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Factors affecting performance expectancy and intentions to use ChatGPT: Using SmartPLS to advance an information technology acceptance framework

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A B S T R A C T

Few studies have explored the use of artificial intelligence-enabled (AI-enabled) large language models (LLMs). This research addresses this knowledge gap. It investigates perceptions and intentional behaviors to utilize AI dialogue systems like Chat Generative Pre-Trained Transformer (ChatGPT). A survey questionnaire comprising measures from key information technology adoption models, was used to capture quantitative data from a sample of 654 respondents. A partial least squares (PLS) approach assesses the constructs' reliabilities and validities. It also identifies the relative strength and significance of the causal paths in the proposed research model. The findings from SmartPLS4 report that there are highly significant effects in this empirical investigation particularly between source trustworthiness and performance expectancy from AI chatbots, as well as between perceived interactivity and intentions to use this algorithm, among others. In conclusion, this contribution puts forward a robust information technology acceptance framework that clearly evidences the factors that entice online users to habitually engage with text-generating AI chatbot technologies. It implies that although they may be considered as useful interactive systems for content creators, there is scope to continue improving the quality of their responses (in terms of their accuracy and timeliness) to reduce misinformation, social biases, hallucinations and adversarial prompts.

1. Introduction

Artificial intelligence (AI) chatbots utilize algorithms that are trained to process and analyze vast amounts of data by using techniques ranging from rule-based approaches to statistical models and deep learning, to generate natural text, to respond to online users, based on the input they received (OECD, 2023). For instance, Open AI's Chat Generative Pre-Trained Transformer (ChatGPT) is one of the most popular AI-powered chatbots. The company claims that ChatGPT "is designed to assist with a wide range of tasks, from answering questions to generating text in various styles and formats" (OpenAI, 2023a). OpenAI clarifies that its GPT-3.5, is a free-to-use language model that was optimized for dialogue by using Reinforcement Learning with Human Feedback (RLHF) – a method that relies on human demonstrations and preference comparisons to guide the model toward desired behaviors. Its models are trained on vast amounts of data including conversations that were created by humans (such content is accessed through the Internet). The responses it provides appear to be as human-like as possible (Jiang et al., 2023).

GPT-3.5's database was last updated in September 2021. However, GPT-4.0 version comes with a paid plan that is more creative than GPT-3.5, could accept images as inputs, can generate captions, classifications and analyses (Qureshi et al., 2023). Its developers assert that GPT-4.0 can create better content including extended conversations, as well as document search and analysis (Takefuji, 2023). Recently, its proponents noted that ChatGPT can be utilized for academic purposes, including research. It can extract and paraphrase information, translate text, grade tests, and/or it may be used for conversation purposes (MIT, 2023). Various stakeholders in education noted that this LLM tool may be able to provide quick and easy answers to questions.

However, earlier this year, several higher educational institutions issued statements that warned students against using ChatGPT for

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academic purposes. In a similar vein, a number of schools banned ChatGPT from their networks and devices (Rudolph et al., 2023). Evidently, policy makers were concerned that this text generating AI system could disseminate misinformation and even promote plagiarism. Some commentators argue that it can affect the students' critical-thinking and problem-solving abilities. Such skill sets are essential aspects for their academic and lifelong successes (Liebrenz et al., 2023; Thorp, 2023). Nevertheless, a number of jurisdictions are reversing their decisions that impede students from using this technology (Reuters, 2023). In many cases, educational leaders are realizing that their students could benefit from this innovation, if they are properly taught how to adopt it as a tool for their learning journey.

Academic colleagues are increasingly raising awareness on different uses of AI dialogue systems like service chatbots and/or virtual assistants (Baabdullah et al., 2022; Balakrishnan et al., 2022; Brachten et al., 2021; Hari et al., 2022; Li et al., 2021; Lou et al., 2022; Malodia et al., 2021; Sharma et al., 2022). Some of them are evaluating their strengths and weaknesses, including of OpenAI's ChatGPT (Farrokhnia et al., 2023; Kasneci et al., 2023). Very often, they argue that there may be instances where the chatbots' prompts are not completely accurate and/or may not fully address the questions that are asked to them (Gill et al., 2024). This may be due to different reasons. For example, GPT-3.5's responses are based on the data that were uploaded before a knowledge cut-off date (i.e. September 2021). This can have a negative effect on the quality of its replies, as the algorithm is not up to date with the latest developments. Although, at the moment, there is a knowledge gap and a few grey areas on the use of AI chatbots that use natural language processing to create humanlike conversational dialogue, currently, there are still a few contributions that have critically evaluated their pros and cons, and even less studies have investigated the factors affecting the individuals' engagement levels with ChatGPT.

This empirical research builds on theoretical underpinnings related to information technology adoption in order to examine the online users' perceptions and intentions to use AI Chatbots. Specifically, it integrates a perceived interactivity construct (Baabdullah et al., 2022; McMillan and Hwang, 2002) with information quality and source trustworthiness measures (Leong et al., 2021; Sussman and Siegal, 2003) from the Information Adoption Model (IAM) with performance expectancy, effort expectancy and social influences constructs (Venkatesh et al., 2003; Venkatesh et al., 2012) from the Unified Theory of Acceptance and Use of Technology (UTAUT1/UTAUT2) to determine which factors are influencing the individuals' intentions to use AI text generation systems like ChatGPT. This study's focused research questions are:

RQ1. How and to what extent are information quality and source trustworthiness influencing the online users' performance expectancy from ChatGPT?

RQ2. How and to what extent are their perceptions about ChatGPT's interactivity, performance expectancy, effort expectancy, as well as their social influences affecting their intentions to continue using their large language models?

RQ3. How and to what degree is the performance expectancy construct mediating effort expectancy – intentions to use these interactive AI technologies?

This study hypothesizes that information quality and source trustworthiness are significant antecedents of performance expectancy. It presumes that this latter construct, together with effort expectancy, social influences as well as perceived interactivity affect the online users' acceptance and usage of generative pre-trained AI chatbots like GPT-3.5 or GPT-4.

Many academic researchers sought to explore the individuals' behavioral intentions to use a wide array of technologies (Alalwan, 2020; Alam et al., 2020; Al-Saedi et al., 2020; Raza et al., 2021; Tam et al., 2020). Very often, they utilized measures from the Theory of Reasoned Action (TRA) (Fishbein and Ajzen, 1975), the Theory of Planned Behavior (TPB) (Ajzen, 1991), the Technology Acceptance Model (TAM) (Davis, 1989; Davis et al., 1989), TAM2 (Venkatesh and Davis, 2000), TAM3 (Venkatesh and Bala, 2008), UTAUT (Venkatesh et al., 2003) or UTAUT2 (Venkatesh et al., 2012). Few scholars have integrated constructs like UTAUT/UTAUT2's performance expectancy, effort expectancy, social influences and intentions to use technologies with information quality and source trust measures from the Elaboration Likelihood Model (ELM) and IAM. Currently, there is still limited research that incorporates a perceived interactivity factor within information technology frameworks. Therefore, this contribution addresses this deficit in academic knowledge.

Notwithstanding, for the time being, there is still scant research that is focused on AI-powered LLM, like ChatGPT, that are capable of generating human-like text that is based on previous contexts and drawn from past conversations. This timely study raises awareness on the individuals' perceptions about the utilitarian value of such interactive technologies, in an academic (higher educational) context. It clearly identifies the factors that are influencing the individuals' intentions to continue using them, in the future.

The following section introduces the readers of this article to relevant theoretical underpinnings that lead to the formulation of hypotheses. It presents a graphical illustration of the proposed research model. Then, the methodology sheds light on the measures that were used to capture the quantitative data. It also provides information on the survey administration and describes the profile of the research participants. Afterwards, the data analysis features the descriptive statistics as well as the findings from partial least squares (PLS) algorithm and from the Bootstrapping procedure. This section reveals the results of the hypothesis testing. In conclusion, this contribution puts forward its theoretical and managerial implications. It identifies the limitations of this study and presents future research avenues.

2. Conceptual framework

2.1. Intentions to use information technologies

There are various theoretical underpinnings that are intended to explain the factors affecting the users' intentions to utilize a wide array of technologies. For instance, the Theory of Planned Behavior (TPB) as well as its predecessor, the Theory of Reasoning Action (TRA) postulate that the persons' attitudes and beliefs would anticipate their behaviors and actions. The former comprises three antecedents, namely, attitudes, subjective norms, and perceived behavioral control. Ajzen (1991) argued that these constructs affect the individuals' behavioral intentions. Previously, Fishbein and Ajzen's (1975) TRA posited that attitudes and subjective norms anticipate the persons' intentions to engage in certain activities. TRA is very similar to TPB, albeit it does not include a perceived behavior control construct.

The behavioral intention can be defined as an individual's readiness to perform given behaviors. Ajzen (1991) contended that the individuals' intentions are assumed to capture the motivational factors that influence behavior. Essentially, they represent the extent to which people are willing to engage in certain activities, or to make an effort to perform specific behaviors. This construct has been widely utilized to explore human actions in various contexts including in psychology, cognitive studies, marketing, information management, technology adoption, et cetera.

Several researchers relied on the behavioral intentions measure to examine the persons' dispositions to adopt information systems. Frequently, it has been featured as an endogenous factor in various studies, including in the Technology Acceptance Model (TAM) (Davis, 1989; Davis et al., 1989; Venkatesh and Davis, 2000). Like TPB and TRA, TAM presumes that the persons' attitudes about information communication technologies (ICT) are a precursor for their behavioral intentions to use them. In addition, it posits that the individuals' perceptions about the usefulness as well as the ease-of-use of ICT can influence their attitudes and intentions to use them.

These theoretical models and their key factors have continuously been validated in different studies (Driediger and Bhatiasevi, 2019; Ho et al., 2020; Kamble et al., 2019; Sohn and Kwon, 2020). Very often, they were expanded, as many researchers integrated new constructs in extant models. For example, TAM2 (Venkatesh and Davis, 2000) and TAM3 (Venkatesh and Bala, 2008) featured additional factors to TAM. The authors sought to investigate the antecedents of perceived usefulness and perceived ease-of-use. Yet, the behavioral intentions to use technology devices and their systems were frequently hypothesized to be an endogenous construct. Table 1 features a summary of the most popular theoretical frameworks that sought to identify the antecedents and the extent to which they may affect the individuals' intentions to use information technologies.

Table 1
A non-exhaustive list of theoretical frameworks focused on (information) technology adoption behaviors.

Theory	Developed by	Measures					
Electronic Service Quality (eSERVQUAL)	Parasuraman et al. (2005)	Ease of use	Website design	Reliability	System availability	Privacy	
		Responsiveness	Empathy	Consumer experience	Trust	Satisfaction	
Electronic retail quality (eTailQ)	Wolfinbarger and Gilly (2003)	Consumer fulfillment	Website design	Privacy/security	Customer service	Satisfaction	
Information Adoption Model (IAM)	Sussman and Siegal (2003)	Argument quality	Source credibility	Information usefulness	Information adoption		
Information technology adoption model (InfTAM)	Camilleri et al. (2023)	Information quality	Source credibility	Functionality	Perceived usefulness	Intention to use the technology	
Innovation diffusion theory (IDT/DOI)	Moore and Benbasat (1991)	Relative advantage	Ease of use	Image	Voluntarism		
		Compatibility	Visibility	Result demonstrability	Adoption		
Interactive technology adoption model (ITAM)	Camilleri and Kozak (2023)	Information quality	Source credibility	Interactive engagement	Perceived usefulness	Intentions to use the technology	
Model of PC utilization (MPCU)	Thompson et al. (1991)	Social factors	Affect toward PC	Complexity of PC use	Job fit with PC		
		Long term consequences of PC use	Facilitating conditions for PC use	PC utilization			
Motivation model (MM)	Davis et al. (1992)	Task importance	Perceived ease of use	Perceived usefulness	Output quality		
		Perceived enjoyment	Intentions to use the technology	Usage behavior			
Net quality (NETQual)	Bressolles et al. (2014)	Ease of use	Information	Design	Reliability	Security/privacy	Interactivity/ personalization
Site quality (SITEQUAL)	Yoo and Donthu (2001)	Ease of use	Aesthetic design	Processing speed	Security		
Social cognitive theory (SCT)	Compeau and Higgins (1995)	Prior performance	Computer self-efficacy	Behavior modelling	Outcome expectations	Performance	
Synchronous technology adoption model (STAM)	Camilleri and Camilleri (2022)	Functionality	Perceived interactivity	Facilitating conditions	Intentions to use the technology		
Technology acceptance model (TAM)	Davis et al. (1989)	Perceived ease of use	Perceived usefulness	Attitudes	Intentions to use the technology	Actual behaviors	
Technology acceptance model (enhanced version TAM2)	Venkatesh and Davis (2000)	Subjective norms	Image	Job relevance	Output quality	Result demonstrability	
		Experience	Voluntariness	Perceived usefulness	Perceived ease of use	Intentions to use the technology	Actual behaviors
Technology acceptance model (enhanced version TAM3)	Venkatesh and Bala (2008)	Subjective norms	Image	Job relevance	Output quality	Computer playfulness	Result demonstrability
		Result demonstrability	Computer self-efficiency	Perception of external control	Computer anxiety	Perceived ease of use	Perceived usefulness
		Experience	Voluntariness	Intentions to use the technology	Actual behaviors		
Theory of planned behavior (TPB)	Ajzen (1991)	Attitudes	Subjective norms	Perceived behavioral control	Intentions to use the technology	Actual behaviors	
Theory of reasoned action (TRA)	Fishbein and Ajzen (1975)	Attitudes	Subjective norms	Intentions to use the technology	Actual behaviors		
Transaction process-based approaches for capturing service quality (eTransQual)	Bauer et al. (2006)	Responsiveness	Reliability	Process	Functionality/ design	Enjoyment	
Unified Theory of Acceptance and Use of Technology (UTAUT1)	Venkatesh et al. (2003)	Performance expectancy	Effort expectancy	Social influence	Facilitating conditions	Gender	
		Age	Experience	Voluntariness in use	Intentions to use the technology	Actual behaviors	
Unified Theory of Acceptance and Use of Technology (Enhanced version - UTAUT2)	Venkatesh et al. (2012)	Performance expectancy	Effort expectancy	Social influence	Facilitating conditions	Hedonic motivations	Price value
		Habit	Age	Gender	Experience	Intention to use the technology	Actual behaviors
Uses and gratifications theory (U&G)	Camilleri and Falzon (2021)	Perceived ease of use	Perceived usefulness	Ritualized use	Instrumental use	Intention to use the technology	

2.2. Performance expectancy

In this case, this research investigates the extent to which users accept and use specific technologies. It builds on Venkatesh et al.'s (2003) UTAUT. These authors referred to performance expectancy when they advanced their theoretical model. They indicated that their "new" construct was similar to Davis' (1989) perceived usefulness as well as to other factors, including to extrinsic motivation from Davis et al.'s (1992) Motivation Model, job-fit from Thompson et al.'s (1991) Model of PC Utilization, relative advantage from Moore and Benbasat's (1991) Innovation Diffusion Theory, and to outcome expectations, that is drawn from Compeau and Higgin's (1995) Social Cognitive Theory. Venkatesh et al. (2003) noted that these factors intended to measure how the use or capabilities of a system were instrumental in improving the individuals' job performance, by accomplishing tasks, by enhancing productivity, and/or by increasing their chances of getting a pay rise.

In the authors' own words, they defined performance expectancy as "the degree to which an individual believes that using the system will help him or her attain gains in job performance". When Venkatesh et al. (2003) put forward their UTAUT, they theorized that the individuals' performance expectancy from technological systems significantly affects their behavioral intentions to use them. Since then, a number of researchers have reported similar results, even though they examined and validated this causal path for a wide array of technologies, in various contexts (Alalwan, 2020; Alam et al., 2020; Al-Saedi et al., 2020; Raza et al., 2021; Tam et al., 2020). In a similar vein, this research presumes that:

H1. The online users' performance expectancy of ChatGPT significantly affects their intentions to use this information technology.

2.3. Effort expectancy

Venkatesh et al. (2003) maintained that their effort expectancy construct is particularly significant during the earlier stages when individuals start acquainting themselves with the technology, in mandatory, as well as in voluntary contexts. They postulated that the individuals' ease of use of technology becomes an insignificant factor over periods of habitual behaviors, after extended usage. These authors noted that UTAUT's effort expectancy construct is synonymous with TAM's and TAM2's perceived ease-of-use as well as with the Model of PC Utilization's complexity construct and with ease-of-use from Innovation Diffusion Theory. Venkatesh et al. (2003) noted that the definitions of these constructs as well as their measuring items were very similar. Whilst Davis (1989) clarified that perceived ease-of-use refers to "the degree to which a person believes that using a particular system would be free of effort", Venkatesh et al. (2003) suggested that; "effort expectancy is the degree of ease associated with the use of the system".

In the main, information systems researchers argue that individuals would be intrigued to use clear and understandable technologies that are uncomplicated and easy to use (Thompson et al., 1991; Venkatesh et al., 2012). Most academic authors hypothesize that the persons' effort expectancy from certain technologies, in terms of their systems' ease-of-use, would increase their likelihood to continue using them in the future (Abbad, 2021; Beh et al., 2021; Queiroz et al., 2021). Previously, Davis's (1989) as well as Davis et al.'s (1989) TAM indicated that perceived ease of use also had a significant effect on perceived usefulness. However, unlike TAM studies (Davis, 1989; Venkatesh and Davis, 2000; Venkatesh and Bala, 2008), few UTAUT/UTAUT2 studies have examined the effects of effort expectancy on performance expectancy of information technologies (Camilleri and Kozak, 2022). This argumentation leads to the following hypotheses:

H2. The online users' effort expectancy of ChatGPT significantly affects their intentions to use this information technology.

H2a. The online users' performance expectancy of ChatGPT partially mediates effort expectancy - intentions to use this information technology.

H3. The online users' effort expectancy of ChatGPT significantly affects the performance expectancy of this information technology.

2.4. Information quality

Generally, the technology adoption models including the extended TAM and UTAUT frameworks, among others, are meant to measure the persons' dispositions to avail themselves of information technologies, and to identify which factors and to what extent they affect their intentions to engage with. Them. The variants of the Elaboration Likelihood Model (ELM) and/or Information Adoption Model (IAM) are intended to clarify whether central and/or peripheral aspects of communication could influence the individuals' attitudes about persuasive content (Cacioppo and Petty, 1981), and/or their perceptions about the usefulness of information (Sussman and Siegal, 2003).

Arguably, in the latter case, the communicated content can influence the persons' perceptions in different ways, as they may not always be willing to evaluate the quality of the messages they receive (Sussman and Siegal, 2003). This argumentation is synonymous with ELM's central route, as recipients of information may opt to carefully assess the content that is presented them. ELM suggests that the quality of elaborated information can influence the individuals' attitudes toward the message. Cacioppo and Petty (1981) contended that people reflect on the content of the message that is conveyed to them. These authors maintained that the recipients of information arrive at a reasoned attitude that is supported by the argument quality. Cacioppo and Petty (1981) among others (E.g. Cheung et al., 2008; Erkan and Evans, 2018; Sussman and Siegal, 2003) clearly distinguished between central and peripheral factors that can influence how individuals elaborate on a persuasive message.

Sussman and Siegal (2003) have built their IAM theoretical underpinnings on the foundations of ELM. Their research model suggested that information quality is a significant antecedent of information usefulness. Over the years, a number of researchers have validated this causal path in different contexts (Jin et al., 2009; Leong et al., 2021; Peng et al., 2016). Erkan and Evans (2018) reported that information quality significantly affects the usefulness of information technologies like shopping websites that feature consumer recommendations. Their study indicated that their respondents appreciated their utilitarian value as they were willing to rely on their user generated content. Similarly, Camilleri and Filieri (2023) reported that information quality significantly affects information usefulness. The latter construct is synonymous with Davis (1989) perceived usefulness factor. Hence, it is related to Venkatesh et al.'s (2012) performance expectancy. This research hypothesizes:

H4. The online users' perceptions about the information quality of ChatGPT's generated responses significantly affect their performance expectancy of this information technology.

2.5. Source trustworthiness

At times, individuals may ignore the quality of the messages they receive. They may do so as they hold preconceived perceptions about the source of the message. This reasoning is related to ELM's theoretical underpinnings. Its proponents argue that according to the peripheral route to communication, there may be different reasons that could affect the receivers' willingness to accept and process the messages that are conveyed to them (Cacioppo and Petty, 1981; Shi et al., 2018). They may not be interested in examining the content they receive. Hence, they will probably rely on subjective cues and on their general impressions about the source (Ferguson and Mohan, 2020). ELM commentators generalize that individuals could be influenced by heuristics (mental shortcuts), particularly if they are not motivated/interested in the messages that are transmitted to them (Bingham et al., 2019; Rohde and Mau, 2021). Alternatively, they may be distracted from scrutinizing their content, and/or do not possess the cognitive abilities and/or may not have the time/opportunity to do so (Hoeken et al., 2020). In this case, the targeted audience may rely on the sources' trustworthiness, rather than on the quality of their arguments.

Various researchers found that peripheral cues in websites and/or social media can have an impact on the individuals' perceptions, attitudes, as well as on intentional behaviors, when they are unable or unwilling to elaborate on the message's content (John and De'Villiers, 2020; Winter, 2020). Very often, they indicated that the persons' attitudes toward communications are influenced by the source's attractiveness, likeability, and credibility in terms of their trustworthiness and expertise (Cacioppo and Petty, 1981). Sussman and Siegal (2003) noted that source credibility positively influences the users' acceptance of knowledge-based systems' recommendations. They went on to suggest that credible sources are persuasive and can play an important role in informational influence. Erkan and Evans (2016) reported that the individuals would rely on the information obtained from social media if they perceive that the source of the content is credible and dependable. A number of empirical studies confirmed that source trustworthiness (or source credibility) is an antecedent of the individuals' perceptions about the usefulness of information (Camilleri and Filieri, 2023; Kang and Namkung, 2019; Onofrei et al., 2022). In a similar vein, this research presumes that this construct can be a significant precursor of performance expectancy. Thus, this study hypothesizes:

H5. The online users' perceptions about the source trustworthiness of ChatGPT's generated responses significantly affect their performance expectancies of this information technology.

2.6. Social influences

The individuals' acceptance and usage of information technologies can be triggered by social influences. This issue is conspicuous with the subjective norm dimension that was discussed in Fishbein and Ajzen's (1975) TRA as well as in Ajzen's (1991). The subjective norm construct raises awareness about possible peer pressures and general beliefs on different issues, from family, friends, work colleagues and from other members in society, on the individuals' intentional behaviors and activities including on their engagement with technology.

Venkatesh and Davis (2000) held that there are three interrelated social forces that can impinge on the users' adoption or rejection of a new system, including subjective norm, voluntariness, and image. They explained that the rationale behind the direct effect of subjective norm on intention is that individuals tend to engage in behaviors, even if they do not like them or their consequences. Yet, they may decide to engage in certain activities if the persons around them think they should. These authors distinguished between mandatory and voluntary usage contexts.

Subsequently, a number of academic colleagues specifically referred to a social influences construct (Camilleri and Kozak, 2022; Venkatesh et al., 2003; Venkatesh et al., 2012) in UTAUT/UTAUT2, or to social factors (Thompson et al., 1991) in the Model of PC Utilization, or to image (Moore and Benbasat, 1991) in Innovation Diffusion Theory. Very often, the researchers who used one of these constructs, indicated that the individuals are expected to comply with certain norms and values in society, particularly in mandatory environments. Such social influences can also influence their perceptions about the acceptance of information technologies that can be utilized for different purposes. They could even induce their adoption.

Venkatesh et al. (2003) suggested that this construct is very important in the early stages of the individuals' experiences with technologies (this reasoning is also congruent with the perceived ease-of-use or effort expectancy constructs), as they will not have to follow their peers' recommendations once they become habituated with them. Several studies confirmed that in many cases individuals are urged by others to conduct specific activities including adopting new technologies (Kamal et al., 2020; Patil et al., 2020; Raza et al., 2021; Zhao and Bacao, 2020). Hence, this study hypothesizes:

H6. Social influences would significantly affect the online users' intentions to use ChatGPT.

2.7. Perceived interactivity

The users of information technologies would usually appraise the systems' attributes and features with colleagues (as well as with family and friends), particularly if they found them to be useful, functional and/or if they exceeded their expectations in terms of their interactivity aspects. Most world-wide web technologies including blogs, social media, review sites, web chatbots, virtual assistants, and the like, can be considered to be interactive, as they involve two-way communications. Yet, the notion of interactivity is often misunderstood, unexplained or underdefined. Relevant academic literature suggests that: (i) the direction of communication, (ii) user control, and (iii) time are three overlapping constructs that can describe the interactivity features of various technologies (McMillan and Hwang, 2002). Firstly, the direction of communication is related to the degree of responsiveness and to the exchange of information (Bauer et al., 2006; Parasuraman et al., 2005). Secondly, user control is associated with functions such as the extent of concurrent participation and to interpersonal, online engagement. Thirdly, the concept of time is linked to the timeliness of immediate feedback.

Web content can be accessed through functional and easy-to-use navigational tools like digital devices and mobile applications (Camilleri and Camilleri, 2022; Kaya et al., 2019; Molinillo et al., 2020). These systems are also meant to facilitate human-to-human, human-to-computer as well as computer-to-human interactions. Online users can create and share their vocal, verbal and visual content with others. They present themselves through their interactive content. This argumentation is synonymous with the social exchange theory that suggests that there is scope for individuals to reciprocate with others as they can obtain informational as well as emotional values from interactions (Cortez and Johnston, 2020; Luqman et al., 2023). Several researchers sought to explore the individuals' perceptions and experiences with interactive media. Song and Zinkhan (2008) posited that the presence or absence of particular design features (e.g. choice of background colors, search options, clickable areas, feedback mechanisms, et cetera) can determine the interactivity levels of certain technologies.

A number of academic commentators made reference to a perceived interactivity construct to examine the individuals' self-presentation (online), their content contribution as well as their exchange of support with other users (Zhang et al., 2014). Zhao and Lu (2012) distinguished between two dimensions: user-to-user interactivity (i.e. interpersonal online engagement) and user-to-system (human-machine interactivity).

Recently, various researchers have even investigated whether the persons' perceptions about interactive artificial intelligence systems like chatbots or virtual assistants for customer services purposes (Peltier et al., 2023). Very often they reported that they were satisfied with the dialogue systems' interactivity features, as they have significantly affected their intentions to continue using them in the future (Baabdullah et al., 2022; Lou et al., 2022). Similarly, this research presumes that:

H7. The online users' perceptions about the interactivity of ChatGPT significantly affect their intentions to use this information technology.

Fig. 1 features the conceptual framework that investigates information technology adoption factors. It represents a visual illustration of the hypotheses of this study. In sum, this empirical research presumes that information quality and source trustworthiness (from Information Adoption Model) precede performance expectancy. The latter construct

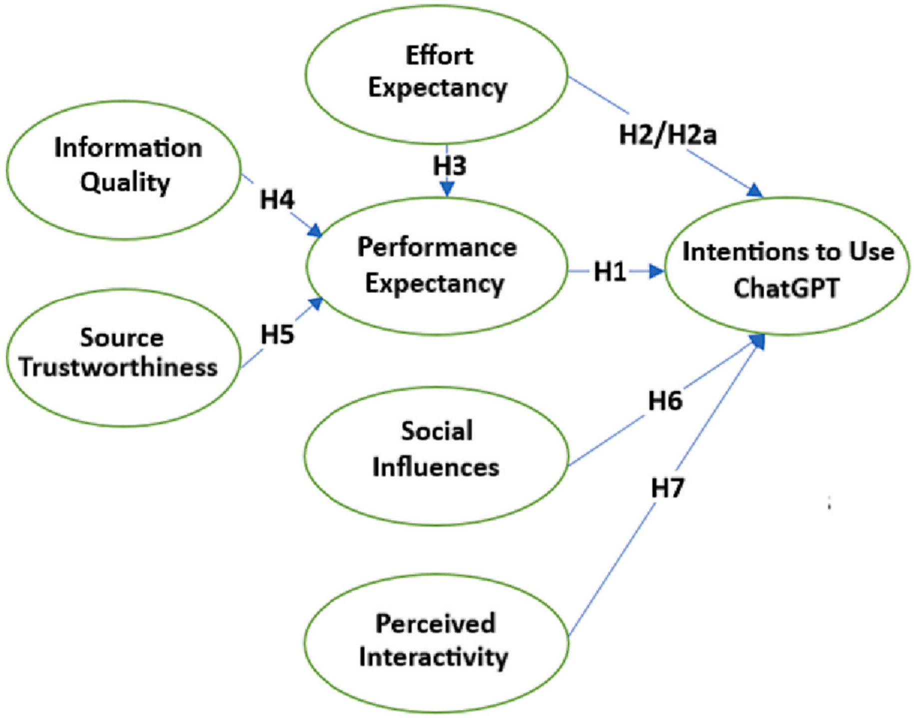

Fig. 1. Information technology acceptance framework.

together with effort expectancy, social influences (from Unified Theory of Acceptance and Use of Technology) as well as the perceived interactivity construct, are significant antecedents of the individuals' intentions to use ChatGPT.

3. Methodology

3.1. The survey administration

Primary data were collected through an online survey questionnaire that was disseminated via an email, among all members of staff as well as students who were enrolled in full time and part time courses in a Southern European university, during the second semester of 2022–2023. There were >13,200 research participants who were targeted for this research about the use of ChatGPT. They were in a position to complete the questionnaire in a few minutes.

This empirical study complied with the research ethic policies of the higher educational institution as well with the EU's (2016) general data protection regulations (GDPR). There was no way that the survey respondents' identity could be revealed, as only aggregate data was required for this quantitative research.

3.2. The survey instrument

The respondents were instructed to answer all survey questions that were presented to them about information quality, source trustworthiness, performance expectancy, effort expectancy, social influences, perceived interactivity and on their behavioral intentions to continue using this technology (otherwise, they could not submit the questionnaire). Table 2 features the list of measures as well as their corresponding items that were utilized in this study. It also provides a definition of the constructs used in the proposed information technology acceptance framework.

The research participants were expected to clearly indicate the extent of their agreement with the survey's measuring constructs in a five-point Likert scale, where 1 represented "strongly disagree" and 5 referred to "strongly agree". The survey was pilot tested among a small group of academic colleagues.

The research participants disclosed their gender as well as their age by choosing one of five age groups in the last part of the survey. They also indicated the highest qualification that they attained at the time of this study.

3.3. The demographic profile of the respondents

After a few weeks, there were six hundred fifty-four (n = 654) respondents who confirmed (through a filter question) that they have used ChatGPT. The frequency table reported 292 males, 338 males and 22 participants who opted not to indicate their gender. The research participants were categorized into 5 age groups (18–28; 29–39; 40–50; 51–61; Over 62). The majority of them were between 18 and 28 years (n = 318). The second largest group involved middle-aged individuals who were between 40 and 50 years (n = 128). Most of the respondents reported that they had completed an undergraduate level of education, as indicated in Table 3.

4. Data analysis

4.1. The descriptive statistics

The findings reported that, in the main, the research participants were agreeing with the statements that were presented to them in the survey questionnaire. The mean values were mostly above 3. Whilst EE1 (M = 4.239) and EE2 (M = 4.18) were the highest mean scores, PI2 (M = 2.908) and IQ2 (M = 2.911) reported the lowest means. The SD values were relatively low as the highest variance figure was 1.216 (for SI1).

4.2. Results from PLS-SEM algorithm

A collinearity assessment revealed that there was no evidence of common method bias in this study. Table 4 illustrates the results of the variance inflation factors (VIF), outer loadings, as well as the constructs' reliabilities, convergent validities, in terms of the average variance extracted (AVE) as well as their discriminant validity values.

Table 2
The list of measures and the corresponding items used in this research.

Construct	Source	Definition	Code	Item
Performance expectancy	Unified Theory of Acceptance and Use of Technology (UTAUT1 and UTAUT2) (Venkatesh et al., 2003; Venkatesh et al., 2012)	The performance expectancy construct is defined as the degree to which individuals believe that using a system will help them improve their job performance.	PE1	ChatGPT offers a useful service.
			PE2	ChatGPT is convenient.
			PE3	ChatGPT provides quick answers to my questions.
			PE4	ChatGPT is enhancing my job performance.
Effort Expectancy	Unified Theory of Acceptance and Use of Technology (UTAUT1 and UTAUT2) (Venkatesh et al., 2003; Venkatesh et al., 2012)	The effort expectancy construct is defined as the degree of ease associated with the use of a system.	EE1	It is easy to use ChatGPT.
			EE2	It is not difficult to access ChatGPT through the digital media.
			EE3	ChatGPT interacts with me in a clear and understandable manner.
			EE4	ChatGPT is user-friendly.
Social Influences	Unified Theory of Acceptance and Use of Technology (UTAUT1 and UTAUT2) (Venkatesh et al., 2003; Venkatesh et al., 2012)	The social influences construct is defined as a process that may lead individuals to change their opinions, beliefs, or behaviors as a result of social interactions with other people.	SI1	People who are important to me think that I should use ChatGPT.
			SI2	People who influence my behaviors recommend that I use ChatGPT.
Perceived Interactivity	Perceived Interactivity (McMillan and Hwang, 2002; Zhao and Lu, 2012)	The perceived interactivity construct is defined as the individuals' perceptions about web-based human-to-human, human-to-computer and/or computer-to-human interactions, in real time.	PI1	ChatGPT provides correct answers to my questions.
			PI2	ChatGPT responds to my questions in real time.
Information quality	Elaboration Likelihood Model (Central Route) (Cacioppo and Petty, 1981), Information Adoption Model (Sussman and Siegal, 2003)	The information quality construct is defined as the individuals' perceptions about the accuracy and reliability of the content they receive.	IQ1	The information I receive from ChatGPT is correct.
			IQ2	The information that is provided from ChatGPT is reliable.
Source trustworthiness	Elaboration Likelihood Model (Peripheral Route) (Cacioppo and Petty, 1981); Information Adoption Model (Cheung et al., 2008)	The source trustworthiness construct is defined as the individuals' perceptions about the sources' credibility and dependability.	ST1	I trust the content that is given by ChatGPT.
			ST2	The information I receive from ChatGPT is dependable.
Intentions to use the information technology (e.g. ChatGPT)	Technology Acceptance Models (TAM, TAM2 and TAM3) (Davis et al., 1989; Davis, 1989; Venkatesh and Davis, 2000; Venkatesh and Bala, 2008); Unified Theory of Acceptance and Use of Technology (UTAUT1 and UTAUT2) (Venkatesh et al., 2003; Venkatesh et al., 2012)	The intentions to use the information technology construct is defined as the individuals' willingness to repeatedly perform specified behaviors including utilizing information technologies (like ChatGPT).	INT1	I am a regular user of ChatGPT.
			INT2	Most probably, I shall continue using ChatGPT, in the near future.

Table 3
The demographic profile of the research participants.

Gender		Age		Qualifications	
Males	292	18–28	318	Cert	14
Females	338	29–39	110	Dip	142
Other	18	40–50	128	B	194
		51–61	74	M	162
		Over 62	20	PhD	136
Preferred not to say	6		4		6
Total (N)	654	Total (N)	654	Total (N)	654

The VIFs were <3.3. The outer loadings ranged between 0.653 and 0.941. The findings confirmed that the reliability values were higher than 0.7. The AVE figures were above 0.6. The constructs' discriminant validities were tested through Fornell and Larcker's (1981) criterion as well as via the HTMT procedure (Henseler et al., 2015). The former reported that the square roots of AVE (in bold) were higher than the other correlation values (within the same columns). In addition, the latter (HTMT) values, on the right-hand side of the bold figures, were lower than 0.9.

The PLS algorithm also provided details about the robustness of the structured model. It clearly indicated the factors' predictive power and shed light on the values of R^2 and f^2. It revealed that the independent constructs affected 53.8 % of the users' performance expectancy and 61.1 % of their intentions to use ChatGPT.

Source trustworthiness had the highest effect on performance expectancy, where $f^2 = 0.3$. Other noteworthy effects were reported between perceived interactivity and intentions to use ChatGPT ($f^2 = 0.245$), and between effort expectancy and performance expectancy ($f^2 = 0.145$). There were lower effects between social influences and intentions to use ChatGPT ($f^2 = 0.090$), between performance expectancy and intentions to use ChatGPT ($f^2 = 0.057$), between information quality and performance expectancy ($f^2 = 0.05$), and between effort expectancy and intentions to use ChatGPT ($f^2 = 0.029$). Fig. 2 depicts the path coefficients of this empirical investigation.

4.3. Results from the Bootstrapping procedure

The bootstrapping procedure was utilized to examine the hypotheses of this study. The findings confirmed the robustness of the proposed structured model. They reported highly significant effects between the exogenous and endogenous constructs, as indicated in Table 5. The most significant link was found in H5, between source trustworthiness and performance expectancy, where $\beta = 0.450$, $t = 8.477$ and $P < 0.001$. Highly significant effects were reported in H7, between perceived interactivity and intentions to use ChatGPT ($\beta = 0.355$, $t = 8.255$, $P < 0.001$), in H3, between effort expectancy and performance expectancy ($\beta = 0.311$, $t = 6.364$, $P < 0.001$), and in H6, between social influences and intentions to use ChatGPT ($\beta = 0.263$, $t = 4.362$, $P < 0.001$). Other significant effects were found in H1, between performance expectancy and intentions to use ChatGPT ($\beta = 0.236$, $t = 3.029$, $P = 0.002$), in H4, between information quality and performance expectancy ($\beta = 0.158$, $t = 2.966$, $P = 0.003$), and in H2, between effort expectancy and

Table 4
The descriptive statistics as well as the construct reliability and validity values.

Construct		Items	Mean	Deviation	Loadings	VIF	Alpha	Rho_A	CR	AVE	1	2	3	4	5	6	7
1	Effort Expectancy	EE1	4.239	0.781	0.795	1.802	0.784	0.805	0.86	0.607	**0.779**	0.299	0.657	0.634	0.442	0.722	0.587
		EE2	4.18	0.791	0.653	1.429											
		EE3	3.758	0.922	0.795	1.65											
		EE4	3.988	0.816	0.859	2.045											
2	Information quality	IQ1	2.988	0.986	0.909	1.835	0.806	0.808	0.911	0.837	0.244	**0.915**	0.333	0.422	0.328	0.428	0.528
		IQ2	2.911	1.014	0.921	1.835											
3	Source trustworthiness	IT1	3.572	0.948	0.907	1.825	0.804	0.808	0.911	0.836	0.544	0.269	**0.914**	0.873	0.89	0.792	0.631
		IT2	3.56	0.913	0.922	1.825											
4	Intentions to use ChatGPT	INT1	3.471	0.992	0.933	2.156	0.845	0.846	0.928	0.866	0.535	0.35	0.721	**0.931**	0.718	0.784	0.749
		INT2	3.563	0.962	0.928	2.156											
5	Perceived Interactivity	PI1	3.168	0.912	0.935	2.358	0.863	0.864	0.936	0.879	0.381	0.275	0.742	0.614	**0.938**	0.554	0.43
		PI2	2.908	0.924	0.941	2.358											
6	Performance Expectancy	PE1	4.138	0.89	0.874	2.817	0.86	0.861	0.905	0.706	0.594	0.355	0.661	0.669	0.478	**0.84**	0.839
		PE2	3.942	0.935	0.822	1.886											
		PE3	3.468	1.069	0.778	1.636											
		PE4	4.119	0.85	0.881	2.752											
7	Social Influences	SI1	3.064	1.216	0.879	1.713	0.784	0.824	0.901	0.82	0.477	0.427	0.512	0.62	0.361	0.697	**0.906**
		SI2	4.012	0.938	0.931	1.713											

intentions to use ChatGPT (β = 0.134, t = 2.767, P = 0.006).

Table 6 summarizes the results of the mediated analyses. The findings reveal that performance expectancy significantly mediates effort expectancy - intentions to use ChatGPT causal path. Table 7 sheds light on the indirect effects within this research model. The results suggest that performance expectancy significantly mediates source trustworthiness – intentions to use ChatGPT link.

5. Discussion and conclusions

5.1. Theoretical implications

This research sought to explore the factors that are affecting the individuals' intentions to use ChatGPT. It examined the online users' effort and performance expectancy, social influences as well as their perceptions about the information quality, source trustworthiness and interactivity of generative text AI chatbots. The empirical investigation hypothesized that performance expectancy, effort expectancy and social influences from Venkatesh et al.'s (2003) UTAUT together with a perceived interactivity construct (McMillan and Hwang, 2002) were significant antecedents of their intentions to revisit ChatGPT's website and/or to use its app. Moreover, it presumed that information quality and source trustworthiness measures from Sussman and Siegal's (2003) IAM were found to be the precursors of performance expectancy.

The results from this study report that source trustworthiness-performance expectancy is the most significant path in this research model. They confirm that online users indicated that they believed that there is a connection between the source's trustworthiness in terms of its dependability, and the degree to which they believe that using such an AI generative system will help them improve their job performance. Similar effects were also evidenced in previous IAM theoretical frameworks (Kang and Namkung, 2019; Onofrei et al., 2022), as well as in a number of studies related to TAM (Assaker, 2020; Chen and Aklikokou, 2020; Shahzad et al., 2018) and/or to UTAUT/UTAUT2 (Lallmahomed et al., 2017).

In addition, this research also reports that information quality significantly affects their performance expectancy/expectancies from ChatGPT. Yet, in this case, this link was weaker than the former, thus implying that the respondents' perceptions about the usefulness of this text generative technology were clearly influenced by the peripheral cues of communication (Cacioppo and Petty, 1981; Shi et al., 2018; Sussman and Siegal, 2003; Tien et al., 2019).

Very often, academic colleagues noted that individuals would probably rely on the information that is presented to them, if they perceive that the sources and/or their content are trustworthy (Bingham et al., 2019; John and De'Villiers, 2020; Winter, 2020). Frequently, they indicated that source trustworthiness would likely affect their beliefs about the usefulness of information technologies, as they enable them to enhance their performance. Conversely, some commentators argued that there may be users that could be skeptical and wary about using new technologies, especially if they are unfamiliar with them (Shankar et al., 2021). They noted that such individuals may be concerned about the reliability and trustworthiness of the latest technologies.

The findings suggest that the individuals' perceptions about the interactivity of ChatGPT are a precursor of their intentions to use it. This link is also highly significant. Therefore, the online users were somehow appreciating this information technology's responsiveness to their prompts (in terms of its computer-human communications). Evidently, ChatGPT's interactivity attributes are having an impact on the individuals' readiness to engage with it, and to seek answers to their questions. Similar results were reported in other studies that analyzed how the interactivity and anthropomorphic features of dialogue systems like live support chatbots, or virtual assistants can influence the online users' willingness to continue utilizing them in the future (Baabdullah et al., 2022; Balakrishnan et al., 2022; Brachten et al., 2021; Liew et al., 2017).

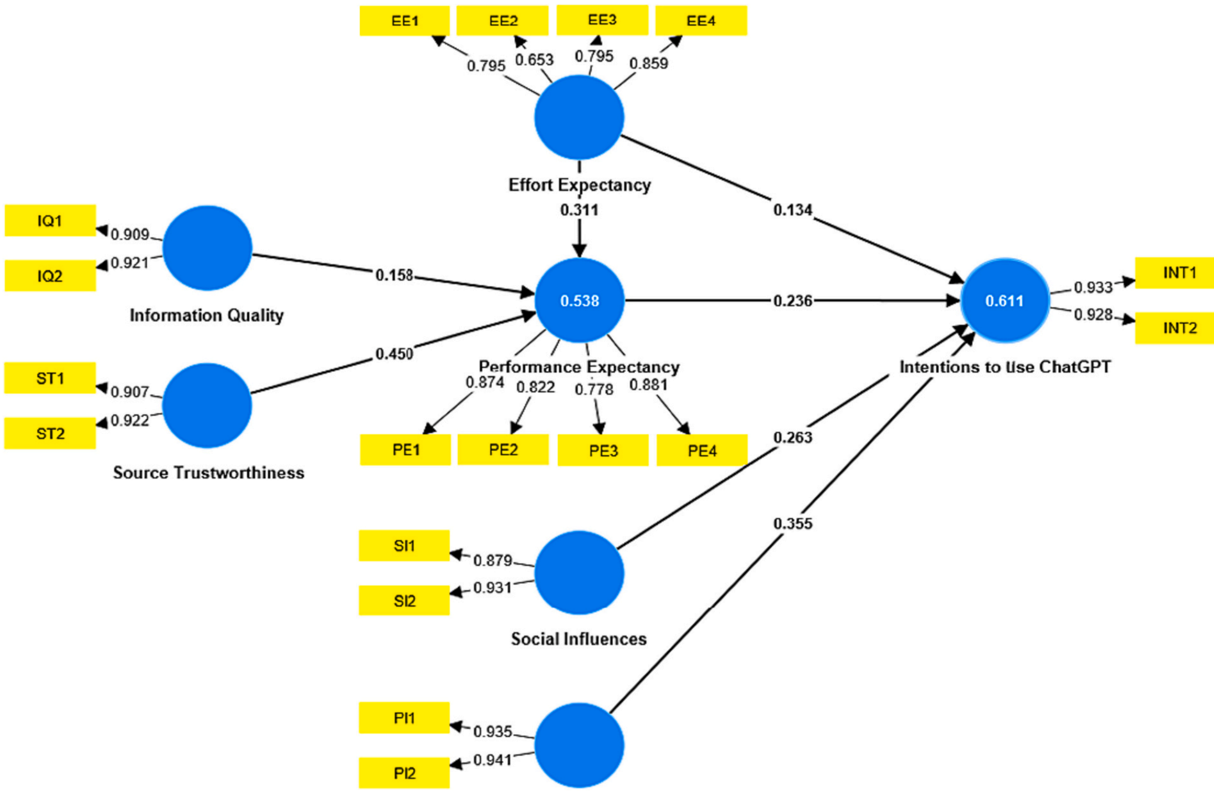

Fig. 2. An illustration of the results from SEM-PLS algorithm.

Table 5
The findings from the Bootstrapping procedure.

	Causal path	Original sample (O)	Standard deviation (STDEV)	T statistics	P values
1	Performance Expectancy → Intentions to Use ChatGPT	0.236**	0.078	3.029	0.002
2	Effort Expectancy → Intentions to Use ChatGPT	0.134**	0.049	2.767	0.006
3	Effort Expectancy → Performance Expectancy	0.311***	0.047	6.634	0.000
4	Information quality → Performance Expectancy	0.158**	0.053	2.966	0.003
5	Source trustworthiness → Performance Expectancy	0.450***	0.053	8.477	0.000
6	Social Influences → Intentions to Use ChatGPT	0.263***	0.060	4.362	0.000
7	Perceived Interactivity → Intentions to Use ChatGPT	0.355***	0.043	8.255	0.000

Note: T > 1.95.
*** P < 0.001.
** P < 0.01.

There are a number of academic contributions that sought to explore how, why, where and when individuals are lured by interactive communication technologies (e.g. Hari et al., 2022; Li et al., 2021; Lou et al., 2022). Generally, these researchers posited that users are habituated with information systems that are programed to engage with them in a dynamic and responsive manner. Very often they indicated that many individuals are favorably disposed to use dialogue systems that are capable of providing them with instant feedback and personalized content. Several colleagues suggest that positive user experiences as well as high satisfaction levels and enjoyment, could enhance their connection with information technologies, and will probably motivate them to continue using them in the future (Ashfaq et al., 2020; Camilleri and Falzon, 2021; Huang and Chueh, 2021; Wolfinbarger and Gilly, 2003).

Another important finding from this research is that the individuals' social influences (from family, friends or colleagues) are affecting their interactions with ChatGPT. Again, this causal path is also very significant. Similar results were also reported in UTAUT/UTAUT2 studies that are focused on the link between social influences and its link with intentional behaviors to use technologies (Gursoy et al., 2019; Patil et al., 2020). In addition, TPB/TRA researchers found that subjective norms also predict behavioral intentions (Driediger and Bhatiasevi, 2019; Sohn and Kwon, 2020). This is in stark contract with other studies that reported that there was no significant relationship between social influences/subjective norms and behavioral intentions (Ho et al., 2020; Kamble et al., 2019).

Interestingly, the results report that there are highly significant effects between effort expectancy-performance expectancy. Many scholars posit that perceived ease of use is a significant driver of perceived usefulness of technology (Bressolles et al., 2014; Davis, 1989; Davis et al., 1989; Kamble et al., 2019; Yoo and Donthu, 2001). Furthermore, there are significant causal paths between performance expectancy-intentions to use ChatGPT and even between effort expectancy-intentions to use ChatGPT, albeit to a lesser extent. Yet, this research indicates that performance expectancy partially mediates effort expectancy-intentions to use ChatGPT. In this case, this link is highly significant.

In sum, this contribution validates key information technology measures, specifically, performance expectancy, effort expectancy, social influences and behavioral intentions from UTAUT/UTAUT2, as well as information quality and source trustworthiness from ELM/IAM and integrates them with a perceived interactivity factor. It builds on

Table 6
The mediated effects of performance expectancy on effort expectancy-intentions to use ChatGPT.

	Causal path	Original sample (O)	Original sample (O)	Original sample (O)	Standard deviation (STDEV)	T statistics	P values	Decision
		Direct effect	Indirect effect	Total effects				
H2	Effort Expectancy → Intentions to Use ChatGPT	0.134**			0.049	2.767	0.006	Supported
H2a	Effort Expectancy → Performance Expectancy → Intentions to Use ChatGPT		0.073**		0.026	2.864	0.004	Supported
	Effort Expectancy → Intentions to Use ChatGPT			0.208***	0.047	4.454	0.000	Supported (partial mediation)

Note: T > 1.95.
*** $P < 0.001$.
** $P < 0.01$.

Table 7
The indirect effects.

Causal path	Original sample (O)	Standard deviation (STDEV)	T statistics	P values
Information quality → Performance Expectancy → Intentions to Use ChatGPT	0.037	0.02	1.867	0.062
Source trustworthiness → Performance Expectancy → Intentions to Use ChatGPT	0.106**	0.039	2.691	0.007

Note: T > 1.95.
** $P < 0.01$.

previous theoretical underpinnings. Yet, it differentiates itself from previous studies. To date, there are no other empirical investigations that have combined the same constructs that are presented in this article. Notwithstanding, this research puts forward a robust Information Technology Acceptance Framework. The results confirm the reliability and validity of the measures. They clearly outline the relative strength and significance of the causal paths that are predicting the individuals' intentions to use ChatGPT.

5.2. Managerial implications

This empirical study provides a snapshot on the online users' perceptions about ChatGPT's responses to verbal queries, and sheds light on their dispositions to avail themselves from ChatGPT's natural language processing. It explores their performance expectations about their usefulness and their effort expectations related to the ease of use of these information technologies and investigates whether they are affected by colleagues or by other social influences to use such dialogue systems. Moreover, it examines their insights about the content quality, source trustworthiness as well as on the interactivity features of these text-generative AI models.

Generally, the results suggest that the research participants felt that these algorithms are easy to use. The findings indicate that they consider them to be useful too, specifically when the information they generate is trustworthy and dependable. The respondents suggest that they are concerned about the quality and accuracy of the content that is featured in the AI chatbots' answers. This contingent issue can have a negative effect on the use of the information that is created by online dialogue systems.

OpenAI's ChatGPT is a case in point. Its app is freely available in many countries, via desktop and mobile technologies including iOS and Android. The company admits that its GPT-3.5 outputs may be inaccurate, untruthful, and misleading at times. It clarifies that its algorithm is not connected to the internet, and that it can occasionally produce incorrect answers (OpenAI, 2023a). It posits that GPT-3.5 has limited knowledge of the world and events after 2021 and may also occasionally produce harmful instructions or biased content. OpenAI recommends checking whether its chatbot's responses are accurate or not, and to let them know when and if it answers in an incorrect manner, by using their "Thumbs Down" button. They even declare that their ChatGPT's Help Center can occasionally make up facts or "hallucinate" outputs (OpenAI, 2023a,b).

OpenAI reports that its top notch ChatGPT Plus subscribers can access safer and more useful responses. In this case, users can avail themselves from a number of beta plugins and resources that can offer a wide range of capabilities including text-to-speech applications as well as web browsing features through Bing. Yet again, OpenAI (2023b) indicates that its GPT-4 still has many known limitations that the company is working to address, such as "social biases and adversarial prompts" (at the time of writing this article). Evidently, works are still in progress at OpenAI. The company needs to resolve these serious issues, considering that its Content Policy and Terms clearly stipulate that OpenAI's consumers are the owners of the output that is created by ChatGPT. Hence, ChatGPT's users have the right to reprint, sell, and merchandise the content that is generated for them through OpenAI's platforms, regardless of whether the output (its response) was provided via a free or a paid plan.

Various commentators are increasingly raising awareness about the corporate digital responsibilities of those involved in the research, development and maintenance of such dialogue systems. A number of stakeholders, particularly the regulatory ones, are concerned on possible risks and perils arising from AI algorithms including interactive chatbots. In many cases, they are warning that disruptive chatbots could disseminate misinformation, foster prejudice, bias and discrimination, raise privacy concerns, and could lead to the loss of jobs. Arguably, one has to bear in mind that, in many cases, many governments are outpaced by the proliferation of technological innovations (as their development happens before the enactment of legislation). As a result, they tend to be reactive in the implementation of substantive regulatory interventions. This research reported that the development of ChatGPT has resulted in mixed reactions among different stakeholders in society, especially during the first months after its official launch. At the moment, there are just a few jurisdictions that have formalized policies and governance frameworks that are meant to protect and safeguard individuals and entities from possible risks and dangers of AI technologies (Camilleri, 2023). Of course, voluntary principles and guidelines are a step in the right direction. However, policy makers are expected by various stakeholders to step-up their commitment by introducing quasi-regulations and legislation.

Currently, a number of technology conglomerates including Microsoft-backed OpenAI, Apple and IBM, among others, anticipated the governments' regulations by joining forces in a non-profit organization entitled, "Partnership for AI" that aims to advance safe, responsible AI, that is rooted in open innovation. In addition, IBM has also teamed up with Meta and other companies, startups, universities, research and government organizations, as well as non-profit foundations to form an "AI Alliance", that is intended to foster innovations across all aspects of AI technology, applications and governance.

6. Limitations and future research

This research validates measures from mainstream information technology adoption models that were tried and tested in previous academic literature. It utilizes performance expectancy, effort expectancy, social influences, behavioral intention from UTAUT/UTAUT2, information quality and source trustworthiness from ELM/IAM, as well as a perceived interactivity construct. These seven constructs were never presented in the same structured model. The findings report the reliability and validity of the constructs used in this empirical investigation. They indicate the robustness of the proposed theoretical framework, as all hypotheses are supported. Hence, future researchers are invited to replicate this study in different settings.

In the future, other scholars could rely on measures that were used in this study. Alternatively, they can choose other measures drawn from extended TAM, TAM2, TAM3, TRA or TPD models, among others (featured in Table 1), to examine the individuals' motivations to engage with AI generative text technologies. Conversely, they may adopt specific IAM constructs that examine perceptions about information quality including information completeness, information accuracy, information timeliness, information reliability, et cetera. Perhaps, prospective researchers may consider exploring other peripheral cues, including source credibility dimensions. They could investigate the moderating effects of demographic variables, including age, gender, level of education and occupation, among others, to better understand the individuals' dispositions to engage with AI chatbots or with other interactive technologies like the Metaverse, among others.

This study's primary data was collected through a cross-sectional survey. Unlike longitudinal studies, such a research instrument provides a snapshot of the research participants' perceptions at a specific point in time. As a result, this quantitative methodology may lend itself to possible limitations. Some colleagues argue that cross-sectional surveys are prone to common method variance (CMV) (see Podsakoff et al., 2023). In this case, the findings confirmed that the variance inflation factors were lower than 3.3, as per the recommended threshold (Hwang et al., 2023). Moreover, the results reported appropriate reliability, as well as convergent and discriminant validity values.

Academic colleagues are invited to utilize other research methods and sampling approaches to capture, analyze and interpret their findings. They may use inductive research designs, to reveal the research participants' in-depth opinions, and to evaluate their experiences with AI text generative technologies. Undoubtedly, this contribution is focused on a contemporary topic in theory and practice. It is still evolving and progressing, as more stakeholders are devoting their energies to continue improving the quality of LLMs. In this light, there is scope for researchers to continue investigating conversational (verbal) capabilities as well as the anthropomorphic (visual and vocal) features of chatbots. Besides, they are also urged to explore the governments' regulatory and quasi-regulatory interventions (to shed light on their principles, soft and hard laws) in this regard.

Author's statement

The corresponding (sole) author of this manuscript confirms that he has no conflicts of interest and that all statements presented in this manuscript are correct.

Research ethics

This research was carried out in accordance with the principles stated in the Declaration of Helsinki and is congruent with the European Union's General Data Protection Regulations (EU, 2016). Ethical approval was obtained from the authors' host institution.

The dataset of this research as well as all the relevant ethical documents are available on request.

CRediT authorship contribution statement

Mark Anthony Camilleri: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The author declares that he has no conflicts of interest.

Data availability

Data will be made available on request.

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