Asian Journal of University Education (AJUE)
Volume 21, Number 3, October 2025

Sustainable Learning through AI Tool Adoption among University Students in Ethiopia Based on an Extended UTAUT Model

Ravishankar Krishnan[1*], KR Sowmya[2], Demelash Misgana Wase[3], Logasakthi Kandasamy[4]

[1]School of Management, Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology., Chennai, India.
vim.ravishankar@veltech.edu.in
[2]Adjunct Researcher, Research Management Centre (RMC), Spectrum International University College (SIUC), Subang Jaya, Selangor, Malaysia.
drkrsowmya@gmail.com
[3]Team Leader, Planning and Budget Preparation, Monitoring and Evaluation Federal Democratic Republic of Ethiopia, Ministry of Education, Ethiopia.
demelashmisganawase79@gmail.com
[4]School of Business, RV University, Bengaluru, India
logasakthik@rvu.edu.in
*Corresponding Author

https://doi.org/10.24191/ajue.v21i3.60

Received: 29 May 2025
Accepted: 13 August 2025
Date Published Online: 31 October 2025
Published: 31 October 2025

Abstract: This study investigates the sustainable integration of Artificial Intelligence (AI) tools into higher education by evaluating the Ethiopian university students' behavioural intentions and actual usage through an extended UTAUT model. Although AI has the potential to transform learning personalization and education quality enhancement, its application in countries with limited resources like Ethiopia is still very low. This study aims to explore which factors influence students' adoption and continued use of AI tools in Ethiopian higher education, and how these factors contribute to long-term educational sustainability. The study incorporates constructs such as Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Trust, Intention to Use, User Behaviour, Sustainability Perception and seeks to examine students' adoption of AI tools concerning their perceived long-term academic outcomes. Data from a survey of 548 students were subjected to analysis using PLS-SEM to evaluate the proposed model. Results indicate that all proposed constructs had significant positive relationships; most notably, Intention to Use and User Behaviour ($\beta = 0.684$) and User Behaviour and Sustainability ($\beta = 0.313$). Incorporating sustainability into the UTAUT framework offers theoretical contributions while practically speaking, the study provides insights for institutional stakeholders to encourage responsible long-term adoption of AI tools in higher education. The results highlight institutional guidance, ethical boundaries, and user-focused design a framework that is crucial for achieving profound and lasting transformations through AI in education.

Keywords: Artificial Intelligence, Ethiopia, Higher Education, PLS-SEM, Sustainable Education, UTAUT, Technology Adoption

1. Introduction

The evolution of global education is substantially influenced by the United Nations' Sustainable Development Goal 4 (SDG 4), which aims to establish education that is inclusive, equitable, and of high quality across all tiers of education (Chien & Knoble, 2024). This objective transcends mere accessibility, stressing the attainment of substantial learning outcomes and the cultivation of sustainable educational settings that equip learners with the skills essential for active engagement in the 21st-century knowledge economy. Even with significant global advancements, nations like Ethiopia still face major challenges in providing access and quality in their higher education systems. Given this, artificial intelligence (AI) can change the technology progress of education and have a great impact on all levels of education and learning. Artificial intelligence deals with the presented systems or tools, such as adaptive education, automatic evaluation, intellectual education, and personalized feedback designed to reproduce an individual's intellectual ability to achieve certain goals and solve complex problems (Saha et al., 2025).

Software applications like ChatGPT, Grammarly, and Gradescope, along with other AI powered tools, are transforming traditional instructional methods by increasing interactivity, efficiency, and customization (Khoso et al., 2023).The pandemic caused a break in the education systems which have now started recovering and AI has become a focal point of building adaptive and sustainable learning environments (Mařík et al., 1989). Although there is widespread focus on enhanced AI education globally, it is still a low-investment focus area in developing countries, particularly in Sub-Saharan Africa. For Ethiopia, AI applications in teaching and learning is still at a dormant stage due to lack of infrastructural flexibility and high digital illiteracy (Dejene & Tilahun, 2024). Ethiopia is undergoing efforts in widening access to higher education, but it still struggles with weak teaching, low sustained learning outcomes, and failure to integrate educational components. The more considerable gap in the literature appears to be a disconnection between AI applications in education with the concept of sustainability, guidance towards a comprehensive shift. Pouring existing frameworks to this context to study their impact stands as an acceptable yet ambiguous approach and they risk drawing inaccurate conclusions without the support of a well-elaborated focus to study. This gap will be fulfilled by examining the issue of sustainable adoption of AI in learning technologies with Ethiopian university students as a case study.

This research analyses the factors affecting students' intention to use and their actual usage of AI tools at higher levels of education using an enhanced UTAUT model which adds Trust, User Behaviour, and Sustainability as additional constructs. The study seeks to determine the role of those elements towards achieving sustainable learning outcomes, especially in under-resourced academic settings. This study not only contributes to the discourse on the integration of AI tools within the context of higher education in Ethiopia, which is relatively less developed, but also incorporates sustainability in education outcomes in adapting the UTAUT framework. With the intention of providing timely responses to issues of how AI can aid in achieving enduring shifts in educational systems in Ethiopian universities, the research employs the modified UTAUT framework aimed at fostering educational standards on a global scale. The multidimensional approach of the study focuses on capturing sustainable learning with the post-pandemic observable behavioural changes of the students, which is crucial for the effective formulation of digital strategies. The findings are useful for university administrators, educators, and education decision-makers concerned with improving system-wide equity, customization, and effective use of technology in instruction and learning processes.

There are several research questions to direct the study: To what degree do Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Trust as a whole affect students' intention to adopt AI-enabled tools in higher education in Ethiopia? In what way does students' intention to employ AI tools affect their actual behaviour and perception regarding sustainable learning effectiveness? Do significant relationships exist among the components of the extended UTAUT framework that might account for students' adoption of AI tools for sustainable quality education?

At last, the present work contributes to the broader conversation around 21st century education by suggesting how AI could be responsively integrated into higher education systems through responsible approaches that nurture adaptable and inclusive academic systems.

2. Literature Review

Incorporating AI in education is increasingly recognized as a strategic innovation to do more than just improve learning and make education high quality. It is an exciting transformation that allows education to be great for everybody and last for a long time so more people can receive quality learning. Globally, there has been a growing recognition of more personalization in the way that teachers teach and to facilitate student learning through AI-driven methods, which excels at automating assessments and streamlining diverse instructional methodologies (Amani et al., 2023). Systems that use smart thinking, tools that understand plain language spoken humanly and sort out data faster than a human brain all of these powerful and exciting technology inventions directly play a really big role in making learning better and keeping people engaged. In developed countries, wider adoption of these tools is significantly strengthened by institutional readiness and educational setups are, owing to solid digital infrastructure and professional development that goes on for teachers step by step (Joseph et al., 2024).

However, in countries such as Ethiopia that aren't quite developed yet and are still developing, there is growing evidence that implementation is pretty limited. The fault lies heavily with deficiencies in infrastructure, high costs involved and a lack of training (Wen et al., 2024). The need for equitable access, particularly in resource-constrained environments, raises critical concerns regarding the scalability and inclusivity of AI in education. Scholars have also burrowed pretty deeply into the social and ethical implications of AI nowadays. For instance, algorithm favouritism for one, and privacy issues too. There's also the risk that training from AI can widen existing divisions when it comes to education (Tran, 2024; Zaman et al., 2025). Therefore, successful adoption of AI for quality education requires not only technological feasibility but also careful consideration of its economic, social, and environmental impact. While AI shows great promise in doing really well for long term learning and aligning with those goals set up by UNESCO related to Sustainable Development Goal 4, evidence on whether this technology integrates smoothly and successfully, especially in areas like Central and Southern Africa, is still pretty underexplored. This gap serves as the central motivation for this study.

2.1. Theoretical Framework: Extended Unified Theory of Acceptance and Use of Technology (UTAUT)

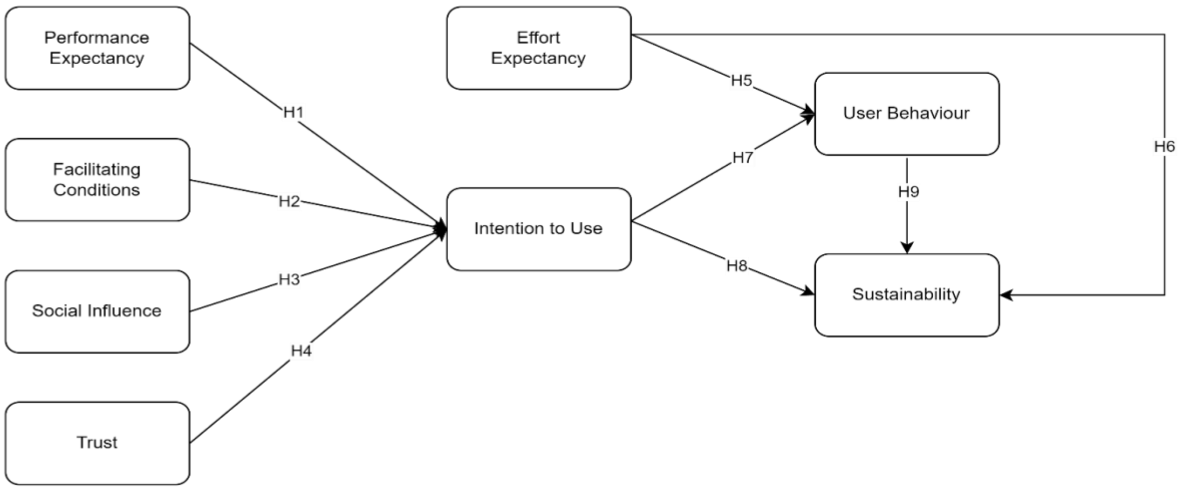
This research utilizes an adapted version of the Unified Theory of Acceptance and Use of Technology AI tools in Higher Education AI and higher education to incorporate adoption and sustainable use to evaluate the UTAUT Framework. This model has consistently performed well in predicting intention and technology usage behaviour across several domains, especially in the context of educational technology. The study is based on the performance moderation factors of UTAUT—Performance Expectancy (PEY), Effort Expectancy (EEY), Social Influence (SOI), Facilitating Conditions (FAC)—with those that are imperative with regard to sustainable AI use: Trust (TRT), User Behaviour (USB), Intention to Use (INT), and Sustainability Perception (SUS).

2.2 Proposed Model and Hypotheses

The study conceptualizes and defines several constructs drawn from the extended Unified Theory of Acceptance and Use of Technology (UTAUT) and relevant literature. Performance Expectancy is about how seriously someone thinks they're going to up their game with using something. It's how much they believe that it will help them do better at work or in school (Abdullah et al., 2023). Effort Expectancy (EEY) is defined as the perceived ease associated with the use of a system (Venkatesh et al., 2021). Social Influence (SOI) captures the extent to which individuals perceive that important others believe they should use the new system (Venkatesh et al., 2021). Facilitating Conditions (FAC) denote the extent to which an individual believes that technical and organizational infrastructure exists to support the use of the system (Chiu & Chiu, 2024). In addition to core elements, Trust (TRT) is also part of the study. Mayer and others defined this as the user's confidence in whether the system or tech works reliably and with integrity. Trust really makes people feel secure and giving them assurance that they can rely and perform effectively with technology and its processes (Eneizan et al., 2019). Intention to Use (INT) represents an individual's motivation or plan to use a system in the future (Jewer, 2018; Lakhal et al., 2013), while User Behaviour (USB) refers to the actual usage patterns or actions performed after the system is adopted (Tang et al., 2025; Yakubu et al., 2025). Lastly, the research also takes into account sustainability perception (SUS), assessing the extend of using technology contributes to larger long-lasting educational and societal impacts (Dittrich et al., 2024; Shu et al., 2020).

Figure 1

Proposed Research Model



The following hypotheses are provided taking into consideration both theoretical and empirical literature:

Performance Expectancy (PEY) and Intention to Use (INT)

As defined by Venkatesh et al. (2021), Performance Expectancy is defined as the extent of belief that system usage will improve one's academic performance. There is evidence that an increase in perceived usefulness raises motivation to adopt technology (Tian et al., 2024). In Ethiopia's higher learning institutions where students enroll with the intention of getting tools that boost academic performance, AI's capabilities for lesson management enhancement would be expected to affect intention to use positively.

H1: PEY is positively associated with INT in students' use of AI-enabled educational tools.

Facilitating Conditions (FAC) and Intention to Use (INT)

Facilitating Conditions reflect the degree to which students believe that supportive infrastructure, access to resources, and institutional guidance exist to help them adopt a technology (Venkatesh et al., 2021). When institutions give adequate support with technology, reliable internet and programs for literacy in technology, students are more eager to try learning tools that make use of artificial intelligence (Grassini et al., 2024; Yakubu et al., 2025).

H2: FAC significantly influences INT in the adoption of AI-enabled educational tools.

Social Influence (SOI) and Intention to Use (INT)

According to Venkatesh et al. (2021), social influence is the extent to which a person believes that significant others in their life, like mentors, teachers, or peers, think they ought to use a specific method. This influence plays a key role in shaping the intention to use (INT) of an individual, which reflects their willingness or intention to adopt the technology. Research suggests that peer support, institutional support and mentoring can significantly increase the willingness of users to adopt digital tools and thus increase their propensity to use them (Sarkam et al., 2022). Positive social impact not only promotes acceptance but also motivates continued involvement in the field of disruptive liability (Baharin et al., 2025; Nikolopoulou et al., 2020).

H3: A positive association exists between SOI and INT in the educational use of AI tools.

Trust (TRT) and Intention to Use (INT)

The user's faith in a technological system's dependability, security, and moral character is referred to as trust (Eneizan et al., 2019). According to Brummernhenrich et al. (2025) students are more likely to use AI tools for academic purposes when they believe they are safe and morally sound (Dhagarra et al., 2020; Pavlou, 2003). When using AI-powered learning platforms, especially in settings with limited resources, a high degree of trust lowers the perceived risks and uncertainties (Hussen, 2022). Additionally, trust encourages long-term participation and frequent use, both of which are necessary to maintain significant learning outcomes in digital learning environments (Shahzad et al., 2024; Uche et al., 2020).

H4: TRT contributes positively to INT among students engaging with AI-powered learning systems.

Effort Expectancy (EEY), User Behaviour (USB), and Sustainability Perception (SUS)

An individual's perception regarding the ease of utilization is defined as effort expectancy (Venkatesh et al., 2021). Systems which are user-friendly and do not require extensive training are more likely to ensure uniform user behaviour and higher chances of enduring adoption (Gunasinghe et al., 2020; Gupta et al., 2018). In addition, such consistent use reinforces enduring learning patterns that are in line with education for impact (Gunasinghe et al., 2020).

H5: EEY has a significant positive effect on USB in the context of AI tool usage.
H6: EEY positively impacts SUS in students' learning with AI-enabled tools.

Intention to Use (INT), User Behaviour (USB), and Sustainability Perception (SUS)

The intention to use a technological system has been identified as one of the main predictors of actual system usage behaviour (Venkatesh et al., 2021). Students' adoption of AI tools within their academic activities, there is a strong tendency for their actual usage to increase (Liu et al., 2025; Xu et al., 2024). Additionally, regular use of such tools improves perceived sustainability owing to the enhancement of experience longevity and quality in education.

H7: INT strongly predicts USB in the educational application of AI.
H8: INT is positively linked to SUS in students' long-term use of AI in education.

User Behaviour (USB) and Sustainability Perception (SUS)

User behaviour is concerned with how often and in what way learners interact with AI tools after they have already adopted them (Zaim et al., 2024). Students who have access to these technologies tend to engage with them more frequently and to understand that their approach to learning is sustainable and forward-looking (Cabero-Almenara et al., 2024; Kim & Son, 2022).

H9: USB demonstrates a positive influence on SUS in sustaining learning outcomes through AI tools.

3. Methodology

3.1 Research Design

This research aims to examine the factors influencing the effectiveness of smart AI tools in education and explore strategies for their long-term integration. It integrates the Unified Theory of Acceptance and Use of Technology (UTAUT) with an added sustainability dimension, specifically tailored to digital learning environments. Emphasizing the importance of environmentally conscious, long-term adoption of educational technologies, the study draws on core UTAUT constructs and incorporates additional components such as user intention, behaviour, and sustainability to understand AI's impact in higher education settings (Hu et al., 2025).

3.2 Questionnaire Design

The questionnaire was developed by adapting validated items from the UTAUT model, with contextual modifications for university-level education. To address gaps in existing literature, new items related to sustainability in AI tool usage were included. This instrument went through a pre-test with a wide group of professionals who work with education to make sure it makes clear sense and is highly relevant. The instrument, structured into 11 sections, begins with demographic questions and then assesses the key theoretical constructs and sustainability factors. Responses were collected using a Likert scale for quantitative analysis.

3.3 Population and Sample

The study is directed toward students of higher education institutions in Ethiopia, with the intent to establish their views on the adoption and sustainability of AI-enabled systems in the processes of learning. The survey was carried out in the students' active learning period which, in relation to the academic calendar, is between August and December 2024. In the preparatory stages of the survey, respondents were purposefully selected based on their relevance to their survey's variables, particularly focusing on respondents whose higher education courses were in progress. In order to have a more informed response, a purposive sampling was adopted and data obtained from students who were reasonably familiar with AI-enabled tools in educational settings. This sample was composed of a wide range of students including undergraduates, postgraduates, and Ph.D. candidates from several faculties, such as engineering, humanities, social sciences, and professional studies. Data collection was mainly done using a Google Forms questionnaire which was shared through social media and school-to-school networks to target higher education students in Ethiopia. In response to the lower than anticipated online response rate from the survey and to accommodate the students who are less exposed in to the digital world, a supplementary physical readable paper survey was also provided.

The combination of methods promoted greater engagement, such as those without internet access and those who chose to answer in-person. With the online answers, the sustained paper surveys resulted in 548 valid answers from the multiple campuses. To keep the data honest, emotionally charged, contradictory, or half-hearted answers were removed from the final assessment. This meticulous data collection process allowed for accuracy and soundness of the study's conclusions, which was in turn directed towards understanding the students' views on the integration, interaction, and impacts of artificial intelligence learning environments in the context of higher education.

4. Data Analysis

In this research, SPSS 22 and Partial Least Square Structural Equation Modeling is the data analysis employed for this research since this methodology is appropriate for complex models with multi-constructs. This applies to our study as this involved students' perceptions towards the sustainable effectiveness of AI-enabled tools related to learning and education. PLS-SEM manifests its utility, especially, in the nature of descriptive research that is prediction or theory test oriented, which perfectly addresses the focus of the current investigation (Hair, J.F., Hult, G.T.M., Ringle, C.M. and Sarstedt, 2017).

First, SPSS 22 was used to analyse the demographic data of student participants to give a contextual descriptive picture of the population sample. Second, the measurement model's CFA was conducted through PLS-SEM on the students' perceptions regarding the sustainable effectiveness of AI-enabled learning tools' use to conduct their learning activities after which the reliability, convergent validity, and discriminant validity of the constructs were assessed. Third, PLS-SEM was used to test the proposed hypotheses on the structural model and the interrelations of the constructs perceived AI usage, learning outcomes, and sustainability. In regard to the findings' statistical significance, path coefficients were confirmed through bootstrapping to ensure the credibility of the results (Sarstedt et al., 2021).

4.1. Participant Information

There were 548 students who took part in this study. Table 1 provides the demographic segmentation of the respondents. Participants are a demographic balance in terms of age, gender, field of study, academic year, previous AI usage, and the level of degree attained. The age distribution reveals th at the highest proportion of participants used (36.4%) are aged 26-30 years, successively followed by 18-21 years (35.1%), and 22-25 years (28.5%). From the data collected, it indicates that the slight majority of respondents were female (53.1%) while 46.9% were male. Concerning the participants' fields of study, highest percentages were reported in Business and Economics (40.6%), followed by Engineering and Technology (28%), Natural Sciences (17.2%), and Health Sciences (14.2%). The year of study distribution indicates that a larger portion of students is in 2nd year (32.2%), followed by an equal proportion of 1st and 4th years (26.4% each) and finally, 15.1% of the sample consists of 3rd-year students. Out of the total respondents, it is interesting to note that 76.4% claimed to have prior encounters with AI educational tools while 23.6% did not. This denotes a fairly high level of usage of AI tools among students. At last, regarding their degree level, the most common are undergraduates (UG) (61.3%), followed by postgraduates (PG) (20.9%) and doctorate students (17.8%).

Table 1

Demographic Profile of Respondents (N=478)

Variable	Category	Frequency	Percent
Age	18-21	192	35.1
	22-25	157	28.5
	26-30	199	36.4
	Total	548	100
Gender	Female	291	53.1
	Male	257	46.9
	Total	548	100
Field of Study	Business and Economics	222	40.6
	Engineering and Technology	154	28
	Health Sciences	78	14.2
	Natural Sciences	94	17.2
	Total	548	100
Year of Study	1st Year	144	26.4
	2nd Year	176	32.2
	3rd Year	83	15.1
	4th Year	145	26.4
	Total	548	100
Previous AI Experience	No	129	23.6
	Yes	419	76.4
	Total	548	100
Degree Programme	UG	336	61.3
	PG	114	20.9
	PhD	98	17.8
	Total	548	100

5. Research Model Assessment and Results

5.1 Model Assessment

For this analysis, PLS-SEM which stands for Partial Least Squares Structural Equation Modeling, was used to evaluate the measurement and structural models. All factor loadings for items corresponding with each construct were over the suggested cutoff of 0.50 (Almufarreh, 2024; Shmueli et al., 2019) which shows that all items were correctly saved into the model. The reliability was assessed through Cronbach's alpha values, which demonstrate the internal consistency and stability of the measurement scales.

Specific values of reliability, as well as validity, are shown in Table 2. Cronbach's alpha values for all constructs have been between 0.797 to 0.903, which is above the cutoff value of 0.70 (Narula et al., 2020). A majority of values were clearly above 0.80, proving superb reliability. Examination of Composite Reliability and Average Variance Extracted establishes convergent validity. All constructs showed composite reliability values of 0.873 to 0.925 which is above the .70 minimum acceptable level. In addition, AVE values were between 0.633 and 0.793 which is above the 0.50 minimum threshold value (Henseler et al., 2015). These results affirm the strong convergent validity of the measurement model. Assessing the discriminant validity was done with the Fornell–Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio, which are two complementary approaches.

As outlined by the Fornell–Larcker criterion, all square roots of AVE values in Table 3 were greater than their correlations with other constructs, clearly fulfilling this requirement. Furthermore, the HTMT values in Table 4 always remained lower than the discriminant validity threshold of 0.85, meaning that the validity of the constructs was indeed established (Henseler et al., 2015).

Table 2

Results of the measurement model

Construct	Items	Indicator Loading	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Effort Expectancy	EEY1	0.774	0.869	0.875	0.911	0.72
	EEY2	0.885				
	EEY3	0.872				
	EEY4	0.858				
Facilitating Conditions	FAC1	0.766	0.807	0.806	0.873	0.633
	FAC2	0.838				
	FAC3	0.793				
	FAC4	0.785				
Intention to Use	INT1	0.845	0.797	0.799	0.881	0.711
	INT2	0.833				
	INT3	0.851				
Performance Expectancy	PEY1	0.802	0.813	0.816	0.877	0.64
	PEY2	0.809				
	PEY3	0.803				
	PEY4	0.787				
Social Influence	SOI1	0.884	0.861	0.864	0.915	0.783
	SOI2	0.887				
	SOI3	0.883				
Sustainability	SUS1	0.846	0.903	0.905	0.925	0.674
	SUS2	0.836				
	SUS3	0.833				
	SUS4	0.782				
	SUS5	0.817				
	SUS6	0.812				
Trust	TRT1	0.872	0.87	0.877	0.92	0.793

Construct	Items	Indicator Loading	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
	TRT2	0.908				
	TRTS3	0.890				
User Behaviour	USB1	0.873	0.829	0.832	0.898	0.746
	USB2	0.844				
	USB3	0.874				

Source: Authors Calculation

Table 3

Discriminant Validity - Fornell-Larcker Criterion

Factors	EEY	FAC	INT	PEY	SOI	SUS	TRT	USB
Effort Expectancy (EEY)	0.848							
Facilitating Conditions (FAC)	0.621	0.796						
Intention to Use (INT)	0.54	0.642	0.843					
Performance Expectancy (PEY)	0.581	0.577	0.624	0.8				
Social Influence (SOI)	0.523	0.555	0.583	0.483	0.885			
Sustainability (SUS)	0.552	0.578	0.707	0.666	0.587	0.821		
Trust (TRT)	0.472	0.499	0.611	0.566	0.613	0.675	0.89	
User Behaviour (USB)	0.527	0.689	0.769	0.573	0.667	0.693	0.617	0.864

Source: Authors Calculation

Table 4

Discriminant Validity - Heterotrait Monotrait Ratio (HTMT)

Factors	EEY	FAC	INT	PEY	SOI	SUS	TRT3	USB
Effort Expectancy								
Facilitating Conditions	0.739							
Intention to Use	0.648	0.799						
Performance Expectancy	0.684	0.71	0.772					
Social Influence	0.606	0.665	0.699	0.576				
Sustainability	0.622	0.676	0.831	0.779	0.665			
Trust	0.542	0.596	0.725	0.668	0.706	0.763		
User Behaviour	0.62	0.842	0.941	0.696	0.789	0.798	0.725	

Source: Authors Calculation

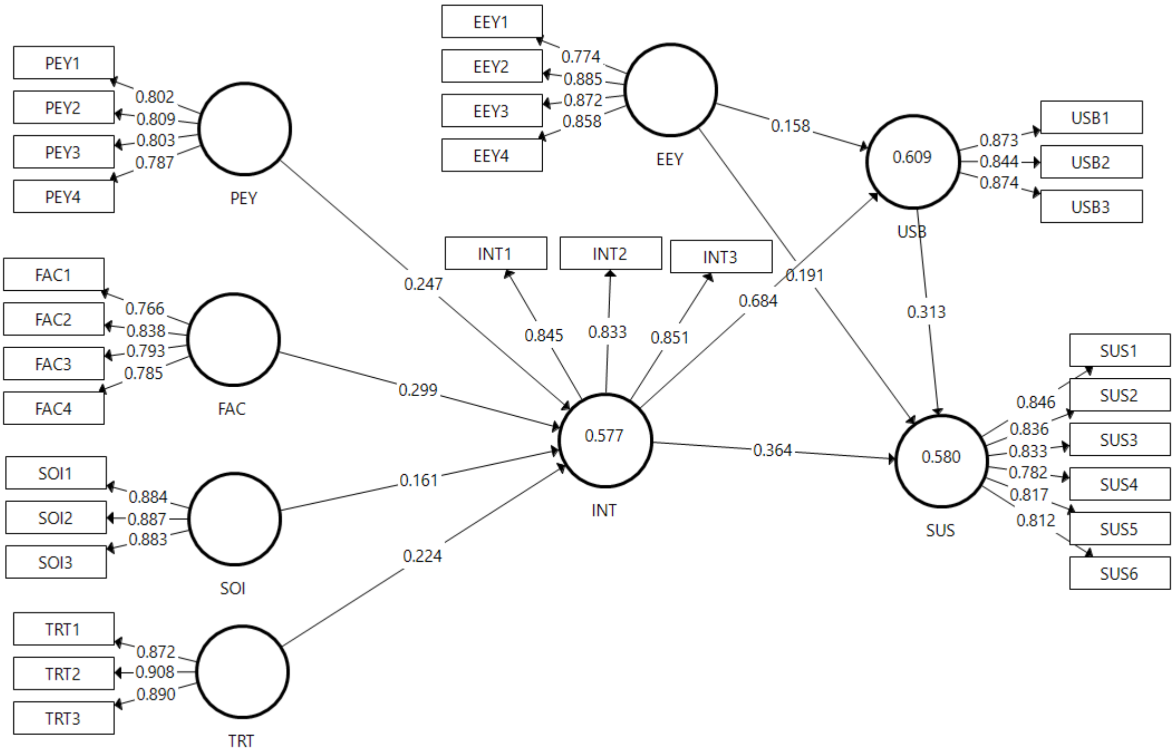
5.2 Structural Model Assessment

After assessing the measurement model for validity and reliability, the structural model was assessed for the different relationships between Effort Expectancy, Facilitating Conditions, Performance Expectancy, Social Influence, Trust, Intention to Use, Sustainability, and User Behaviour (EEY, FAC, PEY, SOI, TRT, INT, SUS, and USB). First, possible multicollinearity among predictor variables was assessed through the use of the Variance Inflation Factor (VIF) method. A recommended VIF cutoff value is below 3.33, which ensures that the results of the regression will be unbiased and free from multicollinearity issues (Diamantopoulos & Siguaw, 2006). The observed study VIF values which were 1.575 to 2.823, were all within that range. No problematic multicollinearity was found.

Afterwards the bootstrapping method with PLS-SEM was used to estimate the statistical significance and confidence intervals for the structural model relationships. Additionally, the R^2 value was computed for each endogenous construct within the structural model to find out the predictive power of the model. The R^2 value describes the likelihood of the variance explain by the predictor variables.

Figure 2

Structural Model Results



As shown in Table 5 and Figure 2, the model's R^2 values provided it with strong predictive power, and in particular the constructs Intention to Use (INT) ($R^2 = 0.577$), Sustainability (SUS) ($R^2 = 0.580$), and User Behaviour (USB) ($R^2 = 0.609$) were all surpassing the usually accepted benchmark (0.20) and thus were of substantial predictive importance in research concerning behavioural sciences (Bazelais et al., 2018; Rasoolimanesh et al., 2017).

Table 5

R^2 of the dependent variables

Construct	R Square	Results
Intention to Use (INT)	0.577	High
Sustainability (SUS)	0.580	High
User Behaviour (USB)	0.609	High

Source: Authors Calculation

5.3 Hypotheses Testing and Structural Model Evaluation

The proposed hypotheses for this specific research were analysed with the use of Partial Least Squares Structural Equation Modeling (PLS-SEM). A bootstrapping analysis to test the significance and relevance of path coefficients with the employment of 5000 resamples at a 95% confidence level was conducted. Detailed results are presented in Table 6 for hypothesis testing along with path coefficients (β), t-values, p-values, decisions on the hypothesis, and other relevant information.

Table 6

*Hypotheses-testing of the research model (significant at * p ≤ 0.01)*

Hypotheses	Relationship	Path	*t*-Value	*p*-Values	Direction	Decision
H1	PEY -> INT	0.247	5.548	0.000	Positive	Supported*
H2	FAC -> INT	0.299	7.313	0.000	Positive	Supported*
H3	SOI -> INT	0.161	3.216	0.001	Positive	Supported*
H4	TRT3 -> INT	0.224	4.612	0.000	Positive	Supported*
H5	EEY -> USB	0.158	4.121	0.000	Positive	Supported*
H6	EEY -> SUS	0.191	4.169	0.000	Positive	Supported*
H7	INT -> USB	0.684	20.28	0.000	Positive	Supported*
H8	INT -> SUS	0.364	6.118	0.000	Positive	Supported*
H9	USB -> SUS	0.313	6.005	0.000	Positive	Supported*

Source: Authors Calculation

Performance Expectancy (PEY) and Intention to Use (INT) are examined in Hypothesis 1 (H1) ($\beta = 0.247$, $t = 5.548$, $p \leq 0.01$). Findings show that students performance expectancy has positive influence on their intention to use AI-enabled educational tools which leads to the conclusion of H1 being supported (Onaolapo & Oyewole, 2018). Hypothesis 2 (H2) studies the effect of Facilitating Conditions (FAC) on Intention to Use (INT) ($\beta = 0.299$, $t = 7.313$, $p \leq 0.01$). Findings revealed that adequate facilitating conditions will positively and significantly enable the adoption of AI tools in education by students, thus confirming H2 (Nikolopoulou, Gialamas, & Lavidas, 2021).

Hypothesis 3 (H3) evaluates the impact of Social Influence (SOI) on Intention to Use (INT) ($\beta = 0.161$, $t = 3.216$, $p \leq 0.01$). The analysis reveals that social influences from colleagues and instructors have a considerable and positive effect on the intentions of learners to adopt AI-enabled learning technologies, thereby confirming the hypothesis H3 (Bahadur et al., 2024). Hypothesis 4 (H4) looks at the role of Trust (TRT) on Intention to Use (INT) ($\beta = 0.224$, $t = 4.612$, $p \leq 0.01$) (Eneizan et al., 2019). The results demonstrate emphatically that the trust posed in AI systems positively and significantly influences the intentions of learners to use AI integrated education theories (Gefen et al., 2003; Prakosa & Sumantika, 2021). Therefore, the hypothesis H4 is true. Hypothesis 5 (H5) analyses the relationship between Effort Expectancy (EEY) and User Behaviour (USB) ($\beta = 0.158$, $t = 4.121$, $p \leq 0.01$). The results show that students who hold the perception that AI tools are user friendly possess higher levels of actual use, thus validating hypothesis H5(Raman & Don, 2013). Hypothesis 6 (H6) investigates the link between Effort Expectancy (EEY) and Sustainability (SUS) ($\beta = 0.191$, $t = 4.169$, $p \leq 0.01$). Findings indicate that learners who consider AI basic educational tools easy to use perceive their usage as more sustainable in the long term (N. Ain et al., 2016). Thus, hypothesis H6 is validated.

H7 analyses the effect of User Behaviour (USB) and the Intention to Use (INT) application which had a calculated value of ($\beta = 0.684$, $t = 20.28$, $p \leq 0.01$). The value proves that there is a strong relationship between students' intention and actual behaviour toward using AI-enabled educational technologies which, in return, highly supports hypothesis H7 (Acosta-Enriquez et al., 2024; N. U. Ain et al., 2016). Do note that along with the hypothesis, H8 examines the impact of Sustainability (SUS) telling us the cost efficiency of educational technologies having AI integrated in them ($\beta = 0.364$, $t = 6.118$, $p \leq 0.01$). Clearly, the result states that intent to use AI-based learning tools will effectively foster the perception of their more AI tools that are sustainable and can be used over a longer period of time (Zhou et al., 2010). Therefore, hypothesis H8 is supported. The last above dealt with former users, thus, H9 deals with more current User Behaviour (USB) ($\beta = 0.313$, $t = 6.005$, $p \leq 0.01$). Clearly showing that current students using an AI tool significantly believe its use will be sustainable and its impact on long-term usage will be effective (Zha, 2020). Therefore, hypothesis H9 has been verified.

5.4 Model Fit, Predictive Significance, and Relevance

The Standardized Root Mean Square Residual (SRMR) serves as a global fit index that assists in evaluating model fit. Further, in the current study, SRMR values for the saturated and estimated models were 0.055 and 0.076, accordingly. Those numbers, which are both less than the threshold value of 0.08, point to a good fit while providing a corresponding strength of explanation of the developed research model (Benitez et al., 2020) Furthermore, relationships among the constructs are tested for the relevance and predictive significance based on Cohen's f-square (f^2) ratios. The boundaries for the default classification of effect size of independent constructs on their dependent constructs are: 0.02 denotes small effects, 0.15 moderate effects, and 0.35 large effects (Cohen, 1988). The model demonstrates strong predictive relevance, particularly Intention to Use (INT), which showed large effect size ($f^2 = 0.848$) on User Behaviour (USB).

Other constructs, like Facilitating Conditions (FAC) ($f^2= 0.119$), Perforamance Expectancy (PEY) ($f^2= 0.081$), and Trust (TRT) ($f^2= 0.062$), had moderate and smaller effect sizes. Social Influence (SOI) had a smaller effect size, but was still relevant ($f^2= 0.033$). Effort Expectancy (EEY) had small but noticeable effects on User Behaviour (USB) ($f^2= 0.059$) and Sustainability (SUS) ($f^2= 0.045$). To measure the generalizability and the predictive accuracy of the model, Stone-Geisser's Q-square (Q^2) was used (Geisser, 1975; Stone, 1974). Q^2 values above 0.15 indicate moderate predictieve relavance, and values greater than 0.35 reflect strong predictive relevance. In this research, the Q^2 values obtained were 0.449 for User Behaviour (USB), 0.404 for Intention to Use (INT), and 0.386 for Sustainability (SUS). These vales confirm robust predictive power; hence the developed model demonstrates strong predictive relevance and can confidently be generalized to similar contexts involving students' adoption and sustained usage of AI-enabled educational tools in the future (van der Vorst & Jelicic, 2019).

6. Discussion and Implications

The objective of this study research how students perceive and what intentions do they hold for future behavioural adoption and use of AI-powered educational tools at Ethiopian higher education institutions. Based on the Unified Theory of Acceptance and Use of Technology (UTAUT), the study developed and tested a conceptual model centered on some very crucial determinant factors of students adoption behaviours which are Performance Expectancy (PEY), Facilitating Conditions (FAC), Social Influence (SOI), Trust (TRT), Effort Expectancy (EEY), Sustainability (SUS),Intention to Use (INT), and User Behaviour (USB).Structural Equation Modeling (SEM) was undertaken with paradigm of Partial Least Squares Structural Equation Modeling (PLS) with a data set collected from five hundred seventy eight university students in Ethiopia.The results give supports to the positive relationship stated in Hypothesis. The first hypothesis was strongly supported, which was the students' performance expectancy will affect their intention to adopt AI-enabled educational tools ($\beta = 0.247$, $p \leq 0.01$). This means that students who have reasonable academic benefits from the use of the AI based systems tend to have greater intention to adopt them. Coping results where performance expectancy is one of the dominant motivators for adopting technology in educational contexts (Nikolopoulou et al., 2020).

As for H2, the hypothesis regarding facilitating conditions was also confirmed ($\beta = 0.299$, $p \leq 0.01$). The notable positive correlation emphasizes the role that infrastructural support, technical aid, and resources have on the students' willingness to use AI-enabled educational tools. Such findings strengthen the already existing evidence that facilitating factors greatly influence technology acceptance, especially in underdeveloped areas where limited resources can significantly hinder educational development(Andrews et al., 2021; Kim & Son, 2022). Regarding H3, which dealt with social norms and peer recommendations, these results had a significant positive effect ($\beta = 0.161$, $p \leq 0.01$). This infers that students are likely to use AI-enabled educational tools when they perceive the members of their academic and social circles positively endorsing such tools. These results confirm previous studies that put social influence as a major contributor towards technology adoption for younger users (Fidani & Idrizi, 2012). Trust (Hypothesis H4) positively and significantly affected the students' intention to use AI-enabled tools ($\beta = 0.224$, $p \leq 0.01$).

The above, which is an excerpt, emphasizes the need for trust in the reliability, security, and ethical use of AI as a core – and in this instance, negative – adoption barrier. Because AI stems from heavy data usage and algorithmic dependencies, the requisite trust is formed through clear policy communication and user education designed for helping, as previous studies suggest (Arbulú Ballesteros et al., 2024; Yakubu et al., 2025). The remaining portion of the model that represents direct user behaviour (Hypothesis H5 and H6) was positively significant with Effort Expectancy's influence on actual behaviour. ($\beta = 0.158$, $p \leq 0.01$). Students that perceive AI as user-friendly and straightforward to implement into their learning processes tend to use these tools more actively. That adds to the conclusions of previous research that emphasized the strong influence of perceived ease-of-use on instructional technology adoption behaviours in educational settings, particularly those that are inexperienced with technology integration (Jain et al., 2022). The same respondents were also intelligent enough to know that non-complex AI educational tools would be more sustainable, thus causing Effort Expectancy to greatly influence students' views on the Sustainability of the tools (hypothesis H6; $\beta = 0.191$, $p \leq 0.01$).

This discusses the need for making user-friendly and straightforward AI systems corresponding with the current conversations that support easier technologies for educational integration (Honig et al., 2025). The Intention to Use had a strong predictive effect on User Behaviour (Hypothesis H7; $\beta = 0.684$, $p \leq 0.01$) which surfaced as one of the most powerful connections examined. This demonstrates that intention serves the role of the most critical factor for the actual usage of the AI-tool, which strengthens the core UTAUT proposition that explicitly stated intentions predicts the use of the tools in classroom settings (Wu et al., 2022). Even more, Intention to Use positively impacted Sustainability perceptions to a greater extent (Hypothesis H8; $\beta = 0.364$, $p \leq 0.01$), suggesting that more positive preliminary intentions to use AI tools leads to greater flexibility of students' long-term usage commitments. This relationship sustains ongoing discussions regarding the relevancy of targeting policies intending to promote sustainable technology use among students (Nikolopoulou et al., 2020; Nikolopoulou, Gialamas, Lavidas, et al., 2021). Lastly, the no less than moderate positive effect of actual User Behaviour on Sustainability perceptions (Hypothesis H9; $\beta = 0.313$, $p \leq 0.01$) verified that consistent use has a beneficial effect on students' perceptions regarding the sustainability of AI tools, thus promoting the formation of positive behaviours and participation over the long term.

The current finding augments earlier research that advocates for a user's frequent participation as pivotal in encouraging habitual technology utilization, which subsequently supports the long-term usage (Makanyeza & Mutambayashata, 2018).

7. Considerations for Higher Educational Institutions

This research has some relevant conclusions regarding available higher education institutions' efforts to incorporate AI-enabled educational tools into teaching and learning processes. Considering the strong positive impact of performance expectancy and effort expectancy on the students' intentions and behaviours, an emphasis must be placed on the design and implementation of AI tools that are easy to use and simple to navigate (Al-Mseidin et al., 2023). In many Ethiopian universities, the exposure to such sophisticated instruments is almost absent, hence the ease and usefulness that can be provided by these technologies should be guaranteed. These technologies will significantly enhance users' guides, aids, and interfaces for the students to perceive their value academically as ease of use. Likewise, the strong impact of the facilitating conditions in the current study indicates the necessity of having strong institutional support. Universities should take the initiative to provide appropriate technological facilities, internet connection, and technical assistance. These limited financial investments not only reduce the negative feelings of students who are exposed to new educational technologies, but also greatly enhance the likelihood that they will adopt and make use of those technologies. If higher education institutions successfully deal with the infrastructural challenges, they will be able to minimize the reluctance and resistance of students and create a desirable environment for the adoption of technology.

Considering social factors, education institutions need to purposefully design social environments that facilitate positive reinforcement and peer pressure to increase the adoption of AI tools by students. Some of the social dynamics that can be leveraged to enhance acceptability include peer-mentoring, collaborative communities, and showcasing positive accomplished students. Encouragement of students and faculty who actively use AI tools in and out of the classroom will foster positive social behaviours as well. Furthermore, the research shows the importance of trust as a determinant of the students' willingness to adopt AI tools. Thus, the data's usage, security, and ethical communication should be clear. There needs to be greater emphasis placed on educating students about the ethical concerns, data privacy contours, and discrimination biases of AI systems. Constructive policies that address trust and clear communication will assist students in building confidence and overcoming the issues of trust, allowing for responsible AI integration. Intention is one of the strongest predictors of user behaviour, therefore, it is essential for higher education institutions to focus on nurturing students' primary intentions through comprehensive interaction and incentive approach.

Instilling interactive and engaging features like gamification or scenario-based training into AI enabled systems could catalyse intrinsic motivation and consequently routine use among the learners. Reinforcement and regular exposure to the tools could help the users change their intention to use the tools to actually consistently utilize them. Additionally, the strong link that exists between user behaviour over time and perceived sustainability indicates, for the purpose of habitual use of AI tools, the establishment of institutional policies that forefront the focus on use rather than non-use is imperative. These tools can be systematically incorporated into the courses along with some refreshers and awareness training so that they can be institutionalized. Faculty members taking an instructional design approach with the inclusion of AI tools would, in turn, yield practical sustainable utilization direction for the students and thus, foster enduring usage practices. Ultimately, the proactive decision-making and leadership of institutions will determine their degree of sustainability when it comes to using AI. Both university managers and decision makers need to set the emphasis in strategic resource priorities to foster rapid technology adoption by making their appreciation evident through institutional objectives, resource deployment, and regulatory policies. Developing clear institutional strategy focused on the application of AI tools not only denotes commitment but also minimizes fragmentation across academic and administrative departments, encouraging rapid adoption of technology.

Therefore, by designing technology that is easy to navigate, providing comprehensive support from institutions, utilizing social dynamics, creating trust, encouraging habitual involvement, guiding strategically, and fostering user-friendly proactive innovations, AI-assisted educational apps can be utilized effectively, ensuring Improvement in student's learning experiences as well as transforming educational practices sustainably.

8. Limitations and Future Research Directions

This study has strengthened our understanding of students' perceptions, intentions, and behaviours towards the sustainable integration of AI-enabled tools in higher education. Despite these valuable insights, some limitations should be noted which would allow for future research and model refinement in order to enhance understanding and applicability within wider educational settings. To begin, the research is limited to Ethiopian higher education institution students. Although the responses provided are meaningfully representative within this context, they are not generalizable to all other regions or countries that have variably different technological infrastructures, digital literacy, or educational culture. The model's generalizability and accompanying perspectives on how cultural, as well as infrastructural, differences affect AI adoption in education would be enhanced through wider multi-regional studies with more diverse student populations. Secondly, although the model is based on the UTAUT framework for its strong reasoning, the rapidly changing landscape of AI in education may bring in new unknown elements. There are new emerging dimensions such as algorithmic transparency, perceived fairness, digital ethics, and institutional digital maturity that are becoming AI acceptance technology issues that need attention.

Integrating such aspects into future models may assist in comprehending adoption behaviour, especially in education sectors that are undergoing rapid digitization. This study, however, utilizes a cross-sectional design, measuring student perceptions in a single class session. Still, technology acceptance is a multi-stage process that is affected by the amount of exposure to the technology, user experience, and institutional aid. This would be useful for future research to follow students' attitudes intentions and behaviours over a longer period of time to foster better understanding of AI adoption sustainability in higher education. Moreover, the study was based purely on the quantitative approach which used closed-ended questionnaires and claim to fame is not valid for such study. For detecting regularities and validating hypothesized relationships, identifying patterns relationships or causal influences is insufficient as students may need contextual factors that shape perceptions and their experiences. In future, we could conduct research with a combined design where quantitative data is collected through surveys and complemented with qualitative data from interviews, focus group discussions or classroom observations. This method would enable a better explanation of how students experience AI in education.

Considering AI tools are still relatively new, students in Ethiopia may not have much exposure or experience with them. Future studies might investigate the relation between various degrees of AI coverage and acceptance as well as the level of digital readiness. In addition, cross-group analyses – faculty, administrators, and support personnel – could shed light on how different social groups understand Artificial Intelligence and how these beliefs impact institutional approaches to change them. To conclude, this study adds to the literature written regarding the integration of artificial intelligence in educational settings; still, it is imperative to conduct further research to enrich the model, broaden understanding of the context, and enable pragmatic approach of policy making regarding the integration of technology in education transformation.

9. Conclusion

The adoption of AI-infused applications in higher education signifies another milestone or evolution of both instructing and learning processes, especially in parts of the world that are yet to embrace digitization. This research adds to available literature on university students' perceptions, willingness, and actual behavioural engagement towards sustainably using AI in education; in this case, Ethiopian university students. The results quite evidently demonstrated that performance expectancy, effort expectancy, facilitating conditions, social influence, and trust are important determinants of students' behavioural intentions toward the adoption of AI-enabled tools. Further, intention to use greatly impacts actual usage behaviour, which subsequently affects perceptions of sustainability, illustrating an important mechanism to anchor for perennial involvement. In this regard, such attitudes and behaviour call for special attention from planners and policymakers who seek to transform higher education systems through the application of new technologies. The research pointed out the need of efficient systems design, adequate institutional support, peer pressure, and ethical visibility as factors that have greater impact on using AI in education and more importantly, to do so responsibly. The study not only examined the existing theoretical relationships but also contributed to theory by providing a rare lens of sustainability into the technology acceptance model, which is usually ignored in related studies.

Although the results are anchored within the Ethiopian confines of higher learning, the rest of the developing world seeking digital transformation will find these implications useful. Integration of AI in Ethiopia has both practical and theoretical gaps that need to be filled which warrants the AI adoption model. Educators, technologists, and academic leaders are called upon to work together to design systems where students can meaningfully and sustainably engage with AI tools. The study prompts research about the customization and scaling of the adoption of AI-enabled learning in different disciplines, student populations, and challenging budgetary contexts. Addressing the necessary prerequisite for educational responses that are inclusive and future-ready, this work brings further quality, equity, and innovation attention within the global higher education arena.

10. Co-author Contribution

The authors state explicitly that there are no conflicts of interest in relation to the publication of this article. Author 1 crafted the study, performed the fieldwork, conducted the literature review and analysis, and wrote a complete draft of the manuscript. Other authors 2 and 3 provided ongoing academic mentorship, enhanced the framework of the study, and provided important suggestions regarding the clarity and sophistication of the manuscript. Author 4 contributions include the drafting of the questionnaire, aiding in data collection, and final proofreading and editing of the paper. All the authors reviewed and accepted the final version of the manuscript.

11. References

Abdullah, H., Sahudin, Z., Bahrudin, N., Bujang, I., & Khalid, K. (2023). Determinants of Educational Technology Acceptance: An Integration of TAM and UTAUT. *Asian Journal of University Education*. https://doi.org/10.24191/ajue.v19i4.24626

Acosta-Enriquez, B. G., Ramos Farroñan, E. V, Villena Zapata, L. I., Mogollon Garcia, F. S., Rabanal-León, H. C., Morales Angaspilco, J. E., & Bocanegra, J. C. S. (2024). Acceptance of artificial intelligence in university contexts: A conceptual analysis based on UTAUT2 theory. *Heliyon*, *10*(19). https://doi.org/10.1016/j.heliyon.2024.e38315

Ain, N. U., Kaur, K., & Waheed, M. (2016). The influence of learning value on learning management system use: An extension of UTAUT2. *Information Development*, *32*(5), 1306–1321. https://doi.org/10.1177/0266666915597546

Al-Mseidin, K. I., Al-Zu'bi, M. A., Al-Mawadieh, R. S. M., & Alelaimat, A. M. (2023). The Integration of AI Applications in Psychological and Educational Counselling for University Students:Opportunities and Challenges. *2023 24th International Arab Conference on Information Technology, ACIT 2023*. https://doi.org/10.1109/ACIT58888.2023.10453762

Almufarreh, A. (2024). Determinants of Students' Satisfaction with AI Tools in Education: A PLS-SEM-ANN Approach. *Sustainability*. https://doi.org/10.3390/su16135354

Amani, S., White, L. L. A., Balart, T., Arora, L., Shryock, K. J., Brumbelow, K., & Watson, K. (2023). Generative AI Perceptions: A Survey to Measure the Perceptions of Faculty, Staff, and Students on Generative AI Tools in Academia. *ArXiv.Org*. https://doi.org/10.48550/arxiv.2304.14415

Andrews, J. E., Ward, H., & Yoon, J. (2021). UTAUT as a model for understanding intention to adopt AI and related technologies among librarians. *The Journal of Academic Librarianship*, *47*(6), 102437.

Arbulú Ballesteros, M. A., Acosta Enríquez, B. G., Ramos Farroñán, E. V, García Juárez, H. D., Cruz Salinas, L. E., Blas Sánchez, J. E., Arbulú Castillo, J. C., Licapa-Redolfo, G. S., & Farfán Chilicaus, G. C. (2024). The Sustainable Integration of AI in Higher Education: Analyzing ChatGPT Acceptance Factors Through an Extended UTAUT2 Framework in Peruvian Universities. *Sustainability (Switzerland)*, *16*(23). https://doi.org/10.3390/su162310707

Bahadur, S. G. C., Bhandari, P., Gurung, S. K., Srivastava, E., Ojha, D., & Dhungana, B. R. (2024). Examining the role of social influence, learning value and habit on students' intention to use ChatGPT: the moderating effect of information accuracy in the UTAUT2 model. *Cogent Education*, *11*(1). https://doi.org/10.1080/2331186X.2024.2403287

Baharin, A. T., Sahadun, N. A., Ramli, S., & Redzuan, N. A. L. (2025). Exploring the Adoption of Generative Artificial Intelligence by TVET Students: A UTAUT Analysis of Perceptions, Benefits, and Implementation Challenges. *Journal of Information Systems Engineering & Management*. https://doi.org/10.52783/jisem.v10i19s.3052

Bazelais, P., Doleck, T., & Lemay, D. J. (2018). Investigating the predictive power of TAM: A case study of CEGEP students' intentions to use online learning technologies. *Education and Information Technologies*, *23*(1), 93–111. https://doi.org/10.1007/s10639-017-9587-0

Benitez, J., Henseler, J., Castillo, A., & Schuberth, F. (2020). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. *Information & Management*, *57*(2), 103168. https://doi.org/10.1016/j.im.2019.05.003

Brummernhenrich, B., Paulus, C. L., & Jucks, R. (2025). Applying social cognition to feedback chatbots: Enhancing trustworthiness through politeness. *British Journal of Educational Technology*. https://doi.org/10.1111/bjet.13569

Cabero-Almenara, J., Palacios-Rodríguez, A., Loaiza-Aguirre, M. I., & Andrade-Abarca, P. S. (2024). The impact of pedagogical beliefs on the adoption of generative AI in higher education: predictive model from UTAUT2. *Frontiers in Artificial Intelligence*, *7*. https://doi.org/10.3389/frai.2024.1497705

Chien, S.-C., & Knoble, C. (2024). Research of Education for Sustainable Development: Understanding New Emerging Trends and Issues after SDG 4. *Journal of Sustainability Research*. https://doi.org/10.20900/jsr20240006

Chiu, M.-Y., & Chiu, F. (2024). Using UTAUT to Explore the Acceptance of High School Students in Programming Learning with Robots. *International Conference on Information Technology Based Higher Education and Training*. https://doi.org/10.1109/ithet61869.2024.10837674

Dejene, W., & Tilahun, D. (2024). How ready are our students for e-learning? Evidence from Ethiopia. *Discover Education*. https://doi.org/10.1007/s44217-024-00359-5

Dhagarra, D., Goswami, M., & Kumar, G. (2020). Impact of trust and privacy concerns on technology acceptance in healthcare: an Indian perspective. *International Journal of Medical Informatics*, *141*, 104164.

Diamantopoulos, A., & Siguaw, J. A. (2006). Formative Versus Reflective Indicators in Organizational Measure Development: A Comparison and Empirical Illustration. *British Journal of Management*, *17*(4), 263–282. https://doi.org/10.1111/j.1467-8551.2006.00500.x

Dittrich, A.-K., Eloff, I., Boon, W., Weinberg, L., Rabani Nia, M., Mathabathe, K. C., & Agostini, E. (2024). Assessing the Professionalism of Teacher Educators in Relation to Sustainability: Developing the Teacher Education and Sustainability Scale (TESS). *Education Sciences*, *14*(9). https://doi.org/10.3390/educsci14091000

Eneizan, B., Mohammed, A. G., Alnoor, A., Alabboodi, A. S., & Enaizan, O. (2019). Customer acceptance of mobile marketing in Jordan: An extended UTAUT2 model with trust and risk factors. *International Journal of Engineering Business Management*, *11*. https://doi.org/10.1177/1847979019889484

Fidani, A., & Idrizi, F. (2012). Investigating students' acceptance of a learning management system in university education: a structural equation modeling approach. *ICT Innovations 2012 Web Proceedings*, *2*(23), 311–320.

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly*, 51–90.

Geisser, S. (1975). The Predictive Sample Reuse Method with Applications. *Journal of the American Statistical Association*, *70*(350), 320–328. https://doi.org/10.2307/2285815

Grassini, S., Aasen, M. L., & Møgelvang, A. (2024). Understanding University Students' Acceptance of ChatGPT: Insights from the UTAUT2 Model. *Applied Artificial Intelligence*, *38*(1). https://doi.org/10.1080/08839514.2024.2371168

Gunasinghe, A., Hamid, J. A., Khatibi, A., & Azam, S. M. F. (2020). The adequacy of UTAUT-3 in interpreting academician's adoption to e-Learning in higher education environments. *Interactive Technology and Smart Education*, *17*(1), 86–106. https://doi.org/10.1108/ITSE-05-2019-0020

Gunasinghe, A., Hamid, J. A., Khatibi, A., & Azam, S. M. F. (2020). The viability of UTAUT-3 in understanding the lecturer's acceptance and use of virtual learning environments. *International Journal of Technology Enhanced Learning*, *12*(4), 458. https://doi.org/10.1504/IJTEL.2020.110056

Gupta, A., Dogra, N., & George, B. (2018). What determines tourist adoption of smartphone apps? An analysis based on the UTAUT-2 framework. *Journal of Hospitality and Tourism Technology*, *9*(1), 50–64.

Hair, J.F., Hult, G.T.M., Ringle, C.M. and Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (2nd Editio). Sage Publications Inc.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015b). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Honig, C., Rios, S., & Desu, A. (2025). Generative AI in engineering education: understanding acceptance and use of new GPT teaching tools within a UTAUT framework. *Australasian Journal of Engineering Education*. https://doi.org/10.1080/22054952.2025.2467500

Hu, L., Wang, H., & Xin, Y. (2025). Factors influencing Chinese pre-service teachers' adoption of generative AI in teaching: an empirical study based on UTAUT2 and PLS-SEM. *Education and Information Technologies*. https://doi.org/10.1007/s10639-025-13353-7

Hussen, A. A. (2022). The Impact of Course Delivery Approach on Students Academic Achievement at Haramaya University. *Asian Journal of University Education*. https://doi.org/10.24191/ajue.v18i2.17988

Jain, R., Garg, N., & Khera, S. N. (2022). Adoption of AI-Enabled Tools in Social Development Organizations in India: An Extension of UTAUT Model. *Frontiers in Psychology*, *13*.

Jewer, J. (2018). Patients' intention to use online postings of ED wait times: A modified UTAUT model. *International Journal of Medical Informatics*, *112*, 34–39. https://doi.org/10.1016/j.ijmedinf.2018.01.008

Joseph, G. V, Athira, P., M, A. T., Jose, D., Roy, T. V, & Prasad, M. (2024). Impact of Digital Literacy, Use of AI tools and Peer Collaboration on AI Assisted Learning- Perceptions of the University students. *Digital Education Review*. https://doi.org/10.1344/der.2024.45.43-49

Khoso, F. J., Ali, N., & Aslam, N. (2023). Use of Chat-GPT and AI Tools by Undergraduates: Students and Teachers' Perspective. *Spry Contemporary Educational Practices*. https://doi.org/10.62681/sprypublishers.scep/2/2/14

Kim, S. M., & Son, Y. D. (2022). A Study on the Intention of Financial Consumers to Accept AI Services Using UTAUT Model. *Journal of Korean Society for Quality Management*, *50*(1), 43–61.

Lakhal, S., Khechine, H., & Pascot, D. (2013). Student behavioural intentions to use desktop video conferencing in a distance course: integration of autonomy to the UTAUT model. *Journal of Computing in Higher Education*, *25*, 93–121.

Liu, N., Deng, W., & Ayub, A. F. M. (2025). Exploring the adoption of AI-enabled English learning applications among university students using extended UTAUT2 model. *Education and Information Technologies*. https://doi.org/10.1007/s10639-025-13349-3

Makanyeza, C., & Mutambayashata, S. (2018). Consumers' acceptance and use of plastic money in Harare, Zimbabwe: Application of the unified theory of acceptance and use of technology 2. *International Journal of Bank Marketing*, *36*(2), 379–392.

Mařík, V., Štěpánková, O., & Zdráhal, Z. (n.d.). *Artificial Intelligence in Higher Education [electronic resource]: CEPES-UNESCO International Symposium Prague, CSFR, October 23–25, 1989 Proceedings*.

Narula, S., Shiva, A., & Shahi, S. (2020). *What drives retail investors' investment decisions? Evidence from no mobile phone phobia (Nomophobia) and investor fear of missing out (I-FoMo)*. *11*, 2–20. https://doi.org/10.31620/JCCC.06.20/02

Nikolopoulou, K., Gialamas, V., & Lavidas, K. (2020). Acceptance of mobile phone by university students for their studies: An investigation applying UTAUT2 model. *Education and Information Technologies*, *25*(5), 4139–4155.

Nikolopoulou, K., Gialamas, V., & Lavidas, K. (2021). Habit, hedonic motivation, performance expectancy and technological pedagogical knowledge affect teachers' intention to use mobile internet. *Computers and Education Open*, *2*, 100041.

Nikolopoulou, K., Gialamas, V., Lavidas, K., & Komis, V. (2021). Teachers' readiness to adopt mobile learning in classrooms: A study in Greece. *Technology, Knowledge and Learning*, *26*, 53–77.

Onaolapo, S., & Oyewole, O. (2018). Performance expectancy, effort expectancy, and facilitating conditions as factors influencing smart phones use for mobile learning by postgraduate students of the University of Ibadan, Nigeria. *Interdisciplinary Journal of E-Skills and Lifelong Learning*, *14*(1), 95–115.

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce*, *7*(3), 101–134.

Prakosa, A., & Sumantika, A. (2021). An analysis of online shoppers' acceptance and trust toward electronic marketplace using TAM Model. *Journal of Physics: Conference Series*, *1823*(1), 012008.

Raman, A., & Don, Y. (2013). Preservice teachers' acceptance of learning management software: An application of the UTAUT2 model. *International Education Studies*, *6*(7), 157–164.

Rasoolimanesh, S. M., Roldán, J. L., Jaafar, M., & Ramayah, T. (2017). Factors Influencing Residents' Perceptions toward Tourism Development: Differences across Rural and Urban World Heritage Sites. *Journal of Travel Research*, *56*(6), 760–775. https://doi.org/10.1177/0047287516662354

Saha, P., Hossain, M., Roy, N. C., Masud, A., & Amin, R. (2025). Unlocking the power of AI in education: students' intentions and AI tool use driving learning success in an emerging economy. *HORIZONS A*. https://doi.org/10.1108/oth-10-2024-0066

Sarkam, N. A., Nasrudin, N. H., Razi, N. F. M., & Junid, R. (2022). Student readiness factors for online distance learning (ODL) among Malaysian Public Universities during COVID-19: A Proposed Conceptual Model. *Asian Journal of University Education*. https://doi.org/10.24191/ajue.v18i4.20014

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial Least Squares Structural Equation Modeling. In *Handbook of Market Research* (pp. 1–47). Springer International Publishing. https://doi.org/10.1007/978-3-319-05542-8_15-2

Shahzad, M. F., Xu, S., & Zahid, H. (2024). Exploring the impact of generative AI-based technologies on learning performance through self-efficacy, fairness & ethics, creativity, and trust in higher education. *Education and Information Technologies*. https://doi.org/10.1007/s10639-024-12949-9

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. *European Journal of Marketing*.

Shu, Y., Ho, S.-J., & Huang, T.-C. (2020). The development of a sustainability-oriented creativity, innovation, and entrepreneurship education framework: a perspective study. *Frontiers in Psychology*, *11*, 1878.

Stone, M. (1974). Cross-Validatory Choice and Assessment of Statistical Predictions. *Journal of the Royal Statistical Society. Series B (Methodological)*, *36*(2), 111–147. http://www.jstor.org/stable/2984809

Tang, X., Yuan, Z., & Qu, S. (2025). Factors Influencing University Students' Behavioural Intention to Use Generative Artificial Intelligence for Educational Purposes Based on a Revised UTAUT2 Model. *Journal of Computer Assisted Learning*, *41*(1). https://doi.org/10.1111/jcal.13105

Tian, W., Ge, J., Zhao, Y., & Zheng, X. (2024a). AI Chatbots in Chinese higher education: adoption, perception, and influence among graduate students—an integrated analysis utilizing UTAUT and ECM models. *Frontiers in Psychology*, *15*. https://doi.org/10.3389/fpsyg.2024.1268549

Tran, T. D. H. (2024). AI Tools in Teaching and Learning English Academic Writing Skills. *Proceedings of the AsiaCALL International Conference*. https://doi.org/10.54855/paic.23413

Uche, D. Ben, Osuagwu, O. B., Nwosu, S. N., & Otika, U. S. (2020). Integrating trust into technology acceptance model (TAM), the conceptual framework for e-payment platform acceptance. *Marketing*, *4*(4), 34–56.

Lin Chenhui, Geethanjali Narayanan, & Harrinni Md Noor. (2024). University-related Factors in Technology Integration: A Quantitative Study in East Coast of China. *Asian Journal of University Education*, *2*. https://doi.org/10.24191/ajue.v20i2.27009

Van der Vorst, T., & Jelicic, N. (2019). *Artificial Intelligence in Education: Can AI bring the full potential of personalized learning to education?*

Venkatesh, V., Venkatesh, V., Venkatesh, V., & Venkatesh, V. (2021). Adoption and use of AI tools: a research agenda grounded in UTAUT. *Annals of Operations Research*. https://doi.org/10.1007/s10479-020-03918-9

Wen, F., Li, Y., Zhou, Y., An, X., & Zou, Q. (2024). A Study on the Relationship between AI Anxiety and AI Behavioral Intention of Secondary School Students Learning English as a Foreign Language. *Journal of Educational Technology Development and Exchange*. https://doi.org/10.18785/jetde.1701.07

Wu, W., Zhang, B., Li, S., & Liu, H. (2022). Exploring Factors of the Willingness to Accept AI-Assisted Learning Environments: An Empirical Investigation Based on the UTAUT Model and Perceived Risk Theory. *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.870777

Xu, S., Chen, P., & Zhang, G. (2024). Exploring Chinese University Educators' Acceptance and Intention to Use AI Tools: An Application of the UTAUT2 Model. *SAGE Open*, *14*(4). https://doi.org/10.1177/21582440241290013

Yakubu, M., David, N., & Abubakar, N. H. (2025). Students' behavioural intention to use content generative AI for learning and research: A UTAUT theoretical perspective. *Education and Information Technologies : Official Journal of the IFIP Technical Committee on Education*. https://doi.org/10.1007/s10639-025-13441-8

Zaim, M., Arsyad, S., Waluyo, B., Ardi, H., Al Hafizh, M., Zakiyah, M., Syafitri, W., Nusi, A., & Hardiah, M. (2024). AI-powered EFL pedagogy: Integrating generative AI into university teaching preparation through UTAUT and activity theory. *Computers and Education: Artificial Intelligence*, *7*. https://doi.org/10.1016/j.caeai.2024.100335

Zaman, S. U., Ali, S. S., Alam, S. H., & Kamal, M. H. (2025). Assessing Student's Behavioral Intentions Towards AI Based Learning Tools. *Journal of Asian Development Studies*. https://doi.org/10.62345/jads.2025.14.1.50

Zha, W. (2020). A study on the user acceptance model of artificial intelligence music based on UTAUT. 한국컴퓨터정보학회논문지, *25*(6), 25–33.

Zhou, T., Lu, Y., & Wang, B. (2010). Integrating TTF and UTAUT to explain mobile banking user adoption. *Computers in Human Behavior*, *26*(4), 760–767. https://doi.org/10.1016/j.chb.2010.01.013