

Research Article

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Modeling AI-Enhanced Learning for Sustainable Cognitive Development: A UTAUT2 and Bloom's Taxonomy Perspective

Suliman Zakaria Suliman Abdalla , Amal Khalfan Rashid Al-Salti

Abstract

Background/purpose. This study examines the behavioral factors influencing the adoption of AI-powered generative technologies in higher education and their impact on students' cognitive engagement—a crucial element of sustainable, inclusive, and high-quality learning, as envisioned by UNESCO's Sustainable Development Goal 4 (SDG4). The study combines Bloom's Taxonomy hierarchical structure with the expanded Unified Theory of Acceptance and Use of Technology (UTAUT2) framework.

Materials/methods. Structural equation modeling (SEM) was utilized to analyze data collected from a sample of 731 university students, aiming to identify the key determinants of GenAI adoption and to assess its subsequent effects across six distinct cognitive domains.

Results. The SEM analysis reveals that performance expectancy, facilitating conditions, and hedonic motivation have a significant influence on AI adoption, underscoring the importance of usefulness, support, and enjoyment in promoting student engagement. The study demonstrates that the adoption of GenAI significantly predicts student engagement, which in turn acts as a critical mediator in enhancing mid-level cognitive performance by improving understanding, application and analysis abilities. In contrast, marginal impacts were found in evaluation and creation domains while remembering did not demonstrate any significant effect.

Conclusion. The study provides evidence-based insights for educators, curriculum designers, and policymakers seeking to leverage GenAI as part of equitable, student-centered, and cognitively enriching AI-enabled learning environments.

1. Introduction

In the context of accelerating technological innovation, artificial intelligence (AI) has emerged as a transformative catalyst, fundamentally redefining the landscape of higher education and driving educational innovation and improvement (Rahiman & Kodikal, 2023; Southworth et al., 2023). AI-powered learning tools and platforms have become integral components of learning environments and facilitate unprecedented transformations in both teaching strategies and student learning trajectory experiences (Celik et al., 2022). Among these tools, intelligent tutoring systems (ITS) and adaptive learning environments have emerged as pivotal innovations and integral components of learning environments. They provide personalized instruction and support tailored to the individual needs of learners in a wide variety of teaching and learning activities (Kabudi et al., 2021; Wang et al., 2024). These systems dynamically adjust the provision of personalized learning guidance and content to support individual learners in acquiring knowledge based on their learning progress, pace preferences, knowledge levels, learning styles and personal characteristics (Gligorea et al., 2023; Strielkowski et al., 2024).

Although AI-based technologies like chatbots, virtual assistance tools, online discussion boards, and adaptive learning systems present incredible opportunities for improved teaching and learning experiences, they also pose a significant challenge for educators and students. Thus, making it an area of interest to explore (Chaudhry et al., 2023; Pradana et al., 2023; Retscher, 2025). Among various AI tools, this study explores university students' perceptions of the educational potential of ChatGPT, a generative AI tool that can assist with various learning tasks involving both knowledge application and creative reasoning (Bozkurt et al., 2023). ChatGPT offers significant potential to enhance students' learning experiences, especially in areas such as accelerating text generation, enhancing writing processes, assisting in literature reviews, text summarization, question-answering, and language translation (O'Connor, 2022; Ray, 2023).

ChatGPT has generated significant interest in higher education, sparking discussion about the challenges of its adoption, especially among students. This has resulted in substantial scholarly research on various aspects of adoption. These aspects include user perceptions and experiences (Hsu et al., 2024; Xu et al., 2024), ethical considerations (Farhi et al., 2023; Mienye & Swart, 2025), implementation challenges (García-López et al., 2025; Tlili et al., 2023; Ray, 2023), subject-specific capabilities (Lo, 2023; Memarian & Doleck, 2023), and adoption drivers (Abdalla, 2025; Almogren et al., 2024; Strzelecki, 2024; Supianto et al., 2024). Although these studies have provided valuable contributions, most have not explicitly explored cognitive learning outcomes associated with ChatGPT usage and most importantly, on Bloom's Taxonomy. Therefore, there remains a significant gap in our understanding of the impact of ChatGPT adoption on hierarchical stages, including remembering, understanding, applying, analyzing, evaluating, and creating.

In fact, there have been only a few studies that have specifically explored aspects related to ChatGPT's impact on cognitive learning domains. For instance, Essel et al. (2024) investigated how the use of ChatGPT affects university students' creative and reflective thinking abilities. Their findings demonstrated that the integration of ChatGPT had a notable impact on students' critical, reflective, and creative thinking skills, as well as on various dimensions of these cognitive processes.

Similarly, Gonsalves (2024) emphasized the role of ChatGPT integration in promoting deeper levels of critical thinking while cautioning against its use as a superficial aid. This study presents a research framework for investigating the effects of AI on cognitive development, offering practical guidance for educators, policymakers, and researchers seeking to refine instructional approaches within AI-enhanced educational settings. Furthermore, it highlights the need to re-examine Bloom's Taxonomy in the context of AI-driven education, in line with Mandai et al.'s (2024) call for specific, actionable strategies that go beyond general expectations. Lubbe et al. (2025) also examined the role

of ChatGPT in cognitive learning, investigating how the integration of AI, Bloom's Taxonomy, and critical thinking can enhance assessment pedagogy to foster self-directed learning. Their study highlighted a gap in the existing literature regarding the conceptualization of assessment frameworks aimed at cultivating higher-order thinking skills within the GenAI-driven higher education context.

The significance of this study lies in addressing this research gap by combining a widely validated technology acceptance framework (UTAUT2) with Bloom's Taxonomy to provide an integrated model that explains both the determinants of generative AI adoption and its cognitive impacts. While prior studies have either emphasized adoption factors or explored limited aspects of cognitive outcomes, no empirical study has systematically examined the mediating role of student engagement in linking AI adoption with Bloom's hierarchical domains of learning. This dual focus makes the study theoretically and practically important for advancing sustainable, student-centered, and cognitively enriching AI-enabled learning environments in the future.

Accordingly, the present study aims to investigate (1) the key behavioral determinants influencing students' adoption of generative AI tools in higher education, and (2) the cognitive learning outcomes associated with their use, as categorized within Bloom's Taxonomy. To achieve this aim, the study is guided by the following research questions:

RQ1: What are the key determinants influencing students' adoption of Gen AI in higher education?

RQ2: How does AI adoption affect student engagement?

RQ3: To what extent does student engagement mediate the relationship between AI adoption and the six cognitive domains of Bloom's Taxonomy?

2. Model and Hypotheses Development

With the increasing integration of AI tools into the higher education learning environment, there is a growing need for research that critically evaluates the viability and effectiveness of existing AI platforms in enriching and enhancing contemporary teaching and learning practices (Ali et al., 2024; Ouyang & Jiao, 2021). Currently, there is a large body of research exploring the behavioral determinants and predictors of student adoption of generative AI in learning (Abdalla, 2025; Ivanov et al., 2024). Other studies have also focused on the learning impact of AI platforms (Popenici & Kerr, 2017; Wang et al., 2024; Zawacki-Richter et al., 2019). The current AI research lacks studies that combine theoretical frameworks that analyze both adoption predictors and learning impact dimensions. To bridge this gap, the current study combines the UTAUT2 theoretical framework (Venkatesh et al., 2012) with Bloom's revised taxonomy (Anderson & Krathwohl, 2001) to create a comprehensive model that examines student adoption of AI content and its effects on cognitive development through hierarchical learning domains. The dual focus of this study aligns with the current academic demands for integrative models that assess both the utility of AI tools and their educational implications (Zawacki-Richter et al., 2019).

The proposed conceptual model in our study hypothesizes that students' behavioral intention to adopt AI-based learning tools is shaped by six core constructs of the UTAUT2 model: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit. Building on these hypotheses, our model tests the impact of AI adoption on student engagement, which in turn is hypothesized to serve as a mediating mechanism between AI adoption and cognitive learning outcomes, as defined by Bloom's six domains (Larsen et al., 2022; Montello et al., 2025). This framework presents a multidimensional analytical framework that captures the key drivers of AI adoption and the underlying cognitive constructs essential for deep learning. The study presents a theoretically driven and empirically assessable model that advances the current discourse on AI-

enhanced learning in the higher education context through the integration of tried-and-tested models from technology acceptance and educational psychology.

2.1. AI Adoption and the UTAUT2 Model

The extended UTAUT represents a widely adopted theoretical model for explaining technology adoption across various contexts, including higher education (Granić & Marangunić, 2019; Tamilmani et al., 2021; Xue et al., 2024). It was introduced by Venkatesh et al. (2012) as an extension of the original Unified Theory of Acceptance and Use of Technology, initially proposed by Venkatesh et al. (2003). To improve the predictive power of behavioral intention and usage behavior regarding digital innovations, three additional constructs—hedonic motivation, price value, and habit—were integrated into the original UTAUT model, which initially comprised performance expectancy, effort expectancy, social influence, and facilitating conditions (Suhail et al., 2024). From a practical perspective, UTAUT2 has been found to be a helpful model in explaining a large amount of variance in technology usage and acceptance behaviors in various university contexts and domains. Several studies have explored various topics such as the adoption augmented reality technology in education (Faqih & Jaradat, 2021), student engagement with robots (Suhail et al., 2024), the use of mobile devices for language learning (Hoi, 2020), mobile learning through virtual platforms (Hameed, & Sumari, 2024), educational transformation through the metaverse (Aideed et al., 2025) and the implementation of the Internet of Things (IoT) in educational practices (Shaqrah & Almars, 2022).

To identify the major factors affecting students' adoption of AI-generated content, this study investigates six UTAUT2 constructs: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit. While UTAUT2 incorporates the price value construct as a determinant of adoption, this study omits it. The price-value construct expresses the perceived trade-off between the costs and benefits of adopting a technology (Tamilmani et al., 2021). The free availability of AI-generated content and educational tools through institutional platforms and open-access AI systems makes cost an irrelevant factor in this context. The conceptual model omitted price value to ensure construct relevance and model parsimony because it does not directly affect voluntary adoption in a cost-free educational environment.

Performance expectancy

Performance expectancy (PE) has been recognized in technology acceptance models as a key determinant of customers' intentions to adopt innovative technologies (Huang, 2023). It refers to the extent to which individuals perceive that utilizing a specific technology will enable them to achieve their job performance goals (Venkatesh et al., 2003). In this study, PE reflects the extent to which students believe that AI-generated content can help them learn more efficiently, understand better, and perform academically better. Technologies such as content summarization, intelligent tutoring, and adaptive analytics have become integral to these systems, offering personalized learning pathways and real-time feedback (Adewale et al., 2024). When the learning benefits are evident, students are likely to embrace such technologies. Accordingly, the present study formulates the following hypothesis:

H1: Performance expectancy has a positive, direct, and significant impact on students' adoption of AI-generated content.

Effort expectancy

According to Venkatesh et al. (2003), effort expectancy (EE) is defined as the "perceived ease of use of a technology or information system" and is known to be a direct determinant of usage intention (Schmitz et al., 2022). This implies that greater ease of use facilitates more seamless adoption of new technologies (Rana et al., 2024). In the present study, EE reflects the extent to which students perceive AI-generated learning tools as easy to use. Interfaces that are intuitive, navigable,

and integrated with voice assistance reduce cognitive load and promote usage. When students find AI tools easy and accessible, they are more likely to adopt them in their learning (Tarhini et al., 2014). Accordingly, it was hypothesized that:

H2: Effort expectancy has a positive, direct, and significant impact on students' adoption of AI-generated content.

Social influence

As defined by Venkatesh et al. (2003), social influence refers to the "extent to which an individual feels that important others think he or she should use the new system or information technology." This construct comprises three variables: subjective norm, social factor, and image (Huang & Kao, 2015). A large body of research has provided strong evidence of the relationship between social influence from family members, peers, colleagues, traditional media, and social networking platforms and technology adoption (Khan, 2022; Merhi et al., 2019; Tseng et al., 2022). For this study, social influence was assumed to mean the influence of peers, instructors and institutional norms on students' choice to use AI-generated content. The adoption likelihood increases when AI tools are endorsed by educators or widely accepted among peers due to perceived legitimacy and social encouragement (Acosta-Enriquez et al., 2024, Changalima et al., 2024). Thus, in accordance with the above arguments, the study puts forward the following research hypothesis:

H3: Social influence has a positive, direct, and significant impact on students' adoption of AI-generated content.

Facilitating conditions

Facilitating conditions as defined in technology adoption models are the factors related to individuals' perceptions of the necessary technical infrastructure or technological resources available to facilitate the adoption of a new technology or system (Venkatesh et al., 2003). The adoption of a particular new technology by end users becomes more likely when they have access to technical expertise and training and when their organization shows high support for technology utilization (Kabra et al., 2017). Research evidence shows that FC constructs strongly influence how users behave regarding technology or information system adoption (Suhail et al., 2024; Tseng et al., 2022). The present study links FC conditions to the provision of technological infrastructure, supportive institutional systems and institutional readiness that help students effectively use AI tools in their learning. The tools comprise AI-powered learning platforms, along with adaptable IT support systems, that enable efficient implementation (Strzelecki, 2024). Therefore, this study assumes that:

H4: Facilitating conditions has a positive, direct, and significant impact on students' adoption of AI-generated content.

Hedonic motivation

Hedonic motivation (HM) is a construct widely used in empirical research on UTAUT2 to describe how people are motivated to utilize new technologies because they find them enjoyable, entertaining, or interesting (Brown & Venkatesh, 2005; Venkatesh et al., 2012). This construct is based on the psychological and experiential aspects of people, which can be influenced by their individual differences and perceived behavioral control (Huang & Kao, 2015; Sitar-Taut, 2021). This study used HM to capture the fun and engagement that students have when using AI tools. The integration of gamification, simulations, and conversational AI agents enhances learning dynamics and enjoyment, thereby increasing willingness to adopt (Acosta-Enriquez et al., 2024; Grassini et al., 2024). This consequently informs the formulation of the following hypothesis:

H5: Hedonic motivation has a positive, direct, and significant impact on students' adoption of AI-generated content.

Habit

Habit is an additional factor relevant to predicting technology adoption (Venkatesh et al., 2012). It reflects an individual's consistent and automatic behavioral response to a specific technology or information, which is shaped by prior usage experiences and established behavioral patterns. Habit may also be described as the extent to which actions are performed automatically as a result of experiential learning and repeated prior use (Cabrera-Sánchez et al., 2021; Kim et al., 2005; Limayem et al., 2007). Within the scope of this study, the habit construct was employed to measure how often students incorporated AI-generated content into their learning routine. Students who regularly interact with AI tutors and feedback tools develop habitual usage patterns, leading to stronger adoption rates. According to this rationale, the study proposed the following research hypothesis:

H6: Habit has a positive, direct, and significant impact on students' adoption of AI-generated content.

AI Adoption and Student Engagement

The relationship between AI adoption and student engagement can be effectively explained through Self-Determination Theory (SDT) (Deci & Ryan, 1985, 2000; Ryan & Deci, 2017). According to this theory, student engagement and motivation are enhanced when three fundamental psychological needs—autonomy, competence, and relatedness—are fulfilled. Consequently, instructors who design learning activities that address these needs are better positioned to foster student engagement in AI-related learning (Xia et al., 2022). AI-generated learning tools, such as personalized feedback systems, intelligent tutors, and adaptive content—enable students to exercise control over their learning pace (autonomy), experience success through scaffolded challenges (competence), and connect with content in meaningful ways (relatedness). The combination of these features promotes internal motivation and enhances student engagement. In this study, we assume that students' readiness to adopt AI tools for learning purposes creates an essential foundation for their involvement with AI-based learning systems. When students actively adopt AI tools, they are more likely to engage behaviorally and cognitively (Adewale et al., 2024; Chen et al., 2020; Hwang et al., 2020; Seo et al., 2021). According to this discussion, the following hypothesis was developed:

H7: AI adoption positively influences student engagement with AI-generated learning content.

Student engagement and Bloom's cognitive domains

Building on the argument that AI-generated content enhances student engagement, this study examines the relationship between cognitive learning outcomes and student engagement. AI learning systems that adapt to students through personalized feedback increase behavioral and cognitive engagement, leading students to actively engage in educational activities. Continuous engagement leads students to better understand the material while advancing through the hierarchical stages of Bloom's taxonomy (Anderson & Krathwohl, 2001). AI-mediated engagement enables students to retain information while simultaneously developing their ability to analyze, evaluate, and create new ideas through synthesis (Stanny, 2016). Based on this rationale, students' engagement with AI-generated content is expected to directly influence all six levels of Bloom's taxonomy by enhancing their motivation, cognitive activation, and meaningful learning experiences. Thus, the following hypotheses were developed:

H8: Student engagement with AI-generated content positively influences students' ability to remember key concepts.

H9: Student engagement with AI-generated content positively influences students' ability to understand learning material.

H10: Student engagement with AI-generated content positively influences students' ability to apply learned concepts in practical contexts.

H11: Student engagement with AI-generated content has a positive influence on students' ability to analyze complex information.

H12: Student engagement with AI-generated content positively influences students' ability to evaluate ideas critically.

H13: Student engagement with AI-generated content positively influences students' ability to create original content and solutions.

The proposed conceptual model, which illustrates the hypothesized relationships among UTAUT2 constructs, AI adoption, student engagement, and Bloom's six cognitive domains, is presented in Figure 1 to guide the structural analysis of this study.

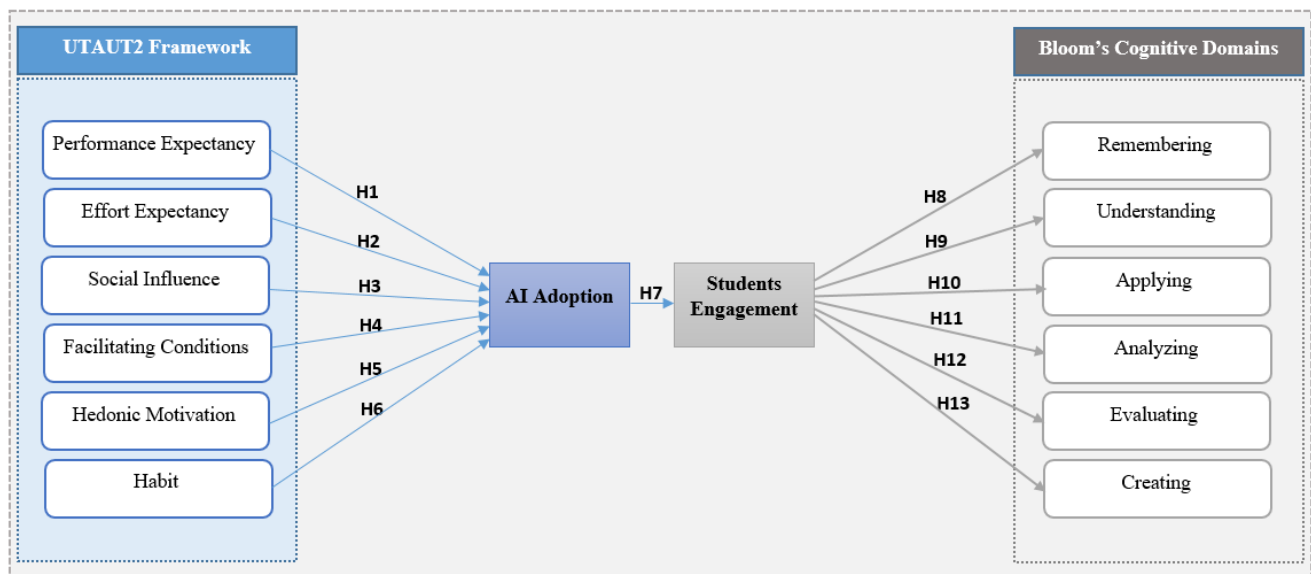


Figure 1. The Proposed Conceptual Framework.

This model illustrates how six UTAUT2 constructs (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit) influence students' adoption of generative AI tools. AI adoption is then hypothesized to enhance student engagement, which subsequently affects all six hierarchical cognitive domains of Bloom's Taxonomy (remembering, understanding, applying, analyzing, evaluating, and creating).

3. Research Method

3.1. Research Design

This study adopts a quantitative research methodology, utilizing a survey-based approach to investigate students' adoption of AI-generated content and its impact on cognitive learning. The design is non-experimental and cross-sectional, focusing on capturing students' perceptions at a single point in time. This approach is appropriate for testing theoretical models and identifying relationships among multiple constructs. To empirically test the proposed model and its associated hypotheses, as shown in Figure 1, the study employs a structural equation modeling (SEM) approach. Confirmatory factor analysis (CFA) was conducted to evaluate the instrument's convergent and discriminant validity. Subsequently, SEM was applied to analyze the causal relationships among the constructs and to assess the overall structural model of the study.

3.2. Measurement Instrument

Grounded in the extended UTAUT model and Bloom's Taxonomy for effective learning, a questionnaire was designed and structured into four sections. The initial section collected respondents' demographic information, including academic year, gender, specialization, GPA, and prior experience with AI. The second section measured AI adoption and the UTAUT2 constructs. AI adoption was measured using four items that assessed behavioral intention, actual usage, and sustained engagement with AI-generated content. The third section that assessed cognitive learning outcomes based on Bloom's Taxonomy. The fourth section examined student engagement as a mediating factor. Each construct was measured using four validated items, adapted from established scales in prior research. Responses were collected using a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Table 1 presents the constructs alongside their respective sources, while Appendix A outlines the constructs and their associated measurement items.

Table 1. Constructs and Their Sources

Construct	Supporting references
Performance expectancy	Romero-Rodríguez et al. (2023). Li & Qin (2023), Wu et al. (2022).
Effort expectancy	Strzelecki (2023), Supianto et al. (2024), Wu et al. (2022).
Social influence	Habibi et al. (2023), Abdalla (2025).
Facilitating conditions	Lavidas et al. (2024); Jin et al. (2025); Grassini et al. (2024).
Hedonic motivation	Romero-Rodríguez et al. (2023).
Habit	Grassini et al. (2024); Strzelecki (2024).
AI Adoption	Almogren et al. (2024); Saha et al. (2025); Strzelecki (2023).
Student engagement	Adewale et al. (2024); Strzelecki (2024).
Bloom's Taxonomy	Herrmann-Werner et al. (2024); Lubbe et al. (2025); Yusuf et al. (2024).

3.3. Validity and Reliability

To ensure the methodological rigor and content validity of the research instrument, an expert panel comprising seven specialists performed a comprehensive assessment of the proposed constructs and their corresponding measurement items. A pilot study involving 36 potential participants was conducted to assess the face validity of the instrument. Minor modifications have been made to the questions for clarity based on feedback from panel experts and students who participated in the pilot sample. The pilot test demonstrated that the constructs had achieved reliability, as indicated by Cronbach's Alpha values greater than 0.8, indicating a good level of reliability. To validate the measurement scale (construct validity), the study employs confirmatory factor analysis (CFA) using AMOS 26. Reliability, convergent and discriminant validity were assessed based on multiple criteria, including Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE), the Fornell-Larcker criterion, and the HTMT ratio.

3.4. Data Collection Procedure and Sampling Strategy

The study targeted undergraduate and graduate students from various academic fields at Sultan Qaboos University in Oman to gather relevant empirical data. To ensure comprehensive representation, a stratified random sampling technique was employed, with proportional allocation across seven academic groups: social sciences, medicine and health, education, science and

engineering, economics and political sciences, agricultural and marine sciences, and law. This approach minimized sampling bias and captured diverse perspectives on the adoption of AI. Data were collected over eight weeks in Spring 2025 through a self-administered online survey, which yielded a minimum sample size requirement of 384 students under conditions of 95% confidence, a 5% margin of error, and a or sample estimation produced a minimum sample size requirement of 384 students under conditions of 95% confidence, 5% margin of error, and 50% response distribution. To reduce non-response bias, additional responses were gathered, resulting in 731 valid cases. The final sample size exceeded the recommended threshold for SEM analysis, as Hair et al. (2019) suggest a minimum of 10 respondents per estimated parameter.

3.5. Data Analysis Procedure

The study employed SEM analysis to analyze the interrelationships among UTAUT2 constructs, AI adoption, and the revised Bloom's taxonomy of cognitive domains. SEM is a multivariate data analysis technique that facilitates the simultaneous estimation of all structural relationships, incorporating both directly measured variables and underlying latent constructs. It also takes into account the measurement errors in the observed variables. The analysis adopts the two-step modeling procedure outlined by Anderson and Gerbing (1988), beginning with a confirmatory factor analysis (CFA) to validate the measurement model, and then proceeding to structural analysis (path analysis). The study used the Analysis of Moment Structures (AMOS version 26) to estimate the theoretical model and test the proposed hypotheses.

CFA was used to validate all latent constructs in the proposed measurement model. Various validation metrics were employed in this study to provide evidence for construct validity, convergent validity, and discriminant validity for each construct (Hair Jr et al., 2020; Hayes et al., 2017). Table 2 presents the threshold criteria. Subsequently, the structural model was estimated to evaluate the hypothesized relationships among the constructs. SEM path analysis was performed to examine the direct effects of UTAUT2 predictors on AI adoption and the subsequent impact of AI adoption on Bloom's Taxonomy learning outcomes. The analysis of mediation effects was conducted using bootstrapping methods, examining student engagement as an indirect link between AI adoption and cognitive learning results. The model fit assessment relied on the Normed Fit Index (NFI) together with the Chi-square value and Root Mean Square Error Approximation (RMSEA). The various fit indices, goodness-of-fit, and their threshold levels were summarized (Hooper et al., 2008).

Table 2. Validity and Reliability Threshold Criteria

Type of Validity/Reliability	Indicator	Threshold	Reference
Convergent Validity	Factor Loadings	> 0.70	Hair et al. (2020); Hair et al. (2019)
	Average Variance Extracted (AVE)	> 0.50	Hair et al. (2020); Hair et al. (2019)
Internal Consistency	Cronbach's Alpha	≥ 0.70	Hair et al. (2020); Hair et al. (2019)
Discriminant Validity	Fornell-Larcker Criterion	√AVE > Inter-Construct Correlations	Fornell & Larcker (1981)
	HTMT Ratio	< 0.85	Hair et al. (2020)

4. Results and Analysis

4.1. Demographic Profile of Respondents

Table 3 presents a summary of the participants' socio-demographic characteristics. The sample comprised 44.9% male and 55.1% female respondents. All academic years were represented in the sample, with the most significant proportion being third-year students (26.8%). The distribution of students' academic performance showed that the largest group had a GPA within the range of 2.50–2.99 (34.6%), followed by those in the 2.00–2.49 range (23.4%). Finally, the distribution of students by academic specialization shows that the majority of respondents were from Arts and Social Sciences (26.8%), followed by Education (20.2%) and Economics and Business (13.1%).

Table 3. Demographic Profile of Respondents

Variable	Category	Frequency	Percentage
Gender	Male	328	44.9
	Female	403	55.1
Academic Year	First Year	109	14.9
	Second Year	138	18.9
	Third Year	196	26.8
	Fourth Year	153	20.9
	Fifth Year	92	12.6
	Sixth Year	43	5.9
Specialization	Science	64	8.8
	Engineering and IT	51	7.0
	Medicine and Health	44	6.0
	Arts and Social Sciences	196	26.8
	Education	148	20.2
	Economics and Business	96	13.1
	Law	49	6.7
	Nursing	34	4.7
	Agriculture and Marine Sci	49	6.7
GPA Category	Below 2.00	21	2.9
	2.00–2.49	171	23.4
	2.50–2.99	253	34.6
	3.00–3.49	136	18.6
	3.50–4.00	83	11.3
	Not reported	67	9.2

4.2. Descriptive Statistics of Study Constructs

The descriptive statistics presented in Table 4 provide important insights about student' perceptions of AI implementation in their learning. The study results show that performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, and AI adoption, as well as student engagement, all received high mean scores (above 4.0). This suggests that students strongly agree regarding the perceived usefulness and ease of utilization of AI tools, their motivational aspects and the habitual use of these tools. The skewness values for these constructs spanned from -2.116 to -0.367 , which shows that most items displayed strong left skewness because students tended to agree with positively phrased statements. The kurtosis values across the constructs ranged from -0.110 to 5.841 , indicating both mesokurtic and leptokurtic distribution patterns. The results indicate that some measurement items had relatively standard distribution shapes, while others had sharper peaks with heavier tails, which supports strong agreement with fewer extreme deviations. The results generally support positive attitudes among students toward AI-supported learning environments and validate the suitability of the dataset for further analysis using SEM, as the data meet the normality assumptions (Lei et al., 2005).

In contrast, the results show that higher-order cognitive constructs (analyzing, evaluating, creating) tend to exhibit lower (mean) scores (in the range of 3.1 to 3.4) compared to lower-order cognitive constructs (most of the average scores are above 4.0). These findings suggest that while students find AI learning tools helpful for supporting core learning activities, they may have difficulties when attempting to use them for more complex cognitive engagement. Although the average scores were lower, the skewness and kurtosis values remained within acceptable levels, indicating a moderate level of variability in the students' responses.

Following the detailed item-level analysis, the descriptive statistics at the construct-level presented (Table 5) show that students generally have positive attitudes about AI-enhanced learning. The majority of constructs received high mean scores above 4.0, indicating strong perceived usefulness, ease of use and motivational engagement. In contrast, higher-order cognitive learning domains had lower mean scores, suggesting potential gaps in advanced cognitive engagement. The distribution of all constructs exhibited negative skewness and leptokurtosis, with skewness values ranging from -0.981 to -2.083 , and kurtosis values ranging from 1.420 to 6.787 . This suggests overall agreement, with minimal deviations from normality. The dataset demonstrated acceptable psychometric characteristics for use with maximum likelihood estimation in structural equation modeling (Byrne, 2010; West et al., 1995).

Table 4. Item-Level Descriptive Statistics, Factor Loadings, Composite Reliability, and Convergent Validity

Latent Variables	Item	Mean	SD	Skewness	Kurtosis	Factor Loading	Cronbach's Alpha	CR	AVE
Performance expectancy	PE1	4.4309	.85469	-2.114	5.379	.883	.923	.924	.754
	PE2	4.3543	.88769	-1.840	3.959	.934			
	PE3	4.0670	.90940	-1.108	1.490	.847			
	PE4	4.1710	.91683	-1.404	2.424	.803			
Effort expectancy	EE1	3.4897	1.01406	-.367	-.110	.717	.834	.839	.567

Latent Variables	Item	Mean	SD	Skewness	Kurtosis	Factor Loading	Cronbach's Alpha	CR	AVE
Social influence	EE2	3.9603	1.04150	-1.110	.796	.791	.884	.887	.664
	EE3	3.5048	1.19516	-.576	-.591	.732			
	EE4	4.1587	.90478	-1.319	2.117	.769			
	SI1	4.0000	.94071	-1.178	1.407	.725			
	SI2	4.1505	1.01863	-1.412	1.674	.851			
	SI3	4.1259	.99755	-1.392	1.790	.930			
	SI4	3.9001	.93904	-.785	.532	.736			
Facilitating conditions	FC1	4.1874	.88312	-1.476	2.921	.726	.852	.853	.593
	FC2	4.2066	.85031	-1.212	1.888	.759			
	FC3	4.3953	.83645	-2.018	5.148	.810			
	FC4	4.3570	.81241	-1.769	4.345	.782			
Hedonic motivation	HM1	4.2380	.88564	-1.445	2.314	.796	.861	.863	.612
	HM2	3.9918	.93483	-1.103	1.292	.780			
	HM3	4.3447	.83840	-1.824	4.286	.814			
	HM4	4.0821	.97859	-1.203	1.267	.738			
Habit	H1	4.1218	.91574	-1.166	1.414	.767	.845	.846	.580
	H2	3.9549	.96905	-.770	.105	.764			
	H3	4.1450	.88413	-1.277	1.948	.809			
	H4	4.2079	.83123	-1.452	2.984	.703			
AI Adoption	AA1	4.4843	.72392	-1.987	5.831	.790	.901	.907	.712
	AA2	4.2941	.77439	-1.413	3.127	.921			
	AA3	4.3365	.76679	-1.606	4.022	.928			
	AA4	4.1833	.87071	-1.338	2.296	.718			
Student engagement	SE1	4.2654	.92936	-1.783	3.530	.748	.877	.882	.653

Latent Variables	Item	Mean	SD	Skewness	Kurtosis	Factor Loading	Cronbach's Alpha	CR	AVE
Remembering	SE2	4.2982	.85287	-1.675	3.715	.929	.859	0.860	.607
	SE3	4.0725	.91199	-1.111	1.471	.817			
	SE4	4.4815	.76972	-2.116	5.841	.722			
	R1	4.1012	.93962	-1.176	1.389	.787			
	R2	3.9261	.97924	-.756	.107	.774			
Understanding	R3	4.1122	.90114	-1.225	1.708	.826	.883	.884	.655
	R4	4.1902	.87160	-1.474	2.770	.725			
	U1	4.1094	.91953	-1.480	2.598	.809			
	U2	4.1491	.85907	-1.435	2.865	.828			
	U3	4.0301	.93438	-1.191	1.640	.848			
Applying	U4	4.2148	.84988	-1.351	2.347	.749	.891	.897	.686
	A1	4.1067	.95636	-1.439	2.280	.891			
	A2	4.1491	.92362	-1.607	3.117	.856			
	A3	3.7579	1.11659	-.832	.095	.731			
	A4	3.9425	1.05700	-1.162	1.060	.826			
Analyzing	AN1	3.3639	.68166	-1.073	1.811	.875	.874	.877	.643
	AN2	3.2791	.74675	-.979	1.041	.816			
	AN3	3.2982	.79121	-1.182	1.347	.795			
	AN4	3.4104	.68134	-1.093	1.500	.712			
Evaluating	E1	3.3064	.70162	-1.055	1.800	.754	.870	.871	.629
	E2	3.3516	.74268	-1.132	1.336	.761			
	E3	3.2380	.70864	-.910	1.399	.815			
	E4	3.2804	.71912	-.985	1.385	.838			
Creating	C1	3.3105	.75897	-.945	1.892	.778	.846	.848	.584
	C2	3.1943	.77849	-.650	1.057	.721			
	C3	3.3092	.80250	-.903	1.023	.827			
	C4	3.1888	.85684	-.634	.108	.726			

Table 5. Construct-Level Descriptive Statistics

Construct	Mean	SD	Skewness	Kurtosis
Performance expectancy	4.2558	.80413	-1.868	4.694
Effort expectancy	3.7784	.85326	-.981	1.420
Social influence	4.0441	.83953	-1.568	2.555
Facilitating conditions	4.2866	.70415	-2.083	6.787
Hedonic motivation	4.1642	.76485	-1.621	4.036
Habit	4.1074	.74491	-1.486	3.229
AI Adoption	4.3246	.68976	-1.903	6.118
Student engagement	4.2794	.74231	-1.986	5.679
Remembering	4.0824	.77446	-1.479	2.999
Understanding	4.1259	.76664	-1.416	3.132
Applying	3.9891	.88260	-1.503	2.841
Analyzing	3.3379	.61937	-1.357	2.950
Evaluating	3.2941	.60931	-1.795	4.708
Creating	3.2507	.66196	-1.334	4.015

4.3. Confirmatory Factor Analysis Results

Confirmatory factor analysis (CFA) was performed to assess and validate the measurement model. Based on the results in Table 4, it can be seen that the model demonstrates strong psychometric properties across all constructs. The results demonstrate that all 64 observed indicators exhibited standardized factor loadings ranging from 0.703 to 0.934, considerably exceeding the established threshold of 0.70 (Hair et al., 2017), thereby confirming strong convergent validity. The average factor loading of 0.799 indicates high item reliability and consistent alignment with their corresponding latent constructs. Cronbach's alphas and composite reliability for the 14 constructs were all higher than the cutoff value of 0.70 (Hair et al., 2020), as shown in Table 4. This suggests that there is adequate internal consistency reliability. A satisfactory degree of convergent validity was also demonstrated by the average variance extracted (AVE) values for each construct, which exceeded the minimum acceptable threshold of 0.5 (Hair et al., 2020), indicating that each latent construct accounted for at least 50% of the variance in its associated measurement items. Finally, multicollinearity was assessed using the variance inflation factor (VIF). As presented in Table 6, the results revealed no serious collinearity concerns, with all the VIF values falling below the recommended threshold of 5 (Hair et al., 2019).

Table 6. Multicollinearity Diagnostics (VIF) for UTAUT2 Predictors of AI Adoption

Construct	Variance inflation factor (VIF)
Performance expectancy	2.921
Effort expectancy	2.149
Social influence	1.093
Facilitating conditions	2.917
Hedonic motivation	2.687
Habit	1.269

Note. VIF was not calculated for the AI Adoption → Student Engagement path, as it involves only one predictor, and multicollinearity does not apply.

Moreover, two well-established approaches for evaluating the discriminant validity of constructs—namely, the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio of correlations—were used in this study to assess the constructs' discriminant validity. To establish discriminant validity, the square root of each construct's AVE must exceed the corresponding inter-construct correlation coefficients among the latent variables. (Fornell & Larcker, 1981). As presented in Table 7, the square roots of the AVE values, located along the diagonal, exceed the inter-construct correlation coefficients of the remaining latent variables. This indicates that our model demonstrates satisfactory discriminant validity. Furthermore, the HTMT values presented in Table 8 surpass the established threshold. The first part of the model (predictors of AI adoption) showed that 20 out of 21 construct pairs had HTMT values below 0.85, and one pair exceeded 0.85 but remained below 0.90, 90 which is still acceptable according to Benitez et al. (2020) and Henseler et al. (2015). The second part of the model (learning outcomes) demonstrated that 26 out of 28 construct pairs had values below 0.85, with two pairs ranging from 0.85 to 0.90. The HTMT criterion supports discriminant validity based on these results.

Table 7. Discriminant Validity – Fornell-Larcker Criterion

Construct	PE	EE	SI	FC	HM	H	AIA	SE	R	U	A	AN	E	C
PE	.868													
EE	.725	.753												
SI	.219	.219	.815											
FC	.682	.551	.275	.770										
HM	.637	.485	.244	.763	.782									
H	.328	.267	.158	.406	.447	.762								
AIA	.636	.463	.256	.742	.692	.369	.844							
SE	.629	.480	.264	.745	.685	.358	.801	.808						

Construct	PE	EE	SI	FC	HM	H	AIA	SE	R	U	A	AN	E	C
R	-.002	-.023	.014	-.011	-.013	-.021	-.016	-.008	.779					
U	.593	.560	.243	.702	.727	.375	.609	.666	.007	.809				
A	.446	.409	.150	.560	.578	.308	.483	.499	.014	.776	.828			
AN	.269	.231	.132	.247	.269	.162	.267	.266	.044	.350	.351	.802		
E	.054	-.036	.024	.108	.113	.060	.062	.060	-.016	.103	.076	.029	.793	
C	.088	.013	.008	.113	.110	.030	.098	.066	-.019	.090	.067	.071	.446	.764

*Note: Diagonal values are the square root of AVE, largest in corresponding rows and columns.

Table 8. Discriminant Validity – HTMT Ratio

Construct	PE	EE	SI	FC	HM	H	AIA	SE	R	U	A	AN	E	C
PE	-													
EE	.835	-												
SI	.244	.257	-											
FC	.771	.662	.316	-										
HM	.719	.580	.279	.896	-									
H	.375	.326	.183	.483	.524	-								
AIA	.700	.546	.288	.847	.788	.425	-							
SE	.703	.573	.301	.865	.796	.422	.888	-						
R	.037	.045	.033	.036	.049	.047	.024	.031	-					
U	.659	.657	.276	.812	.835	.436	.681	.757	.028	-				
A	.497	.479	.170	.647	.665	.356	.539	.567	.052	.847	-			
AN	.302	.275	.151	.288	.311	.186	.298	.302	.058	.395	.393	-		
E	.069	.068	.032	.126	.129	.079	.088	.071	.057	.118	.087	.059	-	
C	.099	.067	.043	.132	.126	.062	.111	.080	.056	.105	.088	.086	.522	-

4.4. Structural Model and Hypotheses Testing Results

Having established sound construct validity and reliability, the structural model was tested to evaluate the hypothesized relationships among the 14 latent variables. Table 9 presents the structural path results. Out of thirteen hypotheses, seven were statistically supported (at the $p < .05$ level), three showed marginal significance, and three were not supported. AI adoption was found to be significantly predicted by performance expectancy ($\beta = 0.304$, $p < .001$), facilitating conditions ($\beta = 0.451$, $p < .001$), hedonic motivation ($\beta = 0.537$, $p < .001$), and social influence ($\beta = 0.058$, $p < .10$, marginally significant). This underscores the significance of contextual and motivational enablers in students' technology use. The lack of significant effects from effort expectancy (H2) and habit (H6)

shows that behavioral automaticity and perceived ease of use may not be important factors in the voluntary adoption of AI tools. Path analysis results also revealed that AI Adoption significantly predicted student engagement ($\beta=0.865$, $p<.001$), which in turn had a statistically significant effect on three of Bloom's cognitive domains: understanding ($\beta=0.743$, $p<.001$), applying ($\beta=0.598$, $p<.001$), and analyzing ($\beta=0.283$, $p<.001$) and demonstrated marginal significance in its effects on evaluating and creating domains. These findings confirm the mediating role of engagement in the process through which AI is translated into cognitive learning outcomes. Figure 2 illustrates the results of the structural equation model, displaying the standardized path estimates among the constructs in the final model.

In terms of predictive power, the model accounted for 54.4% of the variance in AI Adoption ($R^2 = 0.544$) and 74.8% in Student Engagement ($R^2 = 0.748$), underscoring its explanatory robustness. While most of Bloom's higher-order cognitive domains showed limited explained variance, understanding ($R^2 = 0.553$) and applying ($R^2 = 0.358$) demonstrated relatively stronger explanatory power, indicating that AI engagement is more effective in shaping mid-level learning outcomes. These results collectively affirm the empirical defensibility and theoretical coherence of the model, despite the marginal global fit metrics (Hair et al., 2021; Marsh et al., 2004).

Finally, the structural model's adequacy was evaluated using multiple fit indices. Although the comparative fit index (CFI = 0.750) and Tucker–Lewis index (TLI = 0.738) did not reach the commonly accepted threshold of 0.90, the normed chi-square (CMIN/df = 6.355) indicated a marginally acceptable fit, and the root mean square error of approximation (RMSEA = 0.086) fell within the acceptable range. These global fit statistics were counterbalanced by strong evidence of internal consistency and construct validity. All standardized factor loadings exceeded 0.70, composite reliability (CR) values were greater than 0.80, and average variance extracted (AVE) surpassed the recommended threshold of 0.50 across all constructs.

Table 9. Results of the Structural Model

Hypothesis	Path	Estimate (Std.)	Estimate (Unstd.)	S.E.	C.R.	p-value	Result
AI Adoption Model							
H1	AIA $\leftarrow$ PE	0.304	0.185	0.02	9.263	< .001	Supported
H2	AIA $\leftarrow$ EE	-0.049	-0.033	0.021	-1.563	0.118	Not Supported
H3	AIA $\leftarrow$ SI	0.058	0.039	0.021	1.914	0.056	Marginal
H4	AIA $\leftarrow$ FC	0.451	0.324	0.028	11.697	< .001	Supported
H5	AIA $\leftarrow$ HM	0.537	0.353	0.027	13.229	< .001	Supported
H6	AIA $\leftarrow$ H	0.040	0.030	0.023	1.285	0.199	Not Supported
Learning Impact Model							
H7	SE $\leftarrow$ AIA	0.865	0.909	0.053	17.06	< .001	Supported
H8	R $\leftarrow$ SE	-0.010	-0.016	0.063	-0.249	0.803	Not Supported
H9	U $\leftarrow$ SE	0.743	1.007	0.065	15.515	< .001	Supported
H10	A $\leftarrow$ SE	0.598	0.980	0.07	14.038	< .001	Supported
H11	AN $\leftarrow$ SE	0.283	0.332	0.049	6.727	< .001	Supported
H12	EV $\leftarrow$ SE	0.071	0.073	0.042	1.717	0.086	Marginal
H13	C $\leftarrow$ SE	0.074	0.09	0.051	1.758	0.079	Marginal

Note. Std. = Standardized Estimate, Unstd. = Unstandardized Estimate, SE = Standard Error, C.R. = Critical Ratio. $p < .05$ is considered statistically significant. During model refinement, one item each from the performance expectancy and

facilitating conditions constructs was removed due to high residual covariances. This adjustment was made to enhance the overall model fit and minimize measurement redundancy.

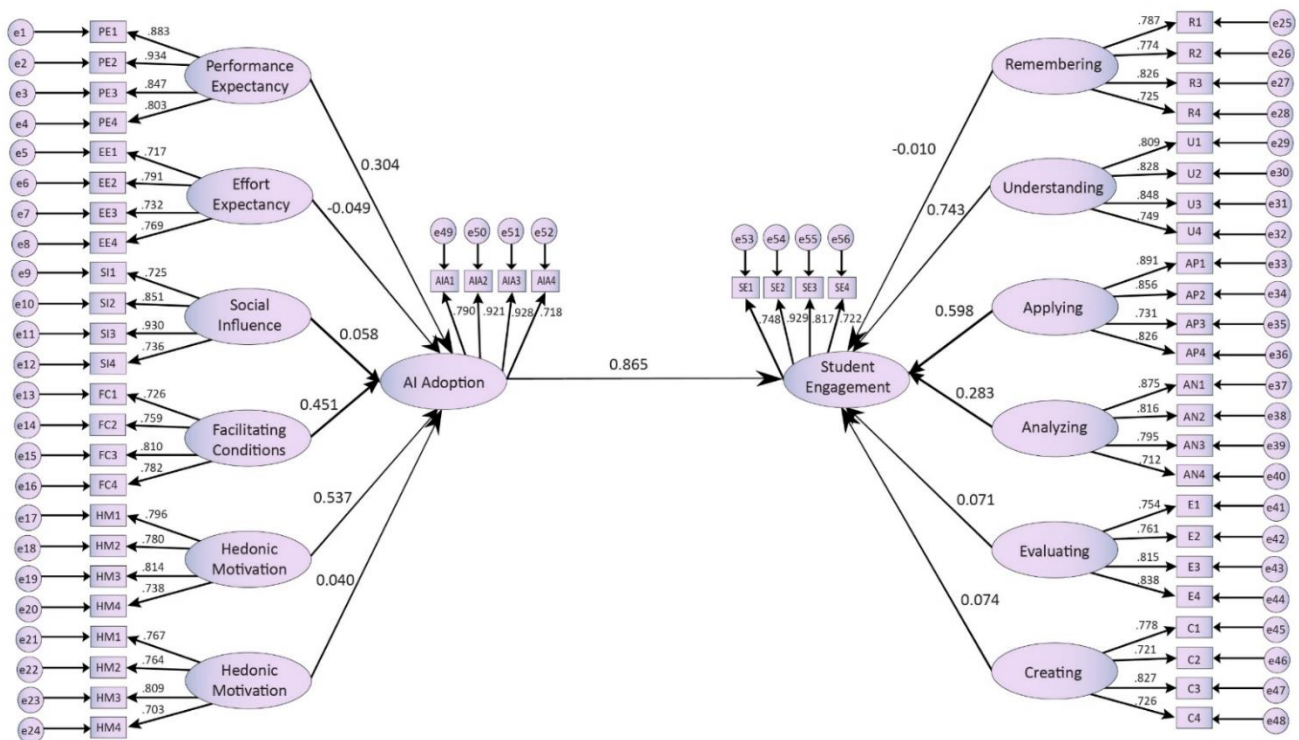


Figure 2. Structural Equation Model with Standardized Path Estimates

5. Discussion and Implications

This study investigates the determinants influencing the adoption of generative AI-supporting tools and examines their effects on university students' engagement and cognitive development outcomes. Drawing upon the extended UTAUT2 model and Bloom's taxonomy. The study addresses essential knowledge gaps by providing a comprehensive and evidence-based model that illustrates how motivational, behavioral, and contextual elements influence students' adoption of an AI tool and the resulting educational advantages. According to structural equation modeling analysis, the study reveals that performance expectancy, facilitating conditions, hedonic motivation, and social influence from the UTAUT2 are crucial factors driving the adoption of AI. The significant role of the hedonic motivation construct ($\beta = 0.353$) indicates that enjoyment and engagement are key driving factors, whereas the relatively strong influence of facilitating conditions ($\beta = 0.324$) implies that certain enabling, institutional, and technical support are necessary for real adoption. These findings are consistent with the results reported in prior studies (Abdalla et al., 2025; Acosta-Enriquez et al., 2024; G. C. et al., 2024; Faraon et al., 2025), which highlight the particular importance of performance expectancy, facilitating conditions, hedonic motivation, and social influence.

Contrarily, the effort expectancy and habit factors had no significant impact, suggesting that today's students—who are already digital natives—may not rely on ease of use or routine behavior when deciding to use AI for learning (Kelly et al., 2023). This diverges from earlier adoption studies in other digital contexts where effort expectancy was often significant, highlighting the uniqueness of GenAI adoption among contemporary student populations.

Furthermore, our SEM analysis shows that AI adoption effectively predicts student engagement ($\beta = 0.909$) confirming engagement as the essential mediating factor in AI-based learning models. The analysis demonstrated significant positive effects on three cognitive domains within Bloom's Taxonomy—understanding, applying, and analyzing—while the effects on evaluating and creating

domains were marginally significant, and remembering showed no significant relationship. This pattern suggests that generative AI tools are most effective in supporting mid-level cognitive processes but may require additional pedagogical strategies to stimulate higher-order thinking. This finding adds nuance to Bloom's Taxonomy in AI-enhanced education.

Taken together, these findings make a unique contribution by offering one of the first integrated models that links UTAUT2 adoption predictors with Bloom's hierarchical cognitive outcomes through the mediating role of student engagement. This provides both theoretical and practical insights that extend beyond prior work, positioning student engagement as the central mechanism through which AI adoption translates into sustainable learning outcomes.

5.1. Theoretical Implications

While the UTAUT2 model has been extensively applied across multiple empirical investigations on technology adoption in the higher education context (Al Salti, 2025; Chávez Herting et al., 2020; Faraon et al., 2025; Grassini et al., 2024; Xue et al., 2024), this study makes an important theoretical contribution by integrating this model with Bloom's Taxonomy cognitive domains to examine the pedagogical impact of generative AI adoption on students' learning outcomes. Unlike previous studies that mainly focus on factors influencing university students' adoption of AI-supporting platforms (Venkatesh et al., 2012; G. C. et al., 2024), this study contributes to the theoretical discussion by showing how AI-supported engagement has varying effects on the six cognitive domains of Bloom's Taxonomy. Our proposed model shows that AI tools significantly enhance mid-level cognitive processes, with relatively good explanatory power. However, they offer less explanatory value for higher-order domains, such as evaluating and creating. This division aligns with current recommendations to investigate not only how students adopt generative AI tools, but also how these tools influence the depth and complexity of learning (Habiballa et al., 2025; Zawacki-Richter et al., 2019).

Furthermore, this study empirically links the adoption of generative AI to Bloom's Taxonomy. By doing so, this study repositions Bloom's hierarchical model as a viable framework in technology-enhanced learning research, an area that is often overlooked. The findings emphasize the significance of cognitive alignment between technology acceptance and the cognitive learning domains of Bloom's taxonomy. They emphasize that generative AI tools may be more effective in facilitating certain cognitive levels than others. This insight opens new avenues for theoretical exploration, suggesting that future technology-enhanced learning research should consider adaptive AI interventions tailored to specific cognitive outcomes rather than generalized usage. In this way, the study provides a multidimensional perspective on the integration of generative AI-powered tools in teaching and learning by building a substantial theoretical bridge between technology acceptance theory and cognitive learning theory.

5.2. Practical and Pedagogical Implications

The practical and pedagogical implications of this study are far-reaching, offering a strategic framework for educators, policymakers, and educational technologists seeking to integrate AI tools effectively into higher education settings. The study findings guide implementation procedures and help institutions develop educational policies, create curriculum, and implement instructional innovations. First, the strong influence of hedonic motivation on AI adoption highlights the significance of learner engagement in technology-mediated education. Prior research on technology-enhanced learning suggests that university students demonstrate a greater propensity to adopt and sustain the use of digital technologies that offer enjoyment and intrinsic motivational benefits (Nikolopoulou et al., 2021; Rudhumbu, 2022; Strzelecki, 2024). Educational institutions should select AI tools that create interactive learning experiences, incorporating gamified and immersive elements to boost student motivation and encourage active participation. The approach supports

constructivist learning principles because students retain information more effectively through meaningful engagement, according to Kuhlmann et al. (2024).

Second, the results highlight the necessity of robust faculty development programs. Given the dynamic nature of AI technologies, instructors must receive continuous training to remain current with pedagogical applications and technological competencies (Zawacki-Richter et al., 2019). Such programs should address both the operational features of AI and its integration into learner-centered teaching strategies. Faculty confidence in using AI tools is a critical enabler of successful adoption, as emphasized by previous studies on digital competency in higher education (Herzallah & Makaldy, 2025; Nazaretsky et al., 2025).

Third, the study's conclusions regarding the limited impact of generative AI-supporting tools on higher-order skills, as defined by Bloom's Taxonomy, necessitated a reevaluation of assessment procedures. While the adoption of AI tools can assist with basic foundational tasks and knowledge retrieval, their actual educational benefits lie in facilitating more complex learning processes. Teachers must design learning tasks that require synthesis, evaluation, and creativity, which represent the highest levels of Bloom's Taxonomy (Anderson & Krathwohl, 2001). These tasks should encourage students to use AI as a tool for inquiry rather than just as a response generator. This approach promotes self-regulated learning and metacognitive awareness among students.

Finally, from a policy and infrastructure perspective, the successful integration of AI in higher education demands a supportive institutional environment. Investment in technological infrastructure, such as high-speed Internet, secure data management systems, and cloud-based platforms, is critical (Abdalla, 2025). Equally important are institutional policies that ensure ethical AI usage, protect student privacy, and promote equitable access to AI tools). Policymakers must recognize that technological equity is crucial to preventing the deepening of existing digital divides.

6. Conclusion

This study provides a comprehensive examination of the factors that lead university student to adopt generative AI tools and their subsequent impact on their learning outcomes. It utilizes an integrated framework that combines the UTAUT2 framework and Bloom's Taxonomy. The study validates structural equation modeling through an empirical analysis of 14 latent constructs in data from diverse students, aiming to understand the motivational, contextual, and cognitive aspects of AI-enhanced learning.

In response to RQ1, the findings show that performance expectancy, facilitating conditions, and hedonic motivation are the strongest determinants of AI adoption, while effort expectancy and habit did not demonstrate significant effects. This emphasizes the importance of both functional utility and intrinsic motivation in shaping students' behavioral intentions. In response to RQ2, the results confirm that AI adoption significantly enhances student engagement, highlighting engagement as a key mediating mechanism in AI-supported learning environments. In response to RQ3, the findings reveal that student engagement has the greatest impact on mid-level cognitive domains (understanding, applying, and analyzing), while its influence on higher-order domains (evaluating and creating) is marginal and its effect on remembering is non-significant.

The study makes two contributions to both theory and practice. First, by combining UTAUT2 with Bloom's Taxonomy of Learning Domains, it enhances current theoretical models of technology-enhanced learning. This integration offers a comprehensive framework for evaluating both the adoption of technology and its educational impact. Second, the study findings provide educational institutions with important practical insights for developing effective curricula, training faculty members, and implementing assessment approaches and AI policies to enhance students learning experiences. The study emphasizes that educational institutions should adopt evidence-based

approaches to utilize AI tools effectively for promoting technology adoption and inclusive learning outcomes.

Despite offering significant insights into the scenario related to AI usage and its pedagogical implications in a higher education setting, there are some limitations that highlight future research opportunities. First, the cross-sectional nature of the study limits the possibility of examining how AI adoption and learning progress over time. A longitudinal study may provide better insights into how students sustain their engagement and how their learning is retained over time. Second, the data were collected from students at a single university, which may restrict the generalizability of the findings across different institutional and cultural contexts. Future research should extend the sample to multiple universities and diverse geographical regions. Third, while Confirmatory Factor Analysis (CFA) was employed to validate the measurement model, no Exploratory Factor Analysis (EFA) was conducted beforehand. Although the constructs were drawn from well-validated prior studies, the absence of EFA may have limited the initial exploration of factor dimensionality. Future studies should consider incorporating both EFA and CFA for greater robustness. Fourth, this study relied solely on student self-reported perceptions; future research could integrate the perspectives of faculty, administrators, and policymakers to provide a more comprehensive understanding of AI adoption in higher education.

Declarations

Author Contributions. S.A: Conceptualization, methodology, data analysis, review-editing and writing, original manuscript preparation. A.A.: Literature review, review-editing and writing, original manuscript preparation. All authors have read and approved the published on the final version of the article.

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Ethical Approval. This research was conducted in accordance with the ethical standards of Sultan Qaboos University. Informed consent was obtained from all participants involved in the study.

Data Availability Statement. The data used in this study can be obtained by sending request e-mail to the corresponding author.

Declaration of generative AI and AI-assisted technologies in the writing process. During the preparation of this work, the authors used ChatGPT4o in order to assist with improving the language and readability of single sentences in the initial drafts. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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