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# ChatGPT in higher education: Investigating bachelor and master students' expectations towards AI tool

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## Abstract
This research explored the attitudes of higher education students toward ChatGPT, an AI tool commonly employed for academic assistance. Our aim was to investigate students' acceptance and use of ChatGPT during their academic pursuits. We targeted two distinctive groups for our study: undergraduate and postgraduate students. Our findings show that various elements influence students' intent to use, as well as their actual use of ChatGPT. Among these factors, performance expectancy proved to be the most influential factor for both groups. However, there was noticeable variation in other determinants, such as social influence, effort expectancy, and hedonic motivation derived from using the tool, which differed significantly between the two groups. The models we used for our research were able to explain 65.3% and 73.5% of the change in behavioral intention for undergraduates and postgraduates, respectively. They also accounted for 49.3% and 59.2% of the change in use behavior among these two groups. This study offers new insights into the dynamics influencing student interaction with AI tools such as ChatGPT in academic settings.

**Keywords** ChatGPT · Higher education · Bachelor students · Master students

## 1 Introduction

The ChatGPT of OpenAI is an inventive language model that transforms educational environments (OpenAI, 2023). Its ability to answer questions in fields such as engineering and mathematics, create text, and compose essays has made it a valuable tool for both students and educators, saving them considerable time and effort. Notably, it aids educators by generating concise, grammatically sound content for

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lectures and academic papers. However, there are also some notable concerns arising from this easily accessible technology (Cooper, 2023).

The integration of ChatGPT in higher education has been met with a mixed response due to concerns over academic integrity. Certain institutions have restricted access to the AI chatbot or, in extreme cases, prohibited it entirely to deter academic dishonesty (Cotton et al., 2024). Some universities are even reconsidering traditional testing methods, such as paper-and-pencil tests (Hsu, 2023). While ChatGPT can indeed augment learning and teaching, it is essential to regulate its use and establish guidelines to promote responsible usage. Several limitations have been identified, such as its dependency on an outdated knowledge database and struggles with basic mathematical problems (Mogali, 2024). Critics have also voiced concerns over the potential unreliability of AI responses and their potential effect on critical thinking and independent learning.

However, the use of ChatGPT is not without its merits. When implemented effectively, it can enhance the educational experience and stimulate critical thinking. Professors can employ it to assess students' understanding of course material or to stimulate deeper contemplation of known subjects (Rudolph et al., 2023). Furthermore, ChatGPT's ability to process and understand complex topics in a matter of seconds saves valuable time, making it a beneficial tool for both students and researchers. As such, AI has the potential to modernize higher education, shifting the focus from rote memorization to critical thinking and better preparing students for real-world scenarios (Mbakwe et al., 2023).

However, this technology also poses potential threats to the academic world. Students could develop a reliance on technology and a deficit in critical thinking and problem-solving abilities by relying on technology to finish their assignments without actually comprehending the underlying concepts. This, coupled with academic dishonesty, can lead to technology misuse. (Perkins, 2023). Furthermore, students' use of technology to plagiarize assignments can diminish the value of the educational process and depreciate the diligence of those who finish their work with their own effort. (Rahimi & Talebi Bezmin Abadi, 2023). Researchers may also misuse the technology by manipulating or fabricating data, compromising the integrity of research. Additionally, GPT-3 may help to maintain negative stereotypes and biases (Thorp, 2023).

In the age of open-source AI such as ChatGPT, new measures should be taken to guarantee the quality of theses, journals, and research papers. Incorporating ethical and responsible usage of such tools into academic programs, along with adopting rigorous ethical principles for research, is important (Lim et al., 2023). Ultimately, the responsible usage of ChatGPT and various AI tools in education can help promote an emerging approach toward learner autonomy, but schools need to provide students with the knowledge and abilities to critique and evaluate information obtained through technology (Anders, 2023).

While some research has been conducted on academic integrity in the context of ChatGPT, there is limited discussion on how students perceive AI tools (Sullivan et al., 2023). Some studies have examined the implications of the ChatGPT in various fields, including tourism education (Ivanov & Soliman, 2023), environmental research (J. Zhu et al., 2023), medical education (Lee, 2024), and scholarly publishing (Lund et al., 2023). They highlighted the benefits of using ChatGPT as a virtual assistant for research and teaching, cautioning against the overreliance on AI tools and emphasizing the need for ethical considerations. However, concerns have been raised about students using AI chatbots such as ChatGPT to cheat, and universities must address these concerns by developing policies and tools to prevent academic dishonesty. There is a need for further studies to investigate the impact of ChatGPT on academic integrity and achievement and students' perceptions of the technology's impacts.

Apart from the numerous benefits of using ChatGPT in higher education, a significant gap exists in the research regarding its adoption and acceptance by university students. This technology is relatively new, and there are limited empirical data on how students perceive and utilize chatbots. Further research is needed to investigate the elements that affect students' acceptance and utilization of ChatGPT, including their prior experience with AI-based technologies, the quality of responses provided by chatbots, and their attitudes toward technology-enabled learning. A deeper understanding of these factors will aid in developing effective strategies to integrate ChatGPT into higher education and maximize its potential to improve students' learning results.

## 2 Literature review

In the recent body of literature, published in the last year, several studies in which the UTAUT or UTAUT2 frameworks were used to assess which factors from these theories are the most influential on the intention to use the ChatGPT among students have been published. The Norwegian study proved that performance expectancy emerged as the construct with the greatest impact on "behavioral intention", followed by "habit" (Grassini et al., 2024), whereas in a highly competitive Chinese context, several studies have shown that "performance expectancy", trust and anthropomorphism are the strongest positive predictors of attitudes (Du & Lv, 2024; Xia & Chen, 2024; Xu & Thien, 2024; Yee et al., 2024; Zheng et al., 2024). In the UK, Nepal, Poland, Egypt, and Ghana, performance expectancy, effort expectancy and social influence significantly impact the adoption intention of ChatGPT for all countries (Arthur et al., 2024; Budhathoki et al., 2024; Strzelecki & ElArabawy, 2024), whereas in Malaysia, elements from UTAUT2, such as hedonic motivation, habit, and facilitating conditions, impact students' continuous intentions to utilize AI tools (Tan et al., 2024). Habit was also found to be the strongest predictor in an Indian study (Sudan et al., 2024). The same approach was used to examine Google Gemini's acceptance and usage in higher education, a competitor to ChatGPT (Doris & Brennan, 2024). Similarly, the same UTAUT framework was used to check the intention to use and actual use among educators in India, Poland and China (Bhat et al., 2024; Strzelecki et al., 2024; Wijaya et al., 2024). Several studies have tested the moderating effect of gender on the use of ChatGPT by students (Arthur et al., 2024; Elshaer et al., 2024; Strzelecki & ElArabawy, 2024).

Other factors, such as ease of use (Abdaljaleel et al., 2024; Acosta-Enriquez et al., 2024), digital competency (Hazaimeh & Al-Ansi, 2024), subjective norms (Ivanov et al., 2024), perceived behavioral control(Al-Qaysi et al., 2024), life satisfaction (Rehman et al., 2024), perceived importance and perceived concerns (Yusuf et al., 2024), also significantly influence the usage of ChatGPT by students. Researchers have also used other theories, such as the technology acceptance model (TAM) (Almulla, 2024), theory of planned behavior (TPB) (Al-Qaysi et al., 2024; Ivanov et al., 2024; Tan et al., 2024), social cognitive theory (Bouteraa et al., 2024), expectancy-value theory (Herani & Angela, 2024) and emotional intelligence (Mosleh et al., 2024). The growing body of recent studies has allowed the formation of a few scoping reviews and meta-analyses in which theories and frameworks were used to study the acceptance and use of the ChatGPT by students (Ali et al., 2024; Bhullar et al., 2024; Nikolopoulou, 2024).

Some recent studies have used qualitative, mixed-method or experimental methods to assess how students or educators perceive the ChatGPT and how to use it in everyday tasks. The findings imply that instructors require assistance in comprehending the breadth and implications of artificial intelligence (AI) and its applications to personalized learning, assessment, and content creation (Mathew & Stefaniak, 2024). Other themes that emerged from asking students how they perceive AI tools include immediacy, equity, and integrity (Holland & Ciachir, 2024). Analyses revealed that positive and negative emotions were associated with education among students (Gupta et al., 2024). Students consider AI tools to be brainstorming partners for writing and reading, enhancing research efficiency and comprehension (Aure & Cuenca, 2024); however, the consequences of using AI tools can be both positive and negative (Ghimire et al., 2024), and while AI tools can generate comprehensive and correct responses, they may have limitations when dealing with more complicated cognitive tasks (Govender, 2024). The typical task for students with ChatGPTs can be summarizing texts and idea generation (Stojanov et al., 2024; Zhu et al., 2024). Over the past year, even more studies have emerged regarding students' acceptance of the ChatGPT. However, the proposed study examining differences between undergraduate and postgraduate students remains unexplored.

The objective of this study is to address the existing research gap regarding the integration of ChatGPT by university students into their learning process. Given that ChatGPT was released only in November 2022, there is currently a limited timeframe available for research and examination. Thus, a cross-sectional study design is deemed appropriate at this stage, as longitudinal data and multiple study approaches are not feasible within this limited period. To conduct a cross-sectional study, we propose utilizing a well-suited theory framework, such as the "Unified Theory of Acceptance and Use of Technology (UTAUT)", to evaluate the level of adoption and utilization of the ChatGPT by higher education students.

The literature contains numerous studies utilizing the UTAUT framework to examine the adoption of new technologies. Some may question the need for more research using established theories in the face of rapidly changing technological landscapes. However, we believe that the advent of free-to-access AI tools such as ChatGPT signals a transformative shift in technology (van Dis et al., 2023). Leveraging proven methodologies such as UTAUT allows us to probe the perceptions and usage patterns of ChatGPT across various stakeholder groups. In particular, we intend to explore how university students, often seen as technologically adept, embrace and utilize this cutting-edge tool.

The following describes how the study unfolds. First, we introduce ChatGPT and discuss its potential use in education, as well as its benefits and drawbacks. Then, we detail the theoretical framework used to investigate ChatGPT acceptance and utilization among higher education students in the methods section. Next, we present our findings for undergraduate and graduate students in the Results section. In our discussion, we draw comparisons with other technology adoption studies, as the literature specifically on ChatGPT adoption remains scant. Our conclusion summarizes our research, acknowledges its limitations, and proposes avenues for future exploration.

## 3 Methodology

Our research aimed to evaluate the adoption and use of the AI tool ChatGPT among students. Therefore, we suggest applying the "Unified Theory of Acceptance and Use of Technology (UTAUT)" model proposed by Venkatesh et al. (2003). The UTAUT consolidates eight prior technology acceptance theories, identifying four variables that influence "Behavioral Intention" and "Use Behavior": "Performance Expectancy", "Effort Expectancy", "Social Influence", and "Facilitating Conditions". The model also recognizes four moderators: "Gender", "Age", "Experience", and "Voluntariness of Use". Venkatesh et al. (2012) later revised the model by introducing three more external variables while removing one moderator. In our study, we aimed to explore the original UTAUT model, which was enhanced with "Hedonic Motivation" and "Personal Innovativeness". The latter, conceived by Agarwal and Prasad (1998), allows for an analysis of how an individual's personal traits may influence their acceptance of novel technologies.

We have chosen to exclude the two external variables added in the UTAUT2 revision, namely, "price value" and "habit". Since ChatGPT is free, "price value" does not apply. Although a premium version, ChatGPT Plus, exists, its extra features are not necessary to leverage the tool effectively. Hence, these factors are omitted from the study. We also do not use "Habit" since the presence of ChatGPT is relatively new, and it is premature to determine whether the use of this AI tool could become habitual. As Dwivedi et al. (2019) noted, the current UTAUT is frequently tested in a modified version, where certain variables are either added or omitted. Additionally, some studies have reported that including too many variables that impact "Behavioral intention" and "Use behavior" can lead to suppressor effects, and some variables may not be significant.

Our aim is to investigate the effects of six external variables on how students accept and use ChatGPT. We will test the effects of "Performance Expectancy," "Effort Expectancy," "Social Influence," "Facilitating Conditions," and "Personal Innovativeness" on "Behavioral Intention" and "Use Behavior" toward ChatGPT in the context of higher education. Since we do not include moderating variables, we plan to test for differences between the two study groups, namely, those with a bachelor's degree and those with a master's degree. We hypothesize that students' study experience, which varies depending on their level of study, significantly influences how they perceive and use ChatGPT.

### 3.1 Hypothesis development

Performance expectancy "refers to an individual's belief that using a system or technology will help them attain improvements in job performance" (Venkatesh et al., 2003). It has been found to be a significant predictor of "behavioral intention" to use information systems. In the context of the study testing the acceptance and usage of ChatGPT by students in higher education, "performance expectancy" refers to students' belief that using the system will help them achieve benefits for their learning practices. In the present context, these findings support students' conviction of the usefulness of ChatGPT for their academic tasks. We propose the following hypothesis:

**H1**: "Performance expectancy positively, directly and significantly influences behavioral intention."

Effort expectancy "refers to the degree of ease associated with using a technology" (Venkatesh et al., 2003). It has been shown to be a significant predictor of "behavioral intention" to use technology. The concept focuses on the extent to which a technology is effort-free and user-friendly. In the context of ChatGPT, "effort expectancy" refers to how simple the system is to use and the degree to which it would require little effort and enable students to be free of distractions. We propose the following hypothesis:

**H2**: "Effort expectancy positively, directly and significantly influences behavioral intention"

Social influence has been identified as a key factor influencing technology adoption and usage, particularly in the early adoption phase (Venkatesh et al., 2003). The impact of "social influence" on "behavioral intention" varies depending on the mandatory or voluntary nature of the situation. In this study, "social influence" refers to how strongly individuals perceive that their close friends and family believe they should use ChatGPT in their higher education activities. We propose the following hypothesis:

**H3**: "Social influence positively, directly and significantly influences behavioral intention."

Facilitating conditions "refers to the degree to which individuals perceive that the necessary technological infrastructure is available to support the use of a new system, such as access to adequate hardware and software" (Venkatesh et al., 2003). While "facilitating conditions" is typically related to both "behavioral intention" and "use behavior" in the UTAUT model, its relevance may be reduced in the case of widely disseminated technologies. In the context of the study testing the acceptance and use of ChatGPT among college students, "facilitating conditions" may be particularly relevant, as they may influence the ease with which students are able to access and use the AI chat. We propose the following hypotheses:

**H4**: "Facilitating conditions positively, directly and significantly influences behavioral intention."
**H5**: "Facilitating conditions positively, directly and significantly influence use behavior."

Hedonic motivation "refers to the pleasure or enjoyment derived from using technology and is an antecedent of Behavioral intention to use a range of technologies" (Venkatesh et al., 2012). In the context of the study on the acceptance and usage of ChatGPT by students in higher education, "Hedonic motivation" is the pleasure or enjoyment that students experience when using AI chats for their studies. It is regarded as a key element of technology adoption because it quantifies the affective aspect of that adoption. Students' opinions of how entertaining and enjoyable the system are likely to have an impact on their decision to use it, and "Hedonic motivation" predicts "Behavioral intention" to use ChatGPT. We propose the following hypothesis:

**H6**: "Hedonic motivation positively, directly and significantly influences behavioral intention."

Personal innovativeness "refers to an individual's willingness to try out new information technology" (Agarwal & Prasad, 1998). It demonstrates the degree to which a person would probably lead the way in experimenting with new technologies and plays a significant role in elucidating the purpose of using new technologies. The adoption and acceptance of new technologies are strongly influenced by "personal innovativeness". In the context of the study testing the acceptance and usage of ChatGPT by students in the higher education process, "Personal innovativeness" refers to a person's readiness to experiment with ChatGPT. Individuals with higher "personal innovativeness" are more likely to have favorable perceptions of AI-chats' usefulness, which may influence their intention to use it. Therefore, high levels of student innovation are expected to strengthen their behavioral intention to use ChatGPT. We propose the following hypothesis:

**H7**: "Personal innovativeness positively, directly and significantly influences behavioral intention"

Behavioral intention, also referred to as "intention to use", is a construct within UTAUT that represents a person's intention to engage in a specific behavior, in this case, using ChatGPT in the higher education process. It forecasts actual use behavior, indicating the likelihood of an individual using the technology in the future. "Behavioral intention" is influenced by "performance expectancy", "effort expectancy", "social influence", and "facilitating conditions", which are the key elements of the UTAUT model. In the context of using ChatGPT in higher education, higher levels of "behavioral intention" are expected to lead to increased adoption and use of the technology by students. We propose the following hypothesis:

**H8**: "Behavioral intention positively, directly and significantly influences use behavior".

Use behavior "refers to the actual usage of a technology or system by individuals". It is a measure of the extent to which individuals actually use the system after accepting it. In the study testing the acceptance and use of ChatGPT by students in the higher education process, use behavior was the measure of how much the students actually used ChatGPT after indicating their intention to use it. Each hypothesis contributes to a better understanding of the relationships between observable and latent variables in the model.

### 3.2 Model proposition

Based on the stated hypotheses and established assumptions of the theoretical model configuration, we present our proposed model in Fig. 1, which comprises eight variables, including six external predicting elements and two dependent variables.

To measure the model, we employed two scales, namely, the scale developed by Venkatesh et al., (2003, 2012) and a scale adopted from Agarwal and Prasad (1998). As we aim to compare the results of the model between two study levels—bachelor's and master's degrees—we included a question about the study degree in the metric section. The measurement scales used were a 7-point Likert scale ranging from "strongly disagree" to "strongly agree" and a scale measuring use behavior from "never" to "several times a day," as presented in Table 1.

### 3.3 Sample characteristics

To establish the final sample size for our study, we considered the recommendations of two different sources. Hair et al. (2011) suggested that a minimum sample

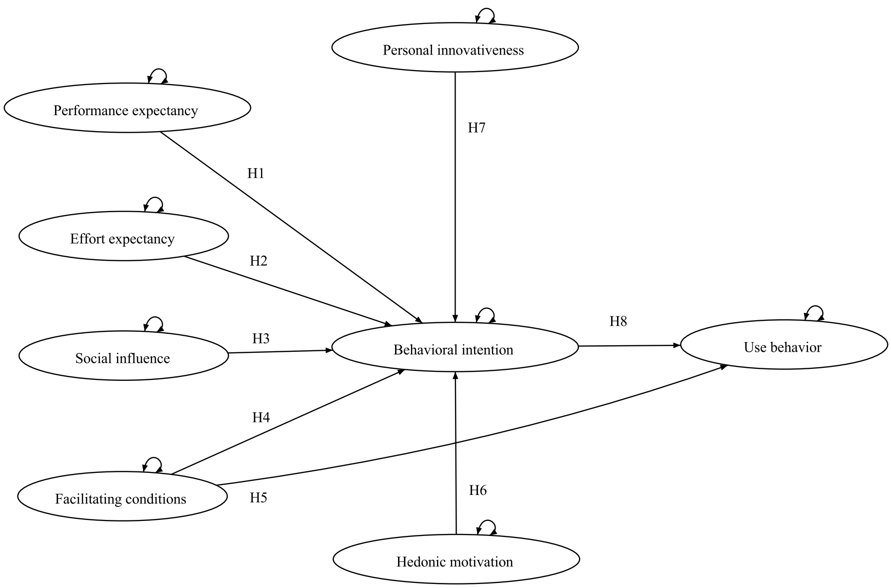


**Fig. 1** Model for testing students' adoption of ChatGPT in the study process

size of 189 is necessary when using the PLS-SEM method to detect $R^2$ values of at least 0.1 with a 5% significance level. Additionally, Arnold (1990) recommended that social science research typically seeks a statistical power of at least 95%. At the beginning of the 2022/23th academic year, the population of public and private universities in Poland was estimated to be approximately 1.2 million students. To determine an appropriate sample size for this population with a 95% confidence level and a margin of error of 5%, the Yamane (1967) formula was employed, which states that "n = (z^2 * p * (1-p))/e^2", where "n represents the sample size, z is the z-score associated with the confidence level (1.96 for 95% confidence level), p is the estimated proportion of the population with the desired characteristic, and e is the margin of error (0.05)". In the absence of an estimate, 0.5 was used as a conservative value to yield the maximum sample size. The calculation resulted in a minimum sample size of 385.

In mid-March 2023, the questionnaire was administered via Google Forms and distributed directly to the email addresses of students enrolled at the University of Economics in Katowice, Poland. The survey was available for a duration of one week. Of the total responses received, 528 were valid. The sample consisted of 228 female students (43.1%), 277 male students (52.5%), and 23 students who chose not to disclose their gender (4.4%). The sample population was divided into two groups based on their degree, with 402 responses from bachelor's degree students and 126 responses from master's degree students. The survey was administered during a period of rapid development in AI, with each month markedly influencing the tool's development. Participants who utilized ChatGPT early in its deployment were identified as early adopters. Additionally, the timing of the survey may have affected tool usage, potentially correlating with periods of coursework submission, significant assignments, or varying by academic discipline.

## 4 Results

To estimate the model, we applied the PLS-SEM algorithm using the path weighting scheme in SmartPLS 4 software (version 4.0.9.1) with default initial weights and a maximum of 3000 iterations. To determine the statistical significance of the PLS-SEM results, we utilized bootstrapping, a nonparametric procedure that runs 5000 samples (Ringle et al., 2022). Reflectively specified constructs were evaluated by analyzing the indicator loadings, where an indicator loading above 0.7 indicates that the construct accounts for more than 50% of the indicator's variance, which demonstrates acceptable item reliability. Table 1 presents the loadings that exceeded the lower bound, except for FC4, which was excluded from further processing in the model.

To assess reliability, we used composite reliability as a standard, with values ranging from 0.70 to 0.95 indicating acceptable to good levels of reliability (Hair et al., 2022). Additionally, we measured internal consistency reliability using Cronbach's alpha, which employs similar thresholds as composite reliability (ρc). To provide an exact and consistent alternative, we also employed an additional reliability coefficient

**Table 1** Measurement scale and factor loadings

| Construct | Item | Scale | Loadings | | |
|---|---|---|---|---|---|
| | | | Bachelor | Master | Complete |
| | PE1 | "I believe that ChatGPT is useful in my studies" | 0.907 | 0.904 | 0.906 |
| | PE2 | "Using ChatGPT increases your chances of achieving important things in your studies" | 0.865 | 0.889 | 0.874 |
| | PE3 | "Using ChatGPT helps you get tasks and projects done faster in your studies" | 0.895 | 0.889 | 0.894 |
| | PE4 | "Using ChatGPT increases your productivity in your studies" | 0.851 | 0.919 | 0.868 |
| Effort expectancy | EE1 | "Learning how to use ChatGPT is easy for me" | 0.874 | 0.854 | 0.870 |
| | EE2 | "My interaction with ChatGPT is clear and understandable" | 0.886 | 0.913 | 0.893 |
| | EE3 | "I find ChatGPT easy to use" | 0.894 | 0.905 | 0.895 |
| | EE4 | "It is easy for me to become skillful at using ChatGPT" | 0.909 | 0.915 | 0.911 |
| Social influence | SI1 | "People who are important to me think I should ChatGPT" | 0.928 | 0.972 | 0.940 |
| | SI2 | "People who influence my behavior believe that I should use ChatGPT" | 0.937 | 0.964 | 0.943 |
| | SI3 | "People whose opinions I value prefer me to use ChatGPT" | 0.931 | 0.955 | 0.937 |
| Facilitating conditions | FC1 | "I have the resources necessary to use ChatGPT" | 0.817 | 0.859 | 0.852 |
| | FC2 | "I have the knowledge necessary to use ChatGPT" | 0.887 | 0.891 | 0.903 |
| | FC3 | "ChatGPT is compatible with technologies I use" | 0.826 | 0.861 | 0.836 |
| | FC4 | "I can get help from others when I have difficulties using ChatGPT" (dropped) | 0.625 | 0.514 | 0.597 |
| Hedonic motivation | HM1 | "Using ChatGPT is fun" | 0.960 | 0.950 | 0.957 |
| | HM2 | "Using ChatGPT is enjoyable" | 0.963 | 0.960 | 0.962 |
| | HM3 | "Using ChatGPT is very entertaining" | 0.713 | 0.773 | 0.725 |
| Behavioral Intention | BI1 | "I intend to continue using ChatGPT in the future" | 0.903 | 0.924 | 0.910 |
| | BI2 | "I will always try to use ChatGPT in my studies" | 0.813 | 0.863 | 0.826 |
| | BI3 | "I plan to continue to use ChatGPT frequently" | 0.935 | 0.952 | 0.940 |
| Personal innovativeness | PI1 | "I like experimenting with new information technologies" | 0.915 | 0.904 | 0.913 |
| | PI2 | "If I heard about a new information technology, I would look for ways to experiment with it" | 0.907 | 0.921 | 0.911 |
| | PI3 | "Among my family/friends, I am usually the first to try out new information technologies" | 0.816 | 0.834 | 0.820 |

**Table 1** (continued)

| Construct | Item | Scale | Loadings | | |
|---|---|---|---|---|---|
| | | | Bachelor | Master | Complete |
| | PI4 | "In general, I do not hesitate to try out new information technologies" | 0.808 | 0.767 | 0.797 |
| 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 | 1.000 | 1.000 |

ρA based on Dijkstra (2010). We assessed the convergent validity of the measurement models using the average variance extracted (AVE) from all items linked to a specific variable. A threshold of 0.50 or higher was deemed acceptable (Sarstedt et al., 2022). Our results for composite reliability, Cronbach's alpha, the reliability coefficient, and the AVE met the quality criteria presented in Table 2.

The Henseler et al. (2015) heterotrait-monotrait ratio of correlations (HTMT) is a measure used to assess discriminant validity. The HTMT ratio is the ratio of the correlation between two variables to the square root of the average of the squared correlations of each variable with itself. A value of HTMT less than 0.9 is considered acceptable and indicates that the constructs have good discriminant validity. The HTMT ratio has been recommended as a useful supplement to other measures of discriminant validity, such as the Fornell–Larcker criterion, when assessing the quality of a PLS-SEM (Henseler et al., 2015). All the values in Tables 3, 4, 5 are below the 0.9 threshold.

The next step in model evaluation is the computation of the coefficient of determination ($R^2$), which measures the extent to which each construct and the overall model can explain variance. The $R^2$ score ranges between 0 and 1, with higher values indicating greater explanatory power. According to general guidelines, $R^2$ values of 0.25, 0.50, and 0.75 are considered weak, moderate, and substantial, respectively, as suggested by Hair et al. (2011). To evaluate the effect size of a variable, a benchmark of $f^2$ values of 0.35, 0.15, and 0.02, indicating large, medium, and small effects, respectively, is often used. An effect size below 0.02 suggests the absence of an impact (Sarstedt et al., 2022).

The findings from the model estimation of the bachelor's, master's, and complete samples are shown in Table 6. The preliminary analysis suggests that the hypotheses confirmed in the bachelor group are also confirmed in the complete sample, while the hypotheses confirmed in the master group differ from those of the bachelor group. Table 7 presents the $R^2$ values for each sample.

Given that the quality criteria were evaluated and met for both groups, we conducted a multigroup analysis to determine whether the group differences were statistically significant. A measurement invariance test was carried out before the multigroup analysis. The MICOM analysis was performed in SmartPLS4 to carry out the measurement invariance test. The original correlations between variables were found to be greater than the correlation permutation mean, thus confirming the invariance. The results of the subsequent stages of the analysis are presented in Tables 8 and 9.

The final outcomes for the path coefficients reveal that there are significant differences among the four paths. Table 9 shows significant differences between the bachelor's group and the master's group.

## 5 Discussion

This study aimed to investigate the adoption of ChatGPT by students as an AI-powered academic aid in their study process, focusing on "behavioral intention" to use and actual "use behavior". We proposed a model based on the established UTAUT theory, which was extended by two additional variables. Moreover, we examined whether there were differences in adoption between students with different levels of

**Table 2** Construct reliability and validity

| | Bachelor | | | | Master | | | | Complete | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Alpha | ρc | ρA | AVE | Alpha | ρc | ρA | AVE | Alpha | ρc | ρA | AVE |
| Behavioral intention | 0.861 | 0.878 | 0.915 | 0.783 | 0.901 | 0.912 | 0.938 | 0.836 | 0.872 | 0.889 | 0.922 | 0.798 |
| Effort expectancy | 0.914 | 0.923 | 0.939 | 0.794 | 0.919 | 0.939 | 0.943 | 0.805 | 0.915 | 0.927 | 0.940 | 0.797 |
| Facilitating Conditions | 0.803 | 0.840 | 0.871 | 0.632 | 0.799 | 0.859 | 0.870 | 0.634 | 0.830 | 0.833 | 0.899 | 0.747 |
| Hedonic motivation | 0.864 | 0.958 | 0.915 | 0.786 | 0.880 | 0.941 | 0.925 | 0.807 | 0.867 | 0.954 | 0.917 | 0.790 |
| Performance expectancy | 0.903 | 0.907 | 0.932 | 0.774 | 0.922 | 0.924 | 0.945 | 0.811 | 0.908 | 0.911 | 0.936 | 0.784 |
| Personal Innovativeness | 0.885 | 0.895 | 0.921 | 0.744 | 0.881 | 0.913 | 0.918 | 0.738 | 0.884 | 0.897 | 0.920 | 0.743 |
| Social influence | 0.925 | 0.926 | 0.952 | 0.869 | 0.962 | 0.966 | 0.975 | 0.929 | 0.934 | 0.937 | 0.958 | 0.884 |

**Table 3** HTMT values—bachelor's degree

| | BI | EE | FC | HM | PE | PI | SI | UB |
|---|---|---|---|---|---|---|---|---|
| BI | | | | | | | | |
| EE | 0.685 | | | | | | | |
| FC | 0.623 | 0.778 | | | | | | |
| HM | 0.767 | 0.751 | 0.788 | | | | | |
| PE | 0.823 | 0.599 | 0.600 | 0.718 | | | | |
| PI | 0.634 | 0.589 | 0.610 | 0.641 | 0.590 | | | |
| SI | 0.560 | 0.421 | 0.493 | 0.435 | 0.555 | 0.390 | | |
| UB | 0.748 | 0.504 | 0.475 | 0.493 | 0.552 | 0.493 | 0.415 | |

**Table 4** HTMT values – master's degree

| | BI | EE | FC | HM | PE | PI | SI | UB |
|---|---|---|---|---|---|---|---|---|
| BI | | | | | | | | |
| EE | 0.503 | | | | | | | |
| FC | 0.629 | 0.893 | | | | | | |
| HM | 0.655 | 0.719 | 0.803 | | | | | |
| PE | 0.876 | 0.579 | 0.677 | 0.725 | | | | |
| PI | 0.622 | 0.658 | 0.634 | 0.663 | 0.603 | | | |
| SI | 0.776 | 0.453 | 0.606 | 0.533 | 0.680 | 0.459 | | |
| UB | 0.738 | 0.610 | 0.662 | 0.486 | 0.621 | 0.605 | 0.558 | |

**Table 5** HTMT values—complete

| | BI | EE | FC | HM | PE | PI | SI | UB |
|---|---|---|---|---|---|---|---|---|
| BI | | | | | | | | |
| EE | 0.637 | | | | | | | |
| FC | 0.627 | 0.799 | | | | | | |
| HM | 0.737 | 0.745 | 0.762 | | | | | |
| PE | 0.841 | 0.595 | 0.593 | 0.723 | | | | |
| PI | 0.624 | 0.604 | 0.607 | 0.644 | 0.588 | | | |
| SI | 0.619 | 0.430 | 0.489 | 0.463 | 0.590 | 0.407 | | |
| UB | 0.749 | 0.535 | 0.556 | 0.495 | 0.576 | 0.517 | 0.456 | |

BI: "behavioral intention", EE: "effort expectancy", FC: "facilitating conditions", HM: "hedonic motivation", PE: "performance expectancy", PI: "personal innovativeness", SI: "social influence", UB: "use behavior"

study experience and thus divided our sample into bachelor's and master's degree students. The findings of this study significantly contribute to the current knowledge of ChatGPT adoption among students, given the limited literature available on this topic. Specifically, few studies have examined the acceptance of ChatGPT in higher education, and to our knowledge, this is one of the first studies exploring students' adoption of ChatGPT.

**Table 6** Path coefficients and the results of the significance tests

| H | Path | Bachelor | | | | Master | | | | Complete | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | β | P values | $f^2$ | Supported | β | P values | $f^2$ | Supported | β | P values | $f^2$ | Supported |
| H1 | PE—> BI | 0.364 | 0.000 | 0.179 | Yes | 0.493 | 0.000 | 0.373 | Yes | 0.416 | 0.000 | 0.229 | Yes |
| H2 | EE—> BI | 0.154 | 0.001 | 0.029 | Yes | −0.134 | 0.169 | 0.022 | No | 0.086 | 0.047 | 0.009 | Yes |
| H3 | SI—> BI | 0.125 | 0.000 | 0.032 | Yes | 0.332 | 0.000 | 0.229 | Yes | 0.173 | 0.000 | 0.059 | Yes |
| H4 | FC—> BI | −0.026 | 0.612 | 0.001 | No | 0.114 | 0.175 | 0.018 | No | 0.007 | 0.876 | 0.000 | No |
| H5 | FC—> UB | 0.102 | 0.010 | 0.014 | Yes | 0.360 | 0.000 | 0.225 | Yes | 0.176 | 0.000 | 0.045 | Yes |
| H6 | HM—> BI | 0.262 | 0.000 | 0.069 | Yes | 0.029 | 0.746 | 0.001 | No | 0.202 | 0.000 | 0.042 | Yes |
| H7 | PI—> BI | 0.104 | 0.003 | 0.018 | Yes | 0.147 | 0.093 | 0.043 | No | 0.101 | 0.002 | 0.017 | Yes |
| H8 | BI—> UB | 0.642 | 0.000 | 0.575 | Yes | 0.513 | 0.000 | 0.458 | Yes | 0.608 | 0.000 | 0.539 | Yes |

**Table 7** $R^2$ values

| | Bachelor | Master | Complete |
|---|---|---|---|
| Behavioral intention | 0.653 | 0.735 | 0.658 |
| Use behavior | 0.493 | 0.592 | 0.518 |

**Table 8** Measurement invariance test

| | Original correlation | Correlation permutation mean | 5.0% | Permutation p value |
|---|---|---|---|---|
| Behavioral intention | 1.000 | 1.000 | 0.999 | 0.579 |
| Effort expectancy | 1.000 | 1.000 | 0.999 | 0.808 |
| Facilitating Conditions | 0.999 | 0.999 | 0.998 | 0.448 |
| Hedonic motivation | 1.000 | 0.999 | 0.997 | 0.492 |
| Performance expectancy | 1.000 | 1.000 | 1.000 | 0.215 |
| Personal Innovativeness | 0.999 | 0.999 | 0.998 | 0.282 |
| Social influence | 1.000 | 1.000 | 1.000 | 0.917 |
| Use behavior | 1.000 | 1.000 | 1.000 | 0.226 |

Our study revealed that “performance expectancy” is the strongest predictor of “behavioral intention” in the use of ChatGPT by students in their study process. The confirmation is positive for both the bachelor’s and master’s groups, with no significant difference between them. Thus, hypothesis H1 is confirmed for both subgroups. This result is consistent with earlier studies in which “performance expectancy” has been found to influence “behavioral intention” in areas such as mobile technologies (Hu et al., 2020) and e-learning systems (Samsudeen & Mohamed, 2019). Our results suggest that students perceive AI-powered chats as useful and helpful aids in their study process. Other studies on ChatGPT in higher education have also emerged, confirming the same results in different samples (Yee et al., 2024; Zheng et al., 2024). The prominence of “performance expectancy” as the strongest predictor of behavioral intention among both bachelor’s and master’s students highlights an important insight: students are motivated to adopt ChatGPT primarily when they perceive it as a tool that can significantly enhance their academic performance. This finding aligns with the principles of the UTAUT, which posits that “performance expectancy” is a fundamental determinant of technology adoption.

For educational institutions, this emphasizes the necessity of demonstrating the tangible benefits of ChatGPT in improving learning outcomes. By integrating ChatGPT into the curriculum in ways that directly support students’ academic goals—such as through interactive learning modules, research assistance, and personalized feedback mechanisms—educators can increase students’ perceived usefulness of the technology. Additionally, tailored strategies that address the specific needs of bachelor’s and master’s students can further enhance engagement (Mohamed et al., 2024). For instance, workshops focusing on foundational skill development may resonate more with bachelor’s students, while sessions on advanced analytical tools might appeal to master’s students.

In our overall sample, “hedonic motivation” was found to be the second strongest predictor of “behavioral Intention”. However, a significant difference was observed

**Table 9** Significant differences between the bachelor's and master's groups

| Path | Original (Bachelor) | Original (Master) | Original difference | Permutation mean difference | 2.5% | 97.5% | Permutation p value | Sig |
|---|---|---|---|---|---|---|---|---|
| PE—> BI | 0.364 | 0.493 | −0.129 | −0.004 | −0.185 | 0.180 | 0.171 | No |
| EE—> BI | 0.154 | −0.134 | 0.287 | 0.001 | −0.197 | 0.208 | 0.004 | Yes |
| SI—> BI | 0.125 | 0.332 | −0.207 | 0.001 | −0.154 | 0.155 | 0.009 | Yes |
| FC—> BI | −0.026 | 0.114 | −0.139 | 0.001 | −0.204 | 0.196 | 0.187 | No |
| FC—> UB | 0.102 | 0.360 | −0.258 | −0.005 | −0.153 | 0.145 | 0.000 | Yes |
| HM—> BI | 0.262 | 0.029 | 0.233 | −0.003 | −0.216 | 0.208 | 0.034 | Yes |
| PI—> BI | 0.104 | 0.147 | −0.043 | 0.002 | −0.153 | 0.155 | 0.591 | No |
| BI—> UB | 0.642 | 0.513 | 0.129 | 0.005 | −0.133 | 0.144 | 0.059 | No |

between the undergraduate and postgraduate groups. Hypothesis H6 – suggesting a positive correlation between "hedonic motivation" and "behavioral intention" – was validated in the undergraduate group but was unsupported among postgraduates. Previous research has presented mixed findings regarding the influence of "hedonic motivation" on "behavioral intention". For example, it was found to have a notable impact on animation usage among university students (Dajani & Abu Hegleh, 2019). Conversely, in research examining the use of learning management systems, the influence of "hedonic motivation" was not substantiated (Ain et al., 2016). One possible explanation for this disparity in our study might be that undergraduate students tend to perceive AI tools as entertaining or playful, whereas postgraduate students might have a more pragmatic view. This possibility warrants further exploration.

Our study revealed that "social influence" has a significant positive impact on "behavioral intention" for both the bachelor's and master's samples. However, the multigroup analysis revealed a significant difference in the strength of the impact. While hypothesis H3 was confirmed for both samples, the path coefficient and the effect size measured by $f^2$ were much stronger for the master sample. Previous studies have also found a positive effect of "social influence" in adoption studies such as Google Classroom (Jakkaew & Hemrungrote, 2017) or augmented reality technology in education (Faqih & Jaradat, 2021). Since ChatGPT technology is not yet widely adopted (despite having 100 million users), bachelor's students may experience weaker social pressure to use this technology than master's students, who may face moderate pressure from those around them. Recent studies have shown that the effect of "social influence" on generative AI acceptance is both significant and not significant. Wijaya et al. (2024), Grassini et al. (2024), and Yee et al. (2024) reported a nonsignificant impact of social influence, whereas Zheng et al. (2024), Strzelecki (2023), and Du and Lv (2024) found this factor to be significant. Additionally, social influence was shown to significantly affect males more than females in relation to ChatGPT usage (Elshaer et al., 2024). The difference in "social influence" might be caused by the characteristic of the measurement items. Some of them are concerning on specific course, some about general assessment solving, or on generative AI use.

In the bachelor sample, our study confirms that "effort expectancy" has a significant positive impact on "behavioral intention", while in the Master sample, hypothesis H2 is not supported. In the bachelor sample, the relationship strength is weak, and it has a small effect size, but in the complete sample, the hypothesis is still supported, although there is no effect. Previous studies have also shown that "effort expectancy" can be positively confirmed in areas such as e-learning adoption (Mehta et al., 2019) but is not supported in areas such as the adoption of MOOCs (Tseng et al., 2022). The weak relationship for "effort expectancy" might be explained by the fact that the students are quick learners, and they do not need to put in much effort to learn how to use new technology, especially when ChatGPT is built in a conversational way.

"Facilitating conditions" is found to have no significant impact on "behavioral intention" for either sample in this study (H4). Previous research has yielded mixed results, supporting this effect in areas such as the acceptance of higher education during social distancing (Sitar-Taut & Mican, 2021) but not supporting it in the study of accepting university students using their phones for their studies (Nikolopoulou et al., 2020). It is possible to hypothesize that access to new technology, internet connectivity, and the user-friendliness of the new platform are factors that often facilitate the use of new technologies, which may explain why students did not encounter any difficulties in using ChatGPT. This finding is consistent with the confirmed hypothesis H5, which states that “facilitating conditions” significantly influence “use behavior”. Students possess the necessary resources and knowledge and are often early adopters of new technologies, which positively affects their “use behavior” toward ChatGPT. Although both samples confirmed this hypothesis, there was a significant difference between them. The relationship is weak with no effect size for the bachelor sample, while the master sample has a weak to moderate relationship but with effect size. The effect of “facilitating conditions” on behavioral intention in recent studies on generative AI acceptance has been found to be either significant or usually not tested. Zheng et al. (2024), Strzelecki (2024), Grassini et al. (2024), Wijaya et al. (2024), Yee et al. (2024) and Elshaer et al. (2024) reported a nonsignificant impact of facilitating conditions on behavioral intention. Only Bhat et al. (2024) found this factor to be significant. The demographics and belonging to developing country might be the reason of difference.

“Personal innovativeness” is found to have significant effect on “behavioral intention” in bachelor sample, while for the master sample, this effect was not supported. For the complete sample, hypothesis H7 is confirmed; however, there is no effect of this variable. In previous studies, this effect has usually been confirmed, as in studies of the acceptance and use of lecture capture systems (Farooq et al., 2017) or students’ intentions to use e-learning (Twum et al., 2022). We assume that students may already be familiar with related technologies, such as chatbots or virtual assistants, which reduces the novelty of ChatGPT and its perceived innovation. We also assume that some students may prefer traditional learning methods, such as in-person lectures and physical textbooks, and may not be as open to technological advancements. Additionally, students may be less willing to use ChatGPT if they are worried about the security and privacy of their personal information.

In relation to the sample size, our model has substantial explanatory power in explaining 65.3% to 73.5% of the variance in “behavioral intention”. Additionally, “behavioral intention” has a strong and significant impact on “use behavior” in both samples, and as a result, the model explains 49.3% to 59.2% of the variance in “use behavior”, which is considered moderate explanatory power.

### 5.1 Theoretical contributions

The contributions of this research to the theory are as follows. To the best of the authors’ knowledge, this is the first study to compare students at different study levels, specifically bachelor’s and master’s students. The MICOM analysis revealed significant differences between the two groups. Younger students tend to be more trusting about AI tools, whereas more experienced students tend to be more cautious in their use of AI-powered tools. Another contribution is the integration of “personal innovativeness” into the UTAUT framework, which has been found to significantly influence “behavioral intention.” Both contributions add to the growing body of knowledge about the intention to use generative AI.

### 5.2 Practical implications

This study showed that students use this tool frequently. This change is inevitable and implies that educators also need to be familiar with this tool. It is essential for educators to recognize when a student has used an AI tool, particularly in situations where academic integrity could be compromised. Another practical implication is that the tool will be used for text correction, text generation, and creating ideas for discussion. Unfortunately, students often trust the output of this tool as if it were true. However, they are not experts in the field and may not be able to recognize when the tool generates incorrect or misleading content. The role of educator is to help students use the ChatGPT wisely.

### 5.3 Limitations and future work

This research has limitations, one of which is the lack of consideration of different study programs. This could be a potential avenue for further research, as there may be variations in the acceptance of AI chat among students in different programs. Another limitation is the cross-sectional nature of the study. After a year and a half of availability of this generative AI tool, it is now a good time to initiate multiple longitudinal studies on how ChatGPT influences students during their study process. These studies should explore how students adapt to the benefits and advantages of the tool, as well as how they manage its obvious limitations and biases.

## 6 Conclusion

The novelty of this research lies in its emphasis on the ChatGPT, a newly developed large language model that has not been thoroughly investigated in relation to higher education. The limited number of previous studies on ChatGPT, particularly on its usage and acceptance in higher education, accentuates the novelty of this research. Thus, the findings of this study could significantly contribute to the understanding of ChatGPT adoption and utilization in higher education and aid in the development of effective educational applications for this technology.

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

### Declarations

**Ethics approval and consent to participate** 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.

**Consent for publication** Informed consent was obtained from all individual participants included in the study.

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