0.00	Supported
H13d	Moderating role of curiosity on the path from facilitating conditions to ChatGPT use	-0.05	-0.08	0.04	Supported
H13e	Moderating role of curiosity on the path from effort expectancy to ChatGPT use	-0.01	-0.02	0.65	Not supported
H13f	Moderating role of curiosity on the path from performance expectancy to ChatGPT use	-0.06	-0.09	0.02	Supported

***: p = 0.00

6 Discussion

In this study, drawing on the UTAUT2 and TTF theory, we attempted to identify the factors affecting ChatGPT use and the main activities individuals do while using ChatGPT and determine whether they continue using ChatGPT and recommend it to others. The moderating role of curiosity in the relationships between various influencing factors and ChatGPT use was also examined.

Regarding the factors influencing ChatGPT use, surprisingly, the results showed that two dimensions of UTAUT2 (i.e., effort expectancy and social influence) and trust did not play a significant role in explaining the use of ChatGPT. Overall, these results are not in line with most previous studies on technology adoption and use (e.g., Alam et al., 2020; Hsu et al., 2017; Jain et al., 2022; Mariani et al., 2023; Onaolapo & Oyewole, 2018; Venkatesh et al., 2012; Yueh et al., 2015). For example, the systematic literature review on AI conducted by Mariani et al. (2023) displayed that trust is one of five key factors that have been found to shape conversational agent adoption. Gupta et al. (2022) also found that, in the context of online housing recommendation system, the conversational interface is more effective than the traditional web interface in developing user trust. On the one hand, this inconsistency may be due to the specificities of ChatGPT. So far, ChatGPT is a new phenomenon, publicly accessible, and free of charge. How ChatGPT is revolutionizing our lives remains indistinct. The regulations as to the validity of the content generated by ChatGPT are not conclusive yet. Thus, the unconditional trust granted to ChatGPT seems, at this stage of development, premature. On the other hand, with the advancement and widespread popularity of AI-based technologies, users are gradually becoming familiar with and have already formed fundamental beliefs for these technologies. As for the non-significant effect of effort expectancy on ChatGPT use, this finding is, however, in accordance with the study by Andrews et al. (2021), indicating that effort expectancy had no effect on the adoption of AI and related new technologies. The reason could be that there is still a vagueness in users on what “AI and related technologies” include (Andrews et al., 2021), such as ChatGPT. In addition, the UTAUT2 was employed in varied study contexts and subjects, which may explain this mixed result. With respect to social influence, in the context of our study, ChatGPT is a novel technology in the world in general and in Vietnam in particular, few Vietnamese have experienced it, implying that the influence of others on using ChatGPT is improbable and that ChatGPT users may not think know how to use ChatGPT gives them professional status.

The findings also revealed four factors (i.e., performance expectancy, facilitating conditions, hedonic motivation, and TTF) that were positively associated with ChatGPT use. Among these four factors, performance expectancy was the strongest influencing factor, denoting that users have confidence in ChatGPT performance. When performance expectancy is high, users are more likely to use this disruptive technology. Indeed, ChatGPT can provide users with benefits such as personalized services, useful, and immediate. It may also help them increase their productivity. Therefore, users use ChatGPT because they believe it is a useful, and convenient solution for their purpose. The result confirms many previous studies indicating that performance expectancy has a positive effect on usage of diverse technologies (Chua et al., 2018; Hsu et al., 2017; Jain et al., 2022; Onaolapo & Oyewole, 2018). With regard to facilitating conditions, the finding is consistent with earlier studies mobilizing the UTAUT (e.g., Venkatesh et al., 2003, 2012) and dealing with the adoption of various social platforms and AI-related technologies like ChatGPT (e.g., Alam et al., 2020; Haller et al., 2021; Hsu et al., 2017; Jain et al., 2022; Kang et al., 2022; Oliveira et al., 2014; Paulo et al., 2018). This result can be explained in several ways. First, users are becoming more skilled in using technologies. Second, equipment and resources (e.g., wifi, 4G, smartphone, tablet, desktop computer, online support) for an effective use of ChatGPT are much more easily accessible nowadays. Concerning hedonic motivation, according to Farah et al (2018), people show more and more interest toward new and innovative technologies because the latter meets their intrinsic pleasure. Thus, disruptive technologies are regarded by users as sources of hedonic motivation, which leads to their adoption (Farzin et al., 2021). For example, Mishra et al. (2022) discovered that hedonic motivation individuals can find while using smart technologies increases their use. Positive emotions generated while using these incredibly powerful technologies are further enhanced by the website’s visually appealing layouts and colors (Malaquias & Hwang, 2016). Moreover, according to Fu & Elliott (2013), new technologies are often endorsed by important people, which makes average individuals more likely to accept them.

Task characteristics and technology characteristics directly predicted TTF, supporting many previous studies (e.g., Lin & Huang, 2008; Oliveira et al., 2014; Paulo et al., 2018). Although ChatGPT has merely appeared in recent months, it has created a worldwide buzz and particularly aroused the curiosity of individuals who have a connection with or are interested in AI-related technologies. Thus, for users who have already used and been aware of numerous ChatGPT functions as well as technology features (especially regarding the provision of ubiquitous, real-time, and reliable data), ChatGPT may help them complete faster and easier their tasks and meet their needs. This elucidates the effect of task characteristics and technology characteristics on TTF. However, task characteristics had a relatively smaller effect on TTF compared with technology characteristics, which is contrary to some previous study (e.g., Sharif et al., 2019; Wang et al., 2020). Indeed, ChatGPT is a new and powerful technology, users may tend to put more focus on the ubiquity, immediacy, and reliability of information delivered by ChatGPT. Also, our study provided support for the strongest positive effect of TTF on ChatGPT use. This result is supported by previous research (e.g., Lin & Huang, 2008; Oliveira et al., 2014; Paulo et al., 2018), inferring that ChatGPT could provide users with the required functions to match their needs, they would use it.

To answer the question “What specific tasks do people use ChatGPT for?”, our study specified that people used ChatGPT to, as a priority, complete tasks such as multilingual translation, search functions, creating useful content, data analysis and management, programming and fixing errors in programming, and creating works of art. The descriptive statistics of the current study showed that among these popular purposes, ChatGPT was more used for multilingual translation, search functions, and creating useful content with the average rating on a 5-point scale of 3.30, 3.28, and 3.28, respectively.

Our study also indicated that ChatGPT use positively and directly affected both intention to continue using ChatGPT and positive WOM. Specifically, ChatGPT use had more effect on the intention to continue using ChatGPT than positive WOM. In addition, the intention to continue using ChatGPT had a significant and strong effect on users' positive WOM about ChatGPT. These findings are consistent with the existing technology literature, revealing that the tendency to adopt a technology is one of the earliest drivers of individuals' actual behaviors (Kang et al., 2022; Yueh et al., 2015). Moreover, users' satisfaction with mobile Internet-based (health) services was found to have a positive and direct effect on positive WOM (Gu et al., 2018).

Finally, our study endeavored to examine the moderating role of curiosity, an individual variable, in predicting the behavioral intention of users to adopt ChatGPT. The findings supported three of six hypotheses that curiosity played a moderating role in the relationships between hedonic motivation, facilitating conditions, and performance expectancy, and ChatGPT use. It was observed that the regression coefficients of these relationships moderated by curiosity were negative, suggesting that if user curiosity increases, there will be less effect of hedonic motivation, facilitating conditions, and performance expectancy on ChatGPT use. These findings can be explained that, at first, users' curiosity about a new technology or platform motivates them to explore that technology or platform for new knowledge acquisition and integration of novel perspectives and experiences (Fang et al., 2018); however, once users are relatively familiar with it (i.e., curiosity decreases), they may focus more on the hedonic aspect, facilitating conditions (e.g., necessary resources to use that technology, support), and performance, which, consequently, increases the effect of these three factors (i.e., hedonic motivation, facilitating conditions, and performance expectancy) on that technology's use.

7 Theoretical contributions

Our study makes significant contributions to the current literature on AI technologies adoption in three main ways.

First, while existing studies attempted to investigate the characteristics, functions, applications, and history of ChatGPT (e.g., Gilson et al., 2023; Rospigliosi, 2023; Rudolph et al., 2023), this paper is among the first to examine users' behavior towards using this emerging technology. With the rapid adoption of ChatGPT researching factors affecting ChatGPT use, continuance intention to use, and WOM can provide initial ideas on how users' behavior is shaped as well as how to improve that behavior. By doing so, the study extends understanding of the users' behavior process to adopt an AI technology by investigating a comprehensive process: actual usage behavior–intention to continue using–WOM in the context of ChatGPT, a new AI technology. Previous studies on technology adoption merely examined factors affecting technology usage (e.g., Farah et al., 2018; Gansser et al., 2021), continuance intention to use technologies (e.g., Liu et al., 2022; Wu & Chen, 2017), or users' technology usage and WOM (Mishra et al., 2022) or vice versa (e.g., Mehrad & Mohammadi, 2017). There has not been any study examining whether continuance intention to use technologies affects WOM. This paper highlights the importance of measuring actual usage behaviors towards AI-related technologies, as these tend to underpin post-usage behavior (i.e., continuance intention to use and intention to recommend).

Second, to gain a more accurate and comprehensive understanding of the tendency of people to accept AI technology and their usage behavior, the traditional UTAUT2 model was extended by integrating the TTF model, trust, and curiosity. Theoretically, using trust as an additional factor in the model can provide new insights for future studies on new technology adoption. Unlike previous studies that revealed trust as an important factor in initiating technology adoption and use (e.g., Alam et al., 2020; Hsu et al., 2017; Jain et al., 2022), our study demonstrated that trust did not influence the use of ChatGPT. This can be explained by the fact that ChatGPT is, so far, a new phenomenon, publicly accessible, free of charge, and the validity of the content generated by ChatGPT is still questionable. This finding requires ChatGPT developers to improve the credibility of the information provided by this chatbot, accordingly, increasing individuals' use and intention to continue using.

Third, this study examined the moderating role of curiosity on the paths from independent factors to ChatGPT use and showed that it moderated on three paths. This interesting and surprising finding contributes to enriching the extant literature by emphasizing the significant moderating role of individuals' curiosity on the impact of various dimensions of the UTAUT2 on AI technology use; especially, it is important to think about the users' seniority of use of a technology when handling their technology use to retain them.

8 Practical implications

This study provides valuable insights into the process of user thinking and decision making regarding actual use, continuance intention to use, and intention to recommend ChatGPT. Based on the statistically significant role of performance expectancy, facilitating conditions, hedonic motivation, and TTF in influencing ChatGPT use, this research can serve as a practical guide for ChatGPT providers, policymakers, and users.

For ChatGPT providers, they need to improve the TTF. They can segregate the market and provide differentiated services to niche users because each country has its own language, and the application of ChatGPT in different languages is encouraged. ChatGPT providers also need to detect limitations and seek user feedback to create optimized tools in the future. In addition, it is vital to increase "openness" to encourage experts to use and bring comments and suggestions for better development of ChatGPT and building other similar AI applications, thereby increasing the suitability for users. Moreover, ChatGPT providers should offer users instantaneous support, thus expanding their ability to use.

Regarding the governments, our research showed that facilitating conditions, hedonic motivation, and performance expectancy were significant influencing factors on ChatGPT use. The Industry 4.0 is essentially "intelligentization", therefore, forcing governments, businesses, and end-users to change (e.g., perception, knowledge, attitude, readiness, behavior) in order to successfully live and work together. It is also necessary for them to together develop the technology convergence environment in which AI will be an essential part. Furthermore, it is crucial to create an environment that encourages individuals and organizations to participate in the creation and effective use of new AI technologies, such as ChatGPT.

Finally, our research demonstrated that technology characteristics (i.e., ubiquitous, real-time, and reliable data provided by ChatGPT) had a positive effect on TTF, which in turn affected ChatGPT use. Thus, we suggest that businesses should develop proper marketing strategies by building a coherent technological ecosystem, enabling ChatGPT to identify their true values and to transfer correct information to users in order to prevent faulty information generated by ChatGPT. This accordingly increases information credibility in a context that ChatGPT is a new phenomenon with a controversy over reliable information and ethical issues.

9 Limitations and future research

This study is not without limitations. Cross-sectional data collected for this research were only significant at a specific time. Increasing AI technology concerns and ChatGPT with new functions (probably) may change user's behavior. Thus, a longitudinal design is needed to examine users' ChatGPT usage and post-usage intentions more comprehensively. Moreover, further research should apply mixed-method approaches (both exploratory and explanatory designs) to explore other important constructs that are suitable for this chatbot and explain the adoption process in greater detail.

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Appendix A: Scales items evaluation

Construct	Source	ID*	Item	Loading	Mean	Cronbach alpha	Std. Deviation	Mode
Task-Technology Fit (TTF)	Goodhue & Thompson (1995) & Lu & Yang (2014)					*0.85*		
		TTF1	1. In my opinion, ChatGPT's functions are suitable for helping me complete my search tasks.	0.76*	3.80		0.86	4.00
		TTF 2	2. In my opinion, ChatGPT's functions are enough to help me complete my search tasks.	0.85*	3.47		0.94	4.00
		TTF 3	3. In general, the functions of ChatGPT fully meet my needs.	0.82*	3.51		0.95	4.00
Technology characteristics (TECHA)	Zhou et al. (2010)					*0.8*		
		TECHA1	1. ChatGPT provides ubiquitous data.	0.66*	3.69		0.94	4.00
		TECHA2	2. ChatGPT provides real-time data.	0.84*	3.56		1.00	4.00
		TECHA3	3. ChatGPT provides reliable data.	0.78*	3.47		0.94	3.00
Task characteristics (TACHA)	Lu & Yang (2014)					*0.86*		
		TACHA1	1. I often need to figure out the problem encountered anytime and anywhere.	0.86*	3.49		0.90	4.00
		TACHA2	2. I often need to gather information for problem solving	0.83*	3.50		0.94	4.00

			anytime and anywhere.					
		TACHA3	3. I often need advice from someone else to make decisions anytime and anywhere.	0.77*	3.38		0.97	4.00
Performance expectancy (PEREX)	Venkatesh et al. (2012)					*0.883*		
		PEREX1	1. I find ChatGPT useful in my daily life.	0.81*	3.54		1.00	4.00
		PEREX2	2. Using ChatGPT increases my chances of achieving things that are important to me.	0.80*	3.55		0.97	4.00
		PEREX3	3. Using ChatGPT helps me accomplish things more quickly.	0.83*	3.60		0.97	4.00
		PEREX4	4. Using ChatGPT increases my productivity.	0.79*	3.48		0.98	4.00
Effort expectancy (EFOEX)	Venkatesh et al. (2012)					*0.89*		
		EFOEX1	1. Learning how to use ChatGPT is easy for me.	0.84*	3.58		0.87	4.00
		EFOEX2	2. My interaction with ChatGPT is clear and understandabl e.	0.82*	3.63		0.88	4.00
		EFOEX3	3. I find ChatGPT easy to use.	0.83*	3.70		0.87	4.00
		EFOEX4	4. It is easy for me to become skillful at using ChatGPT.	0.78*	3.61		0.90	4.00
Facilitating conditions (FACON)	Oliveira et al. (2014)					*0.84*		
		FACON1	1. I have all the necessary	0.75*	3.50		1.01	4.00

			resources to use ChatGPT.					
		FACON2	2. I have the know-how to use ChatGPT.	0.69*	3.56		0.94	4.00
		FACON3	3. If I have any doubts about how to use the ChatGPT service, I do have a support line to help me.	0.80*	3.32		1.03	4.00
		FACON4	4. If I have any doubts about how to use the ChatGPT service, I do have an account manager that helps me.	0.77*	3.33		1.07	3.00
Trust (TRUST)	Afshan & Sharif (2016)					*0.87*		
		TRUST1	1. ChatGPT seems dependable.	0.83*	3.47		0.92	3.00
		TRUST2	2. ChatGPT seems secure.	0.84*	3.43		0.96	3.00
		TRUST3	3. ChatGPT seems reliable.	0.83*	3.46		0.93	3.00
		TRUST4	4. ChatGPT was created to help the users.	0.66*	3.74		0.90	4.00
Hedonic motivation (HEMOT)	Venkatesh et al. (2012)					*0.76*		
		HEMOT1	1. Using ChatGPT is fun.	0.89*	3.71		0.87	4.00
		HEMOT2	2. Using ChatGPT is enjoyable.	0.91*	3.77		0.91	4.00
		HEMOT3	3. Using ChatGPT is very entertaining.	0.54*	3.79		1.50	4.00
Social influence (SOINF)	Venkatesh et al. (2012) & Oliveira et al. (2014)					*0.87*		
		SOINF1	1. My friends and family value the use of ChatGPT.	0.81*	3.34		1.03	3.00

		SOINF2	2. The people who influence my behavior think that I should use ChatGPT.	0.85*	3.34		1.05	3.00
		SOINF3	3. I find ChatGPT trendy.	0.69*	3.57		0.97	4.00
		SOINF4	4. The use of ChatGPT gives me professional status.	0.79*	3.52		1.03	4.00
ChatGPT use (CHUSE)	Venkatesh et al. (2012) & in-depth interviews					*0.92*		
		CHUSE1	1. Search functions on ChatGPT.	0.80*	3.28		1.12	4.00
		CHUSE2	2. Use ChatGPT to create useful content.	0.85*	3.28		1.13	4.00
		CHUSE3	3. Use ChatGPT for data analysis and management.	0.88*	3.18		1.10	3.00
		CHUSE4	4. Use ChatGPT to create works of art.	0.76*	2.91		1.19	3.00
		CHUSE5	5. Use ChatGPT for programming and fixing errors in programming.	0.73*	2.96		1.17	3.00
		CHUSE6	6. Use ChatGPT for multilingual translation.	0.78*	3.30		1.18	4.00
Intention to continue using ChatGPT (INCUS)	Bhattacherjee (2001)					*0.85*		
		INCUS1	1. I intend to continue using ChatGPT in the future.	0.78*	3.60		0.93	4.00
		INCUS2	2. I will always try to use ChatGPT in my daily life.	0.78*	3.50		0.98	4.00
		INCUS3	3. I plan to continue to	0.88*	3.54		0.98	4.00

			use ChatGPT frequently.					
Word-of-mouth (WOM)	Choi (2018)					*0.88*		
		WOM1	1. I would say positive things about ChatGPT to other people.	0.81*	3.51		0.92	4.00
		WOM2	2. I would recommend ChatGPT to someone who seeks my advice.	0.81*	3.51		0.98	4.00
		WOM3	3. I would encourage friends and relatives to use ChatGPT.	0.83*	3.51		0.94	4.00
		WOM4	4. I intend to positively promote ChatGPT.	0.75*	3.46		0.95	3.00
Curiosity (CURIS)	Agarwal & Karahann (2000)					*0.88*		
		CURIS1	1. ChatGPT excites my curiosity.	0.89*	3.70		0.93	4.00
		CURIS2	2. ChatGPT makes me curious.	0.89*	3.73		0.85	4.00
		CURIS3	3. ChatGPT arouses my imagination.	0.76*	3.54		0.95	4.00
ID* stands for identity number of the item Significant at: *: p = 0.00								

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