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A structural model of student continuance intentions in ChatGPT adoption

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Abstract,
ChatGPT has experienced unprecedented acceptance and use, capturing popular and academic attention. With this growth in use comes the need to focus on the determinants of ChatGPT use as the success of a technology or service depends largely on users' continuance intentions. Modeling what influences students' intention to continue using ChatGPT is important to better understand how students search for information and their decision-making process. Using a sample of 106 students, we test a structural model developed using the unified extended-confirmation model. The research model included the following elements: subjective norm, perceived usefulness of continued use, disconfirmation of their expectations from prior use, satisfaction with prior use, and continuance intention. The findings demonstrate support for the proposed research model as the research model explains 60.5% of the variance in continuance intention. In terms of the direct influence on continuance intention, the role of perceived usefulness and satisfaction were documented. The present study has the potential to serve as a starting point for improving our understanding of antecedents of continuance intentions in the context of ChatGPT.

Keywords: ChatGPT, technology acceptance, continuance intention, large language models, artificial intelligence chatbots

INTRODUCTION

In recent years, large language models (LLMs) have been shown to perform extremely well on different natural language processing tasks (Huang et al., 2022). The promising implementations of LLMs have piqued the interest of researchers and practitioners. In fact, LLMs have gone mainstream with the release of ChatGPT–an artificial intelligence (AI) language model developed by OpenAI–in November 2022 (OpenAI, 2022).

To participate in this development, Microsoft made a multiyear, multibillion-dollar investment in OpenAI (The Official Microsoft Blog, 2023). As ChatGPT entered the stage, it brought out visions for both dreamland and doomsday scenarios (Rosenberg, 2022)–as is expected of any technological innovation.

Recent advances in AI-based conversational interfaces, such as ChatGPT, have increased interest among researchers and practitioners, especially in the field of education (Kasneci et al., 2023). In fact, many have noted that ChatGPT's potential disruptive force is likely to be most felt in education (Rosenberg, 2022). While much recent research concerns the broad value that ChatGPT can offer in the context of teaching and learning (Kasneci et al., 2023; Rudolph et al., 2023), there is little about what factors might influence students' intentions to continue using ChatGPT. The success of any novel technology largely depends on their continued use (Bhattacherjee et al., 2015).

As such, it is important to explore what factors play significant roles in shaping users' intention (Doleck et al., 2017a, 2017b) to continue using ChatGPT. Insight into the factors that influence continuance intention can inform efforts to better realize the potential of ChatGPT in teaching and learning. The present article draws on the unified extended-confirmation model (Bhattacherjee, 2001), presented in Bhattacherjee and Lin (2015), to explicate the technology acceptance process in the context of intentions to continue using ChatGPT.

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Contribution to the literature

- ChatGPT is a powerful Artificial intelligence (AI) technology that has the potential to revolutionize education.
- Not much is known about the factors that influence students' intentions to continue using ChatGPT.
- The present study demonstrates how the proposed research model identifies the key factors in predicting students' continued use of ChatGPT, potentially transforming future learning behaviours and educational outcomes.

LITERATURE REVIEW

With a launch that took the online world by storm, the AI based ChatGPT garnered more than one million users within seven days (Altman, 2022) and more than 100 million users within two months of its unveiling (Eysenbach, 2023). This phenomenal growth broke historical records by a mile.

The development of AI and chatbots may be dated to the 1950s, when researchers first started delving into the idea of AI. The first AI software, ELIZA, was developed early on and was intended to mimic human speech (King & ChatGPT, 2023). As the field of AI matured, a research facility termed OpenAI was established in 2015. The claimed purpose of OpenAI, an AI research facility, is to advance and create "friendly AI" in a manner that benefits all of mankind (Brockman et al., 2016; OpenAI, 2015). AI has advanced significantly in recent years, which has sparked the creation of ground-breaking technologies like Open AI's ChatGPT (Mhlanga, 2023).

ChatGPT finds it origins as a chatbot developed from a language model called generative pre-trained transformer (GPT) and can produce response text that is almost identical to typical human speech (Dale, 2021; Lund & Wang, 2023; Sallam, 2023). To process the natural language, the GPT architecture uses a neural network, which produces results according to the meaning of the input text (Brown et al., 2020). GPT is a member of the larger family of LLMs (Kasneci et al., 2023; Shen et al., 2023). LLMs' are based on AI models and are known for their adaptability. GPT improves itself using unlabeled data for generative, unsupervised pre-training and then discriminative, supervised fine-tuning to enhance performance on particular tasks (Budzianowski & Vulić, 2019). The model learns organically during the pre-training phase, similar to how a human may learn in a new situation, while the developers polish the model more carefully and systematically during the fine-tuning phase. Based on the GPT language model technology, OpenAI created the public utility known as ChatGPT (Kirmani, 2022; Lund, & Wang, 2023).

Since its introduction in November 2022, utilizing GPT technology, ChatGPT is the most sophisticated chatbot ever developed (Lund, & Wang, 2023; Mhlanga, 2023; Sallam, 2023; Shen et al., 2023). As ChatGPT can answer in multiple languages and produce intelligent, highly developed responses based on advanced modelling, it is superior to its GPT-based forerunners (Sallam, 2023). It can produce excellent text in a few seconds, however unlike earlier chatbots, ChatGPT has attracted a lot of positive and negative attention regarding student assessment and other issues in higher education (Rudolph et al., 2023).

It has been noted that for common assessment questions that appear in essay assignments, exams, and multiple-choice tests across fields, ChatGPT can offer adequately satisfactory answers. It can draft poetry, analyze data, solve mathematical formulas and engineering puzzles, locate reliable references, compile summaries, offer suggestions, and draw conclusions (Tate et al., 2023; Williams, 2023). It has also shown competence in writing prose and code (Hasty, 2023). Nevertheless, ChatGPT has some fundamental flaws. Since currently the average rate of receiving accurate answers from ChatGPT is too low, Stack Overflow has temporarily banned users from sharing their responses to coding queries generated by ChatGPT. This is all because ChatGPT occasionally provides answers that seem to be right but are factually incorrect or illogical (Wang et al., 2023).

ChatGPT in the Education Environment

Teaching environment

In addition to quizzes, examinations, and syllabuses, ChatGPT may assist instructors in developing class plans, presentations, and other tools (Atlas, 2023). Educators may tap its potential to evaluate their pupils' efforts. Educators can also be motivated to modify and edit these resources in more creative and engaging ways to meet students' learning requirements because they have more time to think and develop new teaching strategies and activities. Herft (2023) suggested that educators can create visual aids, like slides or worksheets, using ChatGPT that explicitly state the learning goals and attainment criteria for a lesson.

Zhai (2023) claims that by utilizing a standardized framework, educators could use ChatGPT to create learning evaluation items while saving time and effort and potentially enhancing the content of the questions. Additionally, ChatGPT can provide an automated marking system with beneficial feedback, which is important for improving students' academic performance. By finding the task's strengths and flaws, ChatGPT can be used to semi-automatically grade students' work (Kasneci et al., 2023). Recent research has also documented the potential of ChatGPT in Second Language (L2) writing pedagogy (Yan, 2023).

Because ChatGPT can produce acceptable writing promptly, some educators are concerned that students will use the site to outsource their assignments. This makes it more challenging to spot instances of copying and plagiarism, which alarms some instructors (Mhlanga, 2023; Rudolph et al. 2023). However, this might be a result of instructors' resistance to altering the methods by which they evaluate students' learning.

The importance of considering how AI will shape the future of education as well as the need for interdisciplinary approaches to the ethical and responsible implementation of AI in educational settings have been emphasized by scholars (Carvalho et al., 2022; Mhlanga, 2023; Paulus & Langford 2022). When a piece of educational technology that has the potential to transform the field is made accessible to the public, it is the responsibility of educators and lawmakers to manage any problems that might arise (Miao et al., 2021; Sharples, 2022).

Learning environment

Students can receive individualized instruction and feedback via ChatGPT based on their unique learning requirements and development. Conversational agents have the potential to provide individualized support to help learners become autonomous and self-directed (Yildirim-Erbasli & Bulut, 2023). AI can also assess a student's interests and learning preferences to make tailored recommendations for subject matter and tools. The usage of personalized recommendations in the classroom can assist students in finding new educational resources or pursuits that are catered to their unique requirements and interests (Baidoo-Anu & Owusu-Ansah, 2023). Recent work by Alneyadi and Wardat (2023) has shown ChatGPT to be an effective tool for enhancing student learning and achievement.

Extending its reach in the field of research, ChatGPT can also be used to help researchers' proficiency and creativity since it can sift through existing research quickly and efficiently and can particularly be useful for aiding in the generation of writing-related ideas (Baidoo-Anu & Owusu, 2023). Similarly, Jarrah et al. (2023) note that ChatGPT can be a valuable writing tool for students.

Like with any new technology, there are questions concerning its applicability and usage, particularly when technology is used to evaluate knowledge or abilities. Many scholars have claimed that ChatGPT also has major drawbacks despite several potential educational benefits (Baidoo-Anu & Owusu-Ansah, 2023; Cotton et al., 2023; Gordijn & Have, 2023). For instance, concerns about the legitimacy of the learning experience were expressed in the context of online learning during COVID-19 (García-Peñalvo, 2023). Concerns have been raised about students using ChatGPT to copy and paste texts without analytically evaluating what has been highlighted or selected from a source, without referencing the original sources, and without being aware of the possibility of plagiarism. Because of this issue, ChatGPT generated text is inappropriate for scholarly work (García-Peñalvo, 2023). Questions about how to differentiate between factual and fictional text produced by ChatGPT and how to identify plagiarism in writing have been expressed (Anders, 2023; Baidoo-Anu & Owusu-Ansah, 2023; Chatterjee & Dethlefs, 2023; Khalil & Er, 2023; King & ChatGPT, 2023).

Against this backdrop, an important open question is what motivates students to continue using ChatGPT. When users are presented a new technology, researchers are keen to understand why users accept the technology and continue its use. There are several models of individual-level technology acceptance and use. The following subsections provide an overview of the theoretical foundations of our research–technology acceptance.

THEORETICAL FRAMEWORK

Technology acceptance is an important field of research (Teo et al., 2019), and it is understood as any effort that aims to explicate the drivers of technology adoption and use (Legris et al., 2003; Teo et al., 2018). Several theories and models have been proffered in the literature to help explicate the factors that drive such decisions (Bhattacherjee & Lin, 2015; Venkatesh et al., 2003): technology acceptance model, theory of reasoned action, unified theory of acceptance and use of technology, the theory of planned behavior, model of PC utilization, innovation diffusion theory, and the social cognitive theory. Despite multiple understandings of the phenomena, these models tend to focus on initial acceptance. Scholars like Bhattacherjee (2001) and Limayem and Cheung (2008) have argued for the inclusion of continuance intention into efforts seeking to examine technology acceptance. Scholars interested in examining the antecedents to technology use suggest that "a given IT cannot be considered successful if its usage is not sustained by users who are expected to benefit from its usage" (Bhattacherjee & Lin 2015, p. 364).

One of the widely used theories to explain antecedents to continuance use is the expectation-confirmation model (ECM) of IT continuance (Bhattacherjee, 2001), according to which users can compare their initial expectations with their actual experiences with a technology. The continuance model also holds that the information system continuance is directly affected by satisfaction and perceived usefulness, with other salient variables, such as subjective norm and disconfirmation holding positions in the model (Bhattacherjee & Lin, 2015). The applicability of ECM has been shown across various contexts and technologies (Ambalov, 2018).

Research Aims

Given these considerations, we focus on the following overarching research question:

Is the extended expectation-confirmation model a valid model for explaining continuance use of ChatGPT?

To address this research questions, we employ the unified extended-confirmation model (Bhattacherjee & Lin, 2015).

Research Model

Drawing from ECM of IT continuance (Bhattacherjee, 2001) and unified extended-confirmation model (Bhattacherjee & Lin, 2015), the present study proposed a research model to better understand the factors that influence students' decisions to continue using ChatGPT. According to ECM, users make cognitive comparisons when making continuance use decisions, and that continuance intentions are influenced by satisfaction, perceived usefulness, and expectation-confirmation (Bhattacherjee, 2001). To proffer an improved explanation of IT continuance, Bhattacherjee and Lin (2015) suggest that technology continuance is driven by reasoned action, emotions, and habits, and propose the inclusions of additional determinants of continuance intentions, such as, subjective norm. Before introducing the elements of the two models, it appears useful to briefly describe the elements.

Subjective norms generally refer to the belief that people that are important to the user will approve and support a particular behavior. In IT use, "feelings of satisfaction arise when people compare their pre-usage expectations (such as perceived usefulness) with IT performance during actual usage". Perceived usefulness of any technology or system is related to "the degree to which a person believes that using a particular system would enhance his or her performance" (Davis, 1989, p. 320). Satisfaction and disconfirmation of expectations are interrelated (Bhattacherjee, 2001). According to Bhattacherjee and Lin (2015): "If perceived performance exceeds initial expectations then users realize positive disconfirmation and satisfaction. But if perceived performance falls short of expectations then expectations are negatively disconfirmed, and users are dissatisfied" (p. 366).

Below are the link specifications of the research model:

H1. Subjective norm (SNM) is positively associated with continuance intention (CIN).

H2. Perceived usefulness of continued use (PUS) is positively associated with CIN.

H3. Disconfirmation of their expectations from prior use (DIS) is associated with PUS.

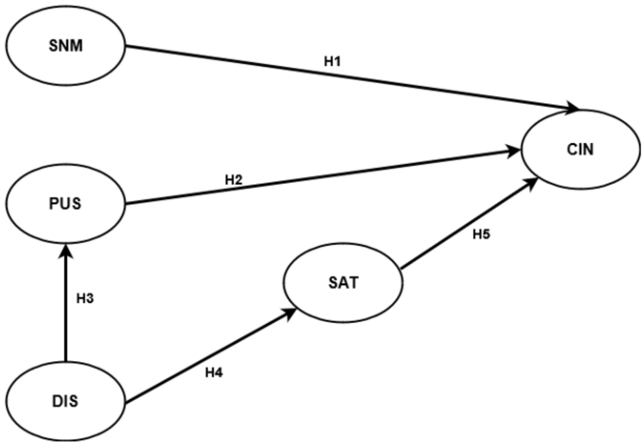

Figure 1. Research model (Adapted from Bhattacherjee, 2001; Bhattacherjee & Lin, 2015)

H4. DIS is associated with satisfaction with prior use (SAT).

H5. SAT is positively associated with CIN.

Figure 1 lays out our research model and expected relationships between our constructs of interest.

METHOD

Procedure

This study was conducted at a university based in North India. After providing informed consent, participants responded to an online questionnaire developed for assessing the constructs in the research model. Participants who responded to the survey were assured anonymity. No participants were compensated for taking part in this study. For the survey, we used a convenience sample.

Participants

We received 120 responses. From this, 14 participants indicated that they had not used ChatGPT. Thus, we used the valid responses from participants (n=106), with a mean age of 18.86 years (standard deviation=1.04). Majority of the respondents were undergraduate students in program of studies related to computing and information systems.

Materials

The survey instrument contained demographic measures (e.g., age and gender) and statements for the constructs in the research model. The statements related to the research constructs were developed using items published in the literature on technology acceptance (Bhattacharjee & Lin, 2015; Bhattacherjee et al., 2015; Joosten et al., 2016). All items were scored on a 7-point Likert-type rating scale ranging from 1=*strongly disagree* to 7=*strongly agree*.

Table 1. Model fit statistics

Measure	Values	Recommended criterion
Average path coefficient (APC)	0.505, p<0.001	Acceptable if p<0.05
Average R-squared (ARS)	0.649, p<0.001	Acceptable if p<0.05
Average adjusted R-squared (AARS)	0.643, p<0.001	Acceptable if p<0.05
Average block VIF (AVIF)	1.618	Acceptable if ≤5
Average full collinearity VIF (AFVIF)	3.220	Acceptable if ≤5

Table 2. Measurement scale characteristics

Construct	Items	Loadings	CRC	AVE
SNM	SNM1	0.844	0.861	0.674
	SNM2	0.809		
	SNM3	0.811		
PUS	PUS1	0.879	0.936	0.785
	PUS2	0.891		
	PUS3	0.908		
	PUS4	0.867		
DIS	DIS1	0.871	0.941	0.801
	DIS2	0.910		
	DIS3	0.915		
	DIS4	0.883		
SAT	SAT1	0.830	0.884	0.718
	SAT2	0.822		
	SAT3	0.888		
CIN	CIN1	0.935	0.967	0.907
	CIN2	0.972		
	CIN3	0.950		

Note. CRC: Composite reliability coefficients & AVE: Average variance extracted

Table 3. Discriminant validity test

	SNM	PUS	DIS	SAT	CIN
SNM	**0.821**	0.420	0.410	0.340	0.340
PUS	0.420	**0.886**	0.848	0.657	0.714
DIS	0.410	0.848	**0.895**	0.762	0.801
SAT	0.340	0.657	0.762	**0.847**	0.687
CIN	0.340	0.714	0.801	0.687	**0.952**

Note. Square roots of average variances extracted shown on diagonal

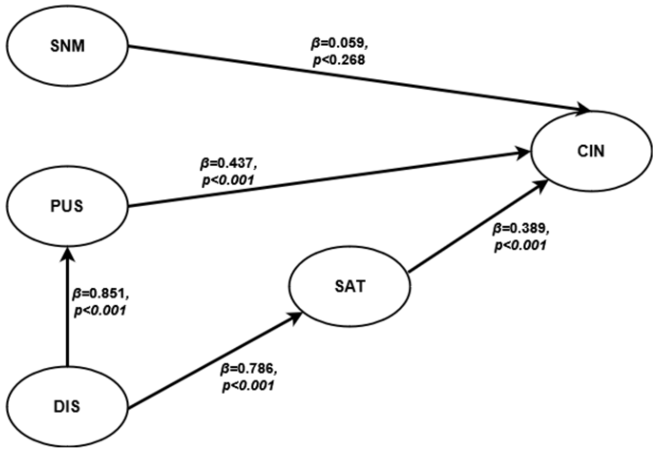

Figure 2. Structural model (Adapted from Bhattacherjee, 2001; Bhattacherjee & Lin, 2015)

RESULTS

The proposed research model was tested using a multivariate statistical technique, partial least squares structural equation modeling (PLS-SEM; Henseler et al., 2016; Kock, 2022a). PLS-SEM is appropriate for exploratory studies, where the goal is to identify key predictors in a proposed research model; moreover, PLS-SEM approach is not strict in sample size and data distribution assumptions (Hair & Alamer, 2022; Kock, 2022a). WarpPLS software (Kock, 2022b) was used for measurement and structural model evaluation. We followed the suggested route with PLS-SEM, that is, we executed the analysis using a two-stage approach, including the assessment of the measurement model and structural model. The sample size was deemed sufficient according to the minimum sample size estimation using the 10-times rule method (Hair et al., 2011).

Measurement Model

Measurement model evaluation guidelines suggested in the literature (Henseler et al., 2016; Kock, 2022a) were followed. Model fit statistics presented in **Table 1** indicate that data fit model well (Kock, 2022a).

The appropriateness of the measurements was assessed (see **Table 2**) and both reliability and validity were established. Item reliability was documented (loadings of all items exceeded 0.70). Adequate internal consistency reliability was established (composite reliability coefficients of the measures exceeded 0.70). Convergent validity of the constructs was confirmed (average variance extracted values exceeded 0.50).

In **Table 3**, discriminant validity was also documented by using the Fornell-Larcker criterion (Fornell & Larcker, 1981), as we find that all the diagonal values are greater than the off-diagonal numbers in the corresponding rows and columns.

Structural Model

The hypotheses were evaluated using the results of the structural model (see **Figure 2**).

Table 4 summarizes the results of the hypotheses testing: path coefficients (β), path significance (p-value), and effect sizes (values of 0.35, 0.15, and 0.02 indicate large, medium, and small effect sizes, respectively according to Cohen, 1988).

All hypotheses were significant except for the association between SNM and CIN (β=0.059; p=0.268). Of note, we found medium to large effect sizes.

Table 4. Hypothesis testing

H	Path	β	p-value	ES	Result
H1	SNM→CIN	0.059	p=0.268	0.022	Not supported
H2	PUS→CIN	0.437	p<0.001	0.313	Supported
H3	DIS→PUS	0.851	p<0.001	0.725	Supported
H4	DIS→SAT	0.786	p<0.001	0.618	Supported
H5	SAT→CIN	0.389	p<0.001	0.271	Supported

Note. H: Hypothesis; β: Path coefficient; & ES: Effect size

Importantly, the research model explains 60.5% of the variance in continuance intention

It is important to understand students' responses to novel technologies, especially ones that can dramatically impact the way that they learn. With the increasing use of ChatGPT, it is important to understand the salient factors that drive students' intentions to continue using ChatGPT.

Based on the unified extended-confirmation model (Bhattacherjee & Lin, 2015), the aim of the present study was to examine the factors influencing students' intentions to continue using ChatGPT. We explored the antecedents of continuance intention and investigated the relationships between these variables via a structural model that examined the relationships between perceived usefulness, subjective norms, disconfirmation, satisfaction, and continuance intentions.

Findings showed that four out of five hypotheses were supported: PUS→CIN (β=0.437; p<0.001); DIS→PUS (β=0.851; p<0.001); DIS→SAT (β=0.786; p<0.001); SAT→CIN (β=0.389; p<0.001). We did not find support for the association between SNM and CIN (β=0.059; p=0.268). Social norm, referred to as the "perceived social pressure to perform or not to perform the behavior" (Ajzen, 1991, p. 188) appears to exert no influence on students' intentions to use ChatGPT; suggesting that the views or evaluation of others are not as important in shaping the intention to use self-use technologies such as ChatGPT (Cho & Jeon, 2023).

The findings show that perceived usefulness and satisfaction both play important roles in continuance intention. We note that perceived usefulness is the most influential factor on continuance intention. This is in line with prior research, which notes that user confirmation of expectation contributes to perceived usefulness and satisfaction (Ambalov, 2018).

We also found that disconfirmation has a positive influence on both perceived usefulness and satisfaction. Importantly, the research model adequately explains students' intentions to continue using ChatGPT (60.5%), suggesting that the research model is capable of explaining a relatively high proportion of variation in continuance intention. It is important to note that the findings are on par with published findings (e.g., Bhattacherjee et al., 2015).

In sum, the current study provides further evidence for the suitability of the unified extended-confirmation model for the investigation of the drives of ChatGPT continuance intentions. The present study can also help researchers and practitioners gain a better understanding of user behaviors and decisions as it relates to ChatGPT use.

Limitations and Future Directions

Despite its contributions, some limitations of this study might be addressed in future research. The present study was guided by unified extended-confirmation model (Bhattacherjee & Lin, 2015). We did not incorporate additional salient variables that could provide an expanded knowledge of factors influencing students' continuance intention decisions. As such, future research could benefit from exploring additional salient variables (e.g., habit). Results cannot be generalized since they are constrained to a convenience sample of students at a North Indian University. The present study used a cross-section design, which means that learners' changing behaviors over time were not modeled. As such future research with a longitudinal design are encouraged. It should be noted that this study only relied on a quantitative approach. Future research could explore mixed-methods investigations, for example, using qualitative approach to further understand students' beliefs influencing their behaviors apropos ChatGPT. Finally, the present study only investigated general continuance intention to use ChatGPT. Future research could benefit by investigating the difference in continuance intention of ChatGPT in and out of the classroom.

Implications

The findings of the current study are important in informing the acceptance and continued use of ChatGPT for educational purposes. The degree to which learners accept and continue to use a technological innovation, such as ChatGPT, can have considerable impact on learners' learning behaviors and outcomes. The present study helped provide empirical evidence to explain the factors affecting learners' continuance intentions to use ChatGPT using (ECM of IT continuance (Bhattacherjee, 2001) and unified extended-confirmation model (Bhattacherjee & Lin, 2015). While much of the educational research focuses on initial acceptance of technology, the present study is important in that it seeks to understand the motivations for continued use of technology. This study also has implications for the burgeoning literature on the use of generative AI in education. For example, educators could provide additional guidance for learners who report dissatisfactory use experiences and/or intend to discontinue ChatGPT use.

CONCLUDING REMARKS

Large language model-based technologies, such as ChatGPT, have garnered widespread attention. However, the salient determinants of learners' continuance intentions to use ChatGPT have received little scholarly attention. The present study provides empirical evidence regarding the factors that influence learners' continued intentions to use ChatGPT. We find that the proposed research model has good explanatory power in modeling antecedents to students' continuance intentions to use ChatGPT. We discovered that students intend to continue to use ChatGPT because they experience satisfaction from use and consider it to be useful. The present study lays the groundwork for future research that helps better explain users' intentions to continue using ChatGPT. We hope this work spurs further investigations centered on modeling antecedents to continuance use of ChatGPT.

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Ethical statement: The authors stated that, as the data was collected using an anonymous Internet-based survey, they used implied informed consent. Participants were presented with the consent information and were informed that their consent is implied by submitting the completed survey. Although the data was anonymous, the authors did not make any guarantees of confidentiality or anonymity, as the security of online transmissions is not guaranteed.

Declaration of interest: No conflict of interest is declared by the authors.

Data sharing statement: Data supporting the findings and conclusions are available upon request from the corresponding author.

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