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Investigation of the moderation effect of gender and study level on the acceptance and use of generative AI by higher education students: Comparative evidence from Poland and Egypt

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Abstract

This study delves into the implications of incorporating AI tools, specifically ChatGPT, in higher education contexts. With a primary focus on understanding the acceptance and utilization of ChatGPT among university students, the research utilizes the Unified Theory of Acceptance and Use of Technology (UTAUT) as the guiding framework. The investigation probes into four crucial constructs of UTAUT—performance expectancy, effort expectancy, social influence and facilitating conditions—to understand their impact on the intent and actual use behaviour of students. The study relies on data collected from six universities in two countries and assessed through descriptive statistics and structural equation modelling techniques, and also takes into account participants' gender and study level. The key findings show that performance expectancy, effort expectancy, and social influence significantly influence behavioural intention. Furthermore, behavioural intention, when considered alongside facilitating conditions, influences actual use behaviour. This research also explores the moderating impact of gender and study level on the relationships among these variables. The results not only augment our comprehension of technology acceptance in the context of AI tools but also provide valuable input for formulating strategies that promote effective incorporation of ChatGPT in higher education. The study underscores the need for effective awareness initiatives, bespoke training programmes, and intuitive tool designs to bolster students' perceptions and foster the wider adoption of AI tools in education.

KEYWORDS

ChatGPT, higher education, moderating effect, technology acceptance

Practitioner notes

What is already known about this topic

- ChatGPT is a tool that is quickly gaining worldwide recognition.
- ChatGPT helps with writing essays and solving assignments.
- ChatGPT raises ethical concerns about authorship, plagiarism and ethics.

What this paper adds

- This study explores students' acceptance of ChatGPT as an aid in their education, which has not been studied previously.
- We used the extended Unified Technology Acceptance and Use of Technology theory to test what factors mostly influence the use of ChatGPT by students.
- We conducted a multiple study in Poland and Egypt based on sampling strategy from six universities.

Implications for practice and/or policy

- ChatGPT is a global game changer and should be incorporated into study programmes.
- The limitations of ChatGPT should be well explained and known since it is prone to making mistakes.
- Higher education teachers should be aware of ChatGPT's capabilities.

INTRODUCTION

Generative AI is a subfield of artificial intelligence (AI) and machine learning (ML) that is capable of creating new and original content, in varied formats such as text, audio, video, pictures and code (Lv, 2023), based on deep learning algorithms that learn to recognize patterns and relationships from vast amounts of input data, which then generate new outputs that are similar in style and structure to the data they were trained on. This subfield has been developing over several decades and is rapidly evolving, due to advances and availability in computational power, large data sets and significant improvements in machine learning algorithms that can be used to create new content (Feuerriegel et al., 2023). The ability of these models to self-formulate new and varied outputs represents a paradigm shift in the field of AI because they are not being explicitly programmed to follow pre-determined rules, or generate specific outputs, like other AI (Feuerriegel et al., 2023).

ChatGPT, created by OpenAI, is an advanced language model based on a generative pre-trained transformer. It utilizes natural language processing techniques to learn from enormous data volumes and produce human-like responses to questions. With a data set of

570gb representing 300 billion words and 175 billion parameters, ChatGPT can be thought of as a computerized conversational partner that can answer questions, provide analysis and even offer opinions (OpenAI, 2023). This version of ChatGPT, GPT-3.5, was utilized at the time the study was conducted (OpenAI, 2023).

Teaching and learning could be revolutionized by ChatGPT in higher education by serving as an AI-powered tool for various tasks (Lim et al., 2023). ChatGPT has the flexibility to function as an independent tool or seamlessly integrate into various systems and platforms utilized within higher education institutions (HEIs). The use of ChatGPT can facilitate students' learning experiences, generate alternative ways of expressing ideas, and based on data supplied by students or teachers, immediately give each student personalized feedback (Hwang & Chen, 2023). Moreover, ChatGPT can be used as a collaboration coach to assist groups in researching and solving problems together, as a guide on the side to navigate physical and conceptual spaces, and as a codesigner to help in the designing or updating of curricula. Additionally, ChatGPT can be employed as an exploratorium to provide tools for exploring and interpreting data, as a study buddy to help students reflect on learning material and as a motivator that offers games and challenges to extend learning. It can act also as a dynamic assessor for students' assignments and other evaluation tasks (Ivanov & Soliman, 2023).

The utilization of ChatGPT in the realm of higher education presents a multitude of challenges and ethical considerations (Lund et al., 2023). A primary concern expressed by numerous universities and educators revolves around the potential escalation of plagiarism and cheating among students. Furthermore, there exist apprehensions regarding the efficacy of current plagiarism detection tools when faced with written content generated by ChatGPT (Cotton et al., 2023; Perkins, 2023). Moreover, the absence of regulation surrounding ChatGPT is also a concern, as it facilitates rapid development without adequate exploration of potential risks and shared protocols. Additionally, the tool's inability to discern between veracity and falsehood, right and wrong, raises concerns pertaining to cognitive bias (Kasneci et al., 2023; Lund & Wang, 2023). Other concerns encompass privacy, accessibility and commercialization, necessitating meticulous deliberation and regulation to ensure fairness and equity in the application of AI tools in higher education (Rudolph et al., 2023). The unique nature of AI calls for dedicated research. Recent study found that providing teachers with AI knowledge and practical experience can reduce their concerns and improve their trust in AI tools. Sessions on AI-powered assessment and the use of an AI tool positively impacted teachers' knowledge, perceptions, attitudes, trust and willingness to adopt AI tools (Nazaretsky, Ariely, et al., 2022).

At present, there is a dearth of peer-reviewed studies specifically concentrating on the usage of ChatGPT by students in third-level education. This research gap is acknowledged, given that ChatGPT was only made available on 30 November 2022, and is still in the research preview stage, allowing users to offer feedback on its functionality (OpenAI, 2023). Nevertheless, it has aroused substantial interest across diverse stakeholder groups, including higher education students who employ this AI-powered tool to assist them in completing their educational assignments (Crawford et al., 2023; Strzelecki, 2023).

The primary aim of this investigation was to analyse the acceptance and utilization of ChatGPT across students in higher education. To attain this goal, the research evaluated four concepts adopted from prior literature that can potentially impact the acceptance and utilization of ChatGPT by students in the context of university education. The study investigated the 'Unified Theory of Acceptance and Use of Technology' (UTAUT) (Venkatesh et al., 2003) towards ChatGPT. The four concepts affecting the acceptance and usage of technology, according to this theory, are: 'performance expectancy', 'effort expectancy', 'social influence' and 'facilitating conditions'. Although some might argue that current literature contains a plethora of studies utilizing UTAUT, suggesting that everything has already been covered in this area, we contend that the sudden and swift increase in ChatGPT users and the tool's nearly global accessibility necessitates a re-examination of this background. This would enable us to contribute to the theory by examining how tertiary education students perceive ChatGPT.

The research rationale was to study the higher education students' expectations towards using the AI-powered tool ChatGPT. Data for this study were collected from higher education students from six universities in Poland and Egypt. The theoretical foundation of the study is the use of the UTAUT framework and the partial least squares method of structural equation modelling. The theoretical model was tested in both samples (one for Polish data and one for Egypt data) and revealed satisfying results for tested hypotheses and moderating effects.

The study is organized as follows. The introduction section presents background information on ChatGPT and briefly describes its potential applications in higher education. This is followed by current literature review section, which covers the limited field of ChatGPT use in academia. The section also introduces the UTAUT theory and its relevance to the use of ChatGPT by students. The method section outlines the process for creating the theoretical model, followed by the results section which presents the estimation of the theoretical model. Finally, the results are discussed, and the implications, limitations and potential avenues for next research are presented.

THEORETICAL BACKGROUND

There has been an increase in interest in the field of technology acceptance and usage, as individuals increasingly rely on technology for their daily activities. An influential theory utilized to elucidate and predict technology acceptance is UTAUT, developed by Venkatesh et al. (2003). UTAUT was constructed by integrating and synthesizing eight pre-existing models of information technology acceptance. These models include the 'Innovation Diffusion Theory (IDT)' (Rogers, 1962), the 'Theory of Reasoned Action (TRA)' (Fishbein & Ajzen, 1975), the 'Social Cognitive Theory (SCT)' (Bandura, 1986), the 'Technology Acceptance Model (TAM)' (Davis, 1986), the 'Theory of Planned Behavior (TPB)' (Ajzen, 1991), the 'Model of PC Utilization (MPCU)' (Thompson et al., 1991), the 'Motivational Model (MM)' (Davis et al., 1992) and a 'model Combining the TAM and the TPB' (Taylor & Todd, 1995). According to Yu et al. (2021), UTAUT is a theory that combines various concepts and user experiences to form a basis for understanding the acceptance process of an information system. This comprehensive model encompasses constructs such as 'Performance expectancy', 'Effort expectancy', 'Social influence' and 'Facilitating conditions', which significantly impact individuals' 'Behavioural intention' to adopt and use a technology. Furthermore, UTAUT considers individual differences, such as gender, age and experience, as moderating factors that influence the aforementioned constructs within the model.

'Performance expectancy' pertains to the extent to which a person perceives that using a technology will enhance their work performance. 'Effort expectancy' characterizes user perception of the ease of use associated with utilizing a technology. 'Social influence' pertains to the degree to which an individual believes that others expect them to use a technology. 'Facilitating conditions' refer to the extent to which a person believes that the resources and support required to use a technology efficiently are readily available. 'Use behaviour' describes the actual utilization of technology by the user and 'Behavioural intention' is the plan to behave in a certain way.

The UTAUT theory has been found to be a reliable measure of higher education students' adoption of technology. Various scholars have tested this theory to assess the intention to use smartphones in the study process (Hoi, 2020; Nikolopoulou et al., 2020), the Google

Classroom platform (Jakkaew & Hemrungrote, 2017; Kumar & Bervell, 2019), blended learning (Azizi et al., 2020), e-learning system (El-Masri & Tarhini, 2017; Samsudeen & Mohamed, 2019), learning management systems (Raman & Don, 2013; Zwain, 2019) and collaborative Web 2.0 applications (Huang et al., 2013) for learning in higher education.

The original UTAUT theory incorporates four moderating elements. However, UTAUT2 version removed one of them (voluntariness of use) and only kept three moderating elements: gender, age and experience. Dwivedi et al. (2019) noted that previous research using UTAUT/UTAUT2 models typically utilized only a portion of the model and frequently neglected moderators. Following this recommendation, we did not include the moderating variable of experience since the use of ChatGPT does not have a long history of availability. Instead, we replaced the moderating variable of age with 'Study level', and we used the original moderating variable of 'Gender'.

Based on the analysis of prior studies that utilized the UTAUT theory, we suggest employing the same hypotheses as those used in the original UTAUT model. Performance expectancy 'is the degree to which a person believes that using the system will enable them to improve their level of job performance' (Venkatesh et al., 2003). In the context of using ChatGPT by students in their study process, it refers to the students' perception that utilizing the system will result in advantages for their learning practices. Specifically, in this particular context, it indicates the students' belief in the usefulness of ChatGPT for their academic tasks. We propose following hypothesis:

H1. The influence of performance expectancy on behavioural intention will be direct and positive and moderated by gender and a study level.

Effort expectancy 'is characterized as the level of comfort associated with using the system'. (Venkatesh et al., 2003). In the study of ChatGPT, 'Effort expectancy' pertains to the ease of use of the system and the extent to which it minimizes distractions and requires minimal effort from students. We propose following hypothesis:

H2. The influence of effort expectancy on behavioural intention will be direct and positive and moderated by gender and a study level.

Social influence 'is characterized as the extent to which a person believes that significant others should implement the new system' (Venkatesh et al., 2003). In the present investigation, 'Social influence' is used to describe the extent to which individuals perceive that their immediate social circle believes that they should integrate ChatGPT into their higher education practices. We propose following hypothesis:

H3. The impact of social influence on behavioural intention will be direct and positive and moderated by gender and a study level.

Facilitating conditions 'are the extent to which a person believes that an administrative and technological framework is in place to support use of the system' (Venkatesh et al., 2003). Within the study aimed at examining the acceptance and adoption of ChatGPT among college students, 'Facilitating conditions' could be especially significant as it has the potential to impact the level of ease with which students are able to utilize the AI chat, including its accessibility. In the original UTAUT model, facilitating conditions is not moderated by gender. We keep this setting and propose following hypothesis:

H4. The influence of facilitating conditions on use behaviour will be direct and positive and moderated by a study level.

Similar to the intention models discussed by Venkatesh et al. (2003), we anticipate that the technology use behaviour will be positively impacted by behavioural intention, as per the established theory.

> **H5.** Behavioural intention will have a significant positive influence on use behaviour.

The model's configuration, as per the proposed hypotheses, is illustrated in Figure 1, which comprises all external and dependent variables from the UTAUT model, along with two moderating variables.

METHODOLOGY

The study employed an online survey to collect data from students at three universities located in Katowice, Poland, namely University of Economics in Katowice, University of Silesia in Katowice and Silesian University of Technology. We have also collected data making multiple study from three universities located in Cairo, Egypt, namely The British University in Egypt, The American University in Cairo and Arab Academy for Science, Technology & Maritime Transport. Participants were recruited from the entire universities' database of active students, and there were no prerequisites for participation. The measurement scale for each variable was developed based on a study by Venkatesh et al. (2012). To measure 'Performance expectancy', four items were adapted, while four items were adapted for 'Effort expectancy', three items for 'Social influence', four items for 'Facilitating conditions' and three items for 'Behavioural intention'. Venkatesh et al. (2012) examined the acceptance and use of 'mobile internet', while this study's scale measures the acceptance and use of 'ChatGPT'. The items for measuring 'Use behaviour' are not known in Venkatesh et al. (2012), but only the two bordering values as 'never' and 'many times per day' are available.

In terms of the measurement scale, a seven-point Likert scale was utilized in Poland, while a five-point Likert scale was presented for respondents in Egypt. The difference in

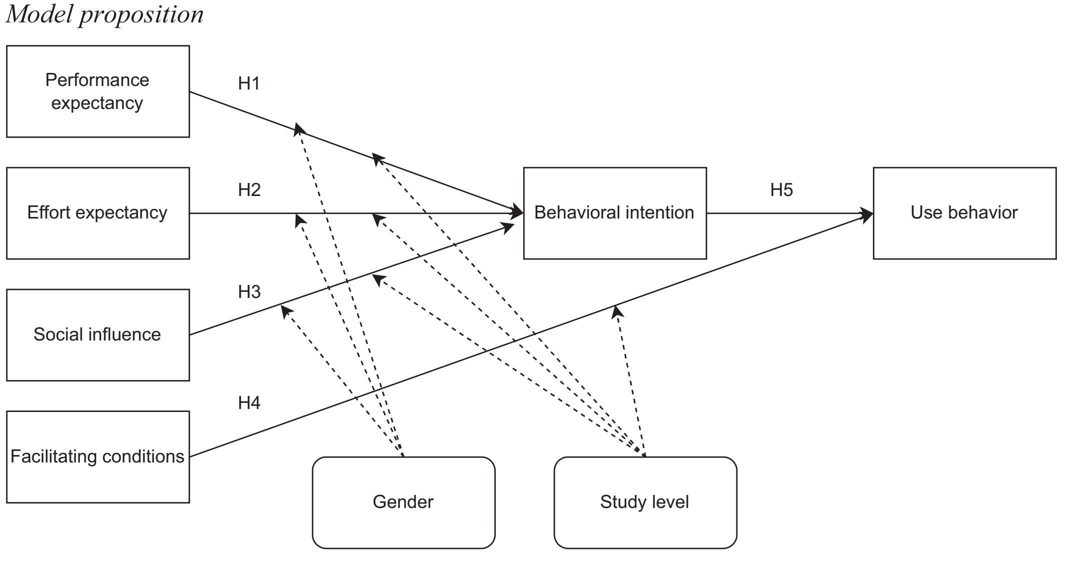

FIGURE 1 Model proposition.

the higher bond of the scale comes from cultural differences, while in Poland, seven-point scale is commonly used, in Egypt the scale is five-point. Each item on the scale ranged from 'strongly agree', which was assigned a value of 7 in Poland or of 5 in Egypt, to 'strongly disagree', which was assigned a value of 1. However, the item 'Use behaviour' was measured with a seven-option scale that included the following response options: 'several times a day', 'once a day', 'several times a week', 'once a week', 'several times a month', 'once a month' and 'never'. Moreover, the variable 'Study level' was assessed using three options. For Poland, it includes a three-year duration for the first study cycle, a two-year duration for the second study cycle leading to a master's degree and the option of being a PhD student. This classification aligns with the principles of the Bologna Process, which divides academic studies into three cycles: the first, second and third cycles. In Egypt, the higher education system is influenced by the French model, but it has its own unique structure. In Egypt, the distribution of study level was adapted to undergraduates (university student) and pre-master's student (modules) as first level; Master's student (thesis level) as second level; and pre-PHD Student (modules), pre-PHD Student (thesis level) and PHD holders as third level. The 'Gender' question provided respondents with three response options: female, male and prefer not to disclose. The third option was only available for Polish respondents. Islam, the predominant religion in Egypt, traditionally recognizes two genders. Therefore, our survey reflects this binary understanding.

Data collection

In March 2023, an online questionnaire was prepared, and a pilot study was carried out to evaluate the validity and reliability of the scales employed. In the pilot study, a total of 36 students were surveyed and requested to provide feedback on the comprehensibility of the scales. The findings indicated that all variables met the pre-determined criteria for both validity and reliability, affirming the consistent reliability of the developed scale in measuring students' levels of acceptance towards ChatGPT in higher education. This conclusion was supported by composite reliability, Cronbach's alpha and reliability coefficients exceeding 0.7, as well as an average variance extracted (AVE) surpassing 0.5. Subsequent to the pilot study, the survey was administered in the end of May to students at the universities located in Katowice, Poland; and Cairo, Egypt. Each invitation clearly outlined the purpose of the study, emphasized voluntary participation and assured complete anonymity of the collected data. The option to leave the study at any time was disclosed to the participants. The survey remained accessible for a duration of 1 month, concluding at the end of June 2023.

The measurement scale utilized in this study is shown in Table 1, providing the corresponding items and the scale source. The scale includes a total of 19 items that were utilized to measure the acceptance and usage of ChatGPT by students. Furthermore, the survey included two supplementary questions to inquire about gender and study level. As for study level, the options were consistent with the previously described cycle division.

Sample characteristics

In this study, the questionnaire was completed by a total of 543 participants in Poland, consisting of 288 males, 232 females and 23 students who chose not to disclose their gender. The sample population can be further described in terms of study cycle, with 406 participants from the first cycle, among whom 30 were in their first year of study, 171 were in their second year of study, and 205 were in their third year of study. Among the second cycle participants, there were 128 students, with 57 being in their first year of study and 71 in their

TABLE 1 Measurement scale.

Construct	Code	Question	Source
Performance expectancy	PE1	'I believe that ChatGPT is useful in my studies'	Venkatesh et al. (2012)
	PE2	'Using ChatGPT increases your chances of achieving important things in your studies'	
	PE3	'Using ChatGPT helps you get tasks and projects done faster in your studies'	
	PE4	'Using ChatGPT increases your productivity in your studies'	
Effort expectancy	EE1	'Learning how to use ChatGPT is easy for me'	
	EE2	'My interaction with ChatGPT is clear and understandable'	
	EE3	'I find ChatGPT easy to use'	
	EE4	'It is easy for me to become skilful at using ChatGPT'	
Social influence	SI1	'People who are important to me think I should ChatGPT'	
	SI2	'People who influence my behavior believe that I should use ChatGPT'	
	SI3	'People whose opinions I value prefer me to use ChatGPT'	
Facilitating conditions	FC1	'I have the resources necessary to use ChatGPT'	
	FC2	'I have the knowledge necessary to use ChatGPT'	
	FC3	'ChatGPT is compatible with technologies I use'	
	FC4	'I can get help from others when I have difficulties using ChatGPT'	
Behavioral intention	BI1	'I intend to continue using ChatGPT in the future'	
	BI2	'I will always try to use ChatGPT in my studies'	
	BI3	'I plan to continue to use ChatGPT frequently'	
Use behavior	UB1	'Please choose your usage frequency for ChatGPT: Never; Once a month; Several times a month; Once a week; Several times a week; Once a day; Several times a day'	Venkatesh et al. (2012)

second year of study. The third cycle of study was represented by nine participants who took part in the survey. In Egypt, a total of 385 participants, consisting of 197 males and 188 females, took part in the study. The sample consisted of 289 undergraduate students (first level), 44 master students (second level), 29 PhD students and 23 PhD holders (third level).

RESULTS

Model estimation

To estimate the model, we utilized the partial least squares of structural equation modelling (PLS-SEM) algorithm with the path weighting scheme in SmartPLS 4 software (Version 4.0.9.2), using default initial weights and a maximum of 3000 iterations (Ringle et al., 2022).

TABLE 2 Item loadings.

Poland		Egypt	
Item	**Loading**	**Item**	**Loading**
BI1	0.909	BI1	0.825
BI2	0.826	BI2	0.862
BI3	0.940	BI3	0.857
EE1	0.872	EE1	0.809
EE2	0.894	EE2	0.813
EE3	0.897	EE3	0.778
EE4	0.913	EE4	0.702
FC1	0.842	FC1	0.919
FC2	0.896	FC2	0.879
FC3	0.817	FC3	0.705
FC4	0.571	FC4	0.598
PE1	0.905	PE1	0.848
PE2	0.869	PE2	0.846
PE3	0.893	PE3	0.762
PE4	0.868	PE4	0.746
SI1	0.939	SI1	0.807
SI2	0.943	SI2	0.861
SI3	0.935	SI3	0.847
UB	1.000	UB	1.000

TABLE 3 Construct reliability and validity.

	Cronbach's alpha		Composite reliability (rho_a)		Composite reliability (rho_c)		Average variance extracted (AVE)	
	Poland	**Egypt**	**Poland**	**Egypt**	**Poland**	**Egypt**	**Poland**	**Egypt**
Behavioural intention	0.872	0.805	0.887	0.806	0.922	0.885	0.797	0.719
Effort expectancy	0.917	0.784	0.929	0.785	0.941	0.859	0.799	0.604
Facilitating conditions	0.824	0.760	0.831	0.896	0.895	0.849	0.741	0.659
Performance expectancy	0.907	0.784	0.909	0.804	0.935	0.860	0.781	0.607
Social influence	0.933	0.789	0.935	0.790	0.957	0.877	0.882	0.704

Additionally, we employed bootstrapping, a nonparametric procedure, with 5000 samples to determine the statistical significance of the PLS-SEM results. We assessed the reflectively specified constructs by analysing the indicator loadings, where an indicator loading greater than 0.7 indicates that the construct explains more than 50% of the variance in the indicator, indicating an acceptable level of item reliability. We present the loadings in Table 2, which are all above the lower bound, except for FC4. Therefore, we removed FC4 from further processing in the model and did not consider it.

Composite reliability is a measure used to evaluate the reliability of a model, with acceptable to good reliability levels demonstrated by results ranging from 0.70 to 0.95 (Hair

TABLE 4 (a) HTMT values (sample in Poland). (b) HTMT values (sample in Egypt).

(a) HTMT values (sample in Poland)						
	Behavioural intention	**Effort expectancy**	**Facilitating conditions**	**Performance expectancy**	**Social influence**	**Use behaviour**
Behavioural intention						
Effort expectancy	0.636					
Facilitating conditions	0.633	0.801				
Performance expectancy	0.841	0.596	0.595			
Social influence	0.619	0.427	0.494	0.584		
Use behaviour	0.751	0.530	0.559	0.577	0.454	
(b) HTMT values (sample in Egypt)						
	Behavioural intention	**Effort expectancy**	**Facilitating conditions**	**Performance expectancy**	**Social influence**	**Use behaviour**
Behavioural intention						
Effort expectancy	0.425					
Facilitating conditions	0.329	0.737				
Performance expectancy	0.588	0.708	0.581			
Social influence	0.549	0.361	0.350	0.531		
Use behaviour	0.449	0.399	0.298	0.427	0.166	

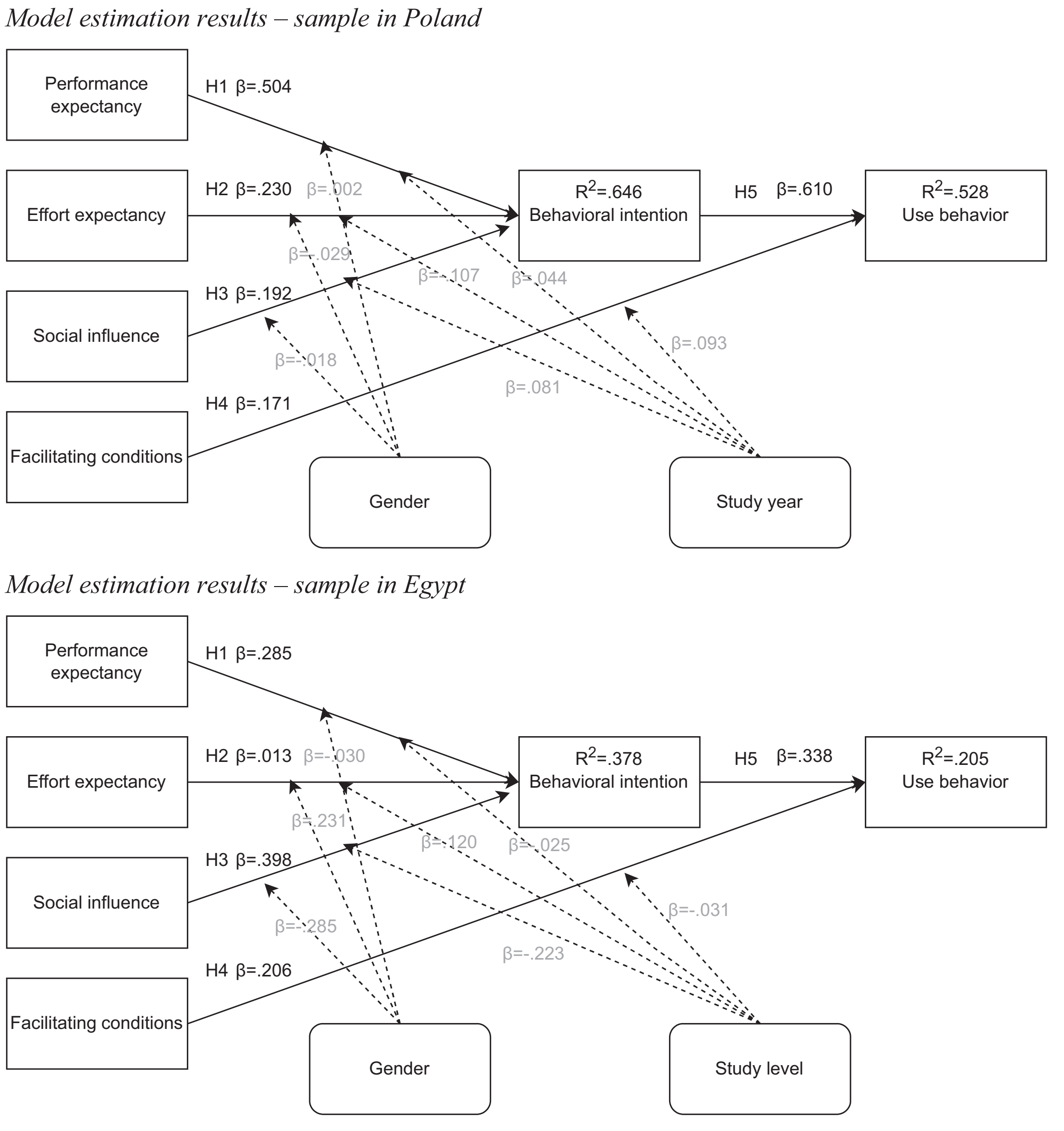

FIGURE 2 (a) Model estimation results—sample in Poland. (b) Model estimation results—sample in Egypt.

et al., 2022). Cronbach's alpha is one more measure of internal consistency reliability, with similar thresholds as composite reliability (ρc). Additionally, a reliability coefficient ρA, developed by Dijkstra (2010, 2014) and later refined by Dijkstra and Henseler (2015), provides an exact and consistent alternative. Convergent validity of the measurement models is assessed by calculating the AVE for all the items associated with a specific reflective variable, with an AVE threshold of 0.50 or higher considered acceptable (Sarstedt et al., 2022). The quality criteria presented in Table 3 were met by the composite reliability, Cronbach's alpha, reliability coefficient and AVE.

To assess the discriminant validity of PLS-SEM, the heterotrait-monotrait (HTMT) ratio of correlations method by Henseler et al. (2015) was utilized. The HTMT threshold of 0.90 is recommended, indicating a potential issue with discriminant validity when constructs are conceptually similar. For more distinct constructs, a lower threshold of 0.85 is suggested

TABLE 5 Path coefficient results.

Path	Sample in Poland				Sample in Egypt			
	Path coefficient	**f^2 effect size**	***p* values**	**Confirmed**	**Path coefficient**	**f^2 effect size**	***p* values**	**Confirmed**
PE→BI	0.504	0.397	0.000	Yes	0.285	0.035	0.000	Yes
EE→BI	0.230	0.099	0.000	Yes	0.013	0.000	0.734	No
SI→BI	0.192	0.072	0.000	Yes	0.398	0.099	0.000	Yes
FC→UB	0.171	0.043	0.000	Yes	0.206	0.049	0.000	Yes
BI→UB	0.610	0.554	0.000	Yes	0.338	0.127	0.000	Yes

TABLE 6 Moderating effects of study level and gender.

Moderating effect	Sample in Poland				Sample in Egypt			
	Path coefficient	f^2 effect size	*p* values	Confirmed	Path coefficient	f^2 effect size	*p* values	Confirmed
Study level × SI → BI	0.081	0.012	0.030	Yes	−0.223	0.045	0.007	Yes
Study level × PE → BI	0.044	0.003	0.301	No	−0.025	0.001	0.662	No
Study level × EE → BI	−0.107	0.023	0.000	Yes	0.120	0.018	0.084	No
Gender × EE → BI	−0.029	0.002	0.402	No	0.231	0.013	0.033	Yes
Gender × SI → BI	−0.018	0.001	0.620	No	−0.285	0.025	0.003	Yes
Gender × PE → BI	0.002	0.000	0.962	No	−0.030	0.000	0.799	No
Study level × FC → UB	0.093	0.018	0.002	Yes	−0.031	0.001	0.451	No

(Henseler et al., 2015). In Table 4, all values are below the 0.85 threshold, indicating no significant discriminant validity concerns.

In the subsequent stage of analysis, the explanatory capability of the model is assessed through the coefficient of determination (R^2), which measures the amount of variance accounted for in each construct. The scale of R^2 ranges from 0 to 1, with higher values indicating greater explanatory power. To provide a general guideline, Hair et al. (2011) suggest that R^2 values of 0.25, 0.50 and 0.75 can be considered weak, moderate and substantial respectively. The effect size of a variable is evaluated using f^2 values of 0.35, 0.15 and 0.02, indicating large, medium and small effects respectively. An effect size below 0.02 indicates no impact (Sarstedt et al., 2022).

PLS-SEM findings are illustrated in Figure 2 and Tables 5 and 6, with standardized regression coefficients (β) shown on the path relationships and R^2 values presented in the variables' squares. The primary observation for sample in Poland reveals that 'Performance expectancy' has the most prominent impact (0.502) on 'Behavioural intention', followed by 'Effort expectancy' (0.232) and 'Social influence' (0.190), explaining 64.6% of the 'Behavioural intention' variance (as indicated by the R^2 value). All three paths also have f^2 size effect above lower bond indicating that each path makes an effect. Conversely, 'Behavioural intention' has the most significant effect (0.608) on 'Use behaviour', followed by 'Facilitating conditions' (0.173). These two variables also have effect size above lower bond and account for 52.8% of the 'Use behaviour' variance.

The primary observation for sample in Egypt reveals that 'Social influence' has the most prominent impact (0.433) on 'Behavioural intention', followed by 'Performance expectancy' (0.280), explaining 37.8% of the 'Behavioural intention' variance (as indicated by the R^2 value). The effect of 'Effort expectancy' was not confirmed in this sample. The two significant paths also have f^2 size effect above lower bond indicating that each path makes an effect. Conversely, 'Behavioural intention' has the most significant effect (0.345) on 'Use behaviour', followed by 'Facilitating conditions' (0.206). These two variables also have effect size above lower bond and account for 20.5% of the 'Use behaviour' variance. Table 5 presents results of the significance tests for the structural model's path coefficients and hypotheses confirmation.

In case of moderating variables of 'Study level' and 'Gender' results show different results for both samples. In sample consisting Polish students only, three moderating effects are statistically significant in the model. Study level significantly moderates the path between 'Social influence' and 'Behavioural intention', the path between 'Effort expectancy' and 'Behavioural intention' and the path between 'Facilitating conditions' and 'Use behaviour'. Other moderating effects are not significant.

In sample consisting Egyptian students, also only three moderating effects are statistically significant in the model. However, we can notice that the effects are higher, because the path coefficients have higher value. Study level significantly moderates the path between 'Social influence' and 'Behavioural intention', but gender significantly moderates the path between 'Effort expectancy' and 'Behavioural intention' and the path between 'Social influence' and 'Behavioural intention'. Moderating effects of 'Study level' and 'Gender' are presented in Table 6.

DISCUSSION

This research utilizes an adapted version of the UTAUT theory to investigate factors affecting the adoption and the use of AI-powered tool, ChatGPT. The findings shed light on the impact such tools have on the learning process.

Our findings show that 'Performance Expectancy' is one of the key determinants of 'Behavioural Intention', aligning with earlier studies regarding learning management systems (Al-Adwan et al., 2022), social networking tools for learning (Al-Adwan et al., 2022) and mobile learning systems (Almaiah et al., 2019). Hypothesis H1 has been confirmed positively for both samples. The study underscores the benefits of AI chat, such as reducing task completion time and providing immediate responses to queries, which can bolster academic performance and in turn, foster an intention to utilize such tools.

Moreover, 'Effort Expectancy' emerged as a crucial influencer of 'Behavioural Intention' confirming hypothesis H2 in the Polish sample. This aligns with studies regarding learning management systems (Al-Mamary, 2022) and humanoid robot assistance in academic writing (Guggemos et al., 2020), but contradicts findings related to massive open online courses (Altalhi, 2021), where 'Effort expectancy' was found to be not significant. Similar results were achieved in the Egyptian sample, not confirming hypothesis H2 in this sample. The study indicates that students who find ChatGPT easy to use and less effort-intensive, providing multi-lingual conversational communication and allowing response refinement, are more likely to use it.

The research revealed that 'Social Influence' significantly influences 'Behavioural Intention' in agreement with studies on mobile learning adoption (Alowayr, 2022) and e-learning system adoption, but diverging from research on interactive whiteboards (Wong et al., 2015) and learning management systems (Zwain, 2019). The results suggest that acceptance and usage of ChatGPT are influenced by external figures, such as instructors, peers and administrators, underlining their vital role in promoting and encouraging students' adoption and use of AI chat systems. Hypothesis H3 has been confirmed positively for both samples, but the hypothesis is defined in a positive way. The current discussion in higher education in this regard tends to be more negative. There are voices that students may believe that using the ChatGPT is not a good learning practice, something that one should not be proud of (Cotton et al., 2023).

Our study unveils that 'Facilitating conditions', as outlined in the original UTAUT model, predict the 'Use behaviour' of ChatGPT, thus hypothesis H4 has been confirmed for both samples. This finding resonates with earlier research on mobile learning systems (Almaiah et al., 2019) and learning management systems (Al-Adwan et al., 2022). However, it contrasts with studies on the adoption of social networking tools (Alvi, 2021) and massive open online courses (Altalhi, 2021). This suggests that students deem the open access and online presence of AI chat as pivotal in enhancing their actual usage. Factors facilitating this usage include availability across web browsers on all platforms, worldwide accessibility, and user-friendly interaction in prevalent languages. Hypothesis H5 was also confirmed positively in both samples, showing that 'Behavioural intention' significantly influences 'Use behaviour'.

Our study also scrutinizes the potential moderating effects of 'Gender' and 'Study level'; however, our findings differ across both samples. Findings in the Polish sample reveal that gender does not significantly influence the model relationships. This is consistent with prior research, such as Dečman (2015), showing that both male and female students demonstrate similar motivation levels towards e-learning. As such, our study does not support the hypothesis that 'Gender' moderates the model relationships. Furthermore, prior studies have either divided sample groups based on gender to examine its moderating effect or dismissed this effect through multigroup analysis, as seen in Alghamdi et al. (2022). However, in the Egyptian sample, two out of three moderating effects are significant. Hence, we conclude that ChatGPT usage by gender needs to be further examine.

Since there was a clear significant and evident difference between the magnitude of gender in Egypt which proved to be much higher and influential than that in Poland, this is a clear point for further exploration. That exploration would aim to investigate further the potential causes for such difference of significance that is so considerable between both population various explanation could enrich our academic understanding of the impact of gender as a moderator in such important relationships in terms either of religious factors, culture factors and social policy and regulatory rules implications.

Critical analytical frameworks addressing gender dynamics and relations in higher education within Polish and Egyptian populations warrant emphasis. The application context of gender norms, contributions and prevailing societal customs plays pivotal roles in determining how gender functions as a moderating factor in higher education and comparable settings (Cislaghi & Heise, 2020). In this regard, Poland might be perceived as occupying an intermediary position within the spectrum of Western and European gender perspectives. It is often seen as less liberal compared to Western Europe and North America but more liberal when juxtaposed against regions like Russia, Eastern European countries, and certain South American and Caribbean nations.

Concurrently, within the more traditional paradigms of the southern Mediterranean, Egypt seems to hold a similar intermediate stance. The Egyptian perspective on gender appears to be more liberal than that of the Persian Gulf and the majority of African nations. However, it leans more conservative when compared to North-western African nations, specifically Tunisia and Morocco (Ayadi & Forouheshfar, 2023). This study identifies a parallel between Egypt and Poland regarding gender dynamics. Both nations, whether within their liberal or conservative contexts, represent a median perspective. This central position could potentially resonate with the more liberal or conservative interpretations of gender within their respective regional contexts.

Regarding 'Study level', the moderating effect was significant in three out of four instances in Polish sample and in one out four in Egyptian sample. It was positively significant in first sample for the relationship between 'Social influence' and 'Behavioural intention', and between 'Facilitating conditions' and 'Use behaviour'. However, the relationship between 'Effort expectancy' and 'Behavioural intention' showed a negative moderating effect. This suggests a variance in the acceptance and usage of ChatGPT among students from different academic levels. In second sample, positive significant relationship was noticed for the relationship between 'Social influence' and 'Behavioural intention'. Further research, delving into the influence of study level on ChatGPT usage by employing multigroup analysis, would be beneficial but is outside the purview of our current study.

Implications

This study carries significant implications for both theory and practical application. It enhances our understanding of key factors influencing the acceptance and integration of AI chat-tools, like ChatGPT, within higher education contexts. The insights gained can be used by policymakers, educators and researchers in higher education to work in tandem with students in incorporating AI tools into their study processes, thereby facilitating the successful adoption of such technologies and fostering productive collaboration among stakeholders.

One crucial finding is the significant role 'Performance Expectancy' plays in shaping students' willingness to adopt and use AI chat-tools. This necessitates efforts to improve students' understanding of the benefits and potentialities of such tools. A solution could lie in deploying effective awareness campaigns, supplemented by training programmes and workshops focusing on the AI chat-tool advantages. Awareness could be amplified via various channels including social media, university websites and open seminars, stimulating students to engage in insightful discussions.

Moreover, the study highlights the importance of 'Effort expectancy', reinforcing the need for user-friendly and easily navigable AI chat-systems. This can incentivize students to persist in using these tools. In response, AI chat-system developers should focus on designing intuitive user interfaces and incorporating accessible features. Such initiatives are aimed at enticing a broader student demographic to interact with these platforms. It is crucial to remember that if students find AI chat-systems too complex for their learning needs, they may discontinue use, even if other conditions are favourable.

'Social influence' plays a pivotal role in shaping students' intentions to utilize AI chat. Therefore, it is evident that university authorities and curriculum managers should leverage 'Social influence' to promote the adoption of ChatGPT. This can be achieved by encouraging instructors and fellow students who are already using AI chat to advocate for its responsible use among students. Peers, especially those who have had positive interactions with ChatGPT, hold significant influence in persuading others to embrace AI chat. Additionally, the university should establish policies and regulations to govern and promote responsible usage of generative AI. For instance, the consideration of optional utilization of ChatGPT for assignments, exams and feedback can be actively explored to facilitate its integration into student workflows.

'Facilitating conditions' play a crucial role in enhancing the utilization of ChatGPT. Therefore, policies concerning the integration of this tool into the study process should prioritize ensuring adequate access, establishing appropriate regulations, defining guidelines for when and how ChatGPT can be used and providing effective instructions on how to formulate prompts and address any potential challenges arising from the system's responses. These measures aim to minimize barriers that may hinder students and instructors from utilizing AI chat. The findings of this study can inform university policymakers in directing their efforts towards increasing student awareness and knowledge regarding the benefits of integrating ChatGPT into their learning process. This can be achieved through the implementation of training programmes designed to give students the necessary skills to effectively incorporate AI-powered chat into the educational system.

AI is more than just a tool; it encompasses profound ethical implications that can transform societal functions and how individuals engage with and view technology. The ethical design and decision-making of an AI system can shape our expectations and perceptions of it, far beyond its basic functionality. If students believe AI tools operate ethically, they are likely to trust and use them more. Understanding this trust is crucial. While the UTAUT theory focuses on the ease of use, from an ethical standpoint, the effort users make to comprehend the AI's decision-making process—its transparency—plays a vital role in acceptance. For instance, if there is societal discourse suggesting that ChatGPT is biased or unfair, it could deter individual adoption.

HEIs can play a proactive role here. They can establish conditions promoting ethical AI use, like clear AI policies, audit trails and mechanisms to address grievances arising from AI-driven decisions. Though the UTAUT framework traditionally associates facilitating conditions with infrastructural or technological support, in the AI context, this should be expanded. It should include training programmes that inform students about ethical AI usage, its societal effects and strategies for managing potential ethical dilemmas.

In recent studies, the adoption and the use of AI-powered tools are more frequently discussed. There are proposed programmes aimed at enhancing teachers' skills in using various AI-powered platforms to improve education. For instance, teachers can participate in dedicated professional development programmes to learn how to use platforms that evaluate students' written assignments (Nazaretsky, Ariely, et al., 2022). On the other hand, there are platforms designed for teachers that can be implemented in schools to enhance learning (Cukurova et al., 2023). Additionally, instruments have been developed to measure how teachers adopt and use AI-powered tools and how they address various concerns, such as trust, the absence of human characteristics and transparency in AI decision-making processes (Nazaretsky, Cukurova, et al., 2022).

Our study focuses on the other aspect of the education process. We examined how students adopt and use generative AI-powered tools. Therefore, the contribution of this research is to provide insights into the factors that influence the adoption of generative AI-powered tools. It is worth noting that ChatGPT is not adaptive and is not specifically designed for educational purposes, which suggests that further studies are needed to explore the use of this platform in educational processes.

The integration of ChatGPT in HEIs holds the potential to deliver personalized and relevant learning experiences to students, streamline administrative procedures and advance research and community engagement. However, it is essential to employ ChatGPT in an ethical manner, taking into account the need to develop individual and institutional capabilities. While certain states and HEIs have implemented restrictions on ChatGPT, most are actively seeking ways to adapt to the growing prevalence and accessibility of AI. HEIs should create platforms for stakeholders to engage in discussions about the impact of ChatGPT and collaboratively devise strategies to adapt and embrace AI technologies. Clear guidelines should be established through negotiations with students and instructors, aligning the use of ChatGPT with course learning objectives. HEIs should also review and update their policies concerning academic honesty and integrity in relation to ChatGPT and similar AI tools. Staff training, peer support, mentoring and the introduction of new programmes and courses focusing on ChatGPT and AI will enhance research and development capabilities while equipping students with advanced expertise. It is crucial to build capacity for understanding and managing ChatGPT, as it cannot replace the indispensability of human creativity and critical thinking.

There is a critical requirement for extensive deliberations regarding the potential utilization, potential risks and inherent limitations of AI tools, underscoring the significance of upholding academic and ethical standards, along with critical thinking and human intelligence playing a paramount role throughout the research endeavour. Proposed solutions should contain developing guidelines and standards, promoting responsible use and engaging with the broader community.

Limitations and future work

This research is subject to certain limitations, although the data collection is not restricted to a single university and the sample is diversified having respondents from six different universities in two countries, still the sample maybe biased by self-reported bias. To enhance the generalizability of the findings, future research should aim to replicate the study model using a multi-site approach that involves students from more universities and other countries.

The survey was distributed during a stormy period concerning AI, wherein each month had a significant impact on the development of the tool. Respondents who used ChatGPT at the beginning of the tool deployment are considered early adopters. Moreover, the tool's usage might be influenced by the time of the year, such as during the submission of coursework, seminal assignments or based on the discipline of study.

In terms of examining the variables influencing ‘Behavioural intention’ and the use of ChatGPT, this study focused solely on the core elements of the UTAUT prototype model. Future studies should investigate other comparable models that look into additional factors to get a more thorough understanding which contributes to students' acceptance of ChatGPT.

Additionally, this study exclusively employed quantitative methods for data analysis. To provide a more holistic perspective, a future study could incorporate a combination of qualitative and quantitative methods, allowing for a deeper exploration of the phenomenon. Furthermore, the study only considered two moderating variables, ‘Gender’ and ‘Study year’. To fully capture the impact of ChatGPT on intent and behaviour, it is worthwhile to investigate the moderating effects of other factors such as field of study and more, in order to better quantify their influence.

AUTHOR CONTRIBUTIONS

Conceptualization; investigation; funding acquisition; writing—original draft; methodology; validation; visualization; writing—review and editing; software; project administration; resources; supervision; data curation; formal analysis: Artur Strzelecki. *Data curation; resources; writing—review and editing; investigation*: Sara ElArabawy.

CONFLICT OF INTEREST STATEMENT

The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this paper.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ETHICS STATEMENT

All procedures performed in this study involving adult human participants were in accordance with the ethical standards of the 1964 Helsinki declaration and its later amendments. Informed consent was obtained from all individual participants included in the study.

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