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Chatgpt Usage in Academia: Extending the Unified Theory of Acceptance and use of Technology with Herd Behavior

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ABSTRACT: This paper is motivated by the widespread availability and usage of AI technology such as ChatGPT in academia. The study adopted the Unified Theory of Acceptance and Use of Technology (UTAUT), herd behavior, and a mediator (website familiarity) to demonstrate behavioral intention to use ChatGPT among university students. A total of 202 valid sample sizes were used, all of which have access to ChatGPT. The structural equation model analysis's outcome indicates that performance expectancy, social influence, facilitating conditions, and imitating others positively affected behavioral intention to use ChatGPT. However, effort expectancy and discounting one's own information did not have a significant effect. Additionally, website familiarity mediated the relationship between performance expectancy, effort expectancy, and social influence but did not mediate the relationship between facilitating conditions and intention to use ChatGPT, respectively. The study suggests AI developers should ensure they offer technologies that can perform and possess the required features that aid users in adopting AI technologies.

KEYWORDS: ChatGPT, UTAUT model, Herd behavior, website familiarity

I. INTRODUCTION

In the current academic space, artificial intelligence (AI) has been postulated to be a necessary evil (Jarrahi, 2019). Some of these AI technologies have generated concerns from various academic stakeholders, such as School presidents, educational boards, professors, lecturers, and supervisors, due to the potential abuses of AI among students (Gao et al., 2022). Contrary to that, some researchers such as Fyfe (2022) and Granić (2022) indicate that AI addresses some of the biggest challenges in education, innovates teaching & learning practices, and accelerates progress towards Sustainable Development Goal 4. According to Unesco (2022), UNESCO is committed to encouraging Member States to harness the potential of AI technologies to achieve the Education 2030 Agenda while ensuring that the core principles of inclusion and equity streamline its application in academia. Popular among the AIs is ChatGPT, which has taken center stage in its usage in academia (Stokel-Walker, 2022).

ChatGPT is a new chatbot created by OpenAI whose functions comprise text generation, answering questions, and completing tasks such as translation and summarization. The inception of ChatGPT has stunned academics with its abilities (OpenAI, 2022, 2023). Given ChatGPT features, research shows it could be used to complete assignments, write books, reports & dissertations, and perform literature reviews (Aydın & Karaarslan, 2022). Students have adopted ChatGPT for various reasons based on general trends and observations. Few studies, for example, Agomuoh (2023); Aydın & Karaarslan (2022), and Bishop (2023) are of the view that the widespread availability of AI tools, their adoption, benefits, and factors leading its adoption are still not well understood. These observations present a critical theoretical challenge in understanding why students have used ChatGPT to perform several educational tasks (Stokel-Walker, 2022).

Subscribers of digital technologies have frequently been compelled to embrace and use a particular technology almost immediately to adjust to the new reality (Erjavec & Manfreda, 2022). Technology adoption has already been the subject of extensive research based on several theoretical underpinnings (Venkatesh et al., 2016). The unified theory of acceptance and use of technology (UTAUT) constitutes one of the most widely and frequently used models to explain how people use and embrace technologies in organizations, academia, and consumer settings (Dwivedi et al., 2019; Jadil et al., 2021), covering a broad spectrum of technologies and contexts (Venkatesh et al., 2016). The emergence of several and the widespread availability of efficient AI technologies has created circumstances and unique conditions where subscribers do not have the luxury to go through the usual decision-making process of adopting technology, preliminary use, and post-adoptive use phase as expressed by Erjavec & Manfreda, (2022).

Movement between these phases happens more quickly and often under different levels of social connectedness, where users are exposed to information resources when making decisions (Granić, 2022). Therefore, a question arises about how and to what degree the effects of the existing UTAUTs (Venkates 2003, 2012, 2023) direct antecedents of technology acceptance vary under this decision-making situation. More so, Venkatesh (2022) suggests that validating the UTAUT theory as a theoretical basis upon which individuals and organizations adopt AI technologies is relevant.

Social and digital connectedness between individuals over the years is said to have increased access to information (Erjavec & Manfreda, 2022). Therefore, with the widespread of AI tools, the subjective norm of potential users of these technologies is affected by the increasing element of social influence, where users have a relatively significant amount of information available from their close social circles when deciding to use a particular technology (Korukcu et al., 2021; Soofi et al., 2020). Additionally, information sources such as social media and online news are usually resorted to, thus making their users more likely to have a uniform standard of behavior (Tankovska, 2021). Users may be more likely to "accede to a single, uniform standard of behavior which is like a type of social norm" when subjected to the latter, according to an already established concept (i.e., herd behavior; Bernheim, 1994).

Herd behavior is referred to in the context of technology acceptance as an occurrence whereby a person imitates others and disregards their own information when embracing technology (Lee et al., 2021). In today's society, people often seek information from sources outside their immediate social circles and rely on observing others' behavior instead of relying solely on their own experiences (Budde-Sung, 2013). This coincides with the way herd behavior and social influence are different from each other (Erjavec & Manfreda, 2022). Researchers have suggested studying the Unified Theory of Acceptance and Use of Technology (UTAUT) in the context of herd behavior, as this phenomenon could be a useful area of research for information management studies (Erjavec & Manfreda, 2022; Popovič, 2016). Kim & Hall (2020) have proposed exploring the relationship between herd behavior and UTAUT, building upon previous research (Popovič, 2016).

While UTAUT has been extensively researched, applied, and expanded upon in various ways by scholars such as Taherdoost (2018) and Venkatesh et al. (2016), there have only been a limited number of studies investigating the impact of herd behavior on technology adoption, including those by Erjavec & Manfreda, (2022) and (Handarkho & Harjoseputro, 2019a). To our knowledge, no prior research has explored the intersection of UTAUT and herd behavior or examined its effects in the context of AI adoption, e.g., ChatGPT.

Previous studies have identified that several web-related elements affect the adoption of technology. Some considered site usability and virtual community building to establish their models (Chang et al., 2016; Crespo et al., 2009). Chang et al. (2016) and Pavlou & Gefen (2004) indicated that website familiarity is one element that encourages technology usage or adoption that has not been well explored. To the best of the researcher’s knowledge, considering the effect of website familiarity on AI technology adoption is rare in literature. This study employed website familiarity to mediate the dimensions of the UTAUT theory to develop a more complete model to unravel the behavioral intention to use ChatGPT since the AI has a website platform that users navigate to perform their tasks.

Given the study gaps enumerated above, this study purports to examine the existing UTAUT model in the circumstances where AI technologies have taken center stage in academia and business to unravel possible mechanisms influencing behavioral intention. This is possible because the proliferation and adoption of AI technologies have created a unique chance for researchers to study the peculiarities of AI adoption and advance theories and practices of individual technology adoption (Erjavec & Manfreda, 2022). This research is in tandem with the recommendation of previous studies on integrating the baseline UTAUT model with other relevant theories to identify new context effects. Given that, the study integrated Herd behavior upon the recommendation of Popovič (2016) and Shen et al. (2016) with the UTAUT model to determine the adoption of AI technologies, specifically ChatGPT.

To answer the main research question, we analyzed a case of university students with a majority below age 30 who are preview to ChatGPT. The reason for choosing students is that they have become increasingly important potential users of AI, such as ChatGPT (Bishop, 2023; Kung et al., 2022). This population category is exposed to the numerous AI available, especially the technologies relating to education (Stokel-Walker, 2022). Given AI's benefits to their education, it has been determined that students are gradually left with no choice but to use them in the face of the concerns raised by educational bodies (Gao et al., 2022; Whitford, 2022). Moreover, the selected group aligns with one of the research propositions to evaluate AI technology adoption by educational stakeholders (Gao et al., 2022).

II. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

A. Generated Pre-Trained Transformer (ChatGPT) usage in academia

ChatGPT is an AI chatbot developed by San Francisco-based startup OpenAI. OpenAI was co-founded in 2015 by Elon Musk and Sam Altman and is backed by well-known investors, most notably Microsoft (Aydın & Karaarslan, 2022). It is one of the numerous examples of generative AI. ChatGPT is part of a new wave of AI that generates highly cohesive, human-like responses to questions, prompts, language translation, and content summaries (Browne, 2023; OpenAI, 2022). According to OpenAI (2023), ChatGPT evaluates various kinds of written text and spoken language and accurately responds to frequently asked questions (FAQs) and customer queries.

ChatGPT continues to be criticized because of concerns about student learning and the potential for plagiarism (Agomuoh, 2023). In another breath, it is believed to have created academic opportunities (Aydın & Karaarslan, 2022). According to Gao et al. (2022), ChatGPT can be deployed to assist world academia. It can enhance the writing skills of students, teachers, and researchers since it is conscientized to produce feedback on style, coherence, and grammar, extract key points, and provide citations (Kung et al., 2022). Researchers' productivity might increase, freeing them to focus on more important tasks (e.g., analysis and interpretation) (Hoang, 2023).

Some studies have demonstrated the ability of ChatGPT to produce high-quality research papers, dissertations, and essays (Stokel-Walker, 2022; Whitford, 2022). Previous research demonstrated ChatGPT's ability to produce superior essays on various subjects. For instance, DaVinci-003 produced excellent short-form physics essays that created First Class in the UK high education system (Bishop, 2023). Additionally, it raised ethical concerns about using ChatGPT in various academic writing contexts, the authorship of AI, and the evaluation of academic tasks like student essays. The subject of indispensable content plagiarism was discussed, and methods for modifying essay settings and instructions were revised (OpenAI, 2023). These arguments highlight the pros and cons of ChatGPT. One question still hanging is what are the enabling factors that have made students adopt this ChatGPT technology, and use them to perform tasks and enhance their performance as research in line with this is rare, and this study posits to unravel it.

B. Unified theory of acceptance and use of technology (UTAUT)

Venkatesh et al. (2003) posit that the UTAUT was developed to respond to several theories on technology acceptance and use via the amalgamation of eight previously validated theories deployed to study acceptance, perception, and readiness toward technology adoption. Venkatesh et al. (2003) include four fundamental antecedents of the intention to use technology in an individual and organizational context: effort expectancy, performance expectancy, social influence, and facilitating conditions. UTAUT was subsequently modified into UTAUT2 to satisfy consumer context by introducing three new factors (habit, price value, and hedonic motivation), giving a new outlook on some of the previously ascertained associations (Venkatesh et al., 2016). The two models have since been broadly and effectively used as technology acceptance models (Venkatesh et al., 2016), covering a broad range of applications, extensions, and integrations (Jadil et al., 2021), while also incorporating a myriad of other constructs including AI (Venkatesh, 2022). As a result, we believe it to be both theoretically and practically relevant as the foundation for this study.

The time factor element of UTAUT indicates three stages of accepting and using technology: adoption, initial use, and post-adoptive use (Erjavec & Manfreda, 2022). The decision for the transition between these stages is centered on training knowledge, trial usage, and other second-hand resources (adoption), utilizing technology to complete their tasks (early use), and engaging in future-level use of the technology (post-adoptive use) (Venkatesh, 2022). The transition between these stages in everyday situations takes some amount of time. In a period of the proliferation of digital technologies and AI, the decision for individuals to use these technologies would be affected (Venkatesh, 2022).

As indicated earlier, even though UTAUT was enhanced to include three variables, the added constructs often produce inconsistent outcomes, so they are mostly excluded from research models (Gopalakrishnan et al., 2021). In cognizance of that, we decided to stick to the original constructs from the UTAUT, adjusted for individual context use to explore the acceptance of ChatGPT by students. We, therefore, coined our hypotheses, lensing the influence of these four determinants on behavioral intention.

C. Effort expectancy and behavioral intention to use ChatGPT

Venkatesh et al. (2016) present effort expectancy as the extent of ease related to the use of technology by individuals. It has been determined that the use of technology can sometimes be challenging. Given that, effort expectancy may be one critical element of behavioral intention and the use of technologies (Nyesiga et al., 2017; Onaolapo & Oyewole, 2018). Moreover, the modern-day interfaces of applications and websites are moving towards making the users' experience easy in navigating the platforms (Metallo et al., 2022; Shariat Ullah et al., 2022). In areas such as transport, health services (Metallo et al., 2022), and marketing services (Chayomchai, 2020), effort expectancy has been determined to influence users positively. Soh et al. (2020) indicate this may not be so in all circumstances. Based on these conclusions, we assert that the effort expectancy of AI has a positive influence on education, as the same has been established by Gao et al. (2022) to be a strong determinant of intention to use ChatGPT. Given this, we propose that:

H1a. Effort expectancy will positively affect students' intention to use ChatGPT

D. Performance expectancy and behavioral intention to use ChatGPT

Venkatesh et al. (2003) capture performance expectancy as the extent to which people benefit from using a particular technology. Past studies have determined stakeholders such as students and teachers are more likely to use and appreciate a specific technology that is beneficial and relevant, such as writing dissertations, articles, and assignments (Dubey & Sahu, 2021; Momani, 2020; Mustapha et al., 2020). In the wake of the numerous AIs flooding the educational space, it has also been determined that it helps individuals perform quick searches and become more efficient in the tasks assigned to them (Fyfe, 2022; Tzeng et al., 2022). ADOU et al. (2021) ascertained the performance expectations of a learning and teaching system among Cocody University students in

Abidjan positively related to their intention to adopt it. The positive influence of performance expectancy has been established among millennials (Dubey & Sahu, 2021). AI technologies that aid users in being efficient, competitive, and avoiding time wastage, such as Smart Content, Learning Environments, and Intelligent Tutoring Systems, have been proven to be associated with education and enhance performance (Venkatesh, 2022; Whitford, 2022). Given this, we propose that:

H1b. Performance expectancy will positively affect students' intention to use ChatGPT.

E. Social influence and behavioral intention to use ChatGPT

According to Venkatesh et al. (2016), the UTAUT described social influence as the degree to which people perceive that other personalities important to them believe they should use technology. Prior literature on UTAUT has shown that the impact of social influence on technology acceptance varies considerably depending on the sources and recipients of the influence (Erjavec & Manfreda, 2022). This could be because of the definition of social influence in the UTAUT, which incorporates normative and informative social influences into a single component (Lukmantara et al., 2021). It is necessary to appreciate that social influence in UTAUT relies heavily on subjective norms (Venkatesh et al., 2016). This implies that individuals can be influenced by acquaintances and minor groups who are important to them, even if this group has not adopted the technology in question. These individuals hold opinions about the technology and can evaluate the potential adopter's decision to adopt it based on these opinions. (Erjavec & Manfreda, 2022). Prior literature determined that social influence positively influences groups like students to respond to class under the "new normal" (Shariat Ullah et al., 2022).

Given that several factors will continuously influence social life, comprehending these influences and exploring ways of effectively managing them is important (Soh et al., 2020). Nevertheless, the specifics of the social influence as determined by UTAUT led us to speculate that it might not effectively explain social impacts. We go into more detail about this and suggest a leeway combining UTAUT with herd behavior to combat these concerns. Given this, we propose that:

H1c. Social influence will positively affect students' intention to use ChatGPT.

F. Facilitating Conditions and behavioral Intention to use ChatGPT

According to Venkatesh (2022), facilitating conditions represent users' view of the resources and support available to undertake a behavior. Numerous studies have ascertained that facilitating conditions affect students' and teachers' intentions to use technologies (Chayomchai, 2020; Shariat Ullah et al., 2022; Tarhini et al., 2017). With the increasing rate of AI and other learning technologies (Fyfe, 2022), the positive influence of facilitating conditions ought to be considered prevalently in the future (Nyesiga et al., 2017). Onaolapo & Oyewole (2018) explored this phenomenon among postgraduate students at the University of Ibadan, Nigeria, and identified a positive association between facilitating conditions and students' acceptance and usage of mobile learning. Given this, we propose that:

H1d. Facilitating conditions will positively affect students' intention to use ChatGPT.

G. Herd behavior and technology adoption

Herd behavior is the reasoning behind the decision-making process whereby decision-makers use information about what everyone else is doing, even though their private information suggests otherwise (Banerjee, 1992). According to Erjavec & Manfreda (2022), this concept has been well explored in finance, organizational decision-making, and consumer behavior. Given the meaning of herd behavior, Antony & Joseph (2017); Erjavec & Manfreda (2022) indicate that it could be construed as a type of heuristic where people situate their decisions kotowing to the majority of decision-makers in their circles by selecting the same actions as that of the majority.

In technology adoption, herd behavior defines people who follow others when employing technology, even when their personal information suggests doing something different. According to Sun (2013); Erjavec & Manfreda (2022), this occurs in two ways: by imitating others (IMI), i.e., following past adopters of a particular technology; discounting own information (DOI), i.e., ignoring personal information when opting to make an adoption decision. Regarding sharing-based applications, an investigation has shown that IMI can positively influence behavioral intention and even offer significant psychological signals to users who are on the fence or unsure of their level of action readiness (Liu & Yang, 2018). Moreover, when people tend to copy the recommendations of others, perceived herd behavior significantly impacts behavioral intention to embrace technology (Theerthaana & Lysander Manohar, 2021). Herding bias has been identified as a component of behavioral biases and has been proven to be a helpful moderator between user actions and behavioral adoption intention (Handarkho & Harjoseputro, 2019).

Additionally, we have already indicated that the UTAUT presents social influence in a subjective norm context where decisions depend on what people deem important. According to Erjavec & Manfreda (2022), this position will diminish or increase with time, based on the number of social contacts and other determinants one might be exposed to. Sunny et al. (2019) indicate that social influence emanates from the social norm and posit fundamentally on information obtained from one's close acquaintances and family who may or may not have accepted a technology. Additionally, it is premised on evaluating other people's perspectives on the use and adoption of technology and how others might approach these topics, leading to favorable or unfavorable judgments of the user or adopter (Sun et al., 2020). Herd behavior, on the other hand, uses a much broader variety of information sources, relies more on other people's observations, and imitates those who have already embraced the technology (Erjavec & Manfreda, 2022). The young generation, which includes students, is easily crowded in their circles, making them adopt and use modern technologies quickly (Dubey & Sahu, 2021). Therefore, ignoring their beliefs that only traditional methods, resources, and services are appropriate may be relevant when considering technology adoption. Sun (2013) asserts that herd behavior can be regarded as a possible determinant affecting behavioral intention of people to adopt a technology. Given this, we propose that:

H2a. Imitating others positively affect students' intention to use ChatGPT

H2b. Discounting one's own information positively affects students' intention to use ChatGPT

H. The mediation role of ChatGPT website familiarity and UTAUT dimensions

The conditioning and design of a website improve users' abilities to understand and explore the related website and the information on the products, ultimately increasing continuous visitation to the website due to greater familiarity (Napitupulu et al., 2017). A familiar website enhances and spikes positive emotional appeals toward a technological platform (Ali Qahur, 2020). Users of a particular technological website or platform who are familiar with the website experience greater ease of use and contentment, hence establishing the perceived efficiency of the website (Burke, 2010).

Familiarity regarding an appreciation of the relevant navigation procedures of a website enhances users' tolerance (Antony & Joseph, 2017). It is asserted that website familiarity (1) helps users to understand better the interrelationships among the various products on the website and what they are used for, (2) aids users to distinguish between relevant from irrelevant information on the platform that can aid users in performing their task (Chang et al., 2016). Familiarity minimizes the complexity of using technology and clarifies how, what, where, and when to access the website, invariably increasing the intention to use a particular technology (Nyesiga et al., 2017; Onaolapo & Oyewole, 2018). Moreover, familiarity creates the structure for future expectations and can aid users in accumulating trust-relevant knowledge about the technology and building user trust (Lukmantara et al., 2021). Chang et al. (2016) determined that website familiarity could influence users' behavior positively. Given this, we propose that:

H3a. Website familiarity mediates effort expectancy and students' intention to use ChatGPT

H3b. Website familiarity mediates performance expectancy and students' intention to use ChatGPT

H3c. Website familiarity mediates social influence and students' intention to use ChatGPT

H3d. Website familiarity mediates facilitating conditions and students' intention to use ChatGPT

I. Conceptual framework

Figure 1 covers the conceptual framework of the role of UTAUT dimensions, herd behavior factors, and website familiarity on behavioral intention, representing the asserted hypotheses.

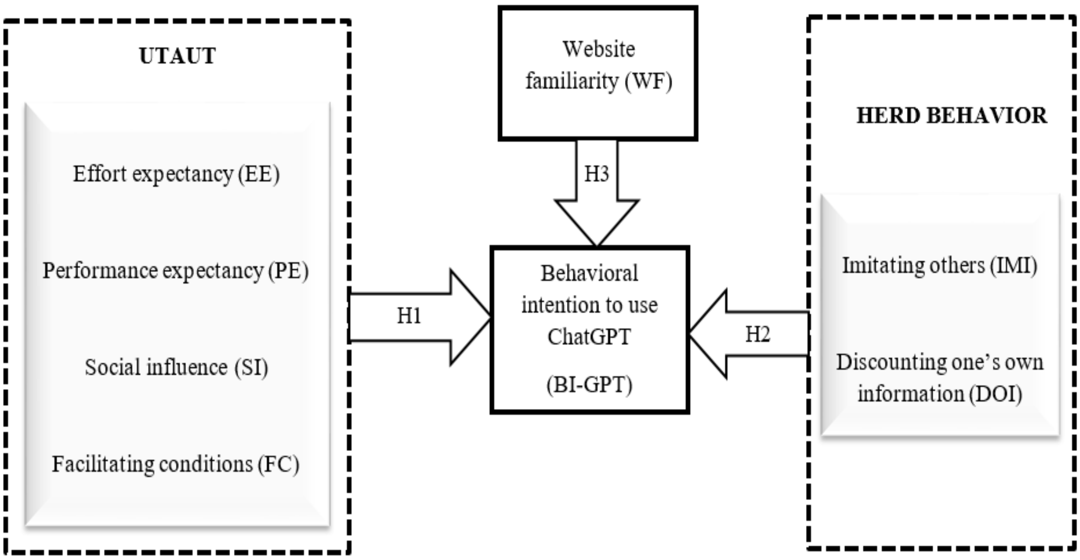

Figure 1. Conceptual framework of students' behavioral intention to adopt ChatGPT

III. METHODOLOGY

A. Sample and data collection

We prepared a survey questionnaire to evaluate the proposed assumptions. The questionnaire covered several elements assessing various UTAUT dimensions, website familiarity, herd behavior factors, and ChatGPT usage behavioral intention. The included questions measure items already validated in the literature in different contexts.

To resolve the research question, we evaluated a sample of university students at the University of Cape Coast, Ghana, who are exposed to the usage of ChatGPT, which is increasingly becoming an academic tool. The questionnaire was administered to undergraduate and postgraduate students in the School of Management and Social Sciences during evening lectures after the Schools' Deans granted permission. The questionnaire was administered through personal research team visits and received back after 20 minutes of administration. We used three weeks in March 2024 to gather the responses from students using the random sampling approach with the help of lecturers during lectures. 253 questionnaires were administered, and 202 were used as the sample size after collecting responses and perusing them to ascertain completed ones. This represents a 79.8% response rate. The features of the sample population are stated in Table 1.

Table 1. Descriptive Analysis Results

Variables		Frequency	percentage（%）	Cumulative percentage（%）
Gender	Males	125	61.9	69.1
	Females	77	38.1	100.00
Age	18-25 years	130	64.4	64.4
	26-30 years	69	34.2	98.6
	31years and above	3	1.4	100.00
Education status	Undergraduate degree	178	88.1	88.1
	Postgraduate degree	24	11.9	100.00
Residence	On-campus	120	59.4	59.4
	Off-campus	82	40.6	100.00
No. of years in university	Less than a year	18	8.9	8.9
	1-2 years	124	61.4	70.3
	3-4 years	60	29.7	100.00

B. Measures

All the constructs were evaluated on a 5-point Likert scale (1-strongly disagree to 5-strongly agree). A 5 and 4-item scale was taken from Venkatesh et al. (2016) to measure performance and effort expectancy, respectively. These scales evaluate the extent to which people adopt technologies based on what the technology adds to the performance of their tasks and the ease of use of the technology. Our study deployed a 3 and 4-item scale from Erjavec & Manfreda (2022) to measure social influence and facilitating conditions, respectively. The study used a 3-item Tarhini et al. (2017) scale to assess behavioral intention. Website familiarity was evaluated using 4 items from Chang et al. (2016) representing the degree of knowledge users have on a particular technology. Lastly, imitating others and discounting one's own information was measured with 3 items from Erjavec & Manfreda (2022).

C. Common method bias (CMB)

Since the collected data revolves around exogenous and endogenous variables via questionnaire simultaneously, CMB may occur and cause data disturbance (Kraus et al., 2020). CMB means a change attributable to the measurement approach rather than a construct of interest (Podsakoff et al., 2012). We deployed Herman's single factor to estimate CMB as suggested by (Podsakoff et al. 2012; Podsakoff & Organ 1986). The fundamental proposition of this approach is that if a more significant amount of CMB is present, a single factor will emerge from the factor analysis, or one general factor will account for the majority of the covariance among the measures. Based on this test, CMB in our research does not posit to have a challenge since the first factor did not account for most of the changes (only 47.27%).

D. Statistical analysis results

The structural equation model (SEM) approach is used to evaluate the hypothesis developed in our study using SmartPLS 4.0. Hair (2021) suggested partial least square structural equation modeling (PLS-SEM) approach is suitable for both complex and simple models. Moreover, the PLS-SEM is deemed more appropriate than CB-SEM when estimating and developing validated constructs (Hair Jr et al., 2014). Our model contains six predictive variables and a mediator. PLS-SEM incorporates two models: the measurement and the structural model.

We consider essential elements such as item reliability, internal consistency reliability, and convergent and discriminant validity in evaluating our model. Table 2 shows the lowest (0.733) and upper (0.935) factor loadings and the threshold value = 0.50, as suggested by Hair Jr et al. (2014). Item EE4 (0.023) and item WF4 (0.123) were dropped because they did not meet the threshold. Therefore, the individual item reliability criterion was satisfied. We estimated the composite reliability (CR) to determine the internal consistency of constructs relying on the threshold of 0.70 as proposed by (Hair et al., 2019). Table 3 shows the lowest

(0.726) and highest (0.890) CR values which satisfy the threshold proposed by (Hair et al., 2019). Hence, there are no issues of internal consistency. The 3rd approach is convergent validity, which is considered using the average variance extracted (AVE). Convergent validity assesses the level to which all research constructs evaluate the same construct (Henseler et al., 2015). The AVE threshold should be >0.50, as Hair Jr et al. (2014) suggested. Table 3 shows the lowest (0.510) and highest (0.669) AVE values, satisfying the criterion.

Table 2. Convergent validity

Constructs	Items	Factor loading (λ)	AVE	Composite reliability (CR)	R^2	Cronbach alpha (α)
	PE1	0.935***				
	PE2	0.775***				
Performance expectancy (PE)	PE3	0.787***	0.667	0.890		0.873
	PE4	0.807***				
	PE5	0.769***				
Effort expectancy (EE)	EE1	0.836***				
	EE2	0.843***	0.659	0.795		0.743
	EE3	0.866***				
	SI1	0.801***				
Social influence (SI)	SI2	0.808***				
	SI3	0.801***	0.646	0.845		0.726
	FC1	0.826***				
Facilitating conditions (FC)	FC2	0.828***				
	FC3	0.754***	0.640	0.818		0.813
	FC4	0.790***				
Imitating others (IMI)	IMI1	0.789***				
	IMI2	0.794***	0.652	0.733		0.732
	IMI3	0.838***				
Discounting one's own information (DOI)	DOI1	0.824***				
	DOI2	0.733***	0.638	0.729		0.716
	DOI3	0.835***				
	WF1	0.837***				
Website familiarity (WF)	WF2	0.797***	0.510	0.726	0.733	0.621
	WF3	0.831***				
Behavioral intention to use ChatGPT (BI-GPT)	BI-GPT1	0.817***				
	BI-GPT2	0.825***	0.669	0.756	0.714	0.753
	BI-GPT3	0.812***				

Abbreviations: AVE = average variance extracted. ***$p \leq 0.001$, **$p \leq 0.01$, *$p \leq 0.05$.

The last criterion is the discriminant validity for the computation of the measurement model. Discriminant validity considers situations where two indicators must vary statistically (Henseler et al., 2015). Fornell & Larcker (1981) provided a traditional approach to determining the discriminant validity, which was later argued by Henseler et al. (2015) as an insufficient metric when dealing with factor loadings with smaller differences, and introduced the HTMT criterion. The HTMT threshold is ≤ 0.85; beyond that, discriminant validity has not been attained (Henseler et al., 2015). Table 4 shows that our study satisfies the HTMT threshold.

Table 3. Discriminant validity

Variables	BIGPT	DOI	EE	FC	IMI	PE	SI	WF
BIGPT	**0.818**	0.501	0.58	0.601	0.515	0.009	0.635	0.651
DOI	0.292	**0.799**	0.408	0.504	0.66	0.432	0.531	0.497
EE	0.388	0.199	**0.812**	0.468	0.572	0.595	0.471	0.620
FC	0.156	0.277	0.298	**0.800**	0.434	0.497	0.506	0.645
IMI	0.250	0.371	0.378	0.229	**0.807**	0.516	0.517	0.491
PE	0.304	0.481	0.167	0.286	0.187	**0.817**	0.521	0.771
SI	0.271	0.266	0.575	0.179	0.370	0.408	**0.804**	0.730

WF	0.193	0.371	0.205	0.349	0.308	0.368	0.314	**0.714**

Note: on the diagonal (in bold), the square root of the AVE values; below the diagonal are the correlations; above the diagonal are the HTMT values.

IV. EMPIRICAL RESULTS

After evaluating the outer model, we tested the study's hypothesis in this section. Table 4 demonstrates that performance expectancy, social influence, facilitating conditions, and imitating others positively relate to behavioral intention to use ChatGPT. The outcome supported H1a, H1c, H1d and H2a. Moreover, effort expectancy and discounting one's own information did not have a significant relationship with behavioral intention to use ChatGPT. Given this, H1b and H2b were not supported.

Using hierarchical regression, the Sobel test equation and the VAF variance accounted, we determined the mediation role of website familiarity and established the level of mediation. Table 5 reports a significant indirect effect of performance expectancy, effort expectancy, and social influence on behavioral intention to use ChatGPT via website familiarity. The significance of these determined indirect relationships was computed using the Sobel test calculator and equations presented below.

Table 4. Hypotheses results and effect size

Paths	Original sample (0)	Sample mean(M)	Standard deviation (STDEV)	T statistics (lO/stdev)	Decision	P values
PE->BIGPT	0.363	0.352	0.131	2.762	Supported	0.006
EE->BIGPT	0.047	0.048	0.087	0.536	Not supported	0.592
SI->BIGPT	0.244	0.239	0.091	2.671	Supported	0.008
FC->BIGPT	0.242	0.243	0.091	2.659	Supported	0.008
IMI->BIGPT	0.193	0.196	0.077	2.507	Supported	0.012
DOI->BIGPT	-0.080	-0.077	0.082	0.974	Not Supported	0.330

*Note: * T-value >1.96, ***p<0.001.*

Table 5. Mediation analysis output

Predictors (IVs)	Mediator (s)	DVs	IVs to mediators (path a)	Mediator(s) to DV (path b)	An indirect effect of IV on DV (a*b)
PE	WF	BIGPT	***β =0.357 SD=0.070 T=5.080	***β =0.771 SD=0.063 T=12.272	0.275***
EE	WF	BIGPT	***β =0.272 SD=0.057 T=4.822	”	0.210***
SI	WF	BIGPT	*β =0.136 SD=0.065 T=2.094	”	0.105*
FC	WF	BIGPT	β =0.124 SD=0.064 T=1.931	”	0.095

Note: *p<0.05, **p<0.01, ***P<0.001. (PE: performance expectancy, EE: effort expectancy, SI: social influence, FC: facilitating condition).

The Sobel test is a mathematical model designed to help test the significance of an indirect effect of a predictor on an outcome variable via a mediator (Sobel, 1982). Preacher & Hayes (2004) state that the Sobel test works with relatively large data samples. The equation designed to undertake the test is indicated below:

$$Z = \frac{a*b}{\sqrt{(b^2)(s_a^2)+(a^2*s_b^2)}} \text{ .... (Equation 1)}$$

Where "a" = unstandardized regression coefficient for the relationship between the predictor and the mediator; "b"= the unstandardized coefficient between the mediator and the dependent construct when the IV is a predictor; and "sa"= standard error of "a", "sb"= standard error of "b". Determining a mediation effect is based on the Z-value (test statistics), the standard error, and the p-value. The study estimated the mediation effects with the above equation and results presented below using the online Sobel Test calculator and the equation. The significance of the z-values relative to the indirect effects of the predictors (a*b) is positioned at **p<.001, *p<.05.

a) Performance expectancy>website familiarity>behavioral intention to use ChatGPT:

$$Z = \frac{0.357*0.771}{\sqrt{(0.771^2)(0.070^2)+(0.357^2)(0.063^2)}}$$ = Z=4.708, ***P= 0.000, SD=0.058

b) Effort expectancy>website familiarity>behavioral intention to use ChatGPT:

$$Z = \frac{0.272*0.771}{\sqrt{(0.771^2)(0.057^2)+(0.272^2)(0.063^2)}}$$ = Z=4.446, ***P= 0.000, SD=0.047

c) Social influence>website familiarity>behavioral intention to use ChatGPT:

$$Z = \frac{0.136*0.771}{\sqrt{(0.771^2)(0.065^2)+(0.136^2)(0.070^2)}}$$ = Z=2.062, *P= 0.0392, SD=0.039

d) Facilitating conditions>website familiarity>behavioral intention to use ChatGPT:

$$Z = \frac{0.124*0.771}{\sqrt{(0.771^2)(0.064^2)+(0.124^2)(0.070^2)}}$$ = Z=1.914, P= 0.056, SD=0.050

Our study followed the variance accounted for (VAF) to validate the mediating effect of website familiarity between UTAUT dimensions and behavioral intention to use ChatGPT (Baron & Kenny, 1986). VAF is used to estimate the ratio of the indirect-to-total effect. According to Nitzl et al. (2016), the VAF equation is:

$$VAF = \frac{path\ a * path\ b}{(path\ a * path\ b) + (path\ c')}$$

If the value of VAF is below 20%, there is no mediation; between 20% and 80%, there is partial mediation; and beyond 80%, there is complete mediation (Hair Jr et al., 2014). Table 6 confirms that website familiarity partially mediates, completely mediates, and partially mediates between performance expectancy, effort expectancy, social influence, and behavioral intention to use ChatGPT, respectively. Hence, H3a, H3b, and H3c is supported, H3d was rejected.

Table 6. Variance accounted for (VAF) of the mediator variable for BIGPT

Paths	β-value	Std. Dev.	T-values	P-values
PE -> BIGPT	0.382	0.081	4.723	0.000
EE -> BIGPT	0.026	0.065	0.393	0.695
SI -> BIGPT	0.301	0.075	4.030	0.000

Variance accounted for (VAF) of the mediator variable for BIGPT

Independent variable	Dependent variable	Mediating variable	Indirect effect	Total effect	VAF (%)	Decision
PE	BIGPT	WF	0.275	0.657	41.86%	Partial mediation
EE	BIGPT	WF	0.210	0.236	88.98%	Complete mediation
SI	BIGPT	WF	0.105	0.406	25.86%	Partial mediation

A. Predictive relevance of the model and effect size

Past studies insist on the need to determine the (Q2) to ascertain the predictive relevance of a model (Shmueli et al., 2019). The blindfolding approach is used to calculate Q2 in SmartPLS. The thumb rule proposed by Cohen (1988) states that 0.02-0.015, 0.15-0.35, and above 0.35 posit smaller, medium, and greater effects, respectively. Table 7 shows that BIGPT (Q2 = 0.447) and website familiarity (Q2 = 0.361) have a greater predictive relevance effect. Therefore, this study shows that exogenous constructs significantly enhance endogenous constructs.

Furthermore, to ascertain the R2 of endogenous variables, some studies postulate calculating each path's effect size (f2) of the inner structural model (Henseler et al., 2015). The value of the f2 indicates whether an exogenous construct significantly affects the endogenous construct. Cohen (1988) states f2 value between 0.02-0.15 – smaller effect, 0.15-0.35 – medium effect, and more than 0.35 – larger effect. Table 8 shows that performance expectancy, social influence, facilitating conditions, and imitating others showed a smaller effect on behavioral intention to use ChatGPT.

Table 7. Effect size of exogenous factors

	f-square (f^2)	Q-square (Q^2)	
PE -> BIGPT	0.038		
EE -> BIGPT	0.002	BIGPT	0.447
SI -> BIGPT	0.036	WF	0.361
FC -> BIGPT	0.035		
IMI->BIGPT	0.033		
DOI->BIGPT	0.006		

V. DISCUSSION AND CONCLUSION

The emergence of ChatGPT has raised eyebrows in academia and created a mixed opinion as some argue for and some are against this artificial intelligence. Against all odds, some students have used ChatGTP to write reports, complete assignments, and write books and articles. Given this, we investigated the factors that led to students adopting ChatGPT to undertake academic tasks. Even though the technology of focus is ChatGTP usage among students, we believe the results apply to future situations on the adoption of artificial intelligence or technology because students are likely to use new technologies that can enhance their academic tasks and responsibilities, while the elements of induce herd behavior will only be more widely spread.

Our study evaluated a model of three factors (i.e., UTAUT dimensions, herd behavior, and website familiarity) on students' behavioral intention to use ChatGPT. We deduced strong evidence that performance expectancy (H1a) is the most influential factor for the analyzed sample. In addition, social influence (H1c) and facilitating conditions (H1d) have a significant impact when considering the adoption of ChatGPT. However, effort expectancy (H1b) did not have an impact on the intention to use ChatGPT, as neither the effect is statistically significant. The result of effort expectancy on behavioral intention is close to zero. In Erjavec & Manfreda's (2022) studies, the effort expectancy effect was not supported regarding online shopping adoption amongst older adults. It has been deduced that effort expectancy has a more substantial impact on M-payment intention (Adou et al., 2021), e-learning adoption (Tarhini et al., 2017), and digital tourism apps usage (Mazan & Çetinel, (2022). Although previous literature reports effort expectancy as a stronger relevant factor in the UTAUT model (Nyesiga et al., 2017; Onaolapo & Oyewole, 2018), our study outcome is quite unexpected in light of ChatGTP usage. The latter might have occurred since most students are now getting to know how to navigate the ChatGTP platform and several essential functions.

Furthermore, the spread of information on ChatGPT seems to have initiated herd behavior, which is also critical when considering issues on technology usage. Participants in our study followed others when considering using ChatGPT because IMI (H2a) had a significant (the highest of the factors) effect on behavioral intention in our model. However, DOI had a negative and insignificant effect on the intention of participants to use ChatGPT. The result on DOI is consistent with that of Erjavec & Manfreda (2022) regarding online shopping adoption.

To unravel individuals in the sample drive to use and navigate the ChatGPT platform to accomplish their tasks, we presented website familiarity to mediate UTAUT dimensions and behavioral intention. We determined the indirect effect of performance expectation (H3a), effort expectancy (H3b), and social influence (H3c) on behavioral intention to use ChatGPT through website familiarity. On the contrary, an indirect effect of facilitating conditions on behavioral intention was not established through website familiarity. In the study of Chang et al. (2016), performance and effort expectancy affected individual understanding of websites and invariably resulted in online shopping. The conditions facilitating the usage of ChatGPT did not influence the website familiarity of participants, which did not result in determining its indirect effect on behavioral intention.

A. Theoretical implications

In cognizance of our study's contribution to theory, our study replicates an extension of the UTAUT model. Given this, it contributes to increasing the generalization of the UTAUT model. Additionally, it increases the accumulated knowledge in the area of research and the field of artificial intelligence acceptance and usage. The study is also rare in that it evaluated the behavioral intention to use ChatGPT from a developing country perspective. In an environment that is being saturated by artificial intelligence, our results from the direct relationships in our model showed that the intention to use ChatGPT is, at first, the result of the perception of its usefulness (performance expectancy), this being the most essential predictor of behavioral intention to use ChatGPT. More so, what others think about using ChatGPT (social influence), is the second strongest determinant of behavioral intention, positing as also an important predictor for our sample population to use ChatGPT (Venkatesh, 2022). According to Nyesiga et al. (2017), the collective opinion of others can have an impact on an individual's intention to use technology (e.g. ChatGPT). Thirdly, the position that technical support, hardware, and software (Chang et al., 2016) available for use, along with knowledge, and skills (facilitating conditions), came out as an important determinant for using ChatGPT. However, effort expectancy influence did not seem to be an influential factor, which suggests that our sample population does not easily and effortlessly use the ChatGPT platform (Erjavec & Manfreda, 2022). Summarily, we have empirically demonstrated that three constructs of the UTAUT model (performance expectancy, social influence, and facilitating conditions) and one (effort expectancy) affect and do not affect intention to use ChatGPT, respectively.

Additionally, our study confirmed the presence of other essential factors that affect the intention to use ChatGPT among students. Due to the creeping prevalence of AIs in academia, we evaluated the influence of herd behavior on the intention to use an AI such as ChatGPT. Researchers have investigated the effect of herd behavior on technology acceptance (Handarkho & Harjoseputro, 2019b; Liu & Yang, 2018b; Shen et al., 2016), but none synergized with the UTAUT with herd behavior considered in the eyes of how one is influenced socially. We took advantage of the prevalent information on several technologies in academia to assess whether the effect of social influence as a subjective norm in technology acceptance models is prevalent when several technologies are recommended to users.

We posited to unravel whether social influence, because of its subjectivity, still affects behavioral intention to use technology in the context of hearing and whether herd behavior has any significant effect. We deduced evidence for inclusion for herd behavior because IMI, as an aspect of the herd behavior factor (Erjavec & Manfreda, 2022), had the least effect on behavioral intention to use ChatGPT in our model. Even though the impact seems the least, it is still significant. It lends support to the notion for students that the proliferation of AI influences the decision-making processes such that they rely on information sources within their close social circles. In our study, we stretch the scope of previous studies indicating that imitating others (IMI) has a positive influence on behavioral intention to use technology, specifically when dealing with hesitant users (Shen et al., 2016) to incorporate the context of extending the UTAUT model with herd behavior as another endogenous mechanism. This research is associated with studies suggesting a new contextual effect in the UTAUT model (Venkatesh et al., 2016) and evaluating the technology choices of individuals (Dwivedi et al., 2019).

Lastly, the study employed website familiarity to explore the indirect association between UTAUT dimensions and behavioral intention to use ChatGPT. According to Chang et al. (2016), familiarity with technology is said to be one that is not well explored when considering relationships between UTAUT dimensions and technology adoption or usage. The current outcome suggests that familiarity plays a significant role in mediating some hypothesized relationships. The mediating role of website familiarity provides a different perspective on the factors that cause individuals to use technology. This is important given that the mediating effect of website familiarity provides insights and essential contributions to further our understanding of factors that aid individuals in using AI technology (Ali Qahur, 2020), in this case, ChatGPT.

B. Practical implications

With the practical implications, the general outcome offers critical insights that would aid technology developers in precisely artificial intelligence to provide the appropriate technology and platforms, as individuals (respondents) always consider features such as performance expectancy, social influence, and facilitating conditions before using artificial intelligence. Firstly, for performance expectancy, the benefits students obtain from using ChatGPT are one of the primary reflections for adopting this AI. If the individuals utilizing the ChatGPT for academic activities and work do not experience the benefits, they may consider using a different technology or AI that will facilitate their work. Hence, AI developers can ensure users by offering apps and websites to give them the expected benefits. Secondly, on social influence, recommendations from others in the circles of users could lead them to adopt artificial intelligence like ChatGPT. Social influence is a significant factor in our study, which could be a pervasive force in altering participants' responses to artificial intelligence. Social influence outcome suggests that students are exposed to influences from social elements. AI developers and relevant technology developers must establish means to exploit the environment of friends, classmates, and teachers that could trigger perceptions that draw out the benefits of using AI like ChatGPT. Despite being ranked as the least influential factor in encouraging the use of ChatGPT, facilitating conditions still have a positive and meaningful impact. AI developers must convey to their users that they possess the necessary technical resources and other supporting elements to aid them in using this technology over an extended period. To sustain users' interest in this innovation, AI developers should have platforms that can continuously educate and inform users about its use and advancements in the application.

The adoption and use of artificial intelligence due to its proliferation is said to be influenced by the information people receive from the media, websites, social networks, and immediate circle of families and friends. The broader scope of elements can give individuals extensive information to make judgments on using artificial intelligence. This has the potency of increasing herd behavior, which can influence technology adoption other than just considering technology in the context of social influence as defined by the UTAUT model. Establishing that imitating others also causes people to adopt a technology, AI developers need to consider exploiting the several outlets or means of their wider social circles that play a significant role in AI usage (e.g., ChatGPT) in the future. This is because herd behavior is an important antecedent of behavioral intention in times where technology is gaining more ground, especially in developing countries. Lastly, this study ascertained that individuals associate themselves with using artificial intelligence on the back of their familiarity with websites, as in the case of ChatGPT. AI developers should provide more information about their products on their websites to aid easy usage and navigation and better understand the attributes of the services offered to users. This would assist AI developers in determining what users want based on the opinions they express on the websites.

C. Limitations and suggestions for future studies

While the present study made valuable contributions to understanding why students in Ghana have adopted AI (ChatGPT), it also had some limitations. The sample size was restricted to only one university due to limited time and financial resources. This university was selected based on the proximity and accessibility to the Deans of the two schools willing to assist the research team. However, there are other universities in other regions of the country, and a study that includes students from these universities may produce different results and help to generalize the findings. Additionally, the research team deliberately selected students from the School of Management and Social Sciences familiar with artificial intelligence, which may have influenced the results. While the sample size was sufficient to meet the requirements of the model, future studies could expand the sample size and cover different universities to gain more detailed insights into the adoption of artificial intelligence, i.e., ChatGPT.

Future research could aim to validate the conceptual model proposed in this study using a different sample population. The study also highlights a potential gap in the UTAUT model, where social influence's importance may decrease in favor of herd behavior. This trend may not be limited to situations where online sources of information, such as social media and online news, hold more weight than opinions from close social contacts. Despite individuals regularly engaging with social media and other media sources, these influences may outweigh the impact of social influence from their immediate circles. Therefore, we suggest that future technology adoption research consider validating herd behavior to complement social influence, especially when potential users rely on information sources beyond their close social connections.

Even though we gathered information on participants' demographic features, we did not consider the potential moderating effect of the demographic constructs in our model. To further enhance the comprehension of AI adoption dynamics in developing countries, it is recommended to incorporate individual-level moderating factors such as age, gender, experience, and cultural values in similar studies. This could potentially yield valuable insights for future research. Lastly, comparative studies between students and workers in Ghana, a developing country context, can provide more informative and investigative results to understand the differences in AI adoption better.

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