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Unveiling Artificial Intelligence-Enabled Transformation Acceptance among Employees in Higher Education Institutions: The Role of Attitude as a Mediator

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Abstract
This study explores the critical role of artificial intelligence (AI) enabled transformation among employees in higher education institutions, a shift essential for enhancing operational efficiency and educational outcomes. The primary aim was to investigate the impact of self-efficacy and technology innovativeness on the acceptance of AI, with attitude as a mediating factor, thus extending the Technology Acceptance Model to understand the dynamics of AI adoption better. Data were collected using a structured survey distributed via email, targeting a purposive sample of employees across various institutions, resulting in 422 valid responses for analysis. The Partial Least Squares Structural Equation Modeling (PLS-SEM) technique was employed to test the hypotheses, providing robust insights into the relationships among variables. Results revealed that both self-efficacy and technology innovativeness significantly influence acceptance, with attitude playing a crucial mediating role. Specifically, self-efficacy contributes positively to forming favourable attitudes, while perceptions of innovativeness substantially enhance the acceptance of AI technologies. These findings highlight the need for higher education institutions to invest in training programs that boost employees' confidence and demonstrate the tangible benefits of AI innovations. For future studies, it is suggested that research could expand on demographic variables and explore the longitudinal impacts of AI exposure. Furthermore, the role of organizational culture and leadership in shaping technology perceptions warrants further investigation. The implications of this study are twofold: theoretically, it extends the TAM framework by integrating new dimensions pertinent to AI adoption, and practically, it provides actionable insights for institutions to facilitate successful AI integration by addressing employee readiness and cultural adaptation. Overall, the study underscores the transformative potential of AI in educational settings and the strategic measures needed to harness it effectively.

Keywords: Self-Efficacy, Technology Innovativeness, Attitude, Acceptance, Artificial Intelligence

Introduction

Artificial Intelligence (AI)-enabled transformation in higher education institutions marks a pivotal shift in how these institutions operate, deliver educational outcomes, and prepare students for the future (Rahiman & Kodikal, 2024). AI technologies facilitate personalized learning experiences, making education more accessible and tailored to individual needs (Sajja et al., 2023). This transformation is essential as it equips institutions to meet the demands of a rapidly evolving job market, emphasizing the importance of digital literacy and innovative learning strategies (George & Wooden, 2023). Current trends highlight the integration of AI in administrative functions, online learning platforms, and data analytics to enhance student engagement and academic performance (Udvaros & Forman, 2023). However, this transformation is not without challenges. Data privacy, the digital divide, and ethical concerns about AI's role in decision-making are prominent (Alam, 2021). Additionally, there is a global disparity in the implementation of AI technologies, with institutions in developed countries often leading the way compared to those in developing regions (AlGerafi et al., 2023; Sikder, 2023). Research gaps remain significant in the AI-enabled transformation of higher education. There is a need for studies examining the long-term impacts of AI on graduates' learning outcomes and employment trajectories (Wagan et al., 2023). Additionally, more research is needed to understand how AI can support faculty development and transform traditional pedagogical approaches (Smith et al., 2022). Investigations into effective models for integrating AI while addressing equity and access issues are crucial (Jorzik et al., 2023). The significance of understanding AI-enabled transformation extends to policymakers, higher education institutions, and employees. For policymakers, this knowledge informs the development of regulations ensuring ethical AI usage and equitable access to advanced technologies (Alam, 2021). Higher education institutions benefit by leveraging AI to improve administrative efficiency and educational quality, thus maintaining competitive advantages (Rahiman & Kodikal, 2024). For employees, AI presents opportunities for professional development through enhanced teaching tools and data-driven insights into student performance (Sajja et al., 2023). This study assesses the direct and indirect relationship between technology innovativeness, self-efficacy, and acceptance of artificial intelligence-enabled transformation among employees in higher education institutions with attitude as a mediator.

Literature Review

Underpinning Theory

The Technology Acceptance Model (TAM), developed by Fred Davis in 1986, is a fundamental framework for understanding user acceptance of technology. It is particularly relevant for studying the acceptance of artificial intelligence (AI)-enabled transformation among employees in higher education institutions. TAM posits that two primary factors, perceived usefulness and perceived ease of use, significantly influence users' attitudes toward technology, affecting their intention to use the technology and, ultimately, their actual usage behaviour (Davis, 1989). In AI-enabled transformation, perceived usefulness refers to the degree employees believe using AI will enhance their job performance. Perceived ease of use denotes the extent to which they feel comfortable using AI without exerting extra effort. When employees perceive AI technologies as useful and easy to use, their positive attitude toward these technologies will likely grow, thereby increasing acceptance rates (Venkatesh &

Davis, 2000). Attitude plays a crucial mediating role within TAM. It bridges the gap between perceptions about the technology and the intention to adopt it, making attitude a vital factor in exploring the relationship between technology innovativeness, self-efficacy, and acceptance. TAM suggests that technology innovativeness can influence perceived ease of use and perceived usefulness. At the same time, self-efficacy can impact employees' confidence in using AI technologies effectively, further shaping their attitudes and ultimate acceptance (Venkatesh, 2000). By applying TAM as an underpinning theory, researchers can systematically assess how different factors influence employee attitudes and acceptance of AI-enabled innovations. This understanding provides insights into theoretical applications and offers practical implications for effectively implementing AI technologies in higher education settings, ensuring that employees are willing and able to embrace technological advancements.

Relationship between Self-Efficacy, Attitude & Acceptance

Self-efficacy, the belief in one's ability to execute tasks and reach goals, is significant in accepting artificial intelligence (AI) technologies, especially when mediated by attitude (Montag et al., 2023). High self-efficacy can lead to a positive attitude toward AI, as individuals feel more capable and confident in learning and utilizing new technologies effectively. This positive attitude, in turn, increases the likelihood of AI acceptance (Obenza et al., 2024). When employees believe they possess the skills necessary to work with AI, they are likelier to develop favourable attitudes toward its use in their tasks (Jia & Tu, 2024). This positive outlook stems from a sense of control and competence, essential components of self-efficacy, leading them to support and adopt AI solutions more readily (Wang & Chuang, 2024). Conversely, low self-efficacy can result in apprehension and resistance, fostering negative attitudes that impede AI acceptance. Attitude acts as a mediator by translating self-efficacy beliefs into behavioural intent (Wang et al., 2023). If employees feel capable (high self-efficacy), their positive attitude toward AI adoption strengthens, contributing to higher acceptance rates (Liao et al., 2023). Therefore, enhancing self-efficacy through training and support boosts confidence and shapes positive attitudes, facilitating smoother adoption of AI technologies in higher education institutions (Chou et al., 2022). This understanding allows educational leaders to design interventions prioritising employee empowerment and capability-building (Ibrahim Hassan et al., 2024). Hence, the following hypotheses were proposed for this study:

H1: *There is a relationship between self-efficacy and acceptance among employees in higher education institutions.*

H2: *There is a relationship between self-efficacy and attitude among employees in higher education institutions.*

H3: *There is a mediating effect of attitude on the relationship between self-efficacy and acceptance among employees in higher education institutions.*

Relationship between Technology Innovativeness, Attitude & Acceptance

The relationship between technology innovativeness and the acceptance of artificial intelligence (AI) is significantly influenced by individual attitudes, serving as a mediator (Montag et al., 2023). Technology innovativeness refers to the degree to which a technology is perceived as novel and advanced. This perception can significantly shape an individual's attitude toward technology (Kelly et al., 2023). Employees who perceive AI technologies as innovative may exhibit a more positive attitude towards them, seeing these technologies as opportunities for enhancing efficiency and gaining a competitive edge (Kandoth & Shekhar, 2022). Attitude, in this context, acts as a crucial mediator. It reflects the employees' predisposition to respond favourably or unfavourably to AI technologies based on their innovativeness (Chang et al., 2024). A positive attitude, fostered by AI's perceived novelty and potential benefits, can enhance the likelihood of acceptance among employees (Labrague et al., 2023). Conversely, if innovativeness is associated with complexity or uncertainty, it might lead to a negative attitude, thus hindering acceptance (Kebah et al., 2019). Ultimately, understanding how technology innovativeness influences attitude and acceptance can guide institutions in higher education to tailor their AI implementation strategies (Kebah et al., 2019). By fostering positive perceptions of innovativeness and addressing concerns, they can enhance attitudes and facilitate smoother, more enthusiastic adoption of AI technologies (Li et al., 2020). This targeted approach ensures that technological innovation translates into practical acceptance and use (Osman et al., 2018). Therefore, the following hypotheses were proposed for this study:

H4: There is a relationship between technology innovativeness and acceptance among employees in higher education institutions.

H5: There is a relationship between technology innovativeness and attitude among employees in higher education institutions.

H6: There is a relationship between attitude and acceptance among employees in higher education institutions.

H7: There is a mediating effect of attitude on the relationship between technology innovativeness and acceptance among employees in higher education institutions.

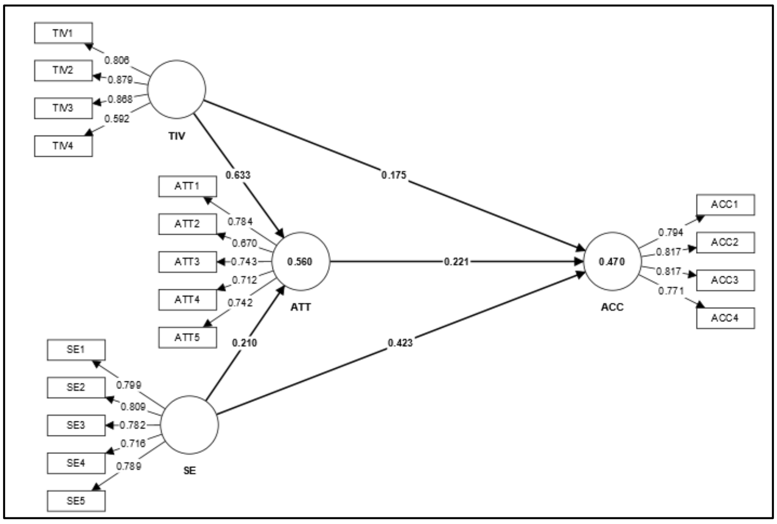

Figure 1: Research Model
Notes: TIV=Technology Innovativeness SE=Self-Efficacy ATT=Attitude ACC=Acceptance

Methodology
This study assessed employee performance in public and private higher education institutions. To achieve this objective, a survey was employed to collect primary data, alongside a comprehensive review of existing literature, to pinpoint dependable and valid metrics. Surveys were distributed via email to selected participants using purposive sampling due to the lack of a complete population list. A total of 18 observed variables were analyzed, including exogenous variables like technological innovativeness, evaluated with 4 items (Son et al., 2019), and self-efficacy, assessed with 5 items (Son et al., 2019). The mediating variable, attitude, was measured using 5 items as per Hair et al (2019), while the dependent variable, acceptance, was evaluated using 4 items following (De Cannière et al., 2009). Each construct was measured using a Likert scale with five levels, from strongly disagree to strongly agree. Of the 573 surveys distributed, 451 were returned, achieving a satisfactory response rate of 78.7% for structural equation modelling (SEM) analysis. Among these, 422 surveys were deemed clean and fit for analysis. Smartpls4 software was chosen for data analysis and hypothesis testing due to its robust structural equation modeling (SEM) capabilities, which align well with the study's goals and follow guidelines by Ringle et al. (2022). Smartpls4 facilitated a detailed analysis of measurement and structural models, effectively examining proposed hypotheses and conducting comprehensive multivariate data analysis.

Data Analysis
Respondents' Profiles
The profile of the respondents provided key insights into the sample characteristics. Regarding gender, males constituted the majority with 61.4%, whereas females represented 38.6%, highlighting a gender imbalance that might not fully reflect the broader population. Regarding age, the largest group of respondents fell within the 41 to 50-year-old range, accounting for 40.8%. This was followed by the 31 to 40-year-olds at 23.5% and the 51 to 60-year-olds at 19.9%. Participants under 30 comprised only 7.1%, and those over 60 comprised

8.8%. This distribution indicates a predominance of middle-aged individuals, with the 41 to 50 and 31 to 40 age brackets making up 64.3% of the sample. Regarding years of service, 30.3% had 11 to 15 years of experience, 28.7% had 16 to 20 years, and 13.5% had 6 to 10 years. A small fraction, 5.9%, had less than 5 years, while 5% had more than 30 years of service. This suggests a high prevalence of seasoned employees, with 59% having 11 to 20 years of experience. As for their positions, 80.3% held academic roles, compared to 19.7% in non-academic roles, indicating a skew towards academic staff. Employer-wise, 65.6% worked in private higher education institutions, while 34.4% were in public institutions, showing more representation from the private sector. Lastly, 98.3% of respondents were inclined to recommend AI-enabled transformation, indicating strong support for such initiatives within the sample.

Common Method Bias

The assessment of common method bias within this study has been conducted using the full collinearity test, as outlined in Table 1. This approach allows researchers to detect potential issues that arise when data is collected using a single method, which may inflate relationships between variables due to shared measurement rather than true underlying associations (Kock, 2015; Kock & Lynn, 2012). The results of the full collinearity test display variance inflation factor (VIF) values for each construct, with acceptance, technology innovativeness, attitude, and self-efficacy all exhibiting VIF values below the common threshold of 3.3. Specifically, the VIF values are as follows: acceptance (1.723), technology innovativeness (1.724), attitude (2.013), and self-efficacy (1.635). These figures suggest minimal risk of common method bias impacting the study's findings, as they conform to the guidelines indicating VIF values should remain under 3.3 to signal the absence of severe multicollinearity issues (Kock, 2015). The relatively low VIF values indicate that the relationships observed among the constructs are unlikely to be exaggerated due to common method variance. Consequently, the study's results can be regarded as valid and reliable, with the assurance that the observed relationships among acceptance, technology innovativeness, attitude, and self-efficacy are not unduly influenced by the measurement method (Kock & Lynn, 2012).

Table 1
Full Collinearity Test

	ACC	TIV	ATT	SE
ACC		1.723	1.725	1.623
TIV	1.724		1.481	1.622
ATT	2.013	1.684		1.819
SE	1.635	1.819	1.587	

Measurement Model

In this study, we utilized the methodology recommended by Hair et al. (2017) to evaluate each measurement at both the first and second-order levels. This method assists in identifying items with loadings below the 0.7 threshold. Our construct reliability and validity analysis revealed that the Average Variance Extracted (AVE) for all constructs ranged from 0.534 to 0.640. These values exceeded the 0.5 benchmarks, indicating strong convergent validity (Hair et al., 2017), as shown in Table 2. The composite reliability for all constructs was also above

0.7, with values ranging from 0.790 to 0.843. Additionally, Cronbach's alpha for all constructs surpassed the 0.7 mark, ranging from 0.784 to 0.838, as detailed in Table 2. Discriminant validity was ensured initially by assessing cross-loadings to confirm each construct's appropriate representation and measurement. Following this, the Hetrotrait-Monotrait (HTMT) ratio was employed for further assessment, in line with the recommended criteria for evaluating discriminant validity in Variance-Based Structural Equation Modeling (VB-SEM) (Henseler et al., 2015). Table 3 presented the HTMT ratios, original sample, and 95% confidence intervals, confirming adherence to the HTMT threshold 0.9. The bias-corrected and accelerated bootstrap confidence intervals remained consistently below 1, reinforcing the constructs' distinctiveness and capability to measure different facets of the phenomenon under investigation.

Table 2
Constructs Reliability and Validity & Items Loadings

Constructs	Items	Loadings	CA	CR	AVE
ACC	ACC1	0.794	0.813	0.816	0.640
	ACC2	0.817			
	ACC3	0.817			
	ACC4	0.771			
ATT	ATT1	0.784	0.784	0.790	0.534
	ATT2	0.670			
	ATT3	0.743			
	ATT4	0.712			
	ATT5	0.742			
SE	SE1	0.799	0.838	0.843	0.608
	SE2	0.809			
	SE3	0.782			
	SE4	0.716			
	SE5	0.789			
TIV	TIV1	0.806	0.797	0.821	0.632
	TIV2	0.879			
	TIV3	0.868			
	TIV4	0.592			

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

Table 3
Hetrotrait-Monotrait (HTMT) Ratios

	ACC	ATT	SE
ATT	0.676		
SE	0.725	0.591	
TIV	0.649	0.882	0.541

Structural Model

In this study, the evaluation of the structural model followed the methodology outlined by Hair et al. (2017), including a concurrent examination of pathway coefficients (β) and coefficients of determination (R^2). The Partial Least Squares (PLS) approach was employed, using 5000 subsamples to determine the significance levels of the path coefficients. The results of the hypothesis tests, which include confidence intervals, path coefficients (beta), t-statistics, and p-values, are detailed in Table 4. This thorough analysis offers valuable insights into the significance and robustness of the relationships between the variables within the structural model (Hair et al., 2017). The hypothesis analysis reveals noteworthy findings.

The analysis of the seven hypotheses in Table 4 reveals significant insights into the dynamics between self-efficacy, technology innovativeness, attitude, and acceptance within the structural model. *Hypothesis 1 (H1)* asserts that self-efficacy positively influences acceptance, demonstrated by a beta value of 0.423, a high t-statistic of 9.674, and a p-value of 0.000, thereby strongly supporting this hypothesis. This result indicates a significant and positive impact of self-efficacy on acceptance, suggesting that individuals with greater confidence in their abilities are more predisposed to embrace new technologies. Similarly, *Hypothesis 2 (H2)* suggests that self-efficacy positively influences attitude, with a beta of 0.210, a t-statistic of 5.321, and a p-value of 0.000, leading to the acceptance of this hypothesis. This demonstrates that increased self-efficacy fosters a more positive attitude towards technology adoption. In *Hypothesis 3 (H3),* the relationship between self-efficacy and acceptance is mediated through attitude, supported by a beta of 0.046, a t-statistic of 3.129, and a p-value of 0.002, suggesting that attitude partially transmits the effect of self-efficacy on acceptance. *Hypothesis 4 (H4)* posits that technological innovativeness positively influences acceptance; with a beta value of 0.175, a t-statistic of 3.018, and a p-value of 0.003, this hypothesis is accepted, indicating that the perceived innovativeness of technology significantly affects the willingness to accept it.

Furthermore, *Hypothesis 5 (H5)* explores the impact of technological innovativeness on attitude, yielding strong support with a very high beta of 0.633, a t-statistic of 18.974, and a p-value of 0.000, showing that the perception of innovativeness enhances positive attitudes towards technology. *Hypothesis 6 (H6)* reveals that a positive attitude significantly increases acceptance, as evidenced by a beta of 0.221, a t-statistic of 4.109, and a p-value of 0.000, supporting this hypothesis and confirming the critical role of attitude in technology adoption. Lastly, *Hypothesis 7 (H7)* confirms the mediating role of attitude in the influence of technology innovativeness on acceptance, with supporting findings of a beta of 0.140, a t-statistic of 4.101, and a p-value of 0.000. This indicates that attitudes effectively mediate the impact of technological innovativeness on acceptance. Thus, the analysis confirms all hypotheses, underscoring the substantial roles of self-efficacy and technology innovativeness in shaping attitudes and acceptance, offering valuable insights into the mechanisms driving technology adoption.

Table 4
Hypotheses Testing Results

Hypotheses	Beta	T-statistics	P-values	2.50%	97.50%	Decision
H1: SE -> ACC	0.423	9.674	0.000	0.336	0.506	*Accepted*
*H2:*SE -> ATT	0.210	5.321	0.000	0.134	0.285	*Accepted*
H3: SE -> ATT -> ACC	0.046	3.129	0.002	0.021	0.080	*Accepted*
H4: TIV -> ACC	0.175	3.018	0.003	0.062	0.287	*Accepted*
H5: TIV -> ATT	0.633	18.974	0.000	0.563	0.694	*Accepted*
H6: ATT -> ACC	0.221	4.109	0.000	0.113	0.324	*Accepted*
H7: TIV -> ATT -> ACC	0.140	4.101	0.000	0.072	0.208	*Accepted*

Notes: significance= $p<0.05$

Table 5 provides a detailed summary of effect sizes and collinearity results, using Cohen's (1992) guidelines for interpretation: small effect sizes range from 0.020 to 0.150, medium from 0.150 to 0.350, and large at 0.350 or above. The effect sizes observed in this study varied from small (0.027) to large (0.738). Variance Inflation Factor (VIF) values, as presented in Table 5, consistently stayed below the relaxed threshold of 5, with the highest VIF recorded as 2.274. This indicates that collinearity is acceptable, allowing for meaningful comparison of effect sizes and interpretation of coefficients within the structural model. The endogenous construct's explained variance is substantial, with an R^2 value of 0.470 (Figure 1). Concerning the mediator, the model accounted for approximately 56% of the variance, reflected by an R^2 value of 0.560.

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

	f^2		VIF	
	ACC	ATT	ACC	ATT
ATT	0.041		2.274	
SE	0.253	0.081	1.335	1.234
TIV	0.027	0.738	2.145	1.234

The model's inferential capability and ability to provide managerial insights were assessed using the PLSpredict method, as delineated by Shmueli et al. (2016, 2019). Table 6 displays the results of the out-of-sample predictive analysis, where instances with Q^2 predictions greater than 0 indicate better performance than standard naive mean predictions. Additionally, the root mean square error (RMSE) values for PLS-SEM predictions surpassed those of the linear model (LM) prediction benchmark in six out of nine cases, highlighting the model's predictive effectiveness (see Table 6).

Further advancing this evaluation, Hair et al (2022), proposed the Cross-Validated Predictive Ability Test (CVPAT) to assess the predictive strength of PLS-SEM results. Liengaard et al. (2021) examined the model's predictive performance using CVPAT and PLSpredict analysis. The CVPAT utilized an out-of-sample prediction approach to measure prediction error and calculate the average loss value. Two benchmarks were used for comparison: predictions based on indicator averages (IA) as a simple benchmark and a linear model (LM) forecast as a more stringent benchmark. For the model to demonstrate superior predictive capability over these benchmarks, the PLS-SEM average loss value must be lower, resulting in a negative difference in average loss. The CVPAT aimed to determine if the discrepancy in average loss values between PLS-SEM and the benchmarks was significantly negative. Table 7 confirms that the average loss value for PLS-SEM was lower than that of the benchmarks, as evidenced by the negative difference, thereby validating the model's superior predictive capabilities.

Table 6
PLSpredicts

Indicators	Q^2predict	PLS-RMSE	LM_RMSE	PLS-LM
ACC1	0.333	0.585	0.590	-0.005
ACC2	0.276	0.601	0.608	-0.007
ACC3	0.270	0.682	0.685	-0.003
ACC4	0.235	0.701	0.703	-0.002
ATT1	0.272	0.630	0.629	0.001
ATT2	0.173	0.616	0.619	-0.003
ATT3	0.181	0.614	0.613	0.001
ATT4	0.303	0.618	0.619	-0.001
ATT5	0.471	0.601	0.531	0.070

Table 7
Cross Validated Predictive Ability Test (CVPAT)

	Average loss difference	t-value	p-value
ACC	-0.161	7.164	0.000
ATT	-0.160	9.058	0.000
Overall	-0.160	9.940	0.000

Ringle and Sarstedt (2016) along with Hair et al. (2018) suggest employing Importance Performance Analysis (IPMA) to assess the significance and efficiency of latent variables in explaining acceptance. The IPMA analysis (Table 8) reveals valuable insights, indicating that Attitude, with an importance of 0.221 and a high performance of 65.708, is currently effective. To sustain this, continued emphasis on positive technological perceptions is suggested. Self-efficacy, however, at 0.469 importance but only 60.59 performance, highlights a gap where targeted training and support could significantly boost confidence and technology acceptance. For Technology Innovativeness, showing 0.315 in importance and 62.747 in performance, improving communication about technology benefits and applications is essential. Enhancing self-efficacy, maintaining positive attitudes, and promoting innovative technology can improve overall effectiveness and model outcomes.

Table 8
Importance-Performance Map (IPMA)

	Importance	Performance
ATT	0.221	65.708
SE	0.469	60.59
TIV	0.315	62.747

Discussion & Conclusion
Discussion
Focusing on attitude as a mediating factor is essential to ensure that technology innovativeness and self-efficacy positively and significantly impact the acceptance of AI-enabled transformation among employees in higher education institutions. The hypotheses testing results demonstrate the pathway relationships substantiated by positive beta values. For instance, the influence of technology innovativeness on attitude, with a substantial beta of 0.633, underscores the need to foster an environment where innovative technologies are not only introduced but also effectively communicated and demonstrated to employees. By showcasing real-world applications and tangible benefits, institutions can cultivate positive attitudes toward these technologies, enhancing acceptance. Similarly, self-efficacy, with a beta value of 0.210 influencing attitude, highlights the importance of developing comprehensive training programs and support systems. Higher education institutions can boost their self-efficacy by empowering employees with the necessary skills and confidence to engage with AI technologies. This leads to a more favourable attitude towards technology adoption. Moreover, the direct relationship between self-efficacy and acceptance, evidenced by a beta of 0.423, emphasizes the strategic need for sustained professional development and peer support networks that allow employees to share experiences and solutions. With attitude serving as a critical mediator, as seen with a beta of 0.221 in its direct influence on acceptance, it becomes crucial for institutions to nurture a culture that values innovation and personal growth continually. By addressing these areas strategically, institutions can significantly enhance the acceptance rate of AI technologies, fostering a seamless transition into AI-enabled environments where employees feel confident and supported, thus maximizing organizational effectiveness.

Theoretical Implications
The study presents significant theoretical implications by expanding upon the Technology Acceptance Model (TAM) within the context of AI-enabled transformation in higher education institutions. Traditionally, TAM focuses on how perceived usefulness and ease of use drive technology acceptance. This research introduces additional elements, such as self-efficacy and technology innovativeness, to deepen the understanding of what influences the acceptance of AI technologies (Chang et al., 2024). Self-efficacy, the belief in one's capabilities to use technology effectively, enriches TAM by underscoring that individuals with greater confidence in their abilities are more likely to develop positive attitudes toward new technologies. This finding broadens the TAM framework by showing how self-efficacy enhances users' perceptions of ease of use and usefulness, leading to a higher likelihood of acceptance (Hassan et al., 2024). The study also highlights the importance of technology innovativeness, suggesting that employees' perceptions of a technology's modernity and

advancement contribute significantly to forming positive attitudes. This aligns with TAM's perceived usefulness aspect, as innovative technologies often promise new efficiencies and benefits, enhancing attitudes that lead to increased acceptance. By emphasizing the crucial role of attitude as a mediator, this study extends TAM by illustrating how initial perceptions about self-efficacy and technology innovativeness translate into acceptance through attitude formation (Liao et al., 2023). This enriched framework offers a more nuanced understanding of AI adoption dynamics, especially in educational settings, providing a holistic model that captures the interplay between individual capabilities, perceptions of technology, and the resulting behavioural intentions. This expanded view contributes to theoretical advancements in technology acceptance literature and guides institutions in designing interventions that enhance both individual and collective readiness for AI transformation.

Practical Implications
The practical implications of this study are profound, offering actionable insights for higher education institutions aiming to facilitate AI-enabled transformation. By highlighting the importance of self-efficacy, institutions can prioritize building employees' confidence in engaging with AI technologies. This can be achieved through targeted training programs, workshops, and ongoing support systems that equip staff with the necessary skills to navigate and utilize new AI tools comfortably. Furthermore, recognizing the influence of technology innovativeness, institutions should focus on clear communication strategies that articulate AI applications' benefits and innovative features. Demonstrating AI's practical applications and success stories can enhance perceptions of its usefulness and promote positive attitudes. Additionally, fostering a positive attitude towards AI is crucial, as it mediates the relationship between self-efficacy, technology innovativeness, and acceptance. This can be cultivated by creating an organizational culture that celebrates technological advances and encourages open dialogue about experiences with AI. Providing platforms for staff to share challenges and successes related to AI can reinforce positive attitudes and acceptance. By addressing these factors, institutions can effectively enhance the acceptance and integration of AI technologies, ultimately leading to more efficient operations and improved educational outcomes. This strategic approach ensures that individual and organizational readiness for AI adoption is robustly supported.

Suggestions for Future Study
Future studies could delve deeper into the nuances of AI-enabled transformation within diverse educational contexts by exploring additional dimensions. First, longitudinal studies could provide insights into how self-efficacy and attitudes evolve over time with continuous exposure to AI technologies, offering a dynamic view of technology acceptance. Investigating the role of organizational culture and leadership in shaping attitudes towards AI could further illuminate factors that facilitate or hinder technology adoption. Additionally, exploring demographic variables, such as age, gender, and disciplinary background, may reveal how different groups perceive and adopt AI differently, enabling more targeted interventions. It would also be beneficial to examine the impact of specific AI applications, such as learning analytics or automated administration tools, to identify which innovations are most effective in enhancing educational outcomes. By expanding the scope of research to include these

aspects, future studies can provide a more comprehensive understanding of AI adoption processes in higher education institutions.

Conclusion

This study enhances the understanding of AI-enabled transformation acceptance in higher education institutions by integrating self-efficacy and technology innovativeness into the Technology Acceptance Model framework. The findings underscore the vital role of self-efficacy in fostering positive attitudes toward AI technologies, highlighting the need for robust training and support. Additionally, the perception of technology innovativeness significantly influences acceptance, suggesting that institutions should emphasize AI applications' modern capabilities and benefits. Attitude emerges as a key mediator, translating confidence and perceptions into a willingness to embrace technological changes. These insights guide institutions to develop strategic initiatives that support employee readiness and positive attitudinal shifts, facilitating smoother AI integration. Extending this model across various educational contexts and exploring additional influencing factors will be crucial for future research. This study emphasizes the need for adaptive educational policies and proactive change management practices to accommodate emerging AI trends. Overall, this study provides valuable theoretical and practical contributions, paving the way for more effective AI adoption strategies in educational environments.

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