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Innovate, Transform, Succeed: Artificial Intelligence-Enabled Transformation Acceptance in Private Higher Education Institutions

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Abstract
This study examines the acceptance of artificial intelligence (AI)-enabled transformation in private higher education institutions, emphasizing its importance for enhancing operational efficiency and educational outcomes. As AI technologies rapidly evolve, understanding employees' acceptance becomes critical for successful implementation. The primary aim of this research is to identify the key factors influencing acceptance, including perceived ease of use, perceived usefulness, self-efficacy, and their mediated effects on employee attitudes. Data for the study were collected through a survey utilizing a purposive sampling technique to target staff members across various departments of selected institutions. A total of 573 surveys were distributed, with 451 returned responses, yielding a response rate of 78.7%. The data analysis was conducted using structural equation modeling (SEM), which allowed for a comprehensive assessment of the relationships among the variables. Hypothesis testing results revealed significant positive relationships for perceived ease of use, self-efficacy, and their mediating effect on attitude towards AI acceptance, while perceived usefulness showed a weaker, non-significant effect. The findings underscore the necessity for institutions to develop user-friendly AI tools, demonstrate tangible benefits, and improve employee self-efficacy through targeted training programs. Suggestions for future research include longitudinal studies to track changes in perceptions over time and cross-institutional comparisons to uncover contextual factors influencing acceptance. Overall, this study contributes to the existing literature on technology acceptance and offers practical implications for private higher education institutions seeking to navigate the complexities of AI integration successfully. Enhancing acceptance among employees will not only facilitate adoption but also promote a culture of innovation in the educational landscape.
Keywords: Perceived Ease of Use, Perceived Usefulness, Self-Efficacy, Attitude, Acceptance

Introduction

The acceptance of Artificial Intelligence (AI)-enabled transformation in higher education institutions (HEIs) is critical for shaping the future of educational delivery and learner experiences. AI has the potential to personalize learning, streamline administrative tasks, and enhance teaching methodologies. However, the successful integration of AI technologies relies on the acceptance of these innovations by educators, administrators, and students (Baytak, 2023). Currently, HEIs are grappling with several challenges regarding AI acceptance. Despite the growing availability and capabilities of AI tools, issues such as a lack of awareness, insufficient training, and resistance to change are common on a global scale (Adarkwah et al., 2023). There exists a divergence in pedagogical beliefs concerning the use of AI, which affects educators' willingness to adopt these technologies (Choi, Jang, & Kim, 2023). While the interest in generative AI technologies is rising, their implementation remains inconsistent across institutions and regions, reflecting a need for more structured acceptance models (Mourtajji & Arts-Chiss, 2024). Significant research gaps persist in understanding the socio-cultural factors influencing attitudes toward AI adoption. Although some studies have explored general acceptance frameworks, specific educational contexts necessitate deeper investigation into the nuances of acceptance (Chen, 2024). Furthermore, ethical challenges related to AI, such as bias and privacy concerns, are often underexplored, limiting comprehensive approaches to acceptance (Chen, 2024). Problems surrounding AI acceptance in HEIs are multifaceted. Institutional barriers, including inadequate infrastructure and budget constraints, alongside personal challenges like fear of job displacement, can impede progress (Ghimire et al., 2024). Additionally, minimal collaboration between educators and technology developers may result in tools that fail to meet users' needs effectively (Abbasi, Wu, & Luo, 2025). The significance of studying AI acceptance is profound for various stakeholders. For policymakers, understanding the dynamics of AI adoption can inform supportive regulations and frameworks that promote educational innovation (Ceylan & Mnzile, 2025). HEIs can leverage insights from research to allocate resources effectively and design targeted training programs for educators and students. For academicians, the findings can contribute to curriculum development and pedagogical strategies that integrate AI meaningfully (Wang & Huang, 2025). Finally, improved acceptance and integration of AI tools can significantly enhance students' learning experiences, fostering greater engagement and success. This study aims to evaluate the direct and indirect relationships between perceived ease of use, perceived usefulness, self-efficacy, and acceptance of artificial intelligence-enabled transformation, with attitude as a mediator among employees in private higher education institutions.

Literature Review

Underpinning Theory

In exploring the acceptance of AI technologies in higher education institutions, the integration of the Technology Acceptance Model (TAM) and Bandura's Self-Efficacy Theory offers a robust theoretical framework. TAM posits that perceived ease of use and perceived usefulness are critical determinants influencing users' attitudes and, subsequently, their acceptance of technology (Davis, 1989). Specifically, when users find an AI tool easy to use and beneficial, they are more likely to develop a positive attitude toward its adoption. Self-Efficacy Theory, as proposed by Bandura (1997), posits that individuals' beliefs in their abilities to execute actions play a significant role in their performance and decision-making. In the context of technology acceptance, if users possess high self-efficacy regarding their capability to utilize

AI tools, they are more inclined to perceive these tools as useful and easy to use. Consequently, higher self-efficacy positively influences both perceived ease of use and perceived usefulness, strengthening a favorable attitude towards the technology. By positioning attitude as a mediator, this integrated framework suggests that perceived ease of use and perceived usefulness, influenced by self-efficacy, shape users' attitudes, ultimately leading to their acceptance of AI technologies. This approach provides a comprehensive understanding of the socio-cognitive factors that govern technology adoption in higher education.

Relationship between Perceived Ease of Use and Perceived Usefulness

The relationship between perceived ease of use and perceived usefulness is fundamental to understanding technology acceptance, particularly within the framework of the Technology Acceptance Model (TAM). Perceived ease of use refers to the degree to which a user believes that using a technology will be free of effort (Davis, 1989). When a technology is easier to use, users are more likely to engage with it without experiencing frustration or complexity (Ratnawati & Darmato, 2024). This ease of use directly influences perceived usefulness, which is the degree to which a person believes that using a particular technology would enhance their job performance or educational outcomes (Alshammari & Babu, 2025). When users find a technology easy to navigate and utilize, they are more apt to recognize its benefits and potential to improve their efficiency or effectiveness (Muazu et al., 2024). Empirical studies have consistently shown that a higher perceived ease of use leads to an increase in perceived usefulness (Davis, 1989; Adarkwah et al., 2023). As users experience fewer barriers when interacting with the technology, they are more likely to appreciate its advantages, resulting in a positive feedback loop that encourages acceptance and adoption (Azzahra& Kusumawati, 2023). This interdependent relationship underscores the necessity for developers and educators to focus on both ease of use and demonstrated usefulness when introducing new technologies in educational settings (Zubir & Abdul Latip, 2024). Hence, the following hypothesis was proposed for this study:

H1: There is a relationship between perceived ease of use and perceived usefulness toward acceptance of artificial intelligence-enabled transformation among employees in private higher education institutions.

Relationship between Perceived Ease of Use, Attitude, and Acceptance

The relationship between perceived ease of use and acceptance of technology in higher education is significantly influenced by attitude, which acts as a mediator in this dynamic. Perceived ease of use refers to the degree to which students and educators believe that a technology can be utilized without substantial effort (Cao et al., 2025). When individuals find educational technologies easy to use, they are more likely to develop a positive attitude toward these tools (Liesa-Orús et al., 2023). This favorable attitude is crucial because it shapes their willingness to embrace and adopt the technology (Osman et al., 2025). As students and educators experience seamless interactions with technology, their positive attitudes toward it strengthen, leading to greater acceptance (Tan et al., 2024). This acceptance is essential for successful technology integration within learning environments, as it impacts engagement, satisfaction, and overall educational effectiveness. Studies indicate that when perceived ease of use enhances positive attitudes, it ultimately fosters a higher likelihood of technology acceptance (Rosli & Saleh, 2024). Thus, educational institutions must prioritize user-friendly interfaces and provide adequate training to enhance perceived ease of use. By doing so, they can cultivate positive attitudes, facilitating a smoother transition to technology acceptance and ultimately enriching the educational experience (Balaskas et al., 2025). Therefore, the following hypotheses were proposed for this study:

H2: There is a relationship between perceived ease of use and acceptance of artificial intelligence-enabled transformation among employees in private higher education institutions.
H3: There is a relationship between perceived ease of use and attitude toward acceptance of artificial intelligence-enabled transformation among employees in private higher education institutions.
H4: There is a mediating effect of attitude on the relationship between perceived ease of use and acceptance of artificial intelligence-enabled transformation among employees in private higher education institutions.

Relationship between Perceived Usefulness, Attitude, and Acceptance
The relationship between perceived usefulness and acceptance of technology in higher education is significantly mediated by attitude. Perceived usefulness refers to the extent to which students and educators believe that a particular technology enhances their academic performance and learning experience (Sharif-Nia et al., 2024). When users recognize the benefits of a technology, they tend to develop a positive attitude toward its utilization (Hazaimeh & Al-Ansi, 2024). This favorable attitude, in turn, leads to a higher likelihood of acceptance and integration into educational practices (Osman et al., 2025). As users experience the practical advantages of technology, such as improved efficiency and accessibility, their positive attitudes are reinforced, ultimately fostering acceptance (Belew et al., 2024). Research suggests that a strong perception of usefulness enhances users' willingness to engage with educational technologies, significantly impacting overall acceptance (Hussain et al., 2025). This relationship emphasizes the importance of demonstrating tangible benefits of technology to users. Educational institutions should focus on effectively communicating the usefulness of new technologies through training and support (Osman et al., 2024). By cultivating a positive attitude towards these technologies, they can facilitate a smoother transition to acceptance, thereby improving educational outcomes and user engagement (Mannan & Maruf, 2024). Thus, the following hypotheses were proposed for this study:

H5: There is a relationship between perceived usefulness and acceptance of artificial intelligence-enabled transformation among employees in private higher education institutions.
H6: There is a relationship between perceived usefulness and attitude toward acceptance of artificial intelligence-enabled transformation among employees in private higher education institutions.
H7: There is a mediating effect of attitude on the relationship between perceived usefulness and acceptance of artificial intelligence-enabled transformation among employees in private higher education institutions.

Relationship between Self-Efficacy, Attitude, and Acceptance

The relationship between self-efficacy and technology acceptance in higher education is significantly mediated by attitude. Self-efficacy, which refers to an individual's belief in their capability to successfully perform tasks, greatly influences how students and educators perceive and engage with technology (Zhang & Cao, 2025). When users possess high academic self-efficacy, they tend to view educational technologies as manageable and beneficial, leading to a more positive attitude towards their use (Asfahani, 2023). This favorable attitude serves as a crucial mediator, bridging the gap between self-efficacy and acceptance. When students and faculty feel confident in their abilities to utilize technology effectively, they are more likely to accept and integrate these tools into their learning environments (Koca, Kılıç, & Dadandı, 2024). Research shows that self-efficacy enhances positive attitudes, which subsequently promotes greater acceptance of technology (Munir et al., 2024). Institutions should prioritize building self-efficacy through targeted training and support, helping users develop confidence in their technological skills (Mohamad & Osman, 2025). This approach not only cultivates positive attitudes but also facilitates a smoother transition to acceptance of new technologies, ultimately enhancing the educational experience (Obenza et al., 2024). Thus, the following hypotheses were proposed for this study:

H8: There is a relationship between self-efficacy and acceptance of artificial intelligence-enabled transformation among employees in private higher education institutions.
H9: There is a relationship between self-efficacy and attitude toward acceptance of artificial intelligence-enabled transformation among employees in private higher education institutions.
H10: There is a relationship between attitude and acceptance of artificial intelligence -enabled transformation among employees in private higher education institutions.
H11: There is a mediating effect of attitude on the relationship between self-efficacy and acceptance of artificial intelligence-enabled transformation among employees in private higher education institutions.

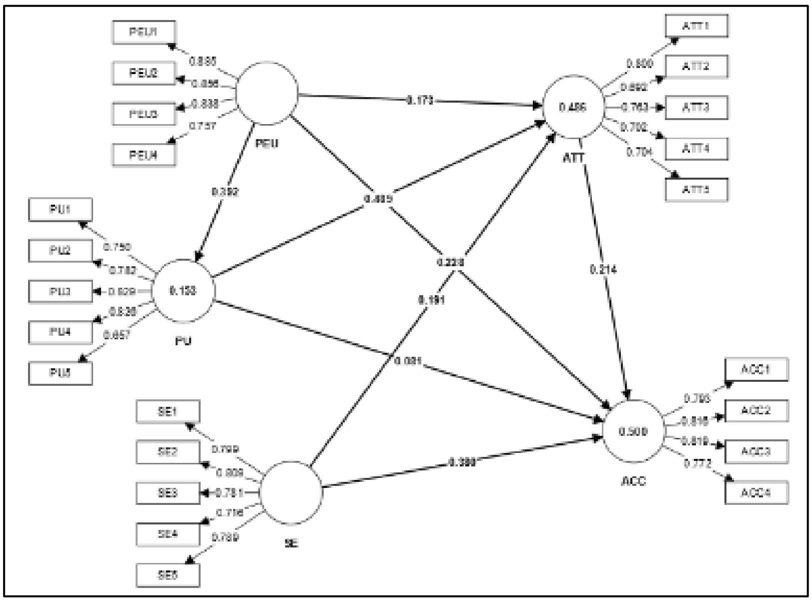

Figure 1: Research Model

Note: PEU=Perceived Ease of Use PU=Perceived Usefulness SE=Self-Efficacy ATT=Attitude ACC=Acceptance

Methodology

This study thoroughly examined the direct and indirect relationships between perceived usefulness, perceived ease of use, self-efficacy, and acceptance, with attitude serving as a mediator among employees in private higher education institutions. Researchers meticulously curated primary data to achieve this objective, ensuring the selection of reliable and valid measurements through an exhaustive literature review. Survey questionnaires were then emailed to chosen participants, employing purposive sampling due to the absence of a comprehensive population list. The analysis scrutinised 23 observed variables, encompassing independent variables such as perceived usefulness (5 items) adopted from Shang et al. (2011), perceived ease of use (4 items) adopted from Shang et al. (2011), and self-efficacy (5 items) adopted from Sherer & Adams (1983), and the mediating variable of attitude (5 items) adopted from Hair et al. (2019), and the dependent variable, acceptance (4 items) adopted from Brock et al. (1998). Respondents evaluated elements within each construct using a Likert scale with five response options, contributing to a comprehensive data set. Out of the 573 distributed surveys, 451 were collected, resulting in a response rate of 78.7%, deemed satisfactory for utilising structural equation modelling (SEM) in data analysis. Among the collected surveys, 422 were identified as clean and suitable for analysis. For data analysis and hypothesis testing, researchers opted for Smartpls4 software, renowned for its application of structural equation modelling (SEM) techniques. Researchers opted for Smartpls4 software, renowned for its proficiency in SEM techniques, for data analysis and hypothesis testing. This choice was driven by the software's robust assessment capabilities and expertise in managing multivariate data analysis, aligning with the study's objectives and adhering to the recommendations of Ringle et al. (2022). Smartpls4 facilitated a meticulous evaluation of proposed hypotheses and conducted extensive multivariate data analysis, enabling a comprehensive assessment of measurement and structural models.

Data Analysis

Respondents' Profiles

The respondent profile provided several significant insights about the sample. In terms of gender, the majority of participants were male, representing 61.4% of the total, while females made up 38.6%. This disparity suggests that the sample may not accurately reflect the larger population. Analyzing the age distribution, the largest segment consisted of individuals aged 41 to 50, who accounted for 40.8% of the respondents. The next largest groups were aged 31 to 40 (23.5%) and 51 to 60 (19.9%). Only 7.1% of participants were under 30 years old, and 8.8% were over 60. This age distribution indicates that the sample was predominantly composed of middle-aged individuals, with the 41-50 and 31-40 age brackets constituting 64.3% of the participants. Regarding years of service, the largest contingent had between 11 to 15 years of experience (30.3%), followed by those with 16 to 20 years (28.7%) and 6 to 10 years (13.5%). A mere 5.9% had fewer than five years of service, while 5% had over 30 years. This suggests that the sample primarily consisted of more seasoned employees, with 59% having between 11 to 20 years of service. Concerning post level, the majority of respondents (80.3%) held academic roles, while 19.7% were in non-academic positions, highlighting a significant bias toward academic staff over administrative or support personnel. The employer distribution revealed that 65.6% of participants were employed by private higher education institutions, while 34.4% worked in public institutions, indicating stronger representation from the private sector. Finally, a compelling 98.3% of respondents expressed a willingness to recommend artificial intelligence-enabled transformation, while only 1.7% would not, demonstrating a high level of endorsement for AI integration.

Common Method Bias

The analysis of common method bias (CMB) is critical in ensuring the validity of findings in behavioral research. Based on the full collinearity values presented in Table 1, it can be observed that all variance inflation factor (VIF) values are significantly lower than the threshold of 3.3 recommended by Kock & Lynn (2012) and Kock (2015). Specifically, the highest VIF value is 2.125 for attitude, while the lowest is 1.347 for perceived ease of use. These results suggest that common method bias is unlikely to threaten the integrity of the data, as no construct exhibits problematic levels of multicollinearity. Consequently, the relationships between acceptance, perceived usefulness, self-efficacy, and attitude can be interpreted with greater confidence. Therefore, based on these findings, researchers can assert that the results are less likely to be influenced by CMB, bolstering the credibility of the study's conclusions regarding the factors affecting technology acceptance in higher education.

Table 1
Full Collinearity

	ACC	PU	ATT	SE	PEU
ACC		1.789	1.689	1.697	1.511
PU	1.851		1.502	1.786	1.804
ATT	2.024	1.598		1.903	2.125
SE	1.759	1.778	1.632		1.725
PEU	1.347	1.549	1.564	1.534	

Measurement Model

The assessment of construct reliability and validity based on the data presented in Table 2 highlights the robust psychometric properties of the study instruments. Cronbach's Alpha (CA) values indicate satisfactory internal consistency across the constructs, with all values exceeding the acceptable threshold of 0.7, demonstrating reliability (Hair, 2017). The CA for acceptance is 0.813, while self-efficacy shows an even higher CA of 0.838. Composite reliability (CR) scores also surpass the threshold of 0.7 for all constructs, further supporting reliability; for instance, perceived ease of use exhibits a CR of 0.868. Average variance extracted (AVE) values provide insights into convergent validity, with acceptance and perceived usefulness having AVEs of 0.640 and 0.595, respectively. Attitude's AVE of 0.538, while acceptable, suggests room for improvement. Item loadings substantiate these findings, with all exceeding the recommended cut-off of 0.6, indicating significant contributions to their constructs. For example, perceived ease of use's items load distinctly, with the highest loading at 0.885 for PEU1. Overall, the results demonstrate that the constructs utilized are well-defined and measured (Hair, 2017). Subsequently, the Heterotrait-Monotrait (HTMT) ratio was employed for further evaluation, adhering to the recommended criterion for scrutinizing discriminant validity in Variance-Based Structural Equation Modeling (VB-SEM) (Henseler et al., 2015). The analysis of the Heterotrait-Monotrait (HTMT) ratios presented in Table 3 reveals that all ratios are below the critical threshold of 0.85 suggested by Henseler et al. (2015). This indicates a lack of significant multicollinearity among the constructs, thereby supporting the discriminant validity of the measures employed in this study.

Table 2
Construct Reliability and Validity & Items Loadings

Constructs	Items	Loadings	CA	CR	AVE
Acceptance	ACC1	0.793	0.813	0.816	0.640
	ACC2	0.816			
	ACC3	0.819			
	ACC4	0.772			
Attitude	ATT1	0.800	0.784	0.786	0.538
	ATT2	0.692			
	ATT3	0.763			
	ATT4	0.702			
	ATT5	0.704			
Perceived Ease of Use	PEU1	0.885	0.855	0.868	0.698
	PEU2	0.856			
	PEU3	0.838			
	PEU4	0.757			
Perceived Usefulness	PU1	0.750	0.829	0.849	0.595
	PU2	0.782			
	PU3	0.829			
	PU4	0.826			
	PU5	0.657			
Self-Efficacy	SE1	0.799	0.838	0.844	0.608
	SE2	0.809			
	SE3	0.781			
	SE4	0.716			
	SE5	0.789			

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

Table 3
Heterotrait-Monotrait (HTMT) Ratios

	ACC	ATT	PEU	PU
ATT	0.676			
PEU	0.584	0.524		
PU	0.573	0.787	0.450	
SE	0.725	0.591	0.436	0.549

Structural Model

This study evaluated the structural model following the methodology outlined by Hair et al. (2017) by examining pathway coefficients (β) and determination coefficients (R^2). The Partial Least Squares (PLS) method utilized 5,000 subsamples to determine the significance of path coefficients. The results, including confidence intervals, beta coefficients, t-statistics, and p-values, are thoroughly detailed in Table 4, offering valuable insights into the significance and strength of the relationships among the variables in the structural model (Hair et al., 2017). The analysis of the hypothesis testing results in Table 4 reveals significant insights into the interrelationships among the constructs studied. *Hypothesis 1 (H1)* posits that perceived ease of use (PEU) positively affects perceived usefulness (PU), supported by a strong beta value of 0.392, a t-statistic of 7.639, and a p-value of 0.000. Thus, H1 is accepted. *Hypothesis 2 (H2)* tests the effect of PEU on acceptance (ACC), yielding a beta of 0.228 and a t-statistic of 4.773, with a p-value of 0.000, leading to the acceptance of H2. Similarly, *Hypothesis 3 (H3)* examines the impact of PEU on attitude (ATT) and shows a beta of 0.173, t-statistic of 3.965, and p-value of 0.000, confirming H3 is accepted. Furthermore, *Hypothesis 4 (H4)* indicates PEU indirectly influences ACC through ATT, with a beta of 0.037 and a t-statistic of 3.075, resulting in a p-value of 0.002. Therefore, H4 is also accepted. In contrast, *Hypothesis 5 (H5)* suggests PU affects ACC but presents a beta of 0.081 and a p-value of 0.153, leading to its rejection. *Hypothesis 6 (H6)* shows PU positively impacts ATT, with a strong beta of 0.489, t-statistic of 11.082, and p-value of 0.000, resulting in H6 being accepted. *Hypothesis 7 (H7)* indicates that PU positively affects ACC through ATT, yielding a beta of 0.105, t-statistic of 3.400, and p-value of 0.001; hence, H7 is accepted. For *Hypothesis 8 (H8)*, self-efficacy (SE) relates positively to ACC, with a beta of 0.380 and a t-statistic of 8.876 (p = 0.000), confirming H8 is accepted. *Hypothesis 9 (H9)* examines the relationship between SE and ATT, showing a beta of 0.191, t-statistic of 4.743, and p-value of 0.000, resulting in acceptance of H9. *Hypothesis 10 (H10)* posits that ATT positively influences ACC, with a beta of 0.214 and a t-statistic of 3.624 (p = 0.000), confirming that H10 is accepted. Lastly, *Hypothesis 11 (H11)* assesses SE's influence on ACC through ATT, displaying a beta of 0.041 and a t-statistic of 2.651, with a p-value of 0.008, leading to H11 being accepted. Overall, the majority of hypotheses are supported, indicating strong interrelationships between the constructs in the context of technology acceptance within higher education.

Table 4
Hypotheses Testing Results

Hypotheses	Beta	T-statistics	P-values	2.50%	97.50%	Decision
H1: PEU -> PU	0.392	7.639	0.000	0.287	0.487	*Accepted*
H2: PEU -> ACC	0.228	4.773	0.000	0.131	0.316	*Accepted*
H3: PEU -> ATT	0.173	3.965	0.000	0.086	0.258	*Accepted*
H4: PEU -> ATT -> ACC	0.037	3.075	0.002	0.015	0.061	*Accepted*
H5: PU -> ACC	0.081	1.429	0.153	-0.030	0.191	*Rejected*
H6: PU -> ATT	0.489	11.082	0.000	0.401	0.572	*Accepted*
H7: PU -> ATT -> ACC	0.105	3.400	0.001	0.046	0.166	*Accepted*
H8: SE -> ACC	0.380	8.876	0.000	0.294	0.462	*Accepted*
H9: SE -> ATT	0.191	4.743	0.000	0.112	0.270	*Accepted*
H10: ATT -> ACC	0.214	3.624	0.000	0.097	0.329	*Accepted*
H11: SE -> ATT -> ACC	0.041	2.651	0.008	0.015	0.075	*Accepted*

Note: Significant at $p<0.05$

Effect Sizes (f^2)

Table 5 provides a detailed summary of effect sizes and collinearity results, measuring effect sizes independently of sample size based on Cohen's criteria (1992): small (0.020 to 0.150), medium (0.150 to 0.350), and large (0.350 or higher). The observed effect sizes ranged from small (0.007) to large (0.336). A significant amount of explained variance for the endogenous construct is evident, with an R^2 value of 0.500 (see Figure 1). For the mediator, the model explained approximately 48.6% of the variance in the structure, as indicated by an R^2 value of 0.486.

Table 5
Effect Sizes (f^2)

	ACC	ATT	PU
ATT	0.047		
PEU	0.079	0.047	0.181
PU	0.007	0.336	
SE	0.201	0.052	

PLSpredict

The PLSpredict results presented in Table 6 offer valuable insights into the predictive performance of the model as recommended by Shmueli et al. (2016, 2019). The Q^2predict values indicate the model's predictive relevance, revealing varying degrees of predictive accuracy across items, with ACC1 showing the highest Q^2predict of 0.313. The PLS-RMSE values also suggest competitive performance, as they generally remain close to the LM-RMSE values, indicating that the structural model performs comparably to the linear model. The slight negative PLS-LM values further confirm that the PLS model is consistently reliable across the constructs, indicating its robustness in prediction efforts. Moreover, the root mean square error (RMSE) values for PLS-SEM predictions consistently surpassed those of the linear model (LM) in seven out of nine cases, highlighting the predictive strength of the proposed model as illustrated in Table 6.

Table 6
PLSpredict

	Q^2predict	PLS-RMSE	LM_RMSE	PLS-LM
ACC1	0.313	0.601	0.602	-0.001
ACC2	0.262	0.602	0.604	-0.002
ACC3	0.277	0.681	0.685	-0.004
ACC4	0.259	0.686	0.689	-0.003
ATT1	0.146	0.682	0.675	0.007
ATT2	0.115	0.640	0.642	-0.002
ATT3	0.151	0.624	0.632	-0.008
ATT4	0.171	0.658	0.66	-0.002
ATT5	0.138	0.768	0.771	-0.003
PU1	0.059	0.797	0.793	0.004
PU2	0.101	0.748	0.751	-0.003
PU3	0.136	0.671	0.679	-0.008
PU4	0.089	0.851	0.832	0.019
PU5	0.036	0.747	0.731	0.016

Cross-Validated Predictive Ability Test (CVPAT)

The results of the Cross-Validated Predictive Ability Test (CVPAT) presented in Table 7 demonstrate the significant predictive capabilities of the model, as endorsed by Hair et al. (2022) and Liengaard et al. (2021). The average loss differences for acceptance (ACC), attitude (ATT), and perceived usefulness (PU) are all negative, indicating that the model's predictions are consistently more accurate than the baseline. With t-values exceeding 3.0 and p-values below 0.001 for all constructs, these results confirm that the model provides a reliable understanding of the relationships among the variables. The overall average loss difference of -0.095 reinforces the model's robust predictive performance.

Table 7
Cross-Validated Predictive Ability Test (CVPAT)

	Average loss difference	t value	p value
ACC	-0.162	7.309	0.000
ATT	-0.078	5.836	0.000
PU	-0.057	3.365	0.001
Overall	-0.095	7.179	0.000

Importance-Performance Map Analysis (IPMA)
The Importance-Performance Map Analysis (IPMA) shown in Table 8 provides insight into the constructs influencing the acceptance of artificial intelligence (AI)-enabled transformation among employees in private higher education institutions, as recommended by Ringle and Sarstedt (2016) and Hair et al. (2018). Among the constructs, self-efficacy (SE) boasts the highest importance score (0.421) but the lowest performance (60.601), indicating a critical need for improvement in this area. In contrast, perceived ease of use (PEU) and attitude (ATT) have moderate importance and performance scores, suggesting they are well-managed but could benefit from enhancements. To enhance self-efficacy, institutions could implement comprehensive training programs aimed at building employees' confidence in utilizing AI tools effectively. This may include hands-on workshops, continuous support, and mentorship programs that encourage skill development and experimentation. By focusing on improving self-efficacy, institutions can foster a culture that embraces AI transformation, ultimately leading to higher acceptance rates among employees.

Table 8
Importance-Performance Map Analysis (IPMA)

	Importance	Performance
ATT	0.214	65.880
PEU	0.337	66.537
PU	0.186	66.508
SE	0.421	60.601

Discussion & Conclusion

Discussion
To enhance acceptance of artificial intelligence (AI)-enabled transformation among employees in private higher education institutions, it is crucial to implement practical strategies targeting interaction with perceived ease of use, perceived usefulness, and self-efficacy, with attitude acting as a mediator. Based on the hypothesis testing results, self-efficacy ($\beta = 0.380$), perceived ease of use ($\beta = 0.228$), and perceived usefulness ($\beta = 0.081$) significantly influence attitude and acceptance, highlighting the need to focus on these constructs to ensure effective AI integration (H8, H2, H5). To strengthen perceived ease of use, institutions should provide user-friendly AI tools and resources, ensuring employees have access to intuitive interfaces that allow for smooth navigation and efficient task completion (Choi et al., 2023). Additionally, focusing on perceived usefulness can be achieved through regular demonstrations of how AI technologies enhance work efficiency and productivity,

thereby showcasing their tangible benefits (Hazaimeh & Al-Ansi, 2024). Moreover, initiatives such as targeted training programs can bolster self-efficacy by empowering employees with the necessary skills and confidence to navigate AI technologies effectively (Koca et al., 2024). Such programs should incorporate hands-on workshops, ongoing support, and mentorship opportunities that promote experimentation with AI tools in real contexts. Addressing challenges related to perceived usefulness, particularly concerning Hypothesis 5 ($\beta = 0.081$), which was not supported, could be a result of employees feeling overwhelmed by technological change or skeptical about the impact of AI on their roles. This indicates that institutions must prioritize open communication about the integration process, encouraging feedback and ensuring employees perceive themselves as active participants in the transition process. Furthermore, collaboration among colleagues can foster a supportive learning environment where employees share insights and experiences on utilizing AI tools, enhancing their collective understanding and acceptance. By fostering an environment that emphasizes self-efficacy through practical training and demonstrating the benefits of AI tools in enhancing productivity and efficiency, private higher education institutions can cultivate positive attitudes and improve acceptance among employees, paving the way for successful AI-enabled transformations. Such strategies not only elevate user experience but also ensure a more engaged and confident workforce ready to embrace technological advancements in education. Ultimately, these concerted efforts will contribute to a smoother transition into AI adoption, supporting the institution's growth and innovation.

Theoretical Implications

The findings from this study contribute significantly to the existing theoretical framework surrounding technology acceptance, particularly in the context of artificial intelligence (AI) integration within private higher education institutions. By emphasizing the roles of perceived ease of use, perceived usefulness, and self-efficacy in shaping attitudes and acceptance, this research reinforces and expands upon established theories such as the Technology Acceptance Model (TAM) (Davis, 1989) and Self-Efficacy Theory (Bandura, 1997). A notable theoretical insight that emerged is the mediating role of attitude, which underscores its critical function in influencing acceptance, thereby suggesting a nuanced interplay between cognitive evaluations and behavioral intentions. This revelation highlights the importance of fostering positive attitudes to facilitate the adoption of AI technologies. Furthermore, the study provides empirical evidence supporting the need for tailored training programs that enhance self-efficacy, aligning with the theoretical premise that higher self-efficacy leads to greater acceptance of new technologies. Additionally, the exploration of perceived ease of use and perceived usefulness as vital determinants underscores their interconnectedness with self-efficacy, suggesting a comprehensive approach in developing strategies for AI implementation. Such an understanding encourages educators and administrators to create environments that not only provide accessible tools but also promote intrinsic motivation and confidence among employees. By integrating these theoretical insights into practice, institutions can craft targeted interventions that not only enhance technology acceptance but also empower employees to adapt to ongoing technological advancements. This holistic approach to understanding technology acceptance may pave the way for more successful AI integration strategies in higher education, fostering innovation and improving educational outcomes across the sector. Ultimately, the interplay between these constructs reveals a rich landscape for further theoretical discourse and application within the field of educational technology.

Practical Implications

The practical implications of this study for private higher education institutions are significant in guiding the successful integration of artificial intelligence (AI) technologies. First, institutions should prioritize the development of user-friendly AI tools that enhance perceived ease of use. By implementing intuitive interfaces and streamlined processes, institutions can facilitate smoother adoption among employees, reducing resistance and enhancing productivity. Second, demonstrating the tangible benefits of AI, such as increased efficiency and improved decision-making, can strengthen perceived usefulness. Regular workshops and training sessions that showcase real-world applications of AI can foster a culture of continuous learning and innovation (Abbasi et al., 2025). Moreover, investing in targeted training programs to bolster self-efficacy is crucial. By empowering employees with confidence and competence in utilizing AI tools, institutions can create a workforce that embraces technological advancements rather than fears them (Ghimire et al., 2025). This can be achieved through mentorship programs and hands-on training, which promote collaboration and knowledge sharing among staff. Additionally, fostering a positive organizational culture that values feedback and encourages open communication will help employees feel more comfortable with the changes brought by AI. By addressing the constructs of perceived ease of use, perceived usefulness, and self-efficacy in a concerted manner, private higher education institutions can effectively enhance acceptance of AI technologies, ultimately leading to improved educational outcomes and operational efficiency (Che Ghazali et al., 2025).

Suggestion for Future Studies

Future studies should explore several avenues to build upon the findings of this research. First, longitudinal studies could assess how perceptions of ease of use, usefulness, and self-efficacy evolve as employees gain more experience with AI technologies. This would provide valuable insights into the dynamics of technology acceptance and how sustained exposure influences attitudes. Second, research could delve into cross-institutional comparisons to identify contextual factors that impact the effectiveness of AI integration, such as institutional culture, leadership support, and resource availability. Additionally, qualitative studies, including interviews and focus groups, could enrich the understanding of employee perceptions and experiences with AI technologies, uncovering underlying concerns and motivations that quantitative data may not fully capture. Finally, examining the role of emotional intelligence and resilience in technology acceptance could provide a deeper understanding of individual differences in responses to change, enhancing strategies for fostering a supportive environment where employees feel empowered and confident in adopting AI innovations. Engaging these varied approaches will yield a comprehensive understanding of AI adoption in educational settings and contribute to the refinement of theoretical frameworks governing technology acceptance.

Conclusion

This study provides important insights into the factors influencing the acceptance of artificial intelligence (AI) technologies among employees in private higher education institutions. By examining the roles of perceived ease of use, perceived usefulness, and self-efficacy, the research underscores the significance of these constructs in shaping positive attitudes and enhancing acceptance of AI innovations. The findings highlight the need for institutions to prioritize user-friendly AI tools, demonstrate their practical benefits, and invest in training programs that bolster self-efficacy. Furthermore, fostering a supportive organizational culture that encourages open communication can facilitate a smoother transition to AI integration. Ultimately, this study contributes to the existing theoretical frameworks around technology acceptance while offering practical recommendations for institutions seeking to navigate the complexities of AI adoption. As higher education continues to evolve amidst rapid technological advancements, understanding these dynamics will be crucial for institutions aiming to enhance operational efficiency and improve educational outcomes.

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