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What Does it Take to Trigger Intention to Use Artificial Intelligence among Students in Higher Education Institutions?

Zahir Osman, Ratna Khuzaimah Mohamad, Nadzurah Kasbun
Open University Malaysia
Email: zahir_osman@oum.edu.my, Ratna_mohamad@oum.edu.my, nadzurahkasbun@oum.edu.my

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Abstract
The increasing integration of Artificial Intelligence (AI) in higher education institutions necessitates a student prepared for this transformative change. This study investigates the factors influencing students' intention to use AI tools in their study. Drawing upon the Technology Acceptance Model (TAM), the research aims to understand how perceived ease of use, and perceived usefulness impact students' intention to use with attitude, and self-efficacy as mediators. Data collection employed a survey instrument distributed to a sample of 319 students from public and private higher education institutions. The survey measured participants' perceptions of AI ease of use, perceived usefulness, attitude towards AI, self-efficacy, and intention to use AI tools in their study. Statistical analysis utilized Partial Least Squares (PLS) to assess the relationships between the proposed variables and test the formulated hypotheses. The results of the hypothesis testing confirmed the positive influence of perceived ease of use and perceived usefulness on students' intention to use AI tools, aligning with TAM principles. Furthermore, the study revealed that attitude and self-efficacy act as mediating factors, bridging the gap between perceived ease of use and perceived usefulness and intention to use. These findings suggest that beyond just the technical aspects of AI, students' perceptions, attitudes, and confidence levels significantly influence their willingness to use AI in their study. The study's implications are significant for organizations implementing AI. By prioritizing the user-centered design of AI tools, emphasizing training and skill development to enhance perceived ease of use, and communicating the benefits of AI to address perceived usefulness, organizations can foster a more positive student attitude towards AI. Additionally, promoting a culture of learning and support can boost student's self-efficacy and ultimately encourage wider usage of AI tools within the organization.
Keywords: Perceived Ease of Use, Perceived Usefulness, Attitude, Learners' Self-Efficacy, Intention.

Introduction

The intention to use artificial intelligence (AI) in higher education institutions is crucial for enhancing the learning experience, improving student outcomes, and increasing institutional efficiency (AlGerafi et al., 2023). AI can adapt instruction to diverse learners, provide personalized feedback, and automate administrative tasks, freeing instructors to focus on teaching (Chatterjee & Bhattacharjee, 2020). However, there are significant research gaps in AI usage in higher education, such as the need for more studies on its impact on student engagement, academic success, and institutional equity (Roy et al., 2022). Addressing these gaps can inform policymakers and institutions about the importance and challenges of AI usage, helping shape its future use in higher education (Chai et al., 2020). The usage of AI in higher education is a complex process that involves various stakeholders, including students, faculty, administrators, and policymakers (An et al., 2023). Understanding the factors that influence the intention to use AI is crucial for successful implementation and integration into teaching and learning practices (Milicevis et al., 2024). The intention to use artificial intelligence (AI) in higher education institutions globally is crucial for enhancing the learning experience, improving student outcomes, and increasing institutional efficiency (Chen et al., 2021). Recent studies emphasize the importance of AI applications as supporting tools for students in higher education, highlighting the role of factors such as performance expectation, effort expectation, social influence, and facilitating conditions in shaping students' behavioral intentions toward AI usage (Chai et al., 2021; Kebah et al., 2019). The usage of AI in higher education institutions is critical for addressing the challenges of digital transformation and ensuring that students are equipped with the skills necessary for the future (Wang et al., 2021). The intention to use artificial intelligence (AI) in higher education institutions is a pressing issue due to the rapid advancements in AI technology and its potential to transform the learning experience. However, several challenges and concerns hinder the usage of AI in higher education (Bonsu & Baffour-Koduah, 2023). One major issue is the lack of awareness and understanding among students and faculty about the capabilities and limitations of AI. This lack of knowledge can lead to skepticism and resistance to AI usage, making it difficult to integrate AI into teaching and learning practices (Chai et al., 2020). Another significant problem is the need for more studies on the impact of AI on student engagement, academic success, and institutional equity (kebah et al., 2019). The current research gap in this area hinders the development of effective policies and strategies for AI usage in higher education (Acosta-Enriquez., et al., 2024). Additionally, there are concerns about the potential biases and ethical issues associated with AI, which can affect the quality of education and the well-being of students (Lavidas et al., 2024). Furthermore, the usage of AI in higher education requires significant investments in infrastructure, training, and support. Implementing AI solutions can be prohibitively expensive for many institutions, especially those with limited resources (Raffaghelli et al., 2022). This financial burden can hinder the usage of AI and limit its potential benefits for students and faculty Wang et al., 2023). This study is significant for policymakers, higher education institutions, and students. For policymakers, understanding the factors that influence students' intentions to use AI can inform the development of policies that support the integration of AI into higher education (Li et al., 2022). This can help ensure that AI is used effectively to enhance the learning experience and improve student outcomes. For higher education institutions, the study can provide valuable insights into the factors that influence students' intentions to use AI. This can help institutions develop strategies to promote the usage of AI and ensure that students are equipped with the skills necessary to succeed in a rapidly changing job market (Kwak et al., 2022). Additionally, the study can help institutions identify potential barriers to AI usage and develop strategies to overcome these barriers. For students, the study can provide valuable insights into the factors that influence their intentions to use AI (Strzelecki, 2023). This can help students make informed decisions about their use of AI and ensure that they are using AI effectively to enhance their learning experience (Osman et al., 2018). Additionally, the study can help students identify the potential benefits and drawbacks of AI and develop strategies to mitigate any negative impacts (Ma & Lei, 2024). This study aims to assess the direct and indirect relationship between perceived usefulness, and perceived ease of use on the intention to use artificial intelligence among students in higher education institutions with attitude and the learners' self-efficacy as mediators.

Literature Review

Relationship between Perceived Ease of Use and Perceived Usefulness

Perceived ease of use refers to the degree to which individuals believe that using a particular system or technology would be free from effort, while perceived usefulness pertains to the belief that utilizing the system would enhance their performance or productivity (Sudaryanto et al., 2023). In the context of AI acceptance in higher education, if students perceive AI systems as easy to use, they are more likely to consider incorporating them into their academic endeavors (Kashive et al., 2020). A user-friendly interface, intuitive design, and seamless integration into existing educational platforms can contribute to this perception(N Wickneswary et al., 2024). Conversely, if students perceive AI systems as cumbersome or complex, their intention to use such technology may diminish (Park & Kim, 2023). Furthermore, the perceived usefulness of AI in higher education plays a pivotal role (Li et al., 2020). Students are more inclined to adopt AI tools if they perceive them as beneficial for enhancing learning outcomes, streamlining academic tasks, or providing personalized assistance (AlGerafi et al., 2023). For instance, AI-powered tutoring systems that adapt to individual learning styles can be perceived as highly useful (Wang et al., 2021). Therefore, the following hypothesis was proposed for this study:

H1: There is a relationship between perceived ease of use and perceived usefulness in the intention to use artificial intelligence among students in higher education institutions

Relationship between Perceived Ease of Use, Attitude & Intention

The relationship between perceived ease of use, attitude, and intention to use artificial intelligence (AI) among students in higher education institutions is crucial for understanding the usage of AI technology (Li et al., 2020). Research has consistently shown that perceived ease of use has a significant positive impact on attitude toward using AI, which in turn influences the intention to use AI (Lu et al., 2023). Studies have found that students who perceive AI as easy to use are more likely to have a positive attitude toward it, which increases their willingness to use it (Sangapu, 2020). Perceived ease of use is also a key factor in determining the intention to use AI, as students who find AI easy to use are more likely to have a higher intention to use it (Zhang et al., 2022). Furthermore, attitude towards using AI is a significant predictor of intention to use AI, as students who have a positive attitude towards AI are more likely to have a higher intention to use it (Zhang et al., 2023). The research has shown that perceived ease of use can have a mediating effect between personal learning environment and attitude (Xu & Zhao, 2018), and satisfaction can mediate between perceived ease of use and intention (Vieira & Almeida, 2021). Thus, the following hypotheses were proposed for this study:

H2: There is a relationship between perceived ease of use and attitude in the intention to use artificial intelligence among students in higher education institutions
H3: There is a relationship between perceived ease of use and intention to use artificial intelligence among students in higher education institutions
H4: There is a relationship between attitude and intention to use artificial intelligence among students in higher education institutions
H5: There is a mediating effect of attitude on the relationship between the perceived ease of use and intention to use artificial intelligence among students in higher education institutions

Relationship between Perceived Ease of Use, Self-Efficacy & Intention

Understanding how students in higher education adopt AI technology hinges on the interplay between perceived ease of use and intention to use AI. Studies (Li et al., 2020; Lu et al., 2023) consistently show that students who perceive AI as user-friendly develop a more positive attitude toward it, ultimately increasing their willingness to use it. This relationship between PEOU and intention to use AI might be influenced by self-efficacy. Self-efficacy refers to a student's belief in their ability to master a task (Chai et al., 2020). Students who find AI easy to use (high PEOU) may experience a boost in self-efficacy regarding using AI for learning purposes. This heightened self-efficacy, in turn, could further strengthen their intention to utilize AI tools (Zhang et al., 2022). For example, a student who finds an AI writing assistant easy to navigate (high PEOU) might develop confidence (high self-efficacy) in using it to improve their writing, leading to a greater intention to integrate this tool into their studies (Zhang et al., 2023). Therefore, universities that want to promote AI usage should focus on designing user-friendly AI interfaces and providing training to enhance student confidence in using them. Hence, the following hypotheses were proposed for this study:

H6: There is a relationship between perceived ease of use and learner's self-efficacy in the intention to use artificial intelligence among students in higher education institutions
H7: There is a relationship between learner's self-efficacy and intention to use artificial intelligence among students in higher education institutions
H8: There is a mediating effect of learner's self-efficacy on the relationship between the perceived ease of use and intention to use artificial intelligence among students in higher education institutions

Relationship between Perceived Usefulness, Attitude & Intention

Students' embrace of AI in higher education hinges on the interplay between perceived usefulness and intention to use. Perceived usefulness refers to a student's belief that AI can enhance their learning experience (Vieira & Almeida, 2021). Studies suggest that students who perceive AI as a valuable learning tool develop a more positive attitude towards it (Wu et al., 2020). This positive attitude acts as a mediator, influencing their willingness to integrate AI into their studies (Zhang et al., 2023). For instance, a student who finds an AI tutor helpful in explaining complex concepts (high perceived usefulness) might develop a more favorable view of AI as a learning aid (positive attitude). This positive attitude, in turn, could lead them to actively seek out and utilize other AI tools for learning (Zhang et al., 2022). Understanding this relationship is crucial for universities. By showcasing the practical benefits of AI in learning, universities can foster positive student attitudes towards AI, ultimately encouraging wider usage of these technologies. Therefore, the following hypotheses were proposed for this study:

H9: There is a relationship between perceived usefulness and attitude in the intention to use artificial intelligence among students in higher education institutions
H10: There is a relationship between perceived usefulness and the intention to use artificial intelligence among students in higher education institutions
H11: There is a mediating effect of attitude on the relationship between the perceived usefulness and intention to use artificial intelligence among students in higher education institutions

Relationship between Perceived Usefulness, Self-Efficacy & Intention
Students in higher education institutions are constantly navigating new learning technologies and resources. Understanding factors influencing their usage is crucial. Research suggests a link between perceived usefulness, intention to use, and self-efficacy (belief in one's ability to perform a task). Perceived usefulness refers to a student's belief that a specific technology or resource will enhance their learning (Huang, 2020b). When students perceive a resource as valuable for achieving academic goals, their intention to use it increases (Tan et al., 2018). However, self-efficacy acts as a mediator in this relationship (Chen et al., 2022). Students with high self-efficacy are more likely to see the benefit of a resource and translate that perception into action. For instance, a student might perceive an online tutoring platform as useful for clarifying complex concepts (Li et al., 2020). However, their intention to utilize it might be hindered by low self-efficacy in navigating the platform. Conversely, a student confident in their technical skills (high self-efficacy) is more likely to explore the platform's features and reap the benefits. This understanding can inform educational practices (Lu et al., 2023). By promoting students' self-efficacy through clear instructions and technical support, educators can empower them to leverage the perceived usefulness of learning resources, ultimately leading to improved learning outcomes. (Kashive et al., 2020). Hence, the following hypotheses were proposed for this study:

H12: There is a relationship between perceived usefulness and learner's self-efficacy in the intention to use artificial intelligence among students in higher education institutions
H13: There is a relationship between attitude and learner's self-efficacy in the intention to use artificial intelligence among students in higher education institutions
H14: There is a mediating effect of learner's self-efficacy on the relationship between the perceived usefulness and intention to use artificial intelligence among students in higher education institutions

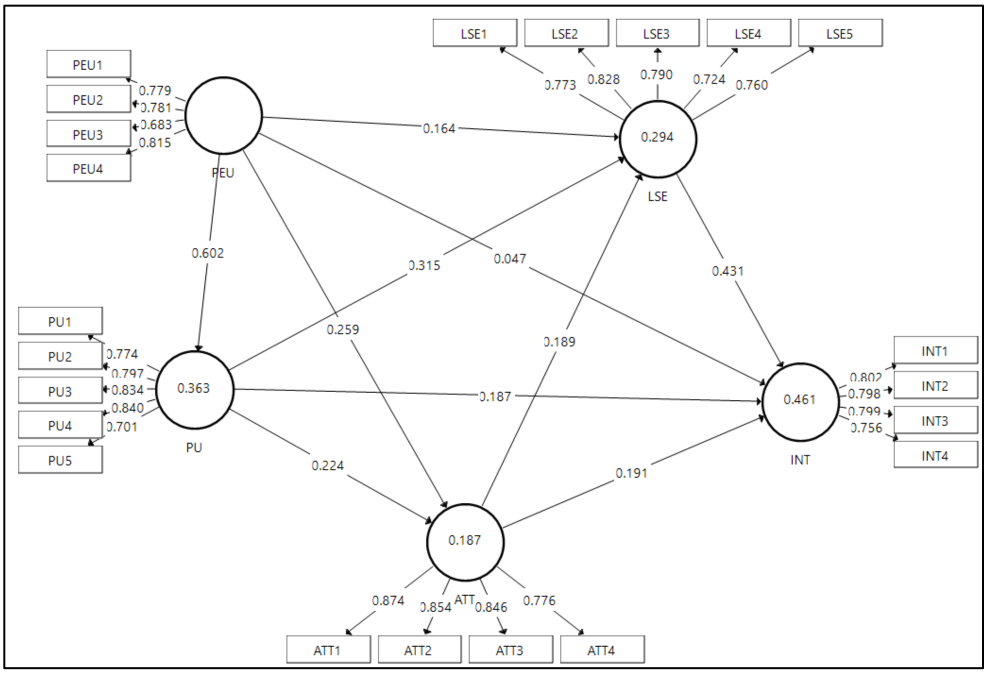

Figure 1: Research Framework
Notes: PU=Perceived Usefulness PEU=Perceived Ease of Use LSE=Learners' Self-Efficacy ATT=Attitude INT=Intention to Use

Methodology
This research investigated the complex interplay between perceived usefulness, perceived ease of use, and students' intention to use artificial intelligence (AI) in higher education. It examined the mediating roles of self-efficacy and attitude. A meticulous data collection process ensured reliable and valid measurements. Existing literature guided the selection of instruments. Researchers curated a survey with 22 observed variables: perceived ease of use (4 items) adapted from Davis (1989); Pan (2020), perceived usefulness (5 items) adapted from the same sources, learner self-efficacy (5 items) from Kang et al (2019), attitude (4 items) from Hair et al (2019), and intention to use (4 items) from (Pan, 2020; Kang et al., 2019). Participants rated each construct on a 5-point Likert scale. A purposive sampling approach was employed due to the lack of a comprehensive population list. Out of 424 distributed surveys, 331 were returned (78.06% response rate), justifying the use of structural equation modeling (SEM) for data analysis. After data cleaning, 319 responses were deemed suitable for analysis. SmartPLS software, recognized for its expertise in SEM, was chosen for data analysis and hypothesis testing due to its robust assessment capabilities and proficiency in handling multivariate data analysis, aligning with the study's goals and recommendations from (Ringle et al., 2022). SmartPLS facilitated a rigorous evaluation of the proposed hypotheses and conducted extensive multivariate data analysis, enabling a comprehensive assessment of both the measurement and structural models.

Data Analysis
Respondents' Profiles
Examining the demographics of this student population, we see a nearly even gender split with females having a slight edge at 51.4% (164 students) compared to males at 48.6% (155 students). The age distribution leans towards those between 31-40 years old, representing

the largest group at 45.1% (144 students). Following closely behind are students under 30 years old at 38.6% (123 students). The remaining age groups see a significant drop-off, with the 51-60-year-olds being the smallest cohort at 3.4% (11 students). Looking at the year of study, we find the most populated year to be the third year with 24.8% (79 students). There's a fairly even distribution between the first and second year with 63 (19.7%) and 68 students (21.3%) respectively. The number of students steadily declines throughout the later years, with only 7.5% (24 students) in their fifth year or above. In terms of level of study, Bachelor's programs hold the majority at 66.8% (213 students). Diploma programs come in at a distant second with 21.6% (69 students), followed by Masters programs at 8.5% (27 students), and Doctoral programs with the fewest students at 3.1% (10 students). Interestingly, the data shows an almost identical number of students enrolled in public universities (155) compared to private universities (164).

Common Method Bias

This section examines common method bias (CMB) assessment in a statistical model. Kock (2015) and Kock & Lynn (2012) proposed a comprehensive collinearity test to address CMB, a method particularly useful for situations where data is collected from a single source. This method relies on variance inflation factors (VIFs) to identify problematic collinearity. A VIF exceeding 3.3 indicates a significant concern for CMB within the model (Kock & Lynn, 2012). Conversely, VIFs below 3.3 suggest that CMB is not a threat (Kock, 2015). As illustrated in Table 1, the calculated VIFs were all below the 3.3 threshold, confirming the absence of CMB in this model.

Table 1
Full Collinearity

	LSE	PEU	PU	ATT	LSE
INT		1.801	1.751	1.708	1.464
PEU	1.642		1.345	1.718	1.628
PU	1.698	1.431		1.596	1.705
ATT	1.278	1.303	1.337		1.336
LSE	1.393	1.699	1.673	1.708	

Measurement Model

This study employed the two-stage assessment approach suggested by Hair et al. (2017) to evaluate the measurement model's reliability and validity. This approach scrutinizes each item for loadings above the 0.7 threshold in both the first and second order (Hair et al., 2017). Examining construct reliability and validity through Average Variance Extracted (AVE), composite reliability, and Cronbach's alpha revealed positive results (Table 2). The AVE for all constructs ranged from 0.587 to 0.703, exceeding the 0.5 benchmark and indicating strong convergent validity (Hair et al., 2017). Composite reliability scores for all constructs were above 0.7, falling within the range of 0.767 to 0.866. Similarly, Cronbach's alpha values for all constructs surpassed 0.7, ranging from 0.764 to 0.858 (Table 2). To ensure discriminant validity, we first assessed cross-loadings in Table 2 to verify that items appropriately represented their intended constructs. We then employed the Heterotrait-Monotrait (HTMT) ratio for further evaluation, adhering to the recommended criteria for discriminant validity in Variance-Based Structural Equation Modeling (VB-SEM) established by Henseler, Ringle, and Sarstedt (2015). The HTMT ratios, original sample values, and 95% confidence intervals presented in Table 3 all confirm adherence to the 0.85 HTMT threshold. Overall, the implemented assessment procedures provide evidence for a reliable and valid measurement model.

Table 2
Construct Reliability and Validity, & Items Loadings

Constructs	Items	Loadings	CA	CR	AVE
Attitude	ATT1	0.874	0.858	0.862	0.703
	ATT2	0.854			
	ATT3	0.846			
	ATT4	0.776			
Intention	INT1	0.802	0.798	0.804	0.622
	INT2	0.798			
	INT3	0.799			
	INT4	0.756			
Learners' Self-Efficacy	LSE1	0.773	0.835	0.839	0.602
	LSE2	0.828			
	LSE3	0.790			
	LSE4	0.724			
	LSE5	0.760			
Perceived Ease of Use	PEU1	0.779	0.764	0.767	0.587
	PEU2	0.781			
	PEU3	0.683			
	PEU4	0.815			
Perceived Usefulness	PU1	0.774	0.850	0.866	0.626
	PU2	0.797			
	PU3	0.834			
	PU4	0.840			
	PU5	0.701			

Notes: CA=Cronbach Alpha   CR=Composite Reliability   AVE=Average Variance Extracted

Table 3
Hetrotrait-Monotrait (HTMT) Ratios

	ATT	INT	LSE	PEU
INT	0.527			
LSE	0.438	0.738		
PEU	0.482	0.528	0.525	
PU	0.432	0.583	0.559	0.727

Structural Model
Following Hair et al (2017), we meticulously evaluated the structural model by examining path coefficients (β) and coefficients of determination (R^2) using the Partial Least Squares (PLS) method. Bootstrapping with 5000 sub-samples determined the significance level of path coefficients. Table 5 presents the hypothesis testing results, including path coefficients (β), t-statistics, and p-values, providing a comprehensive analysis of the relationships among the variables. This detailed examination in Table 4 allows for a nuanced understanding of each hypothesis by dissecting Beta coefficients, T-statistics, and p-values, ultimately revealing

whether each hypothesis is supported. By presenting these results comprehensively, the study offers a deeper and clearer understanding of the interplay between the investigated variables. Examining the results of the t-statistics, we can analyze and interpret the hypotheses regarding user perceptions and behavioral intentions. Perceived ease of use has a strong positive influence on perceived usefulness (*H1*, beta = 0.602, t = 15.364, p = 0.000), supported by a high t-statistic and a very low p-value. Similarly, perceived ease of use has a positive relationship with attitude towards using the system (*H2*, beta = 0.259, t = 3.430, p = 0.001). However, the effect on the intention to use the system (*H3*, beta = 0.047, t = 0.749, p = 0.454) is weak and statistically insignificant. On the other hand, attitude has a positive and statistically significant effect on the intention to use (*H4*, beta = 0.191, t = 3.314, p = 0.001). This pattern holds for the indirect effect of perceived ease of use on intention mediated by attitude (*H5*, beta = 0.049, t = 2.366, p = 0.018). Moving on to self-efficacy, perceived ease of use has a positive influence on the learner's self-efficacy (*H6*, beta = 0.164, t = 2.616, p = 0.009), and self-efficacy, in turn, has a strong positive impact on intention to use (*H7*, beta = 0.431, t = 8.498, p = 0.000). This highlights the positive indirect effect of perceived ease of use on intention mediated by self-efficacy (*H8*, beta = 0.071, t = 2.482, p = 0.013). Likewise, perceived usefulness has a positive relationship with attitude (*H9*, beta = 0.224, t = 3.016, p = 0.003) and intention to use (*H10*, beta = 0.187, t = 3.187, p = 0.002). The indirect effect of perceived usefulness on intention mediated by attitude is also statistically significant (*H11*, beta = 0.043, t = 2.121, p = 0.034). Finally, perceived usefulness has a positive influence on learner's self-efficacy (*H12*, beta = 0.315, t = 5.281, p = 0.000), and attitude also has a positive effect on self-efficacy (*H13*, beta = 0.189, t = 3.219, p = 0.001). The analysis of hypothesis *H14* regarding the indirect effect of perceived usefulness on intention mediated by self-efficacy shows a positive and significant mediating effect (*H14*, beta = 0.136, t = 4.381, p = 0.000)

Table 4
Hypotheses Testing Results

Hypotheses	Beta	T Statistics	P Values	2.50%	97.50%	Decision
H1: PEU -> PU	0.602	15.364	0.000	0.526	0.682	*Accepted*
H2: PEU -> ATT	0.259	3.430	0.001	0.098	0.400	*Accepted*
H3: PEU -> INT	0.047	0.749	0.454	-0.080	0.174	*Rejected*
H4: ATT -> INT	0.191	3.314	0.001	0.085	0.300	*Accepted*
H5: PEU -> ATT -> INT	0.049	2.366	0.018	0.015	0.097	*Accepted*
H6: PEU -> LSE	0.164	2.616	0.009	0.029	0.278	*Accepted*
H7: LSE -> INT	0.431	8.498	0.000	0.334	0.526	*Accepted*
H8: PEU -> LSE -> INT	0.071	2.482	0.013	0.019	0.127	*Accepted*
H9: PU -> ATT	0.224	3.016	0.003	0.059	0.350	*Accepted*
H10: PU -> INT	0.187	3.187	0.002	0.077	0.304	*Accepted*
H11: PU -> ATT -> INT	0.043	2.121	0.034	0.012	0.088	*Accepted*
H12: PU -> LSE	0.315	5.281	0.000	0.204	0.443	*Accepted*
H13: ATT -> LSE	0.189	3.219	0.001	0.075	0.299	*Accepted*
H14: PU -> LSE -> INT	0.136	4.381	0.000	0.085	0.208	*Accepted*

Notes: significance Level $p \leq 0.05$

Drawing on Cohen's (1992) classifications, Table 5 offers a detailed analysis of effect sizes (f^2) in the structural model. These effect sizes are categorized as small (0.020 to 0.150), medium (0.150 to 0.350), or large (0.350 or greater). The observed effect sizes range from a low of

0.002 to a high of 0.569, highlighting the varying strengths of the relationships between the examined variables. Furthermore, Table 5 demonstrates that the Intrinsic Value Inflation Factor (VIF) values remain well below the conservative threshold of 5, with the highest value at 1.771. This level of collinearity ensures the validity of comparisons between effect sizes and the interpretability of coefficients within the model. Figure 1 reveals a substantial degree of explained variance for the endogenous construct (R^2 = 0.461), indicating that the model effectively explains nearly half of the variance in the dependent variable. Similarly, the model demonstrates efficacy in capturing the mediation process, explaining approximately 29.4% of the variance in the mediator construct (R^2 = 0.2294).

Table 5
Effect Sizes(f^2) & Variance Inflation Factor (VIF)

	f^2				VIF			
	ATT	INT	LSE	PU	ATT	INT	LSE	PU
ATT		0.053	0.041			1.281	1.23	
LSE		0.243				1.416		
PEU	0.053	0.002	0.023	0.569	1.569	1.689	1.651	
PU	0.039	0.037	0.086		1.569	1.771	1.63	1.068

To evaluate the model's ability to make generalizable predictions and its practical implications for managers, we employed a rigorous out-of-sample predictive analysis using the PLSpredict method, as recommended by (Shmueli et al., 2016, 2019). Table 6 showcases the clear advantage of PLS-SEM in generating superior predictive accuracy ($Q^2 > 0$) compared to simply using the mean values (naive predictions). Furthermore, the Root Mean Square Error (RMSE) values of the PLS-SEM predictions were consistently lower than those obtained from the linear model (LM) benchmark, highlighting the model's robust predictive capabilities. As detailed in Table 7, in thirteen out of eighteen instances, the RMSE values for PLS-SEM predictions were demonstrably better than those from the LM predictions, further emphasizing the proposed model's strength in making predictions. The introduction of the Cross-Validated Predictive Ability Test (CVPAT) by Hair et al (2022) and its integration with PLSpredict analysis by Liengaard et al (2021) represent significant advancements in predictive modeling methodologies. Moreover, Table 7 bolsters the evidence for PLS-SEM's superior predictive capacities. The consistently lower average loss values compared to both indicator averages and LM benchmarks provide robust support for the model's enhanced ability to make generalizable predictions.

Table 6
PLSpredicts

Indicators	PLS- RMSE	LM-RMSE	PLS-LM	Q^2_predict
ATT1	0.789	0.796	-0.007	0.116
ATT2	0.771	0.779	-0.008	0.093
ATT3	0.779	0.781	-0.002	0.077
ATT4	0.792	0.796	-0.004	0.117
INT1	0.682	0.686	-0.004	0.146
INT2	0.656	0.663	-0.007	0.106
INT3	0.721	0.728	-0.007	0.108
INT4	0.768	0.773	-0.005	0.044
LSE1	0.671	0.671	0.000	0.148
LSE2	0.655	0.654	0.001	0.118
LSE3	0.696	0.697	-0.001	0.093
LSE4	0.736	0.736	0.000	0.071
LSE5	0.669	0.672	-0.003	0.080
PU1	0.755	0.745	0.010	0.201
PU2	0.783	0.778	0.005	0.151
PU3	0.663	0.665	-0.002	0.335
PU4	0.795	0.793	0.002	0.195
PU5	0.700	0.701	-0.001	0.199

Table 7
Cross-Validated Predictive Ability Test (CVPAT)

	Average loss difference	t value	p-value
INT	-0.126	5.011	0.000
LSE	-0.043	3.326	0.000
Overall	-0.101	5.013	0.000

Ringle and Sarstedt (2016) along with Hair et al (2018) introduced Importance Performance Map Analysis (IPMA) to evaluate the significance and effectiveness of latent variables in explaining acceptance, as elaborated in Table 9. The overall impact on intention to use was most pronounced for learners' self-efficacy (0.431), followed by perceived ease of use (0.419), perceived usefulness (0.384), and attitude (0.272), highlighting their relative importance in intention to use artificial intelligence. Attitude scored the highest (67.194), while leaders' self-efficacy had the lowest score (60.487) on a 0-100 scale, indicating better performance for attitude and lower achievement for learners' self-efficacy. Despite ranking first in intention to use artificial intelligence importance, learners' self-efficacy displayed the lowest performance. These findings suggest prioritizing strategies to enhance learners' self-efficacy among students, potentially improving the overall students' intention to use artificial intelligence in higher education institutions.

Table 8
Importance-Performance Map Analysis

Constructs	Total Effect	Performance
ATT	0.272	67.194
LSE	0.431	60.487
PEU	0.419	66.267
PU	0.384	66.372

Discussion

The widespread integration of Artificial Intelligence (AI) in higher education offers a promising avenue for personalized learning and improved student outcomes. However, fostering student acceptance and intention to use these AI tools hinges on critical factors like perceived ease of use, perceived usefulness, attitude, and self-efficacy. Here, we delve into strategies to strengthen these aspects and encourage student usage of AI in educational settings. A foundational step lies in designing user-friendly interfaces. Clear instructions, logical workflows, and minimal technical jargon are paramount. Interactive tutorials, walkthroughs, and readily available help sections can further mitigate initial challenges. Furthermore, empowering students to personalize their AI interaction through interface adjustments, learning style preferences, or the level of AI guidance desired, fosters a sense of control and reduces perceived complexity. Seamless integration within existing Learning Management Systems (LMS) leverages the familiarity of the platform, minimizing the need for students to adapt to a new environment. Communicating the value proposition of AI tools is crucial. Highlighting how AI personalizes learning paths, provides targeted feedback, or automates administrative tasks, freeing up valuable study time, effectively demonstrates the benefits for students. Developing AI tools that address specific learning challenges or goals personalizes the experience. For instance, AI-powered tutors could cater to individual learning styles, while AI chatbots could offer personalized study recommendations. Finally, actively incorporating student feedback on the usefulness and functionalities of AI tools ensures that the technology evolves to align with student needs and expectations. Transparency and control are key to fostering trust. Explaining how AI tools work and the data they collect empowers students and allows them to make informed choices about their data usage and the level of AI intervention. Sharing real-life success stories showcasing how students have benefited from AI-powered learning experiences can dispel anxieties and encourage broader usage. Faculty support plays a vital role in faculty buy-in and enthusiasm can significantly impact student attitudes and willingness to experiment with new technologies. Integrating activities that build essential digital literacy skills for effective AI tool utilization is crucial. Courses on data interpretation, critical thinking, or responsible technology use equip students with the necessary knowledge and confidence to navigate AI tools effectively. Starting with small, achievable tasks that allow students to experience success using AI tools fosters a sense of accomplishment. Gradual skill development and positive reinforcement through micro-challenges and achievements bolster self-efficacy and a sense of competence. Personalized feedback delivered through AI can be a powerful tool. Specific, actionable, and positive feedback guides students toward improvement and boosts their confidence in using the technology. By implementing these comprehensive strategies, higher education institutions can cultivate a learning environment that fosters student usage of AI tools. Focusing on ease of use, perceived usefulness, a positive attitude, and learner self-efficacy empowers students to harness the full potential of AI to enhance their learning experience and achieve their academic goals.

Theoretical Implications

This study sheds light on the theoretical underpinnings of the Technology Acceptance Model (TAM) in the context of students adopting AI tools in higher education. The findings reinforce the core tenets of TAM while offering valuable insights into the mediating effects of attitude and self-efficacy. The study strengthens the established TAM relationships between perceived ease of use and perceived usefulness with the intention to use AI tools. A strong positive correlation between perceived ease of use and perceived usefulness aligns with TAM, suggesting that students who find AI tools easy to use are more likely to perceive them as valuable for their learning. Furthermore, the positive influence of perceived usefulness on intention aligns with TAM, indicating that students who recognize the benefits of AI tools are more likely to use them. The study extends TAM by demonstrating the mediating effects of attitude and self-efficacy on the relationship between perceived ease of use/perceived usefulness and intention. Positive attitudes towards AI tools act as a bridge between their perceived ease of use and the intention to use them. Similarly, self-efficacy, a student's belief in their ability to use AI tools effectively, mediates the relationship between perceived usefulness and intention. These findings enrich TAM by highlighting the psychological factors that influence students' technology usage decisions beyond just ease of use and perceived usefulness. This study offers valuable insights into the nuanced interplay between TAM's core constructs and the mediating effects of attitude and self-efficacy in the context of student usage of AI tools. These findings contribute to a more comprehensive understanding of technology acceptance behavior in educational settings.

Practical Implications

This study offers valuable insights for higher education institutions (HEIs) aiming to successfully integrate Artificial Intelligence (AI) tools into the learning environment. By focusing on the factors influencing student usage, HEIs can create a more welcoming and effective AI experience. The study underscores the importance of perceived ease of use. HEIs should invest in user-friendly AI interfaces with clear instructions, logical workflows, and minimal technical jargon. Interactive tutorials, walkthroughs, and readily available help sections can further reduce initial hurdles. Additionally, allowing students to personalize their interaction with AI tools through interface adjustments or learning style preferences fosters a sense of control and reduces perceived complexity. Perceived usefulness is another critical factor. HEIs must communicate the value proposition of AI tools. Showcasing how AI can personalize learning paths, provide targeted feedback, or automate administrative tasks, freeing up valuable study time, effectively demonstrates the benefits for students. Developing AI tools that address specific learning challenges or goals personalizes the experience and increases perceived usefulness. Transparency and fostering self-efficacy are crucial. HEIs should explain how AI tools work and the data they collect. Building trust empowers students to make informed choices about data usage. Additionally, integrating activities that develop essential digital literacy skills for effective AI tool utilization equips students with the necessary knowledge and confidence. Positive reinforcement through successful micro-challenges using AI tools further bolsters self-efficacy and a sense of competence.

Contextual Implications

This study on student usage intention of AI in higher education offers valuable contextual insights for institutions. Firstly, it highlights the need to consider factors beyond just the technology itself. Perceived ease of use, perceived usefulness, attitude, and self-efficacy all play significant roles in student acceptance. Secondly, the study emphasizes the importance of tailoring AI tools to the specific needs of the student body. A one-size-fits-all approach is unlikely to be successful. Thirdly, the findings underscore the need for faculty buy-in and support. Faculty enthusiasm for AI can significantly influence student attitudes and willingness to experiment with these new tools. Finally, the study highlights the importance of ongoing communication and transparency. Explaining how AI works and addressing student concerns about data privacy can foster trust and encourage wider usage. By understanding these contextual nuances, higher education institutions can create a more supportive environment for integrating AI tools and empowering students to leverage their full potential. By implementing these practical recommendations, HEIs can create a learning environment that encourages student usage of AI tools. This not only fosters a more engaging and personalized learning experience but also empowers students to leverage the full potential of AI to enhance their academic success.

Suggestions for Future Study

Building on this research, future studies can delve deeper into the long-term impact of AI in higher education. Longitudinal studies tracking student perceptions and usage patterns over time could reveal how attitudes and self-efficacy develop alongside experience with AI tools. Furthermore, analyzing student preferences within specific disciplines could inform the creation of targeted AI applications for different learning contexts. The emotional landscape surrounding AI usage intention is another intriguing area. Exploring how emotions like anxiety or frustration influence student behavior could guide strategies for promoting a more positive and supportive learning environment with AI. Finally, investigating the actual impact of AI tools on student performance or engagement in courses would provide valuable insights into the transformative potential of AI for learning outcomes. By pursuing these diverse research avenues, we can gain a richer understanding of student usage intention of AI and its potential to reshape how we learn and teach in higher education.

Conclusion

This study sheds light on factors influencing student usage intention of AI tools in higher education. Mirroring the Technology Acceptance Model (TAM), perceived ease of use and perceived usefulness emerged as key drivers of student intention to use AI. The study further reveals that attitude and self-efficacy act as bridges between these factors and student usage intention. These findings translate into actionable insights for institutions. Prioritizing user-friendly design, clearly communicating the benefits of AI, and fostering trust through transparency is crucial for successful AI integration. The study also emphasizes the importance of considering student needs, faculty support, and ongoing communication within the specific context of each institution. By understanding these factors and implementing these strategies, higher education institutions can create a more supportive environment that empowers students to leverage the full potential of AI and transform their learning experience.

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