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Generative AI, Why, How, and Outcomes: A User Adoption Study

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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 an integrated research model to explore the factors affecting ChatGPT use and its subsequent effects on whether users continue using ChatGPT and recommend it to others. We also examined the main activities of ChatGPT use as well as the moderating role of curiosity in the relationships between various influencing factors and ChatGPT use. We conducted a quantitative study with data that we collected from 671 users in Vietnam. We found that, first, most UTAUT2 and TTF dimensions affected ChatGPT use. Interestingly, contrary to our expectations, effort expectancy, social influence, and trust had no effect on ChatGPT use. Second, ChatGPT use directly influenced intention to continue using ChatGPT and word of mouth (WOM). Third, intention to continue using ChatGPT had a significant effect on WOM. Finally, we found that curiosity acted as a moderator in only three paths from hedonic motivation, facilitating conditions, and performance expectancy to ChatGPT use. With this study, we contribute a unique research model that combines the UTAUT2 and the TTF (including both trust and curiosity) as well as knowledge about 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

Scholars across various fields have begun to use artificial intelligence (AI)—machines that exhibit facets of human intelligence (Flavián et al., 2022; Mariani et al., 2022)—because it provides enormous possibilities for improving people's lives (Berente et al., 2021: Mariani et al., 2022). AI has had significant impacts on human beings in various aspects, such as human decision accuracy or unique human knowledge (Fügener et al., 2021). With its recent launch on 30 November, 2022, ChatGPT (generative pre-trained transformer), a generative (conversational) AI (Dwivedi et al., 2023), 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 and content (Lim et al., 2023; Pan et al., 2023; Susarla et al., 2023). ChatGPT has vast and unique functions in comparison with other modern AI technologies (Dwivedi et al., 2023). However, despite these technologies' popularity, we do not know much with respect to their adoption.

The current literature has focused on:

1) Explaining how to apply generative AI, such as ChatGPT, in various fields, including 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), and medical research (e.g., Dahmen et al., 2023)
2) Discussing ChatGPT's challenges, opportunities, and implications for practice, research, and policy from multidisciplinary perspectives (Dwivedi et al., 2023; Nah et al., 2023b), and
3) Reviewing ChatGPT's major functions (e.g., Aljanabi et al., 2023).

So far, to the best of our knowledge, no research has examined ChatGPT's mass adoption. As Mariani et al. (2023) note in their recent systematic literature review paper on AI, consumer research on AI in general and on conversational agents in particular has grown but remains underexplored. Nah et al. (2023a) have also called for further investigations into 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, as with using products, using technology represents a consumption process; thus, we need to research user behavior toward technology such as ChatGPT. Accordingly, a key research question concerns whether ChatGPT will become a meaningful tool as AI technologies such as 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), and the extended UTAUT2 as a fundamental theoretical framework (e.g., Ateş & Garzón, 2023; Farzin et al., 2021; Gupta et al., 2018). These studies identified several common factors that affect whether users will accept or use technology, such as perceived privacy risks, performance expectancy, facilitating conditions, social influence, and perceived ease of use. However, few studies have used these theories to investigate behavioral intention to use products that explicitly incorporate AI (Gansser & Reich, 2021).

Furthermore, while research has shown these existing models' potential to explain whether users will accept technology, they mainly reflect users' perceptions about it (e.g., performance expectancy and effort expectancy) and 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—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 not only how users perceive a technology but also a fair task-technology fit may shape whether they use a technology such as ChatGPT or not. As Berente et al. (2021) and Nah et al. (2023a) have highlighted, one needs to adopt socio-technical thinking to effectively manage AI.

Accordingly, in this study, we address the above research gaps by investigating users' behavior towards using ChatGPT. Specifically, we address the following research questions (RQ):

RQ1: What factors affect whether users use ChatGPT?

RQ2: What specific tasks do people use ChatGPT for?

RQ3: Do users intend to continue using ChatGPT and recommend ChatGPT?

RQ4: Does users' curiosity towards ChatGPT moderate the relationships between various influencing factors and ChatGPT use?

To address the above research questions, we developed an integrated research model based on the UTAUT2 and TTF. We intentionally combined both models (i.e., UTAUT2 and TTF) for two main reasons. First, researchers recognize UTAUT2 as one of the most complete models that explains technology acceptance and use (Goodhue & Thompson, 1995) and reflects how users perceive the technology and consumption context. Second, TTF allows one 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. We conducted this study in Vietnam, a developing country where ChatGPT remains in its early adoption stage and users' behavior toward ChatGPT unquestionably requires further research. We believe that investigating consumer behaviors towards a chatbot and ChatGPT in particular from a user perspective will inform businesses about the factors influencing ChatGPT use, how individuals use it, and their behavioral intentions after use, which will help businesses improve their technological ecosystems (Mariani et al., 2022; Pizzi et al., 2023).

Our study makes several significant contributions to the literature on technology adoption. First, our research is an early effort to examine whether this emerging technology (i.e., ChatGPT) represents a meaningful tool from a user perspective by drawing on both UTAUT2 and TTF. This paper provides a novel theoretical combination that helps explain users' behavior when using ChatGPT from both theoretical perspectives, which is critical for understanding individuals' behavioral intention towards an emerging technology such as ChatGPT. With this contribution, we also respond to the call that future research needs to investigate AI technology acceptance and adoption (Mariani et al., 2022). Second, we believe our study is the first to shed light on the moderating effect of user curiosity towards an emerging technology and, thus, to explain the relationships between users' perceptions and trust and users' behavior regarding a technology such as ChatGPT more deeply. Third, via examining a comprehensive process (namely, actual usage–continuance intention to use–recommending), we demonstrate the crucial role that ChatGPT use plays in shaping users' intention to continue using and recommending it and, thus, contribute to better explaining users' behavioral process in technology adoption. Finally, we also provide ChatGPT developers, policymakers, and businesses with practical implications to reach more users.

2 Background

Generative AI, such as ChatGPT, relies on 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). Many researchers consider this emerging technology the most advanced chatbot in the world (Rudolph et al., 2023). ChatGPT is an intelligent chatting machine that can follow instructions in a prompt and provide a detailed response (Ouyang et al., 2022). More specifically, this chatbot constitutes a large language model, a machine-learning system that learns autonomously from data, and can create sophisticated and seemingly intelligent writing after being trained on a mammoth text data set (Van Dis et al., 2023). ChatGPT integrates various abilities including academic writing, a search engine, coding, detecting security vulnerabilities, and machine translation (Aljanabi et al., 2023).

According to Statista (2023a), ChatGPT gained one million users just five days after its launch. It attained 3,771 downloads from users around the world in the first ten days of January 2023 (Statista, 2023b). These statistics show that ChatGPT has great potential in the future. However, controversy around the technology's benefits and drawbacks has also emerged. 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 may usher in substantial transformations to journalism and media content and, thus, create a new era that features accessible information and automation.

Furthermore, although ChatGPT's future remains unknown, opportunities and challenges alike have emerged for businesses. As with Google, one can regard ChatGPT as an effective content-curation tool (Dwivedi et al., 2023). The generative responses that it delivers depend on users' queries. An unspecific inquiry may engender inaccurate results and, thus, degrade a brand's value. Thus, marketers need to develop an ecosystem to precisely answer customer requests (Dwivedi et al., 2023). Thus, research that identified specific tasks that users perform while using ChatGPT would help businesses better respond to their expectations. Unfortunately, ChatGPT use remains overlooked (Dwivedi et al., 2023). In the same vein, through a systematic literature review on AI in marketing, consumer research, and psychology, Mariani et al. (2022) identified technology acceptance and adoption, social media and text mining, big data and robots, and social media content analysis as macro clusters that need further research. According to these authors, future research should essentially cover AI technology acceptance and adoption as they evolve further.

Moreover, ChatGPT will undoubtedly remain the focus of many discussions about how generative AI can impact our lives in the years to come. Generative AI will undoubtedly impact businesses, education, government, and many other domains. As a new phenomenon, ChatGPT has sparked mixed opinions (e.g., refer to Lim et al., 2023; Pavlik, 2023) and significant 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 that affect 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 called the "unified theory of acceptance and use of technology" (UTAUT). UTAUT identifies four key constructs (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 used in different technological contexts. For example, its creators formulated it to explain whether people will accept and use technology in an organizational setting with mandated technology use (Shaw & Sergueeva, 2019). Therefore, Venkatesh et al. (2012) extended UTAUT to UTAUT2 by adding hedonic motivation, price value, and habit to it. UTAUT2 also addresses user contexts where individuals use a technology on a voluntary basis by including privacy concerns (Oliveira et al., 2014). Researchers have used UTAUT2 as a powerful framework to effectively explain and analyze 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 users will use a new technology if they find it good enough to execute a particular daily task efficiently (Oliveira et al., 2014). Also, individuals will adopt a technology if its characteristics fit a task's requirements sufficiently well (Goodhue & Thompson, 1995). Therefore, according to Goodhue and Thompson (1995), the TTF includes several main constructs to explain whether users will adopt a new technology: task characteristics, technology characteristics, task-technology fit, and use. Specifically, the match between a task's characteristics and a technology's characteristics determines task-technology fit, which leads users to adopt and use the technology. The fit between tasks and technology refers to the degree to which a technology's features match a task's requirements (Lu & Yang, 2014). Users will likely use a technology when it fits their tasks and improves their performance (Goodhue & Thompson, 1995).

Researchers have mainly applied the TTF model at the organizational level rather than at the user level, but they have recognized the potential to apply it at the individual level (Aljukhadar et al., 2014). Furthermore, so far, it remains unclear whether a good TTF will impact ChatGPT use and how well it will influence its users. Therefore, to further validate the TTF model, researchers still need to apply it in more studies across different contexts (Lu & Yang, 2014). Given ChatGPT's various functions and its advantages and disadvantages, recent studies have paid increasing attention to exploring its application 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 and Lucey (2023) for finance; and Dahmen et al. (2023) for medical settings). Therefore, to pinpoint the factors that help individual users successfully complete tasks and identify their relative importance in predicting task completion, the TTF model appears very appropriate.

3.2 Hypothesis Development

3.2.1 Performance Expectancy

The performance expectancy concept explains how using technology can benefit users 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 their perceptions about whether using ChatGPT improves their performance. Many previous studies have identified performance expectancy as a primary determinant of users' behavioral intention toward a technology (Chua et al., 2018; Hsu et al., 2017; Jain et al., 2022). Therefore, we hypothesize that:

H1: Performance expectancy positively affects ChatGPT use.

3.2.2 Effort Expectancy

Effort expectancy describes how simple or hard users find using a technology (Venkatesh et al., 2012). Herein, in this study, the effort expectancy refers to how easy users find using ChatGPT in their job. Indeed, the more users find ChatGPT easy to use, the more they use it. Users may expect that ChatGPT will help them perform tasks faster and in a more convenient manner. Empirical studies have found effort expectancy to positively affect whether individuals will use a new technology (Hsu et al., 2017; Yueh et al., 2015). Additionally, in a recent study related to AI, Jain et al. (2022) tested and validated the positive relationship between effort expectancy and AI-enabled tool adoption. Therefore, we hypothesize that:

H2: Effort expectancy positively affects ChatGPT use.

3.2.3 Facilitating Conditions

Facilitating conditions refer to the extent to which users are aware of facilities and support systems to perform a behavior (Venkatesh et al., 2003). In the information systems (IS) context, facilitating conditions include both technological and organizational elements planned to eliminate barriers to using an information system, such as financial resources, time, necessary knowledge, and government policies. These elements help to increase users' behavioral intention to use technologies (Hu et al., 2020; Thompson et al., 1991; Venkatesh et al., 2003). Extant research has found 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). Therefore, we hypothesize that:

H3: 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 improves on the predominantly cognitive UTAUT by including hedonic motivation, an affective dimension (Tamilmani et al., 2019). Countless hedonic information systems exist 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 found that hedonic motivation serves as an antecedent in understanding whether individuals will adopt various technologies. Mishra et al. (2022) found a positive relation between hedonic motivation and smart voice assistant use. Therefore, we hypothesize that:

H4: Hedonic motivation positively affects ChatGPT use.

3.2.5 Social influence

Social influence refers to the degree to which individuals perceive people important to them (e.g., family and friends) expect them to use a specific technology (Venkatesh et al., 2003). Indeed, previous studies have identified social influence as a significant antecedent of technology use (Hsu et al., 2017; Jain et al., 2022). Thus, we argue that users will be more willing to use ChatGPT if others approve its use. Therefore, we hypothesize that:

H5: Social influence positively affects ChatGPT use.

3.2.6 Trust

Trust refers to "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 technology (e.g., ChatGPT) as the confidence users place in that technology; thus, users who trust technology regard it as dependable, secure, reliable, and helpful. Users' trust in AI and conversational agents has gained growing attention from researchers (Mariani et al., 2023). Trust plays an essential role in advancing online technology and for lowering the extent to which people fear damage in a technological setting (Afshan & Sharif, 2016). Trust is among the most critical factors that affect users' intention to use an innovative technology when they lack experience with it (Mariani et al., 2023; Oliveira et al., 2014). Concretely, researchers have found trust along with the other four factors (namely, usage convenience, perceived usefulness, enjoyment, and attitude towards technology) 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 whether users adopt e-books. Therefore, we hypothesize that:

H6: Trust positively affects ChatGPT use.

3.2.7 Technology Characteristics, Task Characteristics, and Task-technology Fit

Two technological aspects predict TTF: 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 users' needs, while technology characteristics essentially refer to the extent to which users appreciate a technology's capacity (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-book context has shown that technology and task characteristics significantly positively affect TTF (D'Ambra et al., 2013). Furthermore, previous studies have 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 have a positive association with task-technology fit (Oliveira et al., 2014; Paulo et al., 2018). Therefore, we hypothesize that:

H7: Technology characteristics positively affect TTF.

H8: Task characteristics positively affect TTF.

Lin and Huang (2008) found that perceived TTF had a substantial influence on knowledge management system usage and that knowledge management system self-efficacy had a positive association with perceived TTF. Users will not use a technology in a situation with insufficient TTF (Goodhue & Thompson, 1995). In other words, a good TTF will increase users' technology adoption, whereas a poor TTF will decrease it (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 if it does not improve their ability to execute tasks (Oliveira et al., 2014; Sharif et al., 2019). Previous IS studies also suggest that TTF influences user adoption (Alam et al., 2020; Faqih & Jaradat, 2021; Paulo et al., 2018; Sharif et al., 2019) as TTF positively affects technology use (Lin & Huang, 2008; Oliveira et al., 2014; Paulo et al., 2018). Thus, we argue that, if ChatGPT cannot meet users' requirements to achieve 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. Therefore, we hypothesize that:

H9: TTF positively affects ChatGPT use.

3.2.8 Continuance Intention to Use and Word of Mouth

Continuance intention to use refers to users' intention to continue using a technology until they find an alternative (either an improved version or replacement) (Mathieson, 1991; Bhattacherjee, 2001). In this study, continuance intention to use ChatGPT refers to users' intention to continue using ChatGPT for their daily and professional activities.

Word of mouth (WOM) about technology acceptance or use refers to the amount of exchanged information in relation to using technology among users and potential one (Parry et al., 2012). WOM on technology acceptance or use represents the starting point for whether people will spread good (or bad) words about a particular technology. In addition, continuance results from acceptance behavior as users make both acceptance and continuance decisions when they employ the same set of pre-acceptance variables (Bhattacherjee, 2001). Kim and Malhotra (2005) found that past behavior can predict future information systems use. Yueh et al. (2015) empirically found that actually using a "wiki" system positively affected individuals' continuance intention to use that system. Bhattacherjee (2001) stated that an initial use experience (with an IS or product) influences information systems users' decision to continue using it. 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. Therefore, we hypothesize that:

H10: ChatGPT use positively affects intention to continue using ChatGPT.

H11: ChatGPT use positively affects WOM.

H12: 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 to gain and integrate new ideas and experiences (Fang et al., 2018). Curiosity refers to the extent to which an experience arouses sensory and cognitive curiosity in individuals when interacting with technologies (Webster et al., 1993). During a flow experience, individuals experienced heightened arousal of sensory and cognitive curiosity (Agarwal & Karahanna, 2000). Curiosity suggests that interacting with software invokes excitement about available possibilities through such technology characteristics as color and sound (Webster et al., 1993). Most studies that have adopted 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 understand the role curiosity may play in the relationship between various UTAUT2 constructs (i.e., performance expectancy, effort expectancy, facilitating conditions, hedonic motivation, social influence) and trust and ChatGPT use, we hypothesize that:

H13a: Curiosity moderates the path between trust and ChatGPT use.

H13b: Curiosity moderates the path between social influence and ChatGPT use.

H13c: Curiosity moderates the path between hedonic motivation and ChatGPT use.

H13d: Curiosity moderates the path between facilitating conditions and ChatGPT use.

H13e: Curiosity moderates the path between effort expectancy and ChatGPT use.

H13f: Curiosity moderates the path between performance expectancy and ChatGPT use.

Figure 1 summarizes our research model.

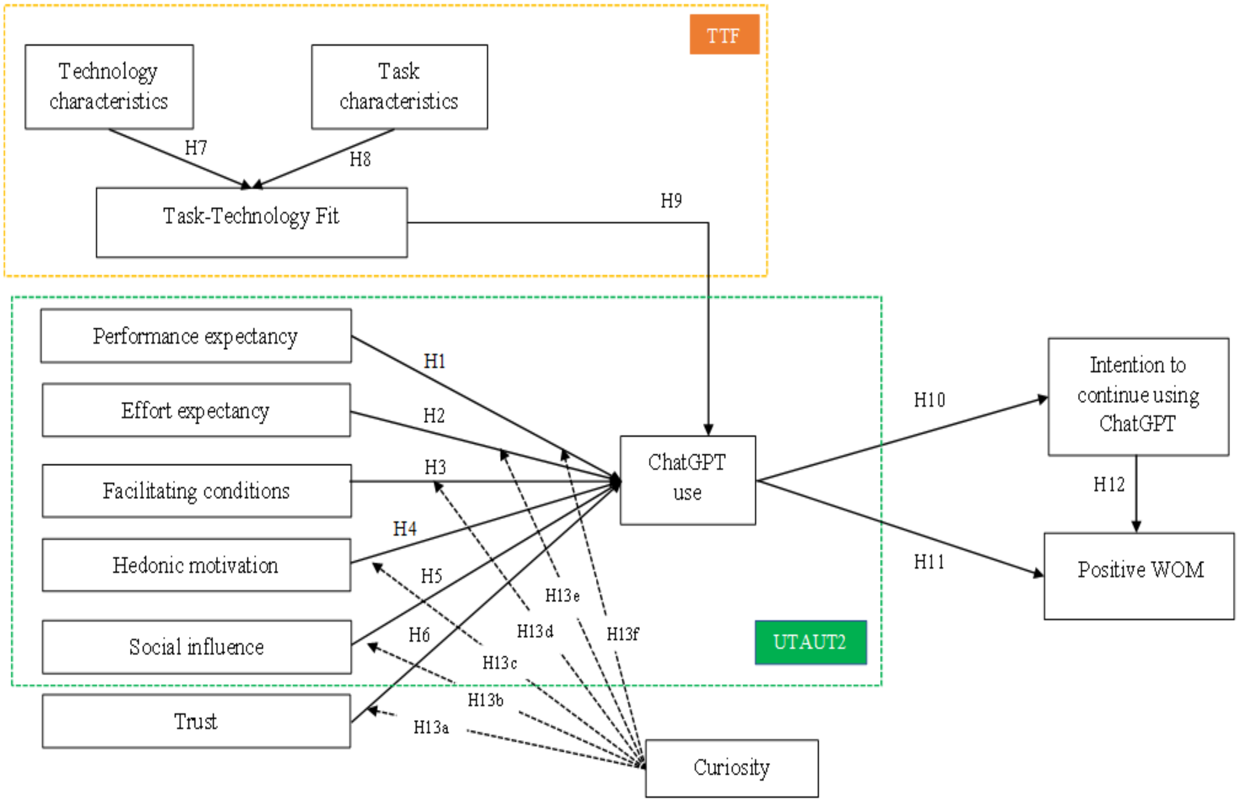

Figure 1. Research Model

4 Methodology

4.1 Research Design and Measurements

In this study, we adopted a quantitative approach to understand how various constructs of UTAUT2 and TTF influence ChatGPT use and how ChatGPT use informs continuance intention to use ChatGPT and WOM. We developed a questionnaire to obtain insights from users. We extracted measurement scales from previous studies and adjusted them to suit the ChatGPT setting. We rated the items for constructs in the research model on a five-point Likert scale that ranged from “strongly disagree” (1) to “strongly agree” (5) except for the ChatGPT use construct. We assessed ChatGPT use by employing respondents’ usage frequency from “never” (1) to “many times per month” (5) (see Appendix A). As the ChatGPT use scale has not existed before, on the basis of Venkatesh et al.’s (2012) scale, we conducted 20 individual in-depth interviews with ChatGPT users to fully capture the various ChatGPT uses while applying the convenience sampling and semantic saturation. We considered items for removal when 25 percent or more of respondents did not consider them appropriate. Accordingly, participants suggested six items for measuring ChatGPT use construct. Additionally, following Hardesty and Bearden (2004), we invited five artificial intelligence professors to evaluate the face and content validity of these six items. As a result, we modified some items linguistically but did not drop any items. The ChatGPT use construct included six items (see Appendix A).

4.2 Sampling and Data Collection

The study population included Vietnamese people over 18 years old who had already used ChatGPT. We employed a convenience sampling technique. We administered the questionnaire both face-to-face and online through popular media channels in Vietnam such as Zalo, Facebook Messenger, and email. To reduce common method bias, in the introduction section of the questionnaire, we explicitly mentioned that we would maintain respondents’ anonymity, that respondents need to choose the options that best describe their experience, and that the questionnaire had no right or wrong answers. We used a filter question early in the questionnaire to ensure we selected only people who had already experienced ChatGPT. From late December, 2022 to mid-February, 2023, we obtained face-to-face data in the four biggest Vietnamese cities (Ha Noi, Da Nang, Nha Trang, and Ho Chi Minh City) in north, central, and south Vietnam. Therefore, the sample somewhat represents the urban population that is prone to using new technologies. Moreover, we purposely administrated the survey in a way to better obtain a sample with a more or less equal proportion of men/women and varied categories with respect to age, occupation, and education (see Table 1). We translated the questionnaire, which we built in English, into Vietnamese before translating it back into English to avoid any inconsistencies. Two bilingual IS experts and two bilingual marketing experts controlled the translation process. We then tested the questionnaire with 10 Vietnamese ChatGPT users. According to the test results, these 10 participants suggested no changes. We used the sample size calculation method that Bollen (1989) suggested for our study. As our model contained 48 measurement parameters in total, the minimum sample size needed to be 240 (based on a 5:1 ratio). However, we aimed for a larger sample size to increase reliability. Moreover, analyzing data using CB-SEM requires a large sample size because this technique builds 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, we included only 671 questionnaires in the analysis after eliminating incomplete questionnaires. Table 1 presents the respondents' socio-demographic data.

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

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

5 Results

5.1 Measurement Model

We first performed an exploratory factor analysis (EFA). We applied principal axis factoring and promax rotation. 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 data's factorial ability. Moreover, the 13 constructs explained about 66.23 percent of the total explained variance. As Appendix A shows, the lowest outer loading was 0.54, while the maximum was 0.91. Therefore, we retained all 48 items for further analysis since they exceeded the 0.50 criterion. Moreover, Appendix A shows the mean, standard deviation, and mode of the 48 items that we 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 largely exceeded 0.70 (see Appendix A) and their CRs obtained from the confirmatory factor analysis (CFA) ranged from 0.80 to 0.92 (see Table 2), which confirmed that the constructs exhibited satisfactory internal consistency reliability (Hair et al., 2010).

In the next step, we established the measurement model to examine the level of model fit. We used the indicators—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)—to assess 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). We used average variance extracted (AVE), CRs, and outer loadings to evaluate the constructs' convergent validity. As Appendix A shows, the outer loadings varied from 0.54 to 0.91 (i.e., higher than the recommended threshold 0.5). Besides, all estimated path coefficients exhibited statistical significance ($p < 0.00$). All CR values exceeded 0.70, and the lowest AVE value was 0.57 (see Table 2). All these results indicate a high level of convergent validity (Hair et al., 2010; Steenkamp & van Trijp, 1991). Additionally, as Table 2 shows, AVEs were higher than the corresponding maximum shared variances (MSVs) and AVEs' square roots were higher than correlation coefficients, which indicates that all components exhibited 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 distort research results (Podsakoff et al., 2003). Furthermore, although measurement errors can come from both random and systematic sources, systematic measurement errors often have a more negative impact on a study's findings (Jakobsen & Jensen, 2015). Thus, we used the Harman single factor 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 percent of the total variance, less than the threshold value (i.e., 50%)). Hence, we identified 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**

On the major diagonal, the square root of AVE appears in bold.
CR = composite reliability, AVE = average variance extracted, MSV = maximum shared variance, 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

We applied the structural equation modelling (SEM) technique to estimate multiple and interrelated dependence relationships (Hair et al., 2010)—an ideal technique to test the hypotheses given the complex relationships among the constructs. Thus, we conducted an SEM to assess how each TTF and UTAUT2 construct affected ChatGPT use and whether the latter 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).

We found that performance expectancy, facilitating conditions, hedonic motivation, TTF had a positive effect on ChatGPT use, which supports H1, H3, H4, and H9. Specifically, TTF emerged as the factor that had the strongest effect on ChatGPT use ($\beta = 0.34$). However, contrary to what we hypothesized, we did not find support for H2, H5, and H6 ($p > 0.10$) (see Table 3).

We found that both ChatGPT use and intention to continue using ChatGPT had a significant effect on WOM, which supports 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 (see Table 3). We also found that technology characteristics ($\beta = 0.36$, $p = 0.00$) and task characteristics ($\beta = 0.31$, $p = 0.00$) related to TTF, which supports H7 and H8 (see Table 3). Next, we found that ChatGPT use had a significant and positive relationship with continuance intention to use ChatGPT ($\beta = 0.32$, $p = 0.00$) (see Table 3), which supports H10.

Finally, we found that curiosity significantly and negatively moderated the paths from hedonic motivation, facilitating conditions, and performance expectancy to ChatGPT use, which supports H13c, H13d, and H13f (see Table 3). However, curiosity did not have a significant moderating effect on the relationships between trust, social influence, effort expectancy, and ChatGPT use, which does not support H13a, H13b, and H13e (see Table 3).

Table 3. Structural Relationships

H	Relationship	β coefficient		P-value	Result
		Unst.	Stan.		
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
Unst. = unstandardized, stan. = standardized.

6 Discussion

In this study, we draw on the UTAUT2 and TTF theory to identify the factors that affect ChatGPT use and the main activities individuals perform while using ChatGPT and to determine whether they continue using ChatGPT and recommend it to others. We also examine the moderating role of curiosity in the relationships between various influencing factors and ChatGPT use.

Surprisingly, we found that two UTAUT2 dimensions (i.e., effort expectancy and social influence) and trust did not play a significant role in explaining ChatGPT use. Overall, these results do not concur 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, in their systematic literature review on AI, Mariani et al. (2023) identified trust as among five key factors that shape conversational agent adoption. Gupta et al. (2022) also found that that a conversational interface developed user trust more effectively than a traditional web interface in an online housing recommendation system context. On the one hand, this inconsistency may have arisen due to ChatGPT's specific nature. Thus far, ChatGPT constitutes a new, publicly accessible, and free-to-use phenomenon. How (and, indeed, if) ChatGPT will revolutionize our lives remains unclear. The quality of the content that ChatGPT generates is not yet conclusive. Thus, the unconditional trust granted to ChatGPT seems, at this stage of development, premature. On the other hand, as AI-based technologies advance and increase in popularity, users will increasingly become familiar with them, and many have already formed fundamental beliefs about them. As for the non-significant effect of effort expectancy on ChatGPT use, this result concurs with Andrews et al.'s (2021) findings that effort expectancy had no effect on whether users would adopt AI and related new technologies. As for why, users may still lack clarity about what “AI and related technologies” include (Andrews et al., 2021), such as ChatGPT. With respect to social influence, in our study’s context, ChatGPT remains a novel technology in the world in general and in Vietnam in particular, and few Vietnamese people have experienced it, which suggests that the influence of other ChatGPT users on a particular individual’s potential ChatGPT use is improbable and that ChatGPT use is not trendy yet.

We also found that four factors (i.e., performance expectancy, facilitating conditions, hedonic motivation, and TTF) had a positive association with ChatGPT use. Among these four factors, performance expectancy had the strongest influence, which denotes that the users had confidence in ChatGPT’s performance. In situations with high performance expectancy, users are more likely to use this disruptive technology. Indeed, ChatGPT can provide users with benefits such as personalized, useful, and immediate services. It may also help them increase their productivity. Therefore, users use ChatGPT because they find it a useful and convenient solution for their purpose(s). The result confirms many previous studies that have found that performance expectancy has a positive effect on whether people will use diverse technologies (Chua et al., 2018; Hsu et al., 2017; Jain et al., 2022; Onaolapo & Oyewole, 2018). With regard to facilitating conditions, the finding concurs with earlier studies that have used the UTAUT (e.g., Venkatesh et al., 2003, 2012) and examined the factors that influence whether users adopt various social platforms and AI-related technologies such as 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). We can explain this result in several ways. First, users continue to become more skilled in using technologies. Second, people can more easily access equipment and resources (e.g., Wi-Fi, 4G, smartphone, tablet, desktop computer, online support) that they need to effectively use ChatGPT nowadays. Concerning hedonic motivation, according to Farah et al (2018), people show more and more interest toward new and innovative technologies since the technologies meet their intrinsic pleasure. Thus, users often regard disruptive technologies as sources of hedonic motivation, which leads to their adoption (Farzin et al., 2021). For example, Mishra et al. (2022) discovered that individuals who find hedonic motivation while using smart technologies increases their use. A website’s visually appealing layouts and colors further enhances positive emotions generated while using these technologies (Malaquias & Hwang, 2016). Moreover, according to Fu and Elliott (2013), important people often endorse new technologies, which makes average individuals more likely to accept them.

We found that task characteristics and technology characteristics directly predicted TTF, which supports many previous studies (e.g., Lin & Huang, 2008; Oliveira et al., 2014; Paulo et al., 2018). Although ChatGPT has only appeared recently, it has created 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 with respect to providing ubiquitous, real-time, and reliable data), ChatGPT may help them more quickly and easily complete their tasks and meet their needs, which supports 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 does not concur with some previous studies (e.g., Sharif et al., 2019; Wang et al., 2020). Indeed, since ChatGPT represents a new and powerful technology, users may tend to put more focus on the ubiquity, immediacy, and reliability of the information that it delivers. Also, we found support for the strongest positive effect of TTF on ChatGPT use. Previous research supports this result (e.g., Lin & Huang, 2008; Oliveira et al., 2014; Paulo et al., 2018), which suggests that, if ChatGPT provided users with the required functions to match their needs, they would use it.

To address the specific tasks that people use ChatGPT for (RQ2), we 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 we obtained showed that, among these popular purposes, respondents used ChatGPT more for multilingual translation, search functions, and creating useful content with the averages of 3.30, 3.28, and 3.28 out of 5, respectively.

Our study also indicated that ChatGPT use positively and directly affected both the 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 concur with the existing technology literature that identifies the tendency to adopt a technology as one of the earliest factors that drive individuals’ actual behaviors (Kang et al., 2022; Yueh et al., 2015). Moreover, research has found users' satisfaction with mobile Internet-based (health) services to have a positive and direct effect on positive WOM (Gu et al., 2018).

Finally, we examined the moderating role of curiosity, an individual variable, in predicting users' behavioral intention to adopt ChatGPT. We found support for three (among six) hypotheses. Specifically, we found that curiosity played a moderating role in the relationship that hedonic motivation, facilitating conditions, and performance expectancy had with ChatGPT use. We observed that these three relationships had negative regression coefficients, which suggests that, if users' curiosity increases, hedonic motivation, facilitating conditions, and performance expectancy will have a lower effect on ChatGPT use. We can explain these findings as follows: 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 they become 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 Contributions, Limitations, and Future Research

7.1 Theoretical Contributions

Our study makes significant contributions to the current literature on AI technologies adoption in three main ways. First, while existing studies have investigated ChatGPT's characteristics, functions, applications, and history (e.g., Gilson et al., 2023; Rospigliosi, 2023; Rudolph et al., 2023), we examine the factors affecting individuals' ChatGPT use and the main activities they do while using ChatGPT and determine whether they continue using ChatGPT and recommend it to others. Accordingly, we extend our knowledge about users' behavior process to adopt an AI technology by investigating a comprehensive process: actual usage behavior–intention to continue using–WOM with respect to ChatGPT, a new AI technology. Previous studies on technology adoption have merely examined factors that affect 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). To our knowledge, no study has examined whether continuance intention to use technologies affects WOM. This paper highlights the need to measure actual usage behaviors towards AI-related technologies since they tend to underpin post-usage behavior (i.e., continuance intention to use and intention to recommend).

Second, to more accurately and comprehensively understand the tendency of people to accept AI technology and their usage behavior, we extended the traditional UTAUT2 model by integrating the TTF model, trust, and curiosity into it. 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), we found that trust did not influence ChatGPT use. We can explain this finding based on the fact that ChatGPT remains a new, publicly accessible, and free-to-use phenomenon, and, at present, ChatGPT produces questionably valid content. This finding suggests that ChatGPT developers should improve the credibility of the information that it provides if they want to increase individuals' use and intention to continue using.

Third, we examined the moderating role of curiosity on the paths from independent factors to ChatGPT use and showed that it moderated 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 that various UTAUT2 dimensions have on AI technology used.

7.2 Practical Implications

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

First, our findings suggest that ChatGPT providers need to improve the TTF. They can segregate the market and provide differentiated services to niche users because each country has its own language(s), and we encourage providers to provide ChatGPT in different languages. ChatGPT providers also need to detect limitations and seek user feedback to create optimized tools in the future. In addition, they need to increase “openness” to encourage experts to make comments and suggestions about developing ChatGPT further and building other similar AI applications, which would increase their suitability for users. Moreover, ChatGPT providers should offer users instantaneous support and, thus, expand their ability to use ChatGPT.

As for governments, we found that facilitating conditions, hedonic motivation, and performance expectancy significantly influenced ChatGPT use. Thus, governments need to create an environment that encourages individuals and organizations to participate in creating and effectively using new AI technologies, such as ChatGPT.

Finally, we found that technology characteristics (i.e., ubiquitous, real-time, and reliable data) had a positive effect on TTF, which, in turn, affected ChatGPT use. Hence, from a businesses’ perspective, for their online visibility and reputation, businesses should identify and display on the Internet their strategic values, which would enable ChatGPT when answering users’ requests related to these values to provide users with right and expected information at any time. Furthermore, technology that provides users with accurate information and meets their requirements is more likely to be adopted.

7.3 Limitations and Future Research

As with any study, this one has certain limitations. We collected our cross-sectional data collected for this research only at a specific time. Increasing AI technology concerns and ChatGPT with new functions (probably) may change users’ behavior. Thus, we need research that adopts a longitudinal design 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 and explain the adoption process in greater detail.

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Appendix A

Table A1. 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 anytime and anywhere.	0.83*	3.50		0.94	4.00
		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 understandable.	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 resources to use ChatGPT.	0.75*	3.50		1.01	4.00
		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

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		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) and 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 use ChatGPT frequently.	0.88*	3.54		0.98	4.00
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

Table A1. Scales Items Evaluation

Curiosity (CURIS)	Agarwal & Karahanna (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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