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Attitude as a Catalyst: The Role of Perceived Ease of Use, Perceived Usefulness, and Self-Efficacy in Shaping Student Intentions to Use Artificial Intelligence in Higher Education

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Abstract

This study investigates the factors influencing students' intention to use artificial intelligence (AI) in higher education institutions, highlighting the critical role that perceptions of ease of use, self-efficacy, and perceived usefulness play in shaping these intentions. The study's primary aim is to explore how these constructs, alongside attitude as a mediator, impact the adoption of AI tools among students. A quantitative research design was employed, utilising a structured survey to collect data from 424 students across various institutions, resulting in 331 valid responses for analysis. Following data cleaning, 319 responses were deemed suitable for further study. The data analysis used Structural Equation Modeling (SEM) through SmartPLS software, allowing for rigorous hypothesis testing. The results indicated significant positive relationships, demonstrating that self-efficacy and perceived usefulness are crucial predictors of students' intention to use AI, while perceived ease of use showed less direct impact. The study concludes with suggestions for future research, including longitudinal studies to understand the evolving influences on AI adoption and qualitative approaches to capture more profound insights into student experiences. Furthermore, it recommends that higher education institutions implement training programs to enhance self-efficacy and simplify user experiences with AI technologies. The implications of this study are significant for educators and administrators, as they underscore the necessity of creating supportive environments that facilitate AI adoption. By enhancing the identified constructs, institutions can effectively empower students to leverage AI, leading to improved academic outcomes and better preparation for the digital workforce. The findings contribute valuable insights into integrating AI into educational practices, advancing the discourse on technology adoption in higher education.

Keywords: Perceived Ease of Use, Perceived Usefulness, Self-Efficacy, Attitude, Intention to Use

Introduction

The intention to use artificial intelligence (AI) among students in higher education institutions is increasingly vital for shaping educational experiences and outcomes in a technology-driven landscape. As AI technologies become more prevalent in various sectors, understanding what drives students to adopt these tools is essential for maximising their educational benefits (Kebah et al., 2019). Various factors influence this intention, including digital literacy, teacher self-efficacy, perceived ease of use, and perceived usefulness (Yao & Wang, 2024). By fostering these attributes among students, institutions can enhance the likelihood of successful AI integration into learning environments . Current global trends indicate a growing interest among students in employing AI technologies for enriched learning experiences, particularly in areas such as language acquisition and special education (Chen et al., 2024; Yao & Wang, 2024). Despite this enthusiasm, challenges, including anxiety surrounding AI adoption and varying self-efficacy levels, present significant barriers to effective utilisation (Hong, 2022). Furthermore, research often overlooks various factors influencing students' intentions, leaving critical gaps in understanding how these elements interact within diverse educational contexts (Li et al., 2020). Research gaps are also evident in examining leaders' roles in facilitating AI adoption and their impact on student engagement and learning outcomes (Khan, 2024). Emphasising leadership performance can clarify how institutional policies and practices can better support students in their AI learning journeys. Additionally, limited studies consider the ethical implications of AI use in education and how these affect student perceptions and intentions (Kebah et al., 2019). This study is important to policymakers and higher education institutions as it provides insights into best practices for AI integration (Osman et al., 2018). By understanding the multifaceted factors that influence students' intentions to adopt AI, educational leaders can develop targeted interventions that enhance engagement, promote critical digital skills, and foster a culture of innovation within higher education (Shao et al., 2024; Chou et al., 2022). Ultimately, this research can improve curricula and instructional methods, benefiting students and the institutions serving them. This study assesses the direct and indirect relationships between perceived ease of use and perceived usefulness of artificial intelligence among students in higher education institutions with attitude as a mediator.

Literature Review

Underpinning Theory

The Technology Acceptance Model (TAM) is a theoretical framework developed by Davis (1989) that seeks to explain user acceptance of technology. It posits that two primary factors, perceived ease of use (PEOU) and perceived usefulness (PU), significantly influence an individual’s attitude toward using a technology, affecting their intention to use it. PEOU refers to the degree to which a person believes using a particular technology will be effort-free. At the same time, PU pertains to the extent to which a person believes that using technology will enhance their job performance or, in the context of education, their learning outcomes (Davis, 1989; Venkatesh & Davis, 2000). In the context of your study on the intention to use artificial intelligence (AI) among students in higher education, TAM provides a robust framework for examining how students' perceptions of AI’s ease of use and usefulness impact their willingness to adopt this technology. Specifically, students' attitudes toward AI, shaped by their beliefs about how easy and beneficial the technology is to their learning experiences, can mediate between perceived ease of use, perceived usefulness, and their intention to utilise AI in their academic pursuits. By applying TAM, your research can uncover critical insights into the factors that drive AI adoption among students, addressing significant gaps in understanding how these perceptions can be positively influenced to enhance educational outcomes (Venkatesh et al., 2012). This alignment with TAM underscores the importance of fostering favourable attitudes to promote effective AI integration in higher education.

Relationship between Perceived Ease of Use, Attitude & Intention to Use

The relationship between Perceived Ease of Use (PEOU) and intention to use technology, with attitude as a mediator, is critical in understanding user adoption behaviours. Research has shown that PEOU significantly influences users' attitudes toward technology, subsequently affecting their intention to use it . For instance, Alkhawaja et al. (2022) assert that when students perceive a system as easy to use, their positive attitude toward utilising it enhances their intention to engage with it. Similarly, Prayudi et al. (2022) emphasise that ease of use influences users' trust and attitudes, pivotal in driving their intention to adopt mobile banking services. Saadé and Kira (2007) further highlight that users' anxiety, influenced by their perceptions of ease of use, can indirectly affect their attitude and technology adoption decisions. By integrating these insights, it becomes evident that a favourable attitude can mediate the impact of perceived ease of use on the intention to use technology (Syaharani & Yasa, 2022). This mediation suggests that efforts to improve perceptions of ease of use can enhance attitudes, thereby increasing the likelihood of intention to adopt technologies like AI, aligning with findings from Chirchir et al. (2019) and the importance of compelling user experiences in technology acceptance. Therefore, the following hypotheses were proposed for this study:

H1: There is a relationship between perceived ease of use and attitude among students in higher education institutions.

H2: There is a relationship between perceived ease of use and intention to use artificial intelligence among students in higher education institutions.

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

Relationship between Perceived Usefulness, Attitude & Intention to Use

The relationship between Perceived Usefulness (PU) and intention to use technology, with attitude acting as a mediator, is a crucial aspect of technology adoption research. PU refers to how users believe a particular technology will enhance their performance or outcomes. Moslehpour et al. (2018) illustrate that when consumers perceive technology as applicable, their positive attitudes significantly influence their intention to make e-purchases, demonstrating the importance of usefulness in driving adoption behaviours. Toros et al. (2024) also highlight that students' perceptions of usefulness and their resulting attitudes towards technology can be enhanced through supportive environments, which fosters stronger intentions to use technology. Saidi et al. (2022) further emphasise that attitude mediates the impact of various supportive factors alongside perceived usefulness, demonstrating how positive perception can lead to higher adoption intentions during challenging times like the COVID-19 pandemic. Similarly, Liesa-Orús et al. (2023) identify a strong link between perceived usefulness, attitude, and technology acceptance, especially among older adults in educational contexts. Overall, these studies underscore the mediating role of attitude in the relationship between perceived usefulness and intention to use, suggesting that improving perceived usefulness can significantly enhance users' attitudes, leading to greater adoption of technologies (Rawashdeh et al., 2021). Hence, the following hypotheses were proposed for this study:

H4: There is a relationship between perceived usefulness and attitude among students in higher education institutions.
H5: There is a relationship between perceived usefulness and intention to use artificial intelligence among students in higher education institutions.
H6: There is a mediating effect of attitude on the relationship between perceived usefulness and intention to use artificial intelligence among students in higher education institutions.

Relationship between Self-Efficacy, Attitude & Intention to Use
The relationship between self-efficacy and intention to use technology, with attitude as a mediator, is a critical area of study in understanding user behaviour. Self-efficacy refers to an individual's belief in their capability to perform specific tasks, significantly influencing their willingness to engage with new technologies. Bai et al. (2024) demonstrate that teachers' technology self-efficacy enhances their attitudes toward technology use, subsequently affecting their behavioural intention to adopt it (Intaratat et al., 2024). This shows how self-efficacy can directly influence attitudes and, in turn, intentions. Similarly, Anwar et al. (2021) find that self-efficacy mediates the relationship between individual traits and entrepreneurial intention, highlighting how one's belief in one's capabilities influences one's attitude, thereby impacting intention. Yousaf et al. (2021) further emphasise this sequential mediation effect, showing that self-efficacy and attitude work together to drive entrepreneurial intentions stemming from educational backgrounds. In a different context, Ali et al. (2021) demonstrate the role of self-efficacy and student satisfaction in the intention to use e-learning, with attitude acting as a mediator. Lastly, Lee et al. (2023) illustrate that self-efficacy and a positive attitude enhance engagement in safe online practices, influencing intentions against phishing attacks. Collectively, these studies underscore the vital mediation role of attitude in facilitating the relationship between self-efficacy and intention to use technology across various contexts. Thus, the following hypotheses were proposed for this study:

H7: There is a relationship between self-efficacy and attitude among students in higher education institutions.
H8: There is a relationship between self-efficacy and intention to use artificial intelligence among students in higher education institutions.
H9: There is a relationship between attitude and intention to use artificial intelligence among students in higher education institutions.
H10: There is a mediating effect of attitude on the relationship between self-efficacy and intention to use artificial intelligence among students in higher education institutions.

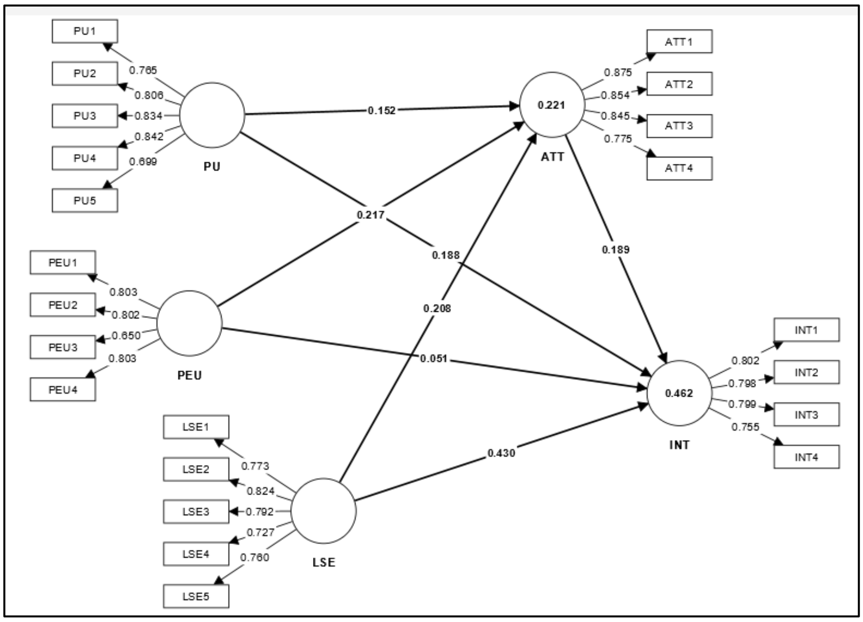

Figure 1: Research Model
Notes: PU=Perceived Usefulness PEU=Perceived Ease of Use SE=Self-Efficacy INT=Intention to Use

Methodology
This study explored the intricate relationships among perceived usefulness, perceived ease of use, and students' intention to use artificial intelligence (AI) within higher education while also analysing the mediating effects of self-efficacy and attitude. A thorough data collection approach was implemented to ensure reliable and valid measurements. The selection of tools was informed by existing literature. The researchers developed a survey encompassing 22 observed variables: perceived ease of use (4 items) adapted from Davis (1989) and Pan (2020), perceived usefulness (5 items) sourced from the same references, learner self-efficacy (5 items) based on Kang et al. (2019), attitude (4 items) following Hair et al. (2019), and intention to use (4 items) adapted from Pan (2020) and Kang et al. (2019). Participants evaluated each construct utilising a 5-point Likert scale. A purposive sampling strategy was applied due to the absence of a complete population list. Out of 424 distributed surveys, 331 responses were received (78.06% response rate), validating the use of structural equation modelling (SEM) for analysis. After data cleaning, 319 responses were considered appropriate for analysis. The research employed SmartPLS software, acclaimed for its SEM capabilities, to analyse data and test hypotheses due to its robust assessment features and ability to manage multivariate data, following study objectives and recommendations from Ringle et al. (2022). SmartPLS enabled a thorough evaluation of the proposed hypotheses and performed extensive multivariate data analysis, facilitating a comprehensive examination of measurement and structural models.

Data Analysis
Respondents' Profiles
An analysis of the demographics of this student population reveals a nearly balanced gender distribution, with females slightly leading at 51.4% (164 students) compared to males at 48.6% (155 students). The age distribution is primarily concentrated in the 31-40 age bracket, which forms the most significant group at 45.1% (144 students). Following closely are

students under 30 years old, constituting 38.6% (123 students). The remaining age categories show a notable decrease, with the 51-60 age group being the smallest at 3.4% (11 students). Regarding the year of study, the third year boasts the highest enrollment at 24.8% (79 students). The first and second years also have relatively similar numbers, with 63 students (19.7%) in the first year and 68 students (21.3%) in the second year. There is a steady decline in enrollment through the later years, resulting in only 7.5% (24 students) in their fifth year or beyond. In terms of the level of study, Bachelor's programs are predominant, accounting for 66.8% (213 students). Diploma programs follow with 21.6% (69 students), while Master's programs enrol 8.5% (27 students), and Doctoral programs have the least representation at 3.1% (10 students). Notably, the data indicates that the number of students in public universities (155) is almost identical to those in private universities (164).

Common Method Bias

In addressing potential standard method bias (CMB) in this study, we utilise the full collinearity assessment as outlined by Kock (2015) and Kock & Lynn (2012). This approach analyses variance inflation factors (VIF) to determine whether CMB significantly impacts the results. Table 1 presents the VIF values for constructs such as Intention (1.801), Perceived Ease of Use (1.642), Perceived Usefulness (1.698), Attitude (1.278), and Self-Efficacy (1.393). Since none of these values exceeds the critical threshold of 3.3, we find that CMB is unlikely to distort the relationships among the constructs. The low VIF values indicate a robust measurement model with adequately distinct constructs, suggesting that response variations are attributable to the constructs rather than a standard method bias. Therefore, we conclude that the risk of CMB affecting the validity of findings is minimal, supporting the credibility and reliability of the study's data and analyses.

Table 1
Full Collinearity

	INT	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 utilised the two-stage assessment method recommended by Hair et al. (2017) to evaluate the reliability and validity of the measurement model. This method examines each item to ensure loadings exceed the 0.7 threshold in the first and second order (Hair et al., 2017). Analysing construct reliability and validity using Average Variance Extracted (AVE), composite reliability, and Cronbach's alpha yielded positive results, as shown in Table 2. The AVE values for all constructs ranged from 0.589 to 0.702, surpassing the 0.5 criterion and indicating robust convergent validity (Hair et al., 2017). Composite reliability scores for all constructs were above 0.7, ranging from 0.772 to 0.868. Similarly, Cronbach's alpha values for all constructs exceeded 0.7, falling between 0.764 and 0.858 (Table 2). To ensure discriminant validity, we first evaluated cross-loadings in Table 2 to confirm that items correctly represented their respective constructs. We then applied the Heterotrait-Monotrait (HTMT) ratio for further assessment, following the criteria for discriminant validity in

Variance-Based Structural Equation Modeling (VB-SEM) set by Henseler, Ringle, and Sarstedt (2015). The HTMT ratios, original sample values, and 95% confidence intervals presented in Table 3 confirm compliance with the 0.85 HTMT threshold. Overall, the assessment procedures demonstrate that the measurement model is reliable and valid.

Table 2
Constructs' Reliability and Validity & Items Loadings

Constructs	Indicators	Loadings	CA	CR	AVE
Attitude	ATT1	0.875	0.858	0.863	0.702
	ATT2	0.854			
	ATT3	0.845			
	ATT4	0.775			
Intention	INT1	0.802	0.798	0.804	0.622
	INT2	0.798			
	INT3	0.799			
	INT4	0.755			
	LSE1	0.773			
Learners'	LSE2	0.824	0.835	0.839	0.602
Self-Efficacy	LSE3	0.792			
	LSE4	0.727			
	LSE5	0.760			
Perceived	PEU1	0.803	0.764	0.772	0.589
Ease of Use	PEU2	0.802			
	PEU3	0.650			
	PEU4	0.803			
Perceived	PU1	0.765	0.850	0.868	0.625
Usefulness	PU2	0.806			
	PU3	0.834			
	PU4	0.842			
	PU5	0.699			

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

In this study, the assessment of the structural model adhered to the methodology outlined by Hair et al. (2017), which involved a comprehensive analysis of pathway coefficients (β) and coefficients of determination (R^2). The Partial Least Squares (PLS) technique was utilised, incorporating 5000 sub-samples to evaluate the significance of the path coefficients. The results of hypothesis testing, which include confidence intervals for path coefficients (beta), t-statistics, and p-values, are meticulously presented in Table 4. This rigorous methodology yields valuable insights into the strength and significance of the relationships among the variables within the structural model. Additionally, Table 5 thoroughly examines each hypothesis, detailing the Beta coefficients, T-statistics, P-values, and conclusions regarding the support for each hypothesis. Consequently, this approach enhances the study's findings by offering a more precise and comprehensive understanding of the interactions between the variables under investigation.

The hypothesis testing results provide a comprehensive analysis of the relationships among the constructs in this study. *H1: PEU -> ATT* examines the impact of Perceived Ease of Use (PEU) on Attitude (ATT), presenting a beta coefficient of 0.217, a t-statistic of 2.992, and a p-value of 0.003, indicating a positive and significant relationship. The confidence interval (0.065, 0.348) further validates this finding, leading to the acceptance of H1. Conversely, *H2: PEU -> INT* explores the relationship between PEU and Intention (INT), revealing a weak beta of 0.051, accompanied by a t-statistic of 0.854 and a p-value of 0.393, suggesting no statistically significant effect; thus, we reject H2. In *H3: PEU -> ATT* -> INT, the mediating role of ATT is analysed, yielding a beta of 0.041, t-statistic of 2.223, and a p-value of 0.026, showing a significant effect, and leading to the acceptance of H3.

H4: PU -> ATT indicates that Perceived Usefulness (PU) positively influences ATT, with a beta of 0.152, a t-statistic of 2.155, and a p-value of 0.031, which prompts acceptance of H4 as the confidence interval (0.004, 0.285) does not include zero. *H5: PU -> INT* shows a significant relationship between PU and INT, with a beta of 0.188, a t-statistic of 3.166, and a p-value of 0.002, leading to the acceptance of H5. However, *H6: PU -> ATT -> INT* assesses the mediating effect of ATT between PU and INT, yielding a beta of 0.029 with a t-statistic of 1.832 and a p-value of 0.067, indicating a lack of significance, resulting in the rejection of H6. *H7: LSE -> ATT* confirms that Learner Self-Efficacy (LSE) significantly affects ATT, with a robust beta of 0.208, a t-statistic of 3.465, and a p-value of 0.001, prompting acceptance of H7.

Similarly*, H8: LSE -> INT* indicates a strong impact of LSE on INT, presented through a beta of 0.430, a t-statistic of 8.529, and a p-value of 0.000, leading to the acceptance of H8. In *H9: ATT -> INT*, the analysis shows that ATT positively influences INT, with the hypothesis demonstrating a beta of 0.189, a t-statistic of 3.357, and a p-value of 0.001, resulting in acceptance of H9. Lastly, *H10: LSE -> ATT -> INT* evaluates the mediating role of ATT in the relationship between LSE and INT, yielding a beta of 0.039, a t-statistic of 2.217, and a p-value of 0.027, which supports acceptance of H10. In summary, the decisions based on the hypothesis testing demonstrate the acceptance of H1, H3, H4, H5, H7, H8, H9, and H10, while H2 and H6 were rejected.

Table 4
Hypotheses Testing Results

Hypotheses	Beta	T statistics	P values	2.50%	97.50%	Decision
H1: PEU -> ATT	0.217	2.992	0.003	0.065	0.348	*Accepted*
H2: PEU -> INT	0.051	0.854	0.393	-0.063	0.172	*Rejected*
H3: PEU -> ATT -> INT	0.041	2.223	0.026	0.012	0.086	*Accepted*
H4: PU -> ATT	0.152	2.155	0.031	0.004	0.285	*Accepted*
H5: PU -> INT	0.188	3.166	0.002	0.076	0.308	*Accepted*
H6: PU -> ATT -> INT	0.029	1.832	0.067	-0.004	0.067	*Rejected*
H7: LSE -> ATT	0.208	3.465	0.001	0.094	0.329	*Accepted*
H8: LSE -> INT	0.430	8.529	0.000	0.330	0.525	*Accepted*
H9: ATT -> INT	0.189	3.357	0.001	0.073	0.296	*Accepted*
H10: LSE -> ATT -> INT	0.039	2.217	0.027	0.013	0.084	*Accepted*

Note: significance p<0.05

Table 5 presents a comprehensive overview of effect sizes (f^2), evaluated according to Cohen's (1992) guidelines, which categorise them as minor (0.020 to 0.150), medium (0.150 to 0.350), or large (0.350 or greater). The effect sizes identified in this analysis ranged from small (0.003) to large (0.243), reflecting the diverse impacts of the variables under investigation. Additionally, the Variance Inflation Factor (VIF) values in Table 5 remained well below the more lenient threshold of 5, with the highest value recorded at 1.746. This suggests a minimal level of collinearity, ensuring that the comparisons of effect sizes and the interpretation of coefficients within the structural model are robust. The endogenous construct demonstrates significant explained variance, as evidenced by an R^2 value of 0.462 (Figure 1). For the mediator, the model successfully accounts for approximately 22.1% of the variance, as indicated by R^2 values of 0.221. This underscores the model's ability to capture mediation dynamics and represent the underlying processes.

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

	f^2		VIF	
	ATT	INT	ATT	INT
ATT		0.052		1.284
LSE	0.041	0.243	1.359	1.414
PEU	0.038	0.003	1.595	1.655
PU	0.017	0.038	1.717	1.746

The conclusions of the model and their managerial implications were rigorously assessed using out-of-sample predictive analysis with the PLSpredict method, as Shmueli et al. (2016, 2019) recommended. Table 6 demonstrates that the application of PLS-SEM yielded significantly better Q^2 predictions (>0) compared to naive mean predictions, consistently reflecting lower Root Mean Square Error (RMSE) values than those from the linear model (LM) benchmarks, thereby highlighting its robust predictive capabilities. Importantly, in all eight instances examined, RMSE values derived from PLS-SEM predictions surpassed those of the LM prediction benchmark, emphasising the proposed model's predictive strength as detailed in Table 6. 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) signify notable advancements in predictive modelling. Furthermore, Table 7 reaffirms the superior predictive abilities of PLS-SEM, indicated by lower average loss values compared to indicator averages and LM benchmarks, which provides compelling evidence of its enhanced predictive performance.

Table 6
PLSpredicts

Indicators	Q^2predict	PLS-RMSE	LM-RMSE	PLS-LM
ATT1	0.149	0.775	0.791	-0.016
ATT2	0.145	0.748	0.770	-0.022
ATT3	0.096	0.772	0.783	-0.011
ATT4	0.147	0.778	0.798	-0.020
INT1	0.343	0.597	0.608	-0.011
INT2	0.234	0.607	0.620	-0.013
INT3	0.247	0.662	0.671	-0.009
INT4	0.193	0.706	0.715	-0.009

Table 7
Cross-Validated Predictive Ability Test (CVPAT)

	Average loss difference	t-value	p-value
ATT	-0.092	3.114	0.002
INT	-0.140	6.509	0.000
Overall	-0.116	5.635	0.000

The Importance-Performance Map Analysis (IPMA) assesses the relationship between the importance and performance of various factors influencing the intention to use artificial intelligence among students in higher education, as outlined by Ringle and Sarstedt (2016) and Hair et al. (2018). Based on Table 8, Self-Efficacy ranks highest in importance at 0.469, followed by Perceived Usefulness (0.217), Attitude (0.189), and Perceived Ease of Use (0.092). Regarding performance, Attitude leads with a score of 67.189, followed by Perceived Usefulness (66.509) and Perceived Ease of Use (66.278), with Self-Efficacy at the lowest performance of 60.514. Institutions should focus on improving Self-Efficacy through targeted workshops and practical experiences with AI technologies to enhance both importance and performance. Additionally, ongoing support should be provided to boost students' confidence and perceived ease of use, fostering a greater intention to use AI in their academic endeavours.

Table 8
Importance -Performance Map Analysis (IPMA)

	Importance	Performance
ATT	0.189	67.189
LSE	0.469	60.514
PEU	0.092	66.278
PU	0.217	66.509

Discussion & Conclusion

Discussion

The intention to use artificial intelligence (AI) among students in higher education can be significantly influenced by perceived ease of use, self-efficacy, and perceived usefulness, with attitude as a critical mediator in this dynamic (Bai et al., 2024). To foster a positive inclination toward AI adoption, institutions must implement strategies to enhance these factors effectively. Perceived Ease of Use (PEU), evidenced by a beta of 0.051, indicates that while its direct effect on intention is not statistically significant, it is still integral in shaping students' attitudes (Hair et al., 2018). Enhancing PEU could involve developing user-friendly interfaces and providing comprehensive training sessions to familiarise students with AI tools. By streamlining the initial user experience and reducing the complexity associated with AI, educational institutions can increase students’ comfort levels, fostering a more positive attitude toward its use. Self-efficacy (LSE), with a robust beta of 0.430, is a critical driver for AI adoption (Alkhawaja et al., 2022). Institutions should consider implementing workshops to boost students’ confidence in AI technologies. Creating hands-on learning environments that allow students to experiment and engage with AI applications can significantly influence their self-efficacy and attitude. A higher sense of self-efficacy correlates strongly with increased willingness to engage with AI since students feel more capable of overcoming potential challenges associated with its application (Saadé & Kira, 2007). Additionally, Perceived Usefulness (PU), indicated by a beta of 0.188, underscores its importance as a predictor of intention to use AI (Chen et al., 2024). Thus, educators must effectively demonstrate the tangible benefits of AI through relevant case studies and examples applicable to students' fields of study. By showcasing how AI can enhance learning outcomes and improve job readiness, educators can reinforce students’ beliefs in the technology's usefulness. Incorporating real-world applications and success stories into the curriculum can further solidify the perceived value of AI, making it more relatable and compelling for students. In conclusion, by strategically enhancing perceived ease of use, self-efficacy, and perceived usefulness, educational institutions can positively influence students' intentions toward AI adoption, leading to more favourable attitudes and promoting effective integration of AI into higher education.

Theoretical Implications

The theoretical implications of this study are closely linked to the Technology Acceptance Model (TAM), which emphasises the relationships between perceived ease of use, perceived usefulness, and user intention. By integrating the constructs of self-efficacy and attitude as mediators, this research extends TAM to encompass the psychological aspects influencing technology adoption among higher-education students. According to Davis (1989), perceived ease of use significantly influences users' attitudes toward technology, ultimately shaping their behavioural intention. This study supports these assertions, highlighting that enhancing perceived ease of use can increase students' comfort levels with AI, facilitating a positive attitude (Hair et al., 2018). Furthermore, the concept of self-efficacy proposed by Bandura (1997) is crucial for understanding how students engage with AI technologies. High levels of self-efficacy empower students to believe in their capabilities, which correlates with higher intentions to use AI tools for academic purposes (Alkhawaja et al., 2022). This study's findings align with previous research suggesting that educational interventions that boost self-efficacy positively impact technology adoption behaviours (Saadé & Kira, 2007). Overall, this study enhances the TAM framework by incorporating self-efficacy and attitude as vital components that influence the adoption of AI in higher education. The findings underscore the importance of fostering a supportive environment that emphasises AI's utility and builds students' confidence in using these technologies effectively, creating a more conducive landscape for technology integration in educational settings.

Practical Implications

The practical implications of this study emphasise the necessity for higher education institutions to foster an environment conducive to adopting artificial intelligence (AI) among students. By focusing on enhancing perceived ease of use, self-efficacy, and perceived usefulness, institutions can implement targeted strategies to facilitate AI integration into academic curricula. Training programs should be established to familiarise students with AI tools, emphasising user-friendly interfaces that simplify initial interactions with the technology. Such initiatives can help alleviate apprehensions associated with AI, thereby increasing students' comfort levels and willingness to engage. Additionally, promoting self-efficacy through hands-on workshops and interactive learning environments is crucial. Institutions can create spaces where students can experiment with AI applications, allowing them to gain practical experience and build confidence in utilising these tools effectively. By demonstrating the direct relevance of AI to students' fields of study and showcasing its practical benefits, educators can bolster perceived usefulness and motivate students to explore AI further. Moreover, ongoing support mechanisms, such as mentoring and resource availability, should be established to encourage continuous engagement with AI technologies. By addressing these areas, higher education institutions can empower students to embrace AI as a valuable tool for enhancing learning outcomes and career readiness, ultimately leading to a more tech-savvy and prepared workforce.

Suggestions for Future Study

Future studies should explore several avenues to deepen the understanding of artificial intelligence (AI) adoption in higher education. First, longitudinal research could examine how the influences of perceived ease of use, self-efficacy, and perceived usefulness evolve as students become more familiar with AI technologies. This could provide insights into the sustainability of these constructs and their impact on intention to use. Additionally, studies could compare AI adoption across different academic disciplines to identify specific factors that may influence the acceptance of AI in various fields of study. Furthermore, qualitative research methodologies, such as interviews or focus groups, could be employed to better understand students' attitudes and experiences with AI, capturing nuanced perspectives that quantitative methods might overlook. Finally, examining the role of institutional support and resources in fostering a culture of AI adoption could yield valuable insights. By addressing these suggestions, future research can contribute to developing more tailored interventions that enhance AI integration within higher education settings.

Conclusion

this study highlights the critical factors influencing the intention to use artificial intelligence (AI) among students in higher education, emphasising the roles of perceived ease of use, self-efficacy, and perceived usefulness, with attitude as a mediator. The findings suggest that enhancing these constructs can significantly improve students' willingness to adopt AI technologies, ultimately facilitating their academic success and preparedness for the workforce. In terms of contextual implications, the study underscores the importance of creating supportive educational environments that foster confidence and competence in AI usage. Higher education institutions are encouraged to invest in training programs and resource development that simplify AI interactions and directly demonstrate the technology's relevance to students' fields of study. By prioritising these aspects, institutions can empower students to embrace AI, contributing to a more innovative and capable generation well-prepared to navigate an increasingly digital world.

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