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Leveraging AI in academia: university students' adoption of ChatGPT for writing coursework (take home) assignments through the lens of UTAUT2

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ABSTRACT

The rapid growth of artificial intelligence (AI) is transforming education, with tools like ChatGPT offering innovative support for university students in tasks such as essay writing and problem-solving. This study examines factors influencing ChatGPT adoption among students in Uganda, using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework. The UTAUT2 model explores performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit as key drivers of technology use. A mixed-method approach was employed, involving a survey of 473 third-year Makerere University Business School students and qualitative interviews. Structural equation modeling (SEM) analyzed relationships between UTAUT2 constructs and students' intentions to use ChatGPT. The findings show that performance expectancy, habit, and social influence significantly impact adoption, while effort expectancy and price value have less influence. This research highlights the potential of AI to enhance academic performance in resource-constrained settings. The insights are valuable for educators and policymakers aiming to integrate AI tools effectively in developing countries, addressing barriers like limited digital literacy and technological access. The study provides a foundation for strategies that support the adoption of AI in higher education, enhancing learning outcomes in Uganda's unique socio-economic context.

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ChatGPT adoption; UTAUT2 framework; university students; artificial intelligence in education; digital literacy

SUBJECTS
Artificial Intelligence; Information & Communication Technology (ICT); Information Technology

Introduction

The rapid advancement of artificial intelligence (AI) has significantly impacted various fields, including education. AI-driven tools are transforming traditional educational practices, offering innovative solutions for both teaching and learning (Elkatmis, 2024; Foroughi et al., 2024; Kyambade et al., 2025a, 2025b). Among these tools, ChatGPT, developed by OpenAI, has emerged as a prominent language model capable of understanding and generating human-like text. This capability positions ChatGPT as a valuable resource for university students, particularly for assisting with coursework-related tasks such as essay writing, problem-solving, and information synthesis (Lai et al., 2024; Surya Bahadur et al., 2024). Despite the evident potential of ChatGPT in academia, the extent to which university students are adopting this technology for their coursework remains underexplored. Understanding the factors that influence students' acceptance and use of ChatGPT is crucial for policymakers, educators, and technology developers aiming to integrate AI tools effectively into educational settings. The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model provides a robust theoretical framework for this investigation. The UTAUT2 model, developed by Venkatesh et al. (2012), extends the original UTAUT model by incorporating additional constructs such as hedonic motivation, price value, and habit. These constructs, along with performance expectancy, social influence, effort expectancy, and facilitating conditions, offer a comprehensive lens through which to analyze technology adoption behaviors.

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Previous studies have demonstrated the applicability of the UTAUT2 model in various contexts, including mobile learning (Chao, 2019; Liu et al., 2025), healthcare technology (Hoque & Sorwar, 2017), and e-government services (Abdullah et al., 2016). However, its application to the adoption of AI tools like ChatGPT in academic settings is still in its nascent stages. By employing the UTAUT2 model, this study aims to provide a nuanced understanding of the factors that drive university students to integrate ChatGPT into their coursework. Performance expectancy refers to the degree to which students believe that using ChatGPT will enhance their academic performance. Effort expectancy relates to the ease of use of ChatGPT, while social influence considers the impact of peers and educators on students' adoption decisions. Facilitating conditions encompass the resources and support available for using ChatGPT. Hedonic motivation captures the fun or enjoyment derived from using the tool, and price value assesses the cost-benefit analysis of its usage. Finally, habit reflects the extent to which students have integrated ChatGPT into their regular academic routines. Understanding these factors is essential for fostering a supportive environment that encourages the effective use of ChatGPT in academia. This study not only contributes to the academic discourse on educational technology adoption but also offers practical implications for developing strategies that enhance AI integration in higher education.

In Uganda, the integration of AI in education is still in its nascent stages. The country's higher education sector faces unique challenges, including limited access to technological resources, varying levels of digital literacy, and infrastructural constraints (Kyambade et al., 2025b; Nanfuka & Ikoja-Odongo, 2019). Despite these challenges, there is a growing recognition of the potential benefits of incorporating AI tools like ChatGPT into academic settings to enhance learning outcomes and streamline academic tasks. Understanding the factors that influence university students' acceptance and use of ChatGPT for their coursework in Uganda is crucial for policymakers, educators, and technology developers aiming to integrate AI tools effectively into educational settings. This study seeks to address this gap by examining the determinants of ChatGPT adoption among Ugandan university students.

There is a paucity of studies that specifically focus on how university students in developing countries perceive and utilize AI tools for their coursework. Most research on AI in education has been conducted in developed countries, where technological infrastructure and digital literacy levels are considerably higher (Holmes et al., 2019; Luckin et al., 2016). Consequently, the unique challenges and opportunities associated with AI adoption in developing countries have received insufficient attention. The application of UTAUT2 model to study the adoption of AI tools in academic settings is still in its early stages. While the model has been employed to investigate various technological adoptions (Biloš & Budimir, 2024), its use in examining the acceptance of AI tools like ChatGPT by university students for coursework is limited. This represents a critical gap in understanding the factors that drive or hinder AI adoption in educational contexts, especially in environments where resource constraints and technological infrastructure may differ significantly from those in more developed regions. There is a need to understand how specific constructs of the UTAUT2 model such as performance expectancy, hedonic motivation, effort expectancy, price value, facilitating conditions, social influence, and habit affect the adoption of AI tools in the unique cultural and socio-economic context of Uganda.

There are two primary *reasons* why the findings of this study might not be the same as those of other studies on other technologies. First of all, ChatGPT's innovative and ground-breaking generative capabilities set it apart from other AI systems (Lai et al., 2024; Surya Bahadur et al., 2024). Given ChatGPT's innovative evaluation support, it's possible that students may adopt the technology largely because of its outstanding functionality. When contrasted with empirical research on other technology, this might produce different results. Nevertheless, few research explicitly examined ChatGPT adoption (Choudhury & Shamszare, 2023; Elkatmis, 2024; Surya Bahadur et al., 2024; Lai et al., 2024). Second, intellectual excellence is emphasized heavily in Uganda's educational system (Kyambade et al., 2024a, 2024b, 2024c). The outcomes of high-stakes tests, which are used to decide a student's eligibility for progressively fewer educational possibilities, have a significant impact on the student's achievement in a highly competitive society (Kennedy, 2007). While parents or teachers at large-scale tutorial centers frequently offer assessment support to primary and secondary school students (Mugambwa et al., 2025), there aren't many personal tutors or tutorial centres in Uganda that cater only to university students. Furthermore, university students may find it difficult to get assessment support due to the specialized and complex course material, which could make them turn to ChatGPT in order to get timely help. In this situation, some students would put the alleged advantages of using ChatGPT in tests ahead of any apparent drawbacks. Therefore, examining ChatGPT's uptake in Ugandan universities becomes an

interesting undertaking. By incorporating both quantitative and qualitative research conducted in Uganda, the study expands upon the UTAUT2 paradigm. In the context of developing nations like Uganda, it offers some support for the UTAUT2 paradigm.

Literature review

Theoretical review

A well-known paradigm for examining technology adoption across industries and regions is the Unified Theory on Acceptance and Use of Technology (UTAUT). Venkatesh et al. (2003) validated this comprehensive model, which was assembled from eight models, using four key predictors of intention to adopt technology: facilitating conditions (FC), social influence (SI), performance expectancy (PE), and effort expectancy (EE). Numerous elements, including perceived utility, technology compatibility, and its effect on job performance, can influence users' perceptions of PE (Brachten et al., 2021; Surya Bahadur et al., 2024). People's past experiences with the technology, its perceived technical capabilities, its complexity, and the availability of assistance for its adoption all have an impact on EE (Muriithi et al., 2016). Users' important others, such as friends, classmates, coworkers, instructors, and family members, maybe the source of SI (Venkatesh et al., 2003). FC includes the tools, instruction, and technical assistance that users receive from their teachers in order to use the technology (Oye et al., 2014). According to the paradigm, real use of technology is determined by the intention to accept it. Forty percent of the variable in technology use in organizational settings and fifty-six percent of the variance in business intelligence can be explained by the UTAUT constructs. Age, gender, experience, and voluntary use all moderate the influence of predictors (Venkatesh et al., 2003). However, the majority of empirical research only included a portion of the UTAUT model, and modifiers were often removed (Biloš & Budimir, 2024; Foroughi et al., 2024; Surya Bahadur et al., 2024).

The use of the UTAUT model to analyze ChatGPT acceptability in many contexts has gained popularity recently. Menon and Shilpa (2023) interviewed Indian consumers in a semi-structured manner. According to the findings, ChatGPT adoption is strongly predicted by PE, EE, SI, and FC. The acceptance of ChatGPT among students from Polish, Nepalese, and UK public institutions was investigated by Budhathoki et al. (2024) and Strzelecki (2024a, 2024b). Their results showed that the parameters that predicted students' BI to use ChatGPT were PE, EE, and SI. Foroughi et al. (2024) looked at what factors influence Malaysian university students' acceptance of ChatGPT for educational purposes. According to the results, EE and PE significantly influenced users' intentions to utilize ChatGPT. However, EE was determined to be an unimportant driver of ChatGPT use for learning among Indonesian university students in Habibi et al. (2023) study. Despite ChatGPT's critical function in assessment assistance, its use in the assessment setting has not been the subject of any empirical research.

Hypotheses development

Performance expectancy and intention to use

According to Venkatesh et al. (2003), people are more willing to adopt technologies if they think they *would* improve their ability to perform their tasks. It relates to the extent to which students believe that using ChatGPT will enhance their learning in the context of the study. According to recent studies by Camilleri (2024), Elkatmis (2024), Surya Bahadur et al. (2024), Polyportis and Pahos (2025), and Strzelecki (2024a, 2024b), there is a favorable correlation between performance expectancy and intention to use. The following theory is put out in light of the empirical data presented:

H1: Performance expectancy positively impacts intention to use ChatGPT among Ugandan university students.

Effort expectancy and intention to use

Venkatesh et al. (2003) claim that individuals favor simple systems. The importance of effort anticipation has been positively highlighted by a number of research. For example, Sobaih et al. (2024) discovered

that students were more willing to use AI chatbots if they thought they were simple to use. Similar to this, integrating AI into education makes learning easier for kids, making it a potent tool for effective learning with less work (Tashtoush et al., 2024). According to Almahri et al. (2020) and Elkatmis, 2024; Surya Bahadur et al. (2024) students' decision to utilize ChatGPT was largely influenced by their perception of its ease of use. Based on these conversations, the following hypothesis is put forth:

H2: Effort expectancy positively impacts intention to use ChatGPT among Ugandan university students.

Social influence and intention to use

Social influence, according to Venkatesh et al. (2003), is the degree to which people are influenced by the viewpoints of others they respect. The UTAUT model has been used in numerous research to examine social impact. According to research by Menon and Shilpa (2023), Biloš and Budimir (2024), Strzelecki (2024a, 2024b), and Foroughi et al. (2024), for instance, students were more inclined to utilize ChatGPT if they believed that others they respected thought it was a good idea. Thus, the following hypothesis has been taken into consideration in this study:

H3: Social influence positively impacts the intention to use ChatGPT.

Facilitating conditions and intention to use

Facilitating conditions are the degree to which an individual feels prepared to employ a new system (Venkatesh et al., 2012). These same features are highlighted as facilitating conditions in earlier research, such as Grassini et al. (2024). It's interesting to note that earlier research that used UTAUT to investigate ChatGPT in various settings discovered a favorable relationship between these resources and students' readiness to use the technology. Kwak et al. (2022), for instance, looked at Korean nursing students and discovered that their decision to adopt AI-based healthcare solutions was greatly influenced by their access to the appropriate resources. Research on chatbots in general has revealed similar results (Alam et al., 2020; Surya Bahadur et al., 2024). Based on these suppositions, the research suggested:

H4: Facilitating conditions positively impact the intention to use ChatGPT.

Hedonic motivation and intention to use

When it comes to technology, enjoyment may be a strong motivation. Venkatesh et al. (2012) claim that people appreciate fun technology. We refer to this element of delight as hedonic motivation. In the area of ChatGPT, it is supported by numerous studies. Foroughi et al. (2024) investigated Malaysian students' attitudes toward ChatGPT using PLS-SEM. They discovered that students were more likely to use it for their academics if they loved using it. In a similar vein, Rodriguez et al. (2023) polled university students in Spain and Surya Bahadur et al. (2024) in Nepal and discovered a relationship between the students' overall desire to use ChatGPT, how embedded their use of it became, and how much fun they had using it. This favorable relationship between enjoyment and technology use has also been demonstrated by a number of other studies (Nikolopoulou et al., 2021; Tashtoush et al., 2023). Thus, the current investigation aims to verify the following hypothesis:

H5: Hedonic motivation positively influences intention to use ChatGPT.

Learning value and intention to use

Price value was a component of the original UTAUT2 model, but since this study concentrated on ChatGPT 3.5's free edition, the cost is not an issue. Learning value was thus included in the study. This speaks to how beneficial students think ChatGPT is as a learning aid, especially when it comes to their educational journey. Other studies provide strong support for the notion that learning value is a critical component in the adoption of educational technology (Zwain, 2019). For example, research by Zwain

(2019) and Zacharis and Nikolopoulou (2022) revealed that students favored eLearning platforms that facilitate successful learning. Likewise, Dajani and Hegleh (2019) and Surya Bahadur et al. (2024) discovered a favorable correlation between students' propensity to use a specific tool or platform and their perception of the worth of learning something. The study makes the following assumption based on these premises:

H6: Learning value positively impacts the intention to use ChatGPT.

Habit and intention to use

According to Venkatesh et al. (2012), habit is the degree to which utilizing a technology becomes automatic. To put it another way, we are more inclined to continue using technology the more integrated it becomes into our daily lives. Numerous research on the usage of educational technology hasdemonstrated the importance of this habit notion. For instance, studies on learning management systems (Zwain, 2019; Surya Bahadur et al., 2024), e-learning platforms (Zacharis & Nikolopoulou, 2022), and mobile learning (Kyambade et al., 2023; Yu et al., 2021) have all discovered that habit influences students' propensity to continue using these resources. Remarkably, Strzelecki (2024a, 2024b) discovered that habit was the best indicator of whether or not students would use ChatGPT for their academic work. Almahri et al. also discovered similar beneficial associations between habit and ChatGPT use (2020). The following theory is put forth in light of the previously mentioned studies:

H7: Habit positively impacts intention to use ChatGPT.

Methodology

Research design

The study adopted a mixed-method approach. Structural equation modeling (SEM) approach used in this study, examined the correlations between the latent variables that were modified and expanded from the UTAUT framework. Confirmatory factor analysis (CFA) and path analysis are two multivariate techniques that are combined in the SEM approach (Vanneste et al., 2013). In order to determine if the individual and collective constructs complied with the requirements for convergent, content, and discriminant validity, we first performed a CFA in accordance with Hair et al. (2019). To make sure there are no biased data, a common method bias test is also run in conjunction with the measurement model.

The case study design, one of the qualitative research methodologies, was also used in this investigation. According to Merriam (2013), Elkatmis (2024), and Kyambade et al. (2024c), qualitative research is a method that observes a realistic and holistic description of events and perceptions in their natural surroundings. It is regarded as a fundamental approach to understanding life. Conversely, the case study design is a research methodology that permits a thorough analysis of one or more occurrences, settings, social groupings, or interrelated systems (Büyüköztürk et al., 2016). A case study's objective is to carry out in-depth research on a certain topic in order to find outcomes relevant to a specific circumstance (Kyambade et al., 2024c; Elkatmis, 2024). The research case focuses on third-year students' coursework writing experiences with ChatGPT.

Survey instrument

The questionnaire has two sections for quantitative data. The purpose of the first section, which had 29 descriptions, was to investigate the factors that influence participants' intention to use ChatGPT. The second section was created to gather demographic data. Table 1 lists the 29 manifest items, their descriptions for assessing the seven latent variables, and the references to previous research (Lai et al., 2024; Surya Bahadur et al., 2024). To better suit our inquiry into the usage of ChatGPT in assessment settings, the descriptions from earlier studies were changed. Using a 5-point Likert scale that goes from 'strongly disagree' to 'strongly agree', participants were asked to rate how much they agreed with the

Table 1. Survey instrument.

Performance expectancy (PE) - Modified from UTAUT model (Venkatesh et al., 2003) and UTAUT 2 model (Lai et al., 2024; Surya Bahadur et al., 2024; Venkatesh et al., 2012)	
PE1	I believe that ChatGPT is useful in my studies.
PE2	Using ChatGPT would improve my learning experience performance.
PE3	Using ChatGPT would increase my productivity in learning.
PE4	Using ChatGPT would enhance my effectiveness in learning.
PE5	Using ChatGPT would make learning easier.
PE6	I find ChatGPT useful in my learning.
Effort expectancy (EE) - Modified from the UTAUT model (Lai et al. 2024; Surya Bahadur et al., 2024; Venkatesh et al., 2012)	
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 skillful at using ChatGPT.
Social influence (SI) - Modified from the UTAUT 2 model (Lai et al. 2024; Surya Bahadur et al., 2024; Venkatesh et al., 2012)	
SI1	People who are important to me think I should use ChatGPT in my studies.
SI2	People who influence my behavior think I should use ChatGPT for my studies.
SI3	People whose opinions I value prefer I should use ChatGPT for my studies.
Facilitating conditions (FC) - Modified from the UTAUT 2 model (Lai et al. 2024; Surya Bahadur et al., 2024; Venkatesh et al., 2012)	
FC1	I have the resources I need to use ChatGPT for my studies.
FC2	I have the knowledge necessary to use ChatGPT for my studies.
FC3	ChatGPT is compatible with other ICT tools I use in my studies.
FC4	I can get help from others when I face difficulties learning using ChatGPT.
Hedonic motivation (HM) - Modified from UTAUT 2 model (Lai et al. 2024; Surya Bahadur et al., 2024; Venkatesh et al., 2012)	
HM1	Using ChatGPT in my studies is fun.
HM2	Using ChatGPT in my studies is enjoyable.
HM3	Using ChatGPT in my studies is very entertaining.
Learning value (LV) - Modified from the UTAUT 2 model (Venkatesh et al., 2012; Surya Bahadur et al., 2024; Lai et al. 2024)	
LV1	Using ChatGPT increases my knowledge and helps me to be successful in my studies.
LV2	ChatGPT is a very effective educational tool and helps me to improve my learning process.
LV3	ChatGPT saves me time in searching for materials.
Habit (HB) - Modified from UTAUT 2 model (Lai et al. 2024; Surya Bahadur et al., 2024; Venkatesh et al., 2012)	
HB1	I often use ChatGPT for my studies.
HB2	I am used to using ChatGPT for my studies.
HB3	The use of ChatGPT has become a habit for me.
Intention to use (IU) Modified from UTAUT 2 model (Lai et al. 2024; Surya Bahadur et al., 2024; Venkatesh et al., 2012)	
IU1	I intend to continue using ChatGPT in the future.
IU2	I will always try to use ChatGPT in my studies.
IU3	I plan to continue to use ChatGPT frequently.

Source: primary data.

descriptions. Since the types of assessments are not specifically mentioned in the questionnaire, summative and formative assessments are both included under the term 'assessments'. The purpose of the study was to gather quantitative information regarding the factors that encourage and hinder students' use of ChatGPT for assessment purposes.

A semi-structured interview form created by the researcher was used to gather research data. After a thorough assessment of the literature, the interview form was customized for bachelor's degree candidates. A semi-structured interview form was constructed after a question pool was formed based on the literature study (Elkatmis, 2024). Academics from the university's computing and education departments, including specialists in educational coursework writing and ChatGPT and artificial intelligence specialists within the Computer and Instructional Technologies department, were consulted in order to verify the form's content validity. On the basis of the experts' input, the necessary modifications were implemented. Lastly, four trial interviews were done to assess the questions' intelligibility, and the form was adjusted accordingly (Kyambade, 2023; Elkatmis, 2024). Bachelor's degree students' feelings, ideas, and opinions about their coursework (take-home assignment) writing experiences with ChatGPT, as well as the advantages or disadvantages of ChatGPT for coursework writing, were the main topics of the interview form that was created.

Sampling and data collection

Convenience sampling was used to gather data for the questionnaire survey in August 2024 following a preliminary trial involving 70 students. Third-year students at Makerere University Business School in Uganda were given the questionnaire at random. Hair et al. (2019) criteria, which call for 5 to 10 replies per item, were used to estimate the sample size due to the difficulty of calculating the size of the entire

population. Given that the questionnaire consists of 29 items, a sample size of 140–280 is deemed sufficient for this investigation. 487 individuals, or 98% of the total, reported having previously used ChatGPT out of the 498 questionnaires that were delivered. No information revealing the identity of survey respondents was collected; the information collected from respondents is kept highly confidential, and the electronic data files containing their information are password-protected. A total of 473 useable questionnaires were collected after 14 were eliminated due to incomplete information; this is deemed sufficient for the study because the sample size is greater than 280.

The study was conducted in the final six weeks of the spring semester of the 2023–2024 academic year as part of a bachelor's degree requirement. Initially, students' general knowledge of ChatGPT was assessed. Once it was confirmed that most participants were familiar with ChatGPT, a 30-minute lecture was provided to explain the study's goals and applications. One-on-one interviews were conducted in the researcher's office to ensure participants felt secure and comfortable. Participants were given instructions about the study's purpose, methodology, and the intended use of findings. During the 15–20 minute interview sessions, demographic data was collected, and both written and spoken responses were documented (Yılmaz & Altınkurt, 2011; Elkatmis, 2024). This interview approach is deemed most effective for qualitative research (Kyambade et al., 2024c; Elkatmis, 2024). The researcher ensured balanced speaking time, avoided dominance, and maintained the focus of discussions (Kyambade et al., 2024c).

Efforts were made to create a comfortable interview setting, and the recordings were later reviewed. The study's target group was third-year bachelor's degree students at Makerere University in the 2023–2024 academic year, forming the study universe (Arseven, 1993; Karasar, 1999). Purposive sampling, specifically 'convenient situation sampling', was employed to select participants, as it provides quick access and allows a deeper investigation of the research topic (Büyüköztürk et al., 2016). The study group consisted of 18 participants, evenly split between 9 female and 9 male students.

The data collected was analyzed using the 'content analysis' method, a fundamental qualitative data analysis approach. The process aimed to identify ideas and relationships that explain the gathered data. The analysis involved four stages: coding the data, identifying themes, organizing the codes and themes, and interpreting the results (Elkatmis, 2024; Kyambade et al., 2024c). The goal of content analysis is to convert nonverbal data into quantitative form (Balcı, 2009). Responses were coded and presented as frequency and percentage values. To ensure reliability, another expert reviewed the transcripts, and an agreement formula was used to compare the coders' results, achieving an 81% consistency rate, above the 78% threshold required for reliability (Miles & Huberman, 1994; Elkatmis, 2024). The data was then analyzed and interpreted using direct quotations while maintaining ethical standards by anonymizing participants with codes like KI.

Quantitative results

Demographic analysis

Table 2 displays the demographic profile of the participants. The results demonstrate that there were significantly more female participants (65.01%) than male participants (34.99%), which is indicative of the high percentage of female students. Most participants (86.54%) were from eight Ugandan higher education institutions and were 22 years of age or younger. Participants came from a wide range of fields. The percentage of participation was evenly split throughout the university.

Table 2. Demographic profile of participants (N = 473).

Variable	N	%age
Gender		
Male	163	34.99
Female	310	65.01
Age		
18–20 years old	232	48.86
21–22 years old	180	37.68
Above 22 years old	61	13.46

Source: primary data.

Confirmatory factor analysis

Analyzing the measurement model's goodness of fit (GOF) indices is the first stage in the CFA process. Table 3 lists the measurement model's GOF indices together with the values that have been suggested by previous research. We can infer from the aforementioned numbers that the measurement model fits the data well and doesn't need any modifications.

Analyzing each construct's convergent validity and reliability is the second phase of the CFA. Table 4 displays the outcomes of the CFA. Table 4 shows that all 28 items have factor loadings greater than 0.5, indicating that these indicators maintain the factors' meanings. The average variance extracted (AVE) values that have been published fall between 0.666 and 0.769, exceeding the widely accepted cutoff of 0.5 that Fornell and Larcker (1981) recommend. The measurement is deemed credible since the composite reliability (CR) values, which range from 0.888 to 0.930, are higher than the recommended cutoff of 0.6 (Bagozzi & Yi, 1988). However, all of Cronbach's alpha values fall beyond the suggested cutoff of 0.7, ranging from 0.847 to 0.906 (Nunnally & Bernstein, 1994). This demonstrates that each latent construct's manifest indicators have a low enough measurement error and are closely connected. The discriminant validity of the constructs was further investigated in this study using the standards put forth by Fornell and Larcker (1981).

Although the Normed Fit Index (NFI) value of 0.885 is slightly below the conventional threshold of 0.90, it is important to contextualize this finding within the overall assessment of model fit. Previous research indicates that lower NFI values can still reflect an acceptable model fit when considered alongside other fit indices, particularly when those indices demonstrate strong support for the model

Table 3. Goodness of fit indices of the CFA model.

Fit index	Modified Model	Recommended values	Source
CFI	0.986	≥0.90	Bagozzi and Yi (1988), Byrne (2013)
TLI	0.986	≥0.90	Hair et al. (2019), Ho (2006)
NFI	0.885	≥0.90	Marsh & Hocevar, 1985; Schermelleh-Engel et al., 2003
RMSEA	0.012	≤0.10	Schumacker and Lomax (2010)

Source: primary data.

Table 4. Reliability and validity of measurement model.

Constructs	Items	M	SD	Loadings	a Value	CR	AVE	VIF
Performance expectancy (PE)	PE1	5.078	1.639	0.831	0.803	0.814	0.664	1.587
	PE2	5.059	1.532	0.771				3.036
	PE3	4.724	1.612	0.703				2.543
	PE4	4.924	1.395	0.746				2.853
	PE5	5.609	1.388	0.799				2.155
	PE6	5.302	1.431	0.739				2.514
Effort expectancy (EE)	EE1	5.570	1.483	0.718	0.880	0.810	0.808	2.243
	EE2	5.204	1.459	0.875				2.645
	EE3	5.618	1.368	0.756				2.402
	EE4	4.872	1.523	0.779				1.552
Social influence (SI)	SI1	4.457	1.578	0.836	0.918	0.823	0.834	3.001
	SI2	4.510	1.459	0.814				3.619
	SI3	4.523	1.460	0.862				2.719
Facilitating conditions (FC)	FC1	5.235	1.506	0.812	0.712	0.875	0.647	1.841
	FC2	5.108	1.452	0.835				1.987
	FC3	5.038	1.391	0.846				1.877
	FC4	5.045	1.424	0.747				1.519
Hedonic motivation (HM)	HM1	4.508	1.614	0.877	0.878	0.901	0.718	2.325
	HM2	5.069	1.520	0.930				3.167
	HM3	4.715	1.455	0.905				2.616
Learning value (LV)	LV1	4.712	1.470	0.902	0.943	0.826	0.876	2.672
	LV2	4.649	1.489	0.929				3.111
	LV3	5.400	1.514	0.825				1.816
Habit (HB)	HB1	4.589	1.752	0.849	0.855	0.814	0.705	2.563
	HB2	4.487	1.717	0.930				3.128
	HB3	3.872	1.824	0.837				2.457
Intention to use (IU)	IU1	5.102	1.580	0.878	0.897	0.808	0.910	2.021
	IU2	4.557	1.727	0.895				2.459
	IU3	4.413	1.578	0.917				2.879

Note. SD: standard deviation; M: mean; AVE: average variance explained; a: Cronbach's alpha; CR: composite reliability; VIF: variance inflation factor. Source: primary data.

(Marsh & Hocevar, 1985; Schermelleh-Engel et al., 2003). In this study, the CFI and TLI values of 0.996 suggest an excellent fit, reinforcing the adequacy of the measurement model despite the NFI result. Therefore, while the NFI value does not meet the conventional cutoff, the overall fit of the model remains robust, providing confidence in the validity of our findings.

According to the findings in Table 5, each construct's square root of the AVE value is higher than the correlations between it and the other constructs. This demonstrates discriminant validity by showing that the model's constructs are unique and measure several ideas. The results presented in Table 5 demonstrate strong evidence of discriminant validity for the measurement model, as each construct's square root of the Average Variance Extracted (AVE) value exceeds the correlations between it and other constructs. This indicates that the constructs—Intention to Use (IU), Performance Expectancy (PE), Hedonic Motivation (HM), Habit (HB), Effort Expectancy (EE), Social Influence (SI), and Leisure Value (LV)—are distinct and effectively measure different concepts within the context of ChatGPT adoption.

Common method bias

According to Podsakoff et al. (2003), common method bias is a systematic inaccuracy in research data that results from the measuring process itself rather than the constructs being tested. When data is collected for every variable in a single study using the same methodology, bias may result. The common method bias threat was assessed in our study using Kock's (2015) methodology because all of the data was gathered using self-report questionnaires. We looked at the Variance Inflation Factors (VIFs) in the inner model and performed a comprehensive collinearity test to see if the model is free from common method bias. Kock (2015) states that the model is free from common method bias if all VIFs are equal to or less than 3.3. The findings demonstrate that all VIFs, which range from 1.00 to 1.52, are less than 3.3, showing that structural equation modeling was used to evaluate the hypotheses.

Following validation of the measurement model, we looked at how PE, EE, SI, FC, LV, HB, and HM affected IU in the suggested model. The loading values and path coefficients of the path lines in the PLS algorithm technique are shown in Table 6. The t-values of H1 (route PE → IU) and H7 (way HB → IU) are the highest and lowest, respectively, at 3.845 and 0.530. With the exception of H4 and H7, every hypothesis put forth in this study is supported.

The findings confirm H1 by showing a positive and significant connection between PE and IU ($t = 3.845$; beta $= -0.166$; $p < 0.01$). In support of H2, the results also show a positive and significant connection between EE and IU ($t = 2.661$; beta $= 0.119$; $p < 0.01$). Similarly, the results show a negative connection between SI and IU ($t = 2.215$; beta $= -0.104$; $p < 0.05$), which supports H3. The results, however,

Table 5. Discriminant validity of measurement model.

	IU	PE	HM	HB	EE	SI	LV
IU	0.854						
PE	0.127	0.877					
HM	−0.162	0.039	0.87				
HB	−0.101	−0.039	−0.021	0.877			
EE	0.103	0.139	−0.048	0.134	0.877		
SI	0.053	0.154	0.09	−0.038	0.02	0.816	
LV	0.137	0.008	−0.018	−0.047	0.087	0.037	0.843

Source: primary data.

Table 6. Hypotheses results.

Hypotheses	Beta	*p*-values	t-values	Decision
H1: PE →IU	−0.166	0.000***	3.845	Supported
H2: EE → IU	0.119	0.005***	2.661	Supported
H3: SI → IU	−0.104	0.019**	2.215	Supported
H4: FC → IU	−0.047	0.234	0.834	Not Supported
H5: HM → IU	0.111	0.007***	2.528	Supported
H6: LV → IU	0.083	0.078*	1.803	Supported
H7: HB → IU	0.041	0.411	0.530	Supported

Note: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.
Source: primary data.

contradict H4 because there is no significant correlation between FC and IU (t = 0.834; beta =−0.047; $p > 0.10$). Additionally, the data confirm H5 by showing a strong positive connection between HM and IU (t = 2.528; beta = 0.111; $p < 0.01$). H6 is slightly supported by the results on the relationship between LV and IU (t = 1.803; beta = 0.083; $p < 0.10$). However, the results show a negligible correlation between HB and IU (t = 0.530; beta 0.041; $p > 0.10$), hence H7 is supported.

Qualitative results

In accordance with the predefined sub-problems, the results and remarks expressing the perspectives of Bachelor's degree students regarding their coursework writing experiences with ChatGPT are analyzed and given in the following order. First, Table 7 summarizes the facts concerning participants' knowledge of ChatGPT, an artificial intelligence application.

The views of the graduate students who took part in the study about their knowledge and experience with ChatGPT are taken into consideration under the topics of 'Knowledge Status' and 'Usage Status' when looking at Table 7. As a result, the vast majority of participants (68.75%) stated that they were unaware of ChatGPT. Three people (18.75%) reported knowing and applying it in relation to the usage status theme, while two participants (12.5%) reported learning and gaining experience for homework. As a result, it is acknowledged that just two people possess expertise. As a result, it is clear that a sizable percentage of graduate students lack sufficient knowledge of ChatGPT and have little experience with this artificial intelligence tool. This circumstance emphasizes the need for educational programs to raise students' knowledge of ChatGPT and similar technologies. The following are some of the participant responses that fall under the purview of the study question:

KI 5: ChatGPT is something I've never heard of. Is this technology new?

KI 9: Although I am aware of ChatGPT, I haven't made considerable use of it. I am aware of its versatility, though, and I do occasionally take advantage of its features.

KI 1: For my coursework, I use ChatGPT to learn and get experience. It was really beneficial!

The research also looked at the feelings, ideas, and opinions of bachelor's degree students about their experiences using ChatGPT for coursework writing. Regarding this, Table 8 displays the results that were achieved.

The overall opinions of graduate students regarding their experiences using ChatGPT in coursework writing have been compiled under four major themes and fifteen sub-themes after looking at Table 8. First off, a sizable percentage of participants (14.3%) reported that ChatGPT had been useful in helping them construct their writing assignments and that they had found it to be quite advantageous in this respect. Furthermore, according to 9.5% of participants, ChatGPT helped them acquire new viewpoints. Additionally, positive impacts have been recorded in terms of improving vocabulary (6.3%), fixing grammatical faults (3.2%), and encouraging a passion for writing (3.2%).

According to 'Usage and Auxiliary Functions', some students have characterized ChatGPT as a friend who makes writing and assignments more fun (9.5%), an acknowledged helper in all areas (6.3%), a tool that speeds up the text creation process (8%), and a tool that promotes personal growth by assisting people in discovering who they are (11.1%). Additionally, 3.2% of participants said that ChatGPT makes it feel like they are speaking with a human. Nonetheless, some students have also brought attention to ChatGPT's possible drawbacks. While 8% of participants find the responses untrustworthy and 3.2% find

Table 7. Students' ChatGPT Information and Experiences.

Themes	Sub-Themes	N	%
Knowledge Status	Not knowledgeable	11	61.1
Usage Status	I am knowledgeable and often use it	04	22.2
	I have gained knowledge and experience for assignments	03	16.7
Total		18	100

Source: primary data.

Table 8. Views of students on writing coursework experiences using ChatGPT.

Themes	Sub-themes	f	%
Effects on writing coursework	Enhances and is very beneficial to the development of writing coursework	09	14.3
	Contributes to developing a different perspective	06	9.5
	Contributes to the expansion of vocabulary	04	6.3
	A good guide in correcting grammatical errors	02	3.2
	Develops the desire and enthusiasm to write	02	3.2
UsageandAuxiliary functions	A friend that makes the writing process and assignments fun	06	9.5
	A knowledgeable assistant in every field	04	6.3
	Accelerates the text creation process	05	8
	Supports personal development, aiding self-discovery	07	11.1
	Gives the feeling of conversing with a human	02	3.2
Negative Effects	Has the potential to make the human mind lazy	05	8
	The answers provided are not reliable	02	3.2
	Alarming as an alternative to humans in many areas	04	6.3
	Irregular responses create additional workload	02	3.2
Recommendations	Awareness training should be provided for proper use	03	4.8
Total		63	100

Source: primary data.

Table 9. Students' views on how ChatGPT assists in the writing coursework.

Themes	Sub-Themes	f	%
Contributions to the writing process	Helped develop new ideas	09	49.9
	Using suggestions and alternative expressions made the text more diverse and fluent	03	16.7
	Ensured the text became more qualitative	03	16.7
Negative feedback	Deficiencies in correcting grammatical errors	03	16.7
Total		18	100

Source: primary data.

it disconcerting that ChatGPT could be a viable replacement to humans in many areas, 6.3% of participants believe that ChatGPT has the potential to make the human mind sluggish.

In addition to adding to the effort (6.25%), the erratic and robotic style of the responses may deter people from writing by making them feel unworthy (3.2%). Regarding the 'Recommendations', 4.8% of participants stated that awareness training has to be offered to encourage the thoughtful usage of ChatGPT. A critical approach to the topic is suggested by the inclusion of the hazards that come with the benefits that technology offers on the agenda. Among the viewpoints of participants are:

KI 10: My expectations were far exceeded by the encounter. Though somewhat scary, the program is often extremely excellent. This kind of technological advancement will eliminate the need for human experience and wisdom. Over time, people might get mechanical and become a generation that doesn't move or think. I believe that technology will keep developing, and we must learn how to use it properly. We must use technology responsibly rather than becoming its slaves.

KI 5: Like a tutor, ChatGPT can give us organic and fulfilling solutions to a lot of our queries. Through the creation of various expressions, innovative thoughts, and distinct recommendations, it assisted me in making my text more effective and qualitative. It accelerated my text-writing process and helped me fix my errors. I think it will be really helpful for a lot of time-constrained research work, like assignments and articles.

After looking at Table 9, two major themes emerged from graduate students' opinions about how ChatGPT has aided their coursework writing process. They are described as 'negative feedback' and 'contributions to the writing process'. Regarding 'Contributions to the Writing Process', 49.9% of participants said that ChatGPT assisted them in coming up with fresh concepts while they were writing. Second, according to 16.7% of participants, ChatGPT added diversity and fluidity to the writing by offering recommendations and alternative phrasing. 16.7% of participants in the theme's last category said that ChatGPT improved the text's quality. In reference to 'negative feedback', 16.7% of participants identified shortcomings in ChatGPT's grammatical error correction capabilities. In conclusion, it should be noted that ChatGPT has limits with regard to its grammar corrections, even if it provides substantial benefits in terms of encouraging original thought, raising text quality, and improving text flow. From this angle, it can be claimed that ChatGPT can enhance coursework writing assignments; however, more

study is required in the area of grammar. The following participant viewpoints serve as examples of this aspect:

KI 7: When writing about any subject or tale, ChatGBT was really helpful in establishing the setting and creating descriptions. Engaging with ChatGBT can provide us with a variety of viewpoints, inspire us with fresh concepts, and support the development of innovative methods. Working with ChatGBT allows us to get ideas and inspiration, find new words or idioms, and improve the fluency of our texts.

KI 4: My text reached a new level thanks to ChatGPT's alternative word suggestions. It also assisted me in adding additional qualitative elements to my essay. I can tell, though, that it falls short in fixing grammatical problems. It might be able to fix grammatical problems using any extra plugin.

The opinions of students regarding the recommendations, edits, and substitute phrases offered by ChatGPT during coursework writing can be categorized into two primary themes by looking at Table 10. These are stated as 'negative feedback' and 'contributions of suggestions and corrections'. Regarding the 'Contributions of Suggestions and Corrections' subject, 27.8% of participants said that ChatGPT's corrections and suggestions were really beneficial. Furthermore, 16.7% of participants said that ChatGPT's recommendations helped them view the topic from a different angle. Likewise, 16.7% of participants reported that ChatGPT's recommendations improved their ability to express themselves and made the texts more interesting. According to 11.1% of participants, ChatGPT's provision of alternative expressions enhanced the text's uniqueness. However, 16.7% of participants in the 'negative feedback' theme have noted that the expressions in ChatGPT's recommendations were fake, fabricated, and mechanical. Additionally, 11.1% of participants said that ChatGPT's vocabulary was inadequate and constrained. All things considered, it is thought that ChatGPT's suggestion and correction features could help with the writing process and enhance the coursework writing process by providing a variety of viewpoints. The following are some instances of participant thoughts on this:

KI 3: In order to get the most out of this application in terms of originality, one should apply their own thinking abilities in addition to taking inspiration from ChatGBT. I can claim that my coursework writing experience with ChatGPT has demonstrated my ability to write wonderfully, to see things from several angles, and to greatly enhance my writing. Even after completing the assignment, I discovered that I was not aware of my writing prowess until reading the final paragraphs. I came to see that if I wanted to, I could write lengthy and interesting texts with ChatGPT support. I noticed an improvement in my writing assignments as a result of my writing experience with ChatGPT. My vocabulary has also improved as a result of ChatGPT's ability to provide numerous appropriate synonyms for words that are already in use. This gives your mind room to accommodate new terms. I experienced a mental opening, enlargement, and clarification. I believed that my writing skills had improved as a result of my coursework writing experience with ChatGPT.

KI 12: In terms of word usage, I don't believe it is inadequate. Nevertheless, the language used in its recommendations seems artificial and robotic. After that, some modifications are required. Alternative expressions add uniqueness and interest to the content when they are employed properly and sparingly.

After looking at Table 11, three major themes emerged from graduate students' opinions about how ChatGPT improves writing assignments. 'Highly effective', 'somewhat effective', and 'partially effective'

Table 10. Students' Views on Suggestions, Corrections, and Alternative Expressions While Engaging in Writing Coursework with ChatGPT.

Themes	Sub-Themes	f	%
Contributionsof Suggestions and Corrections	ChatGPT's suggestions and corrections are very helpful	05	27.8
	ChatGPT's suggestions provide different perspectives on the subject	03	16.7
	ChatGPT's suggestions make the texts interesting and help in expression	03	16.7
	ChatGPT offering alternative expressions contributes to the originality of the text	02	11.1
Negative Feedback	The expressions in ChatGPT's suggestions are mechanical, artificial, and contrived	03	16.7
	ChatGPT's vocabulary usage is limited and insufficient	02	11.1
Total		18	100

Source: primary data.

Table 11. Students' opinions on the impact of ChatGPT on writing coursework.

Themes	Sub-Themes	F	%
Highly Effective	Very influential on writing coursework	10	55.6
Somewhat Effective	Contributes to writing coursework at a normal level	04	22.2
Partially Effective	Has some effect on writing coursework	04	22.2
Total		18	100

Source: primary data

Table 12. Students' views on the speed of the writing process by ChatGPT.

Themes	Sub-Themes	N	%
Speed Status in Writing coursework	Yes	13	72.2
	No	05	27.8
Total		18	100

Source: primary data.

are the terms used to describe them. According to the 'Highly Effective' theme, ChatGPT has significantly improved writing assignments, according to half of the participants (55.6%). According to 22.2% of participants in the 'Somewhat Effective' theme, ChatGPT has helped them write their assignments at a normal level. Finally, 22.2% of participants reported that ChatGPT had some impact on their ability to write assignments. In conclusion, half of the participants said that ChatGPT has improved their writing assignments to a high degree, while the other half said that the effect is moderate or non-existent. Although the extent of this benefit differs among students, this result can be regarded as ChatGPT typically offering a favorable contribution to writing coursework. Among the viewpoints of participants are:

KI 6: For me, ChatGPT has been a great source of motivation. Since I was the one who created the text's direction and path, I didn't let it direct me too much. I only used it to generate ideas for themes I was unfamiliar with, to fill in the blanks regarding historical locations and topics, and to construct alternate phrases, which I thought to be useful in this regard.

KI 13: I can state that ChatGPT significantly improves writing or coursework writing skills if you utilize it properly and intentionally.

After looking at Table 12, two sub-themes emerged from the students' opinions of ChatGPT's acceleration of coursework writing. They've been divided into 'yes' and 'no'. According to the theme of 'Acceleration of Writing coursework', the vast majority of participants (72.2%) said that ChatGPT speeds up coursework related to writing. However, according to 27.8% of participants, ChatGPT does not speed up writing assignments. In conclusion, the overwhelming majority of participants think that ChatGPT speeds up coursework related to writing. According to this research, ChatGPT generally improves the writing process. A tiny minority of students, however, hold a different opinion. As a result, the following are some participant viewpoints:

KI 7: When I lack sufficient knowledge or am unfamiliar with a subject, I believe it can be helpful. For instance, it made it easy for me to locate information about coffee shops in Paris if I was unfamiliar with them, and because of its suggestions, I was able to find everything on one page with descriptions.

KI 14: It's easy to construct a sentence and get started, but it can be very difficult to add supporting details. ChatGPT greatly eases these challenges. Furthermore, giving you a unique notion enables you to move forward without over analysing it and come up with alternatives.

Discussion

Using the UTAUT2 model, this study investigated the variables influencing the intention to use ChatGPT. The findings supported hypothesis H1 by showing a significant positive connection between performance expectancy and students' intention to use ChatGPT. This aligns with prior research indicating that

students are more likely to adopt AI-based learning tools when they perceive them as enhancing their academic performance (Budhathoki et al., 2024; Duong et al., 2024; Foroughi et al., 2024; Grassini et al., 2024). Given these findings, educational institutions should emphasize the practical benefits of ChatGPT to reinforce its perceived value and encourage adoption.

Hypothesis H2 was also supported, indicating that effort expectancy significantly influences students' intention to use ChatGPT. This result is consistent with previous studies that highlight how ease of use affects technology adoption in educational settings (Budhathoki et al., 2024; Duong et al., 2024; Strzelecki, 2024a, 2024b). Students who perceive ChatGPT as user-friendly are more inclined to integrate it into their learning processes. These findings suggest that user training and awareness campaigns could further facilitate its adoption.

The study also confirmed hypothesis H3, revealing a significant positive relationship between social influence and students' intention to use ChatGPT. This is in agreement with previous studies (Biloš & Budimir 2024; Strzelecki, 2024a, 2024b; Sobaih et al., 2024), which emphasize the role of peer and instructor recommendations in technology adoption. According to these research, social circles such as peer or teacher recommendations have an impact on pupils. Given their benefits and drawbacks, educators should provide advice on how to use AI-based learning resources responsibly (Kyambade et al., 2024b). However, instructors' attitudes on the adoption of developing technologies in teaching and learning are crucial for the successful use of AI-based learning tools (Tashtoush et al., 2024). This uniformity can be explained in a number of ways. First, normative influence encourages people to adopt actions that are deemed appropriate by respected individuals or influential peers. If these people support ChatGPT, others will probably do the same to blend in with what is considered normal. Second, through evaluations, recommendations, and shared experiences, informational impact inside social networks disseminates important insights regarding ChatGPT's dependability and usefulness. Students' perceptions of ChatGPT and their plans to use it are influenced by this. Third, peer, instructor, or expert endorsements increase ChatGPT's legitimacy as a teaching tool. Students become more assured of its effectiveness and social acceptance as a result. Peer pressure in social and academic settings might also encourage students to utilize ChatGPT in order to fit in and not feel excluded. Additionally, good attitudes are reinforced and ChatGPT usage is encouraged through social reinforcement when others utilize it successfully. Finally, students gain a deeper understanding of ChatGPT's capabilities and advantages through interacting with other users. ChatGPT usage is increased by this cooperative learning environment. All things considered, students' decisions to use ChatGPT for educational purposes are greatly influenced by social influence.

Contrary to expectations, hypothesis H4 was not supported, indicating no significant correlation between facilitating conditions and students' intention to use ChatGPT. This finding contradicts studies that have established a strong link between infrastructural support and technology adoption (Alam et al., 2020; Foroughi et al., 2024; Grassini et al., 2024; Kwak et al., 2022). The lack of significant findings in this study could be attributed to limited institutional support, inadequate IT infrastructure, or insufficient training in Ugandan universities (Budhathoki et al., 2024; Kyambade & Namatovu, 2025). Future research should explore strategies to enhance institutional support for AI adoption in higher education.

Hypothesis H5 was supported, indicating a strong positive correlation between hedonic motivation and students' intention to use ChatGPT. This suggests that students are more likely to adopt ChatGPT when they find it engaging and enjoyable (Foroughi et al., 2024; Rodriguez et al., 2023; Strzelecki, 2024a, 2024b; Tashtoush *et al*., 2023, Tashtoush *et al*., 2023,). This finding highlights the importance of designing AI tools with interactive and engaging features to enhance student motivation and learning experiences.

The study also confirmed hypothesis H6, showing a strong positive correlation between learning value and students' intention to use ChatGPT. This result aligns with prior research (Zacharis & Nikolopoulou, 2022; Foroughi et al., 2024), reinforcing the notion that students are more inclined to use AI-based learning tools when they perceive them as beneficial for their education. These findings suggest that institutions should integrate ChatGPT into curricula to enhance its perceived learning value. This implies that students are more likely to use ChatGPT if they believe it to be a useful learning tool. (Zacharis & Nikolopoulou, 2022; Foroughi et al., 2024) This conclusion is consistent with previous empirical investigations. According to this research, there is a strong association between learning value and

the intention to utilize ChatGPT, which highlights how crucial it is to acknowledge AI-based tools like ChatGPT in educational settings.

Lastly, hypothesis H7 was slightly supported, indicating a significant relationship between habit and students' intention to use ChatGPT. This finding is consistent with previous studies that emphasize the role of habitual behavior in technology adoption (Grassini et al., 2024; Biloš & Budimir, 2024; Strzelecki, 2024a, 2024b). While habitual usage may not always be an immediate predictor, prolonged exposure to ChatGPT can reinforce its integration into students' learning routines (Hu et al., 2022; Kim *et al*., 2023). This suggests that as students become more familiar with ChatGPT, habitual usage will play an increasingly significant role in their continued adoption of the tool. Although the data did not support a strong predictive relationship in this study, it is important to recognize the role of habit as a construct in influencing technology usage intentions, as established in prior research (Grassini *et al*., 2024; Biloš & Budimir, 2024; Strzelecki, 2024a, 2024b). This aligns with the findings of Venkatesh et al. (2012), who emphasize that habitual behavior is a critical factor in technology acceptance and usage. Furthermore, research by Limayem and Cheung (2008) highlights that habitual usage can significantly impact user intention over time, suggesting that while habitual use may not have manifested as a significant predictor in this instance, the theoretical foundation supports its relevance in the broader context of technology adoption. The lack of significant findings may reflect the nascent stage of habit formation among the student population using ChatGPT for their assignments. As this study explores emerging behaviors, the weak correlation observed may indicate that students have not yet developed strong habitual patterns associated with ChatGPT usage, warranting further investigation into how habits evolve over time in educational contexts (Bagozzi, 2007; Thong et al., 2011). Despite the statistical insignificance of H7, its inclusion in this research provides valuable insights into the emerging role of habit in technology adoption. This highlights the need for future studies to examine how user familiarity and increased exposure to tools like ChatGPT may strengthen the predictive power of habit over time, as suggested by the works of Hu et al. (2022) and Kim et al. (2023). Moreover, the limited prior experience of participants with ChatGPT may also explain the observed weak correlation, suggesting that as students become more acquainted with the tool, the influence of habit could become more pronounced (Rahim et al., 2022). While the findings do not demonstrate statistical significance, they contribute to understanding the complexities of predicting technology usage intentions in higher education. The nuances of habit's influence on usage intentions present an important area for future exploration, underscoring the evolving nature of students' interactions with technology (Hwang et al., 2021; Foroughi et al., 2024).

Nonetheless, because ChatGPT is still relatively new to Ugandan higher education, students' and teachers' lack of familiarity with it or adoption difficulties may lessen the influence of effort expectations on their desire to use the program. The facilitating conditions are often a significant predictor of the desire to use ChatGPT, according to recent studies (Grassini et al., 2024; Kwak et al., 2022; Alam et al., 2020). However, other research indicates that facilitating conditions do not necessarily influence the intention to use, therefore the conclusion has not been able to be more broadly generalized in different contexts (Budhathoki *et al*., 2024; Foroughi et al., 2024; Almahri et al., 2020; Twum et al., 2022).

The lack of institutional support and technical infrastructure is the reason for the negligible impact of facilitating conditions on the intention to use ChatGPT (Foroughi et al., 2024; Kyambade & Namatovu, 2025). For instance, according to Budhathoki et al. (2024), Uganda lacks the necessary information technology (IT) infrastructure, resources, training, and policies to enable ChatGPT's successful integration. The last finding is that hedonic motivation and students' intention to use ChatGPT are positively correlated (Foroughi et al., 2024; Strzelecki, 2024a, 2024b; Rodriguez et al., 2023; Tashtoush et al., 2023,). However, research suggests that hedonic incentive may not always have a major impact on students' intention to utilize the tool, therefore this link is not always consistent (Grassini et al., 2024; Sudan et al., 2024). Students may not always find their interactions with ChatGPT to be entertaining, engaging, or delightful, which can lead to this unpredictability. Additionally, how pupils view and interact with new technologies may be influenced by Uganda's cultural views and surrounding factors. Hedonic motivation and intention to use ChatGPT may not be strongly correlated if people are skeptical of new technologies or prefer traditional approaches.

The surprising findings of the study may be influenced by Uganda's unique cultural context. Traditional teaching methods have long been valued in Ugandan school culture (Sah et al., 2024). Despite the potential of technologies like ChatGPT to enhance performance, students may undervalue

them due to a preference for conventional approaches. Additionally, technological openness in Uganda varies significantly (Pangeni, 2016). Educators and students may hesitate to use ChatGPT due to limited knowledge or a lack of confidence in its efficacy. Moreover, interpersonal relationships are highly valued in Ugandan society, with a preference for direct interactions with peers and teachers over using AI tools like ChatGPT. In contrast, studies from developed countries indicate that a culture fostering innovation and technological integration in learning environments drives the acceptance of educational technologies (Strzelecki, 2024a, 2024b). In these settings, the perceived ease of use and performance benefits of tools like ChatGPT significantly influence students (Foroughi et al., 2024; Rodriguez et al., 2023). The high value placed on technological innovation and skill contributes to broader adoption of AI tools (Tashtoush et al., 2023; Kyambade et al. 2024a; Surya Bahadur et al., 2024). However, Uganda's distinct cultural environment presents several challenges for adopting new tools like ChatGPT. Traditional educational practices, which favor established methods over new technologies, may hinder the adoption of ChatGPT (Sah et al., 2024). Additionally, widespread skepticism about new technologies and insufficient institutional support for AI integration further delay its acceptance (Budhathoki et al., 2024).

Overall, this study provides valuable insights into the factors influencing ChatGPT adoption among students. While performance expectancy, effort expectancy, social influence, hedonic motivation, learning value, and habit significantly impact intention to use, facilitating conditions do not. The findings underscore the need for targeted interventions to promote AI adoption in higher education, particularly by addressing infrastructural and institutional barriers. Future studies should examine how these factors evolve over time and across different educational contexts.

Theoretical implications

By focusing on cutting-edge AI technology (ChatGPT) with significant implications for educational practices, this study contributes to the growing body of work on technology adoption. By investigating the elements that influence students' intention to utilize ChatGPT in the context of higher education in a least-developed nation, the study closes a gap in the literature. Additionally, by applying the UTAUT2 model especially to the adoption of ChatGPT in higher education settings, the study expands on it. A popular theoretical framework that incorporates a number of variables affecting people's decisions to accept new technology is UTAUT2. In particular, the study found that students' inclination to use ChatGPT was significantly predicted by social impact, learning value, and habit. The study's conclusions offer fresh perspectives on how these UTAUT2 parameters function in relation to ChatGPT and other AI technologies. It demonstrates, for instance, that although effort expectancy, facilitating conditions, performance expectancy, and hedonic motivation are significant, they might not be enough to predict the intention to use ChatGPT in educational settings if social influence, learning value, and habit formation are not taken into account. The results of the study provide empirical support for the UTAUT2 model's broader application in the context of integrating AI in higher education. The study expands the use of UTAUT2 in an educational setting by substituting the concept learning value for pricing value.

Practical implications

The study's conclusions have a wide range of applications for educators, legislators, and ChatGPT developers. In order to make ChatGPT a consistent component of students' educational experiences, educators must concentrate on encouraging the development of habits by integrating it into regular academic tasks and classroom activities. Additionally, they ought to highlight ChatGPT's educational advantages by elucidating how it might improve academic performance and offering training sessions to optimize its capabilities. Making the most of social influence is essential. Teachers can promote peer learning by leading group discussions in which students discuss their ChatGPT experiences and enlisting faculty members to support its use. For ChatGPT's usage in education, policymakers must provide thorough standards that address ethical issues and best practices. The smooth integration of ChatGPT into educational settings will also be made possible by funding technological infrastructure and assisting educators' professional development. By refining ChatGPT's interface and usability in response to user

feedback, developers should concentrate on improving the user experience. Increasing openness about ChatGPT's information sources and response generation process will foster user understanding and trust.

Conclusions

The teaching and learning process in education has undergone a significant transformation because to the extraordinary rise of generative AI technologies like ChatGPT. Researchers are very interested in learning more about how students view and plan to utilize ChatGPT for academic purposes as a result of this change. Using the UTAUT2 model, this study investigated the factors influencing Ugandan university students' intention to use ChatGPT. Habit, learning value, and social influence were found to have a favorable effect on the intention to use ChatGPT, while hedonic incentive, performance expectancy, effort expectancy, and facilitating conditions had no discernible effect. This emphasizes how important peer recommendations and acceptance among the student body are in encouraging the use of ChatGPT. The need to enhance ChatGPT's learning resource capabilities and content correctness is further highlighted by students' increasing impression of ChatGPT as a valuable educational tool. Students in higher education have made using ChatGPT a habit, demonstrating its increasing dependence. In order to encourage the appropriate and responsible use of AI-based learning technologies, it is necessary to provide suitable guidance and formulate policies.

Limitations and future research directions

The study has several limitations. First, its cross-sectional design may introduce biases related to the timing of data collection. For example, students' intentions to use ChatGPT might vary during different academic periods, such as exam times or based on recent experiences with similar technology. These unconsidered temporal effects could distort the findings. Additionally, the use of self-reported measures may lead to response biases like recall or social desirability bias, where participants might provide answers they believe are expected or socially acceptable rather than reflecting their true intentions or behaviors. Moreover, the study's focus on a single university in Uganda limits the generalizability of its findings beyond this specific context. To address these limitations, future research could adopt longitudinal designs to better assess causal relationships between variables over time. By collecting data at multiple time points, researchers could capture the dynamic nature of students' intentions to use ChatGPT, allowing for a more in-depth analysis of causality. Expanding the study to include multiple universities and countries would also enhance generalizability, providing a broader understanding of the phenomenon across different contexts.

Authors'contributions

Afulah Namatovu: Involved in the conception and design, or analysis and interpretation of the data; the drafting of the paper, revising it *critically* for intellectual content; the final approval of the version to be published; and agreement to be accountable for all aspects of the work. The has read and approved the final version of the manuscript.

Mahadih Kyambade: Involved in the conception and design, or analysis and interpretation of the data; the drafting of the paper, revising it critically for intellectual content; the final approval of the version to be published; and agreement to be accountable for all aspects of the work. The has read and approved the final version of the manuscript.

Disclosure statement

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

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