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To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology

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ABSTRACT
ChatGPT is an AI tool that assisted in writing, learning, solving assessments and could do so in a conversational way. The purpose of the study was to develop a model that examined the predictors of adoption and use of ChatGPT among higher education students. The proposed model was based on a previous theory of technology adoption. Seven predictors were selected to build a model that predicted the behavioral intention and use behavior of ChatGPT. The partial-least squares method of structural equation modeling was used for data analysis. The model was found to be reliable and valid, and the results were based on a self-reported data of 534 students from a Polish state university. Nine out of ten proposed hypotheses were confirmed by the results. Habit was found to be the best predictor of behavioral intention, followed by performance expectancy and hedonic motivation. The dominant determinant of use behavior was behavioral intention, followed by personal innovativeness. The research highlighted the need for further examination of how AI tools could be adopted in learning and teaching.

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Introduction

ChatGPT, an AI-powered chatbot released by OpenAI, is equipped with a large language model that enables it to generate original text in response to prompts given by users. This technology, launched in November of last year, is available for free through an OpenAI account (OpenAI, 2023). However, the rise of generative AI, of which ChatGPT is an example, has raised concerns about its potential impact on various industries and institutions. One potential application of ChatGPT is in the realm of higher education, where it presents an opportunity to reconsider the purpose of assessment and how it can enhance learning. Rather than simply turning to software for assessment, institutions can use ChatGPT to teach critical thinking, writing, and the role of AI in today's world. In this way, ChatGPT is considered as a valuable tool in innovative and inclusive teaching, learning, and assessment that aligns with a transformative relationship with knowledge.

To explore the ChatGPT's potential applications in higher education, different areas can be discussed as software is producing fake citations (Cooper, 2023), developing assignments (Sullivan et al., 2023), supporting essay writing (Crawford et al., 2023), and encouraging critical reflection on AI's use in society (van Dis et al., 2023). As universities weigh the implications of AI chats, some academic teachers have already incorporated it into their assignments to expose its limitations and challenge the technology. Universities are considering how ChatGPT may impact higher education teaching and learning in the future, as the possibilities of this technology are vast and potentially game-changing (Lim et al., 2023).

By reviewing current published peer-reviewed papers about the usage of ChatGPT in higher education and academia, several emerging topics can be identified. These include the usage of ChatGPT

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in general education (Cotton et al., 2023), although most of the ongoing discussion is focused on its use in medical education (Gilson et al., 2023). Some researchers have interviewed ChatGPT and asked about its influence on education (Lund & Wang, 2023), while others have raised concerns and benefits in academic research, writing, publishing, authorship, and other general fields (Perkins, 2023). Some of the papers consist only of letters, commentaries, or editorials and may not have gone through a formal review process. This is because utilizing of ChatGPT in academia and higher education is relatively new and is still being explored.

We have observed a research gap in the current literature, which primarily focuses on academic teachers and scientists' views on ChatGPT and its future. However, we recognize that students are crucial stakeholders who wish to incorporate ChatGPT into their higher education process. As the AI tool was launched recently, there is limited knowledge regarding students' acceptance of this new technology and its use. Therefore, we propose to conduct a study to investigate students' acceptance of this technology, its predictors, and the level of acceptance. To measure technology acceptance, we propose to employ components of a well-established "Unified Theory of Acceptance and Use of Technology (UTAUT2)" (Venkatesh et al., 2003, 2012).

We are aware that some may believe that everything has been said about the application of the UTAUT2 theory. However, recent studies show that the UTAUT2 model is being used to test new technologies introduced into higher education, such as animation (Dajani & Abu Hegleh, 2019), lecture capture system (Farooq et al., 2017), e-learning platforms (Zacharis & Nikolopoulou, 2022), mobile devices (Hoi, 2020) and learning management systems (Raza et al., 2022; Zwain, 2019). Therefore, we have chosen to use this theoretical foundation to develop a proposition that explains the acceptance and usage of ChatGPT by students.

The study is organized as follows. The introduction section provides preliminary information about the creation of ChatGPT and the debates surrounding its use in academia and education. The method section details the UTAUT2 model and its implementation to assess students' acceptance and utilization of ChatGPT in university education. We also present a modified measurement scale specifically for ChatGPT in university education. In the next section, we demonstrate the results of the structural modeling equation using the partial least squares method, as well as the theoretical model estimation, followed by a discussion of our findings. Finally, we emphasize the novelty and contribution of this study in this section.

Method

In this study, we are utilizing components of the well-established "Unified Theory of Acceptance and Use of Technology (UTAUT2)" developed by Venkatesh, Thong, and Xu (2012). UTAUT identifies seven predictors of technology usage and intention to use, including "Performance Expectancy", "Effort Expectancy", "Social Influence", "Facilitating Conditions", "Hedonic Motivation", "Price Value", and "Habit". We propose to modify the list of predictors by removing "Price Value", as the current use of ChatGPT is free for everyone. Although a ChatGPT Plus version is available for $20 per month, it provides benefits such as faster response time and priority access to new features. Nonetheless, the ChatGPT remains free for everyone at present. We would like to introduce "Personal Innovativeness" as an additional predictor in the model as described by Agarwal and Prasad (1998). In this study, we define "Personal Innovativeness" as an individual's willingness and capacity to adopt and utilize ChatGPT in their higher education process, which involves a proactive and, at times, risk-taking approach to innovation, openness to change, and eagerness to learn new things.

Hypothesis development

Performance expectancy "refers to the degree to which an individual expects that using a particular technology will improve their performance in achieving specific tasks or goals" (Davis, 1989; Venkatesh & Davis, 2003). El-Masri and Tarhini (2017) found that "Performance expectancy" plays a crucial role in the adoption of educational systems within academic settings. This notion is supported by several studies that have shown the significant influence of "Performance expectancy" on learners' "Behavioral intention" to embrace innovative educational technologies. For example, Kumar and Bervell (2019) demonstrated this relationship in the context of Google Classroom, while Arain et al. (2019) and Raman and Don (2013) explored it in the context of mobile learning and learning management systems, respectively. In the context of a study testing the acceptance and usage of ChatGPT by students in higher education, "Performance expectancy" would refer to the extent to which students believe that using ChatGPT would enhance their academic performance or productivity. Followed hypothesis is proposed:

H1: Performance expectancy has direct and significant impact on Behavioral intention

Effort expectancy "refers to the degree to which an individual expects that using a particular technology will be free of effort" (Moore & Benbasat, 1991; Venkatesh & Davis, 2003). Recent research has highlighted the substantial impact of "Effort expectancy" on learners' "Behavioral intention" to adopt various educational technologies. For example, studies conducted by Hu et al. (2020) and Raza et al. (2022) found that Effort Expectancy played a significant role in the adoption of mobile learning and learning management systems, respectively. Similarly, Jakkaew and Hemrungrote (2017) identified the influence of Effort Expectancy in the context of specific platforms like Google Classroom. "Effort expectancy" in the context of a study would describe the degree to which students believe that ChatGPT is simple to use and requires little effort to interact with. Followed hypothesis is proposed:

H2: Effort expectancy has direct and significant impact on Behavioral intention

Social influence "refers to the degree to which an individual perceives that people who are important to them think they should use a particular technology" (Ajzen, 1991; Fishbein & Ajzen, 1975; Venkatesh & Davis, 2003). Numerous studies have established that "Social influence" plays a vital role in determining users' "Behavioral intention" to adopt technology in education. This has been demonstrated in various contexts, including mobile learning (Nikolopoulou et al., 2020), e-learning platforms (Samsudeen & Mohamed, 2019), and learning management systems (Ain et al., 2016). "Social influence" in this study refers to how much students believe their colleagues, teachers, or other influential members of their social environment are supporting or encouraging them to use ChatGPT. Followed hypothesis is proposed:

H3: Social influence has direct and significant impact on Behavioral intention

Facilitating conditions "refers to the degree to which an individual perceives that the necessary resources and support are available to use a particular technology effectively" (Taylor & Todd, 1995; Venkatesh & Davis, 2003). Studies have demonstrated that "Facilitating conditions" is a crucial determinant of both learners' "Behavioral intention" and "Use behavior" and is recognized as one of the most significant factors in determining an individual's technology usage. Additionally, "Facilitating conditions" has been identified as a critical factor in the adoption of various educational technologies, such as mobile learning (Kang et al., 2015), e-learning platforms (Osei et al., 2022), and augmented reality (Faqih & Jaradat, 2021) in higher education. "Facilitating conditions" would refer to how much students believe they have access to the AI tool despite its high demand, as well as their availability of technical support and ChatGPT training. Followed hypotheses are proposed:

H4: Facilitating conditions has direct and significant impact on Behavioral intention

H5: Facilitating conditions has direct and significant impact on Use behavior

Hedonic motivation "refers to the degree to which an individual is motivated to use a particular technology for its inherent enjoyment, pleasure, or novelty" (van der, 2004; Venkatesh & Xu,, 2012). Research has indicated that "Hedonic motivation" plays a crucial role in technology adoption in various educational contexts. For instance, Dajani and Abu Hegleh (2019) found that "Hedonic motivation" was a significant factor in animation usage among university students, while Azizi et al. (2020), Twum et al. (2022), and Zwain (2019) reported its influence on the adoption of mobile learning, e-learning platforms, and learning management systems, respectively. "Hedonic motivation" in this setting would refer to the degree to which students find ChatGPT entertaining or enjoyable to use, as well as the degree to which they enjoy discovering new technological AI tools. Followed hypothesis is proposed:

H6: Hedonic motivation has direct and significant impact on Behavioral intention

Habit "refers to the degree to which an individual's use of a particular technology is automatic or ingrained as a routine behavior" (Limayem et al., 2007; Venkatesh & Xu, 2012). Research has established that Habit plays a crucial role in determining students' "Behavioral intention" to use technology in tertiary education. This is especially true in the context of mobile learning, as evidenced by studies conducted by Ameri et al. (2020) and Yu et al. (2021). Similarly, Zacharis and Nikolopoulou (2022) identified the influence of Habit on the adoption of e-learning platforms, while Alotumi (2022) found Habit to be a crucial factor in the utilization of specific platforms like Google Classroom. Regarding a study, "Habit" can be defined as the level to which students have established a regular and consistent pattern of using ChatGPT as part of their academic routine. This may include factors such as frequency of use, duration of use, and the degree to which ChatGPT has become integrated into their workflow. Followed hypothesis is proposed:

H7: Habit has direct and significant impact on Behavioral intention

H8 Habit has direct and significant impact on Use behavior

Personal innovativeness "refers to an individual's willingness and ability to adopt and use new technology in their daily life" (Agarwal & Prasad, 1998). Studies examining the adoption of various educational technologies have shown that Personal innovativeness is an essential addition to the UTAUT2 model in higher education contexts. For example, Twum et al. (2022) found that Personal innovativeness significantly influences the adoption of e-learning platforms. Similarly, Dajani and Abu Hegleh (2019) identified Personal innovativeness as a crucial factor in the usage of animation among university students, while Farooq et al. (2017) found it to be a determinant in the adoption of lecture capture systems. Additionally, Sitar-Taut and Mican (2021) found that Personal innovativeness plays a vital role in the adoption of mobile learning during social distancing. In the study's context, personal innovativeness would pertain to the level of willingness among students to embrace innovative technological tools like ChatGPT and their perceived ability to acquire and master new technological skills. Followed hypothesis is proposed:

H9: Personal innovativeness has direct and significant impact on Use behavior

Behavioral intention "refers to an individual's subjective likelihood or intention to use a particular technology in the future" (Davis, 1986; Venkatesh & Xu,, 2012). "Behavioral intention" would refer to the degree to which students intend to use ChatGPT in the higher education process.

It is a significant indicator of actual technology use and is influenced by the other UTAUT2 model constructs. Use behavior "refers to the actual usage of a technology by an individual, after having formed behavioral intentions towards its use" (Venkatesh & Davis, 2012). Use behavior in this study refers to the frequency, duration, and patterns of usage as well as the degree to which students actually use ChatGPT in their academic work. The use behavior is also be influenced by habit.

This study has included "Study year" and "Gender" as moderating variables that may affect the relationships between the model predictors and the "Behavioral intention" and "Use behavior" of ChatGPT. We have chosen to use only two moderators in the model due to the difficulty in measuring the original moderator "Experience", given the short time that ChatGPT has been available to users. "Gender" is employed in a similar manner to the original theory, but we have substituted

"Age" with "Study Year". We will not inquire about respondents' specific age but rather their study year and level. Our theoretical model is presented in Figure 1, which includes seven predictors, six of which are originally from the UTAUT2 model, and an additional external variable, "Personal Innovativeness".

Measurement scale

The method used for data collection involved the use of a seven-point Likert scale that provided respondents with options ranging from "strongly disagree" to "strongly agree". To measure use behavior, a 7-options scale was utilized with response options ranging from "never" to "several times a day". To standardize model estimation for each option, we have established a numerical metric scale ranging from 1 to 7. This scale is defined as follows: "Never" corresponds to 1, "Once a month" corresponds to 2, "Several times a month" corresponds to 3, "Once a week" corresponds to 4, "Several times a week" corresponds to 5, "Once a day" corresponds to 6, and "Several times a day" corresponds to 7. A detailed presentation of the measurement scale and descriptive statistics is available in Table 1.

We utilized a total of 30 items, 18 of which were adapted from Venkatesh et al.'s (2003, 2012) studies that developed the UTAUT and UTAUT2 models. The original items from these studies

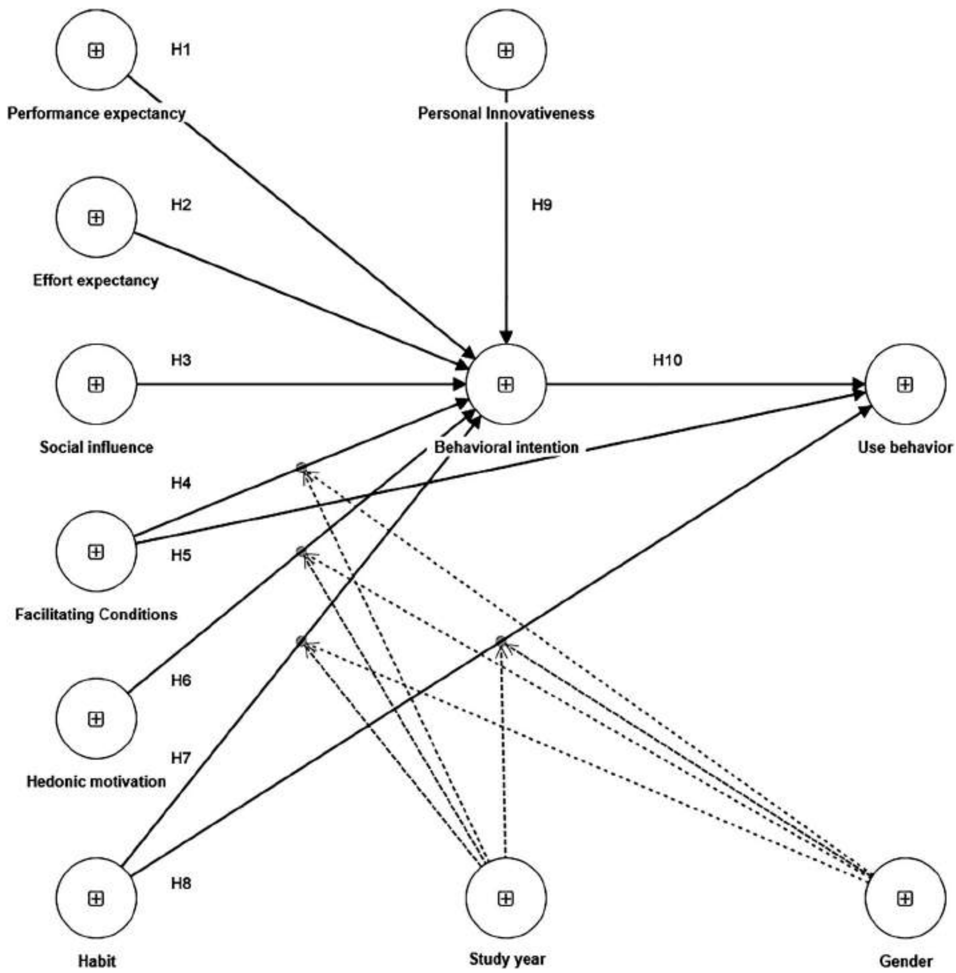

Figure 1. A proposition for ChatGPT acceptance and use model.

pertained to “using the system” and “using mobile Internet”, respectively. We modified these items to refer to “using ChatGPT” in this study. “Performance expectancy” consists of four items that are oriented towards using ChatGPT “in studies”. Similarly, “Effort expectancy” contains 4 items, “Social influence” has 3 items as per UTAUT2, “Facilitating conditions” has 4 items, and “Behavioral intention” has 3 items. These variables were initially introduced in the 2003 version of UTAUT. Additionally, “Hedonic motivation” has 3 items and “Habit” has 4 items, as per the UTAUT2 version from 2012. “Use behavior” is measured with a 7-option scale, and only 1 item was utilized in this study. Venkatesh et al.’s (2012) original study did not provide details on how “Use behavior” was measured. In this study, the use of ChatGPT was measured on a 7-option scale ranging from

Table 1. Measurement scale and factor loadings.

Construct	Item	Items	Loading	Mean	St.dev.	Adapted from
Performance expectancy	PE1	“I believe that ChatGPT is useful in my studies”	0.905	5.147	1.696	Venkatesh et al. (2003, 2012)
	PE2	“Using ChatGPT increases your chances of achieving important things in your studies”	0.870	4.702	1.789	
	PE3	“Using ChatGPT helps you get tasks and projects done faster in your studies”	0.895	5.548	1.619	
	PE4	“Using ChatGPT increases your productivity in your studies”	0.867	4.873	1.857	
Effort expectancy	EE1	“Learning how to use ChatGPT is easy for me”	0.870	5.687	1.507	Venkatesh et al. (2003, 2012)
	EE2	“My interaction with ChatGPT is clear and understandable”	0.893	5.629	1.450	
	EE3	“I find ChatGPT easy to use”	0.895	5.821	1.400	
	EE4	“It is easy for me to become skillful at using ChatGPT”	0.912	5.732	1.427	
Social influence	SI1	“People who are important to me think I should ChatGPT”	0.939	3.944	1.580	(Venkatesh & Xu, 2012)
	SI2	“People who influence my behavior believe that I should use ChatGPT”	0.943	3.903	1.590	
	SI3	“People whose opinions I value prefer me to use ChatGPT”	0.937	3.897	1.629	
Facilitating conditions	FC1	“I have the resources necessary to use ChatGPT”	0.853	3.944	1.580	Venkatesh et al. (2003, 2012)
	FC2	“I have the knowledge necessary to use ChatGPT”	0.903	3.903	1.590	
	FC3	“ChatGPT is compatible with technologies I use”	0.829	3.897	1.629	
	FC4	“I can get help from others when I have difficulties using ChatGPT” (dropped)	0.595	3.944	1.580	
Hedonic motivation	HM1	“Using ChatGPT is fun”	0.955	5.819	1.537	(Venkatesh & Xu, 2012)
	HM2	“Using ChatGPT is enjoyable”	0.962	5.756	1.505	
	HM3	“Using ChatGPT is very entertaining”	0.729	5.210	1.716	
Habit	HT1	“The use of ChatGPT has become a habit for me”	0.893	5.819	1.537	(Venkatesh & Xu, 2012)
	HT2	“I am addicted to using ChatGPT”	0.846	5.756	1.505	
	HT3	“I must use ChatGPT”	0.783	5.210	1.716	
	HT4	“Using ChatGPT has become natural for me”	0.890	5.819	1.537	
Behavioral Intention	BI1	“I intend to continue using ChatGPT in the future”	0.905	5.371	1.789	(Venkatesh & Xu, 2012)
	BI2	“I will always try to use ChatGPT in my studies”	0.832	3.383	1.912	
	BI3	“I plan to continue to use ChatGPT frequently”	0.939	4.433	2.048	
Personal innovativeness	PI1	“I like experimenting with new information technologies”	0.914	5.752	1.591	(Agarwal & Prasad, 1998)
	PI2	“If I heard about a new information technology, I would look for ways to experiment with it”	0.910	5.379	1.667	
	PI3	“Among my family/friends, I am usually the first to try out new information technologies”	0.823	5.363	1.784	
	PI4	“In general, I do not hesitate to try out new information technologies”	0.786	5.288	1.767	
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”	1.000	3.435	1.597	(Venkatesh & Xu, 2012)

"never" to "several times a day". Finally, the remaining four items were adapted from Agarwal and Prasad's (1998) study. Before administering the new scales developed for this study to the targeted audience, a pilot study was conducted with 36 students (18 women and 18 men) from the bachelor study program to test their efficacy. Each construct met the reliability and validity criteria, and discriminant validity was confirmed (Fornell & Larcker, 1981; Hair et al., 2013).

Sample characteristic

For a Partial Least Squares Structural Equation Modeling (PLS-SEM), choosing the right sample size is crucial to ensuring the accuracy and validity of the findings. In PLS-SEM studies, the sample size is not fixed and is dependent on a number of variables, including the model's complexity, the number of latent variables and indicators, the magnitudes of the effects, and the desired level of statistical power (Hair et al., 2013). While others recommend that the sample size to indicator ratio should be at least 5:1 or 10:1, some researchers recommend a minimum sample size of 100–200 observations (Kock, 2018). For this study, a significant sample size of 300 observations is required because there are 30 indicators in use (Table 1).

The questionnaire was distributed via Google Forms and sent directly to the email addresses of students at the University of Economics in Katowice, Poland, at the beginning of March 2023. The survey remained open for one week. A total of 534 valid responses were collected, resulting in a response rate of 3.99%. The sample consisted of 229 female students (42.9%), 282 male students (52.8%), and 23 students who preferred not to disclose their gender (4.3%). The sample size was diverse in terms of academic progress, with 29 students from the first year (5.4%), 170 students from the second year (31.8%), and 200 students from the third year (37.5%) of the bachelor's degree program. The sample also included 57 students from the first year (10.7%) and 69 students from the second year (12.9%) of the master's degree program and nine PhD candidates (1.7%).

Results

To estimate the model, we used the PLS-SEM algorithm with the weighting path scheme in SmartPLS 4 software (Version 4.0.9.1) with a maximum of 3000 iterations and default initial weights, and employed bootstrapping, a nonparametric procedure, running 5000 samples, to determine the statistical significance of the PLS-SEM results, as recommended by Ringle et al. (2022). Reflectively specified constructs were analyzed using the indicator loadings, and an indicator loading above 0.7 suggested that the construct accounted for more than 50% of the variance in the indicator, indicating an acceptable level of item reliability. Table 1 presents the loadings, which exceed the lower bond. Item FC4 with the question "I can get help from others when I have difficulties using ChatGPT" was removed from further processing in the model because it was vague due to too low loadings value. It was not considered, leaving the model with 29 items used to estimate the model.

Composite reliability is a standard for evaluating reliability, with results ranging from 0.70 to 0.95 indicating acceptable to good levels of reliability (Hair et al., 2022). Internal consistency reliability was measured using Cronbach's alpha, which uses similar thresholds as composite reliability (ρc). Another reliability coefficient ρA, based on Dijkstra (2010), was also used to provide an exact and consistent alternative. The average variance extracted (AVE) from all items linked to a specific reflective variable was used to assess the convergent validity of the measurement models, and an AVE threshold of 0.50 or higher was deemed acceptable (Sarstedt et al., 2022). Composite reliability, Cronbach's alpha, reliability coefficient, and AVE met the quality criteria presented in Table 2.

To analyze discriminant validity in PLS-SEM, the preferred method is the heterotrait–monotrait ratio of correlations (HTMT) introduced by Henseler et al. (2015). A HTMT threshold of .90 is recommended to ensure discriminant validity, particularly when constructs are conceptually similar, whereas a threshold of .85 is more appropriate for more distinct constructs. In Table 3, all values fall below the .85 threshold, indicating good discriminant validity.

Table 2. Construct reliability and validity.

	Cronbach's alpha	Reliability coefficient	Composite reliability	AVE
Behavioral intention	0.872	0.882	0.922	0.797
Effort expectancy	0.915	0.927	0.940	0.797
Facilitating Conditions	0.827	0.830	0.897	0.743
Habit	0.879	0.915	0.915	0.730
Hedonic motivation	0.867	0.951	0.917	0.790
Performance expectancy	0.907	0.909	0.935	0.782
Personal Innovativeness	0.882	0.896	0.919	0.740
Social influence	0.934	0.936	0.958	0.883

Table 3. HTMT values.

	BI	EE	FC	HT	HM	PE	PI	SI	UB
BI									
EE	.636								
FC	.629	.798							
HT	.767	.376	.384						
HM	.740	.744	.760	.412					
PE	.841	.596	.595	.613	.725				
PI	.621	.597	.610	.402	.639	.586			
SI	.612	.420	.489	.503	.462	.583	.407		
UB	.748	.538	.559	.629	.496	.577	.516	.451	

Note: PE: performance expectancy; EE: effort expectancy; SI: social influence; FC: facilitating conditions; HM: hedonic motivation; PV: price value; HT: habit; PI: personal innovativeness; BI: behavioral intention; UB: use behavior.

The coefficient of determination (R2) is then assessed to determine the explanatory power of each construct and the overall model. R^2 ranges from 0 to 1, and higher values indicate larger explanatory power. As a general rule of thumb, R^2 values of 0.25, 0.50, and 0.75 are considered weak, moderate, and substantial, respectively (Hair et al., 2011). To determine the effect size of a variable, f^2 values of 0.35, 0.15, and 0.02 correspond to large, medium, and small effects, respectively, and values below 0.02 suggest an absence of impact (Sarstedt et al., 2022).

Figure 2 displays the results of the PLS-SEM analysis, with standardized regression coefficients indicating the relationships between the variables and R^2 values presented within the circles. The analysis revealed that the strongest predictor of "Behavioral intention" was "Habit" having a coefficient of .351, followed by "Performance expectancy" (.261) and "Hedonic motivation" (.221), which together accounted for 73.4% of the variance in "Behavioral intention". Positive effect on "Behavioral intention" were also observed for "Social influence" (.099), "Effort expectancy" (.085), and "Personal innovativeness" (.086), but these relationships did not have a significant f^2 effect size. Conversely, "Behavioral intention" had the most significant impact (.415) on "Use behavior", followed by "Habit" (.251) and "Facilitating conditions" (.179), accounting for 56.3% of the variance in "Use behavior". The only hypothesis that was not supported is H4, as we did not confirm the effect of "Facilitating conditions" on "Behavioral intention". The significance tests for the structural model's path coefficients and hypotheses confirmation are presented in Table 4.

We have incorporated moderating relationships of "Gender" and "Study year" into the model, which were hypothesized a priori and specifically tested. The results of the moderating effect of "Gender" and "Study year" are presented in Table 5. The findings reveal that none of the two moderating variables had a significant impact on the tested relationships between predictors and dependent variables.

Discussion

Our research adds to the current understanding of how ChatGPT is perceived by students. Although there is limited literature on this topic, particularly in the context of higher education, our findings

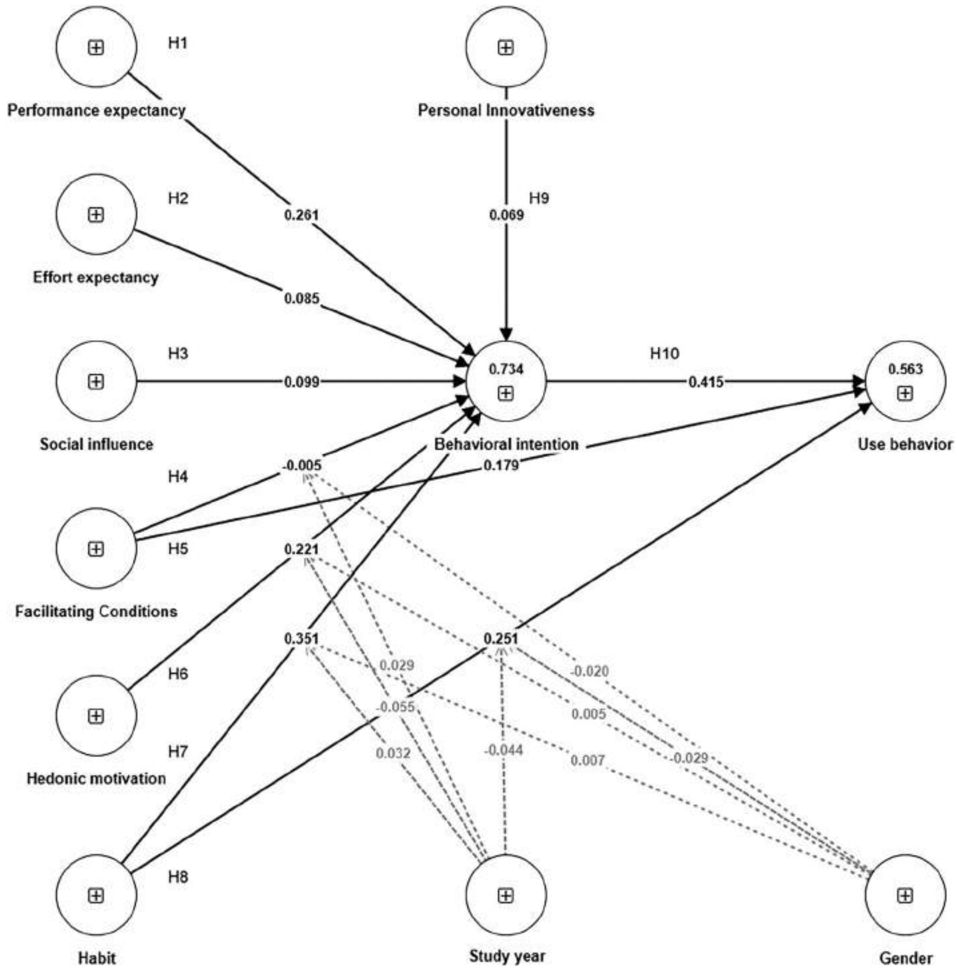

Figure 2. The results for ChatGPT acceptance and use model.

have significant implications for expanding the conversation on the use of AI chat technology as an academic aid. We utilized the core constructs from UTAUT2 scale and "Personal innovativeness" to evaluate the acceptance and usage of ChatGPT, and all seven external variables met the reliability and validity standards. Our results confirm that three variables – "Performance expectancy", "Habit", and "Hedonic motivation" – are positively associated with "Behavioral intention", aligning with El-Masri and Tarhini (2017) study on users' acceptance of e-learning system.

Table 4. Path coefficients and the results of the significance tests.

Hypothesis	Path	Coefficient	*P* values	f^2	Confirmed
H1	Performance expectancy → Behavioral intention	.261	.000	.100	Yes
H2	Effort expectancy → Behavioral intention	.085	.028	.011	Yes
H3	Social influence → Behavioral intention	.099	.002	.023	Yes
H4	Facilitating Conditions → Behavioral intention	−.005	.906	.000	No
H5	Facilitating Conditions → Use behavior	.179	.000	.051	Yes
H6	Hedonic motivation → Behavioral intention	.221	.000	.064	Yes
H7	Habit → Behavioral intention	.351	.000	.287	Yes
H8	Habit → Use behavior	.251	.000	.074	Yes
H9	Personal Innovativeness → Behavioral intention	.069	.026	.010	Yes
H10	Behavioral intention → Use behavior	.415	.000	.162	Yes

Table 5. Moderating effects.

Path	Coefficient	*P* values	f^2	Moderating effect
Study year x Habit → Behavioral intention	.032	.192	.003	No
Study year x Habit → Use behavior	−.044	.196	.005	No
Study year x Facilitating Conditions → Behavioral intention	.029	.391	.002	No
Study year x Hedonic motivation → Behavioral intention	−.055	.118	.005	No
Gender x Habit → Behavioral intention	.007	.775	.000	No
Gender x Habit → Use behavior	−.029	.334	.002	No
Gender x Hedonic motivation → Behavioral intention	.005	.911	.000	No
Gender x Facilitating Conditions → Behavioral intention	−.020	.615	.001	No

Our study confirms the previous findings of Venkatesh and Xu, (2012) and Yu et al. (2021) regarding the strong association between "Performance expectancy" and "Habit" in the acceptance of emerging technologies in higher education. Specifically, in the context of AI-powered chat technology like ChatGPT, our results indicate that students are comfortable adopting new technologies and that their frequency of use contributes to the development of habitual behavior. The majority of technology acceptance studies in higher education have also found that "Habit" has a significant positive impact on "Behavioral intention". For example, studies have shown that "Habit" positively influences the acceptance and use of learning management system (Zwain, 2019) and e-learning adoption (Osei et al., 2022). However, our findings differ from those of Ain et al. (2016), who discovered no direct impact of "Habit" on "Behavioral intention" to use learning management systems, as well as Twum et al. (2022), who discovered no direct effect of "Habit" on "Behavioral intention" to use e-learning. Our study also proves the significant relationship between "Habit" and "Use behavior", consistent with the original UTAUT2 model.

We found that "Performance expectancy" is the second strongest predictor of "Behavioral intention". These results are consistent with previous research that has demonstrated a positive correlation between "Performance expectancy" and "Behavioral intention" in various contexts, such as learning management software (Raza et al., 2022), and mobile learning (Kang et al., 2015). Moreover, "Performance expectancy" has been identified as a significant predictor of "Behavioral intention" in other studies, such as Edumadze et al.'s (2022) investigation of students' perception of using video conferencing tools and Wong et al.'s (2015) study on the intention to use interactive whiteboards. Our findings suggest that students are more likely to adopt functional technologies like ChatGPT when they have high levels of "Performance expectancy".

Our study showed that there is a positive relationship between "Hedonic motivation" and "Behavioral intention" to use ChatGPT. Students perceive AI chat as enjoyable and entertaining, possibly because of the dialogue-based interface that interacts with users and allows for various types of conversations within the boundaries set by the ChatGPT authors. It is consistent with earlier studies on the adoption of new technologies in higher education, such as massive online open courses (Tseng et al., 2022) and e-learning platforms (Samsudeen & Mohamed, 2019). On the other hand, our findings are contradictory to studies that examined the use of Google Classroom (Alotumi, 2022) and in e-learning adoption (Mehta et al., 2019).

Our study shows that both "Effort expectancy" and "Social influence" have a significant positive effect on "Behavioral intention", although their f^2 values are less than 0.02. Among all the variables, "Effort expectancy" received the highest mean values in students' responses, indicating a widespread use of AI-powered chat technology and no issues with interacting with ChatGPT. This finding suggests that the effort required to use this technology in higher education is low and does not affect "Behavioral intention". Similar results have been reported in studies on the use of e-learning platforms during social distancing (Zacharis & Nikolopoulou, 2022) and Microsoft PowerPoint use in higher education (Chávez Herting et al., 2023). As early adopters and quick learners, students often find new technologies easy to use and quickly become skilled at using them.

The impact of "Social influence" on the "Behavioral intention" to use ChatGPT is low, according to our study. The use of the AI-powered chat is more likely among early adopters who have a welleducated background and are not influenced by external factors. Because ChatGPT is a relatively new technology and has not yet gained widespread adoption, our findings imply that there is no social pressure to adopt it. However, as universities develop policies regarding the use of AI tools like ChatGPT, "Social influence" may become more relevant. Previous studies have shown "Social influence" to be a significant factor in "Behavioral intention" in areas such as mobile devices (Hoi, 2020) and mobile learning (Ameri et al., 2020), while other studies such as Kumar and Bervell (2019) or Alotumi (2022) on Google Classroom acceptance did not find such significance.

Our study found that the "Facilitating conditions" had no significant impact on "Behavioral intention". Although this construct initially included an item FC4, which was removed from the model because its loading was below the expected value of 0.7, it still did not have a significant effect on "Behavioral intention". However, it did have a significant impact on "Use behavior" as per the original UTAUT model. Our findings suggest that students find ChatGPT's interface easy to use, and it is available in several languages, requiring only prompts to operate. No additional resources or devices are necessary, and it works independently. Prior research on the adoption of technology has also reported that "Facilitating conditions" have no effect on "Behavioral intention" (Ameri et al., 2020; Arain et al., 2019).

"Personal innovativeness", was found to have a slightly positive effect on "Behavioral intention", although its f^2 value was less than 0.02. This result suggests that students may have limited experience with ChatGPT and may not be familiar enough with using it. The model we used explains 73.4% of the variation in "Behavioral intention", indicating a substantial explanatory power. Furthermore, "Behavioral intention" has a significant and direct impact on "Use behavior", which is explained by the model to a moderate extent of 56.3%.

The uniqueness of this study is its emphasis on ChatGPT, a recently developed language model that has not been extensively investigated in the context of higher education. The scarcity of previous studies on ChatGPT, particularly regarding its use and acceptance in higher education, emphasizes the novelty of this research. Consequently, the outcomes of this study could significantly contribute to the understanding of ChatGPT adoption and utilization in higher education and assist in developing effective educational applications for this technology.

Conclusion

The objective of this research was to investigate the acceptance of ChatGPT among students and validate the significant influence of "Habit", "Performance Expectancy", and "Hedonic Motivation" on the "Behavioral Intention" to use ChatGPT. However, this research is limited by the fact that the sample was drawn from only one state university in Poland, although it was diverse in terms of students' academic backgrounds. Since ChatGPT use in higher education is still an emerging area of research, future studies can further evaluate the scale employed in this study and improve it for future research.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Notes on contributor

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Data statement

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

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