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Shaping the Future: Artificial Intelligence-Enabled Transformation Acceptance in Higher Education Institutions

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Abstract

This study investigates the factors influencing employee acceptance of AI-enabled transformation in digital HEIs, focusing on the mediating roles of self-efficacy and attitude. Drawing upon the Technology Acceptance Model (TAM), the study examines the direct and indirect relationships between perceived ease of use, perceived usefulness, and acceptance, incorporating self-efficacy and attitude as essential mediators. Primary data was collected through a survey questionnaire distributed to employees of digital HEIs. A total of 422 valid responses were included in the analysis, representing a satisfactory response rate of 78.4%. Structural equation modelling (SEM) was employed using SmartPLS4 software to assess the measurement and structural models and test the proposed hypotheses. The results revealed that perceived ease of use and perceived usefulness directly influence acceptance, with self-efficacy and attitude serving as significant mediators. Importance-performance map analysis (IPMA) further highlighted each latent variable's relative importance and performance in explaining acceptance. To ensure the practical impact of perceived ease of use and perceived usefulness on acceptance, HEIs should focus on fostering self-efficacy and promoting a positive attitude among employees. Providing comprehensive training programs, emphasising the benefits of AI, and creating a culture of innovation can significantly contribute to the successful adoption of AI-enabled transformation. Future research could explore the longitudinal effects of interventions to enhance employee readiness to change and investigate the role of organisational culture and leadership support in facilitating AI

adoption. The findings have important implications for institutional leaders and policymakers, as they can develop targeted strategies to promote the successful integration of artificial intelligence technologies in digital higher education institutions.
Keywords: Perceived Ease of Use, Perceived Usefulness, Self-Efficacy, Attitude, Acceptance

Introduction

Artificial intelligence (AI) is a transformative force in digital education within higher education institutions, heralding a new era of innovation and evolution. Integrating AI in educational settings is not merely advantageous but indispensable for fostering a learning environment that is personalised, efficient, and engaging but also adaptive to the diverse needs of modern learners (Zawacki-Richter et al., 2019). Recent trends underscore a pronounced shift towards harnessing AI to elevate teaching methodologies, streamline administrative workflows, and elevate educational outcomes to unprecedented levels. Institutions are increasingly cognizant of AI's potential to overhaul conventional educational paradigms and align with the dynamic requirements of the digital era (George & Wooden, 2023). A critical focal point within this landscape is the acceptance of AI-enabled transformation among employees in higher education institutions (Intaratat et al., 2024). This pivotal issue ensures that staff members embrace and effectively leverage AI technologies in their daily professional endeavours (Ghosh & Bhattacharyya, 2021). The challenge lies in surmounting resistance to change, allaying concerns regarding job security, and furnishing comprehensive training and support mechanisms to facilitate a seamless transition toward AI-driven systems (Yu & Nazir, 2021). Despite the remarkable strides in AI technology, a notable research gap persists in comprehending the factors that influence the acceptance of AI-enabled transformation among employees in higher education (Zawacki-Richter et al., 2019). This knowledge void presents a compelling opportunity for further exploration and investigation to delineate the key drivers and impediments to successful implementation (Yang & Shankar, 2023). The significance of delving into the acceptance of AI-enabled transformation in digital higher education institutions extends its impact to policymakers, institutions, and employees alike (Rudolph et al., 2024). Policymakers can leverage insights from this research to craft well-informed strategies that foster the seamless integration of AI in education. Institutions stand to gain by acquiring a nuanced understanding of navigating the challenges inherent in AI adoption and optimising the advantages offered by these technologies (Ghosh & Bhattacharyya, 2021). For employees, this research serves as a beacon, offering invaluable guidance on embracing AI to augment their work processes, enhance efficiency, and adapt to the ever-evolving landscape of digital education (Huang et al., 2023). This study scrutinises the direct and indirect relationships between perceived usefulness, perceived ease of use, acceptance, self-efficacy, and attitude mediating among employees of higher education institutions.

Literature Review

Underpinning Theory

The Technology Acceptance Model (TAM) (Davis, 1989) is a widely used theoretical framework for understanding and predicting user acceptance of information technologies. The model posits that an individual's intention to use a technology is primarily determined by two key factors: perceived usefulness (PU) and perceived ease of use (PEOU). Perceived usefulness refers to the degree to which a person believes using a particular technology will enhance their job performance or learning outcomes (Aladwan et al., 2023). On the other hand, perceived ease of use reflects the extent to which a person believes using the technology will be free of effort. TAM further suggests that PEOU directly influences PU, as technologies that are easier to use are more likely to be perceived as valuable. PEOU and PU, in turn, shape an individual's attitude toward using the technology, ultimately determining their intention to use and actual usage behaviour (ALkindi et al., 2022). Recent extensions of TAM have incorporated additional factors, such as self-efficacy, to explain technology acceptance better. Self-efficacy refers to an individual's belief in using technology effectively (Aladwan et al., 2023). Studies have shown that self-efficacy can influence PEOU and PU, as individuals with higher self-efficacy tend to perceive technologies as more straightforward and valuable. By applying TAM to the context of AI-enabled transformation in digital higher education institutions, this study investigates the direct and indirect relationships between PU, PEOU, and acceptance, as well as self-efficacy and attitude mediating among employees. This theoretical framework provides a solid foundation for understanding the factors that influence the acceptance of AI technologies in higher education and can inform strategies for promoting successful implementation.

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

The relationship between perceived ease of use and acceptance of artificial intelligence-enabled transformation in higher education institutions, with self-efficacy as a mediator, plays a crucial role in shaping the successful integration of AI technologies (AlGerafi et al., 2023). Perceived ease of use, reflecting individuals' perceptions of the simplicity and user-friendliness of AI tools, directly influences their acceptance (Saqr et al., 2023). Educators who find AI tools easy to use are more likely to embrace their incorporation into teaching practices, emphasising the significance of user-friendly interfaces in facilitating acceptance (Tan et al., 2023). This direct correlation underscores the importance of ensuring that AI technologies are intuitive and accessible to users, promoting a smoother adoption process (Kebah et al., 2019). Moreover, self-efficacy, which refers to individuals' belief in their ability to utilise AI tools successfully, mediates the relationship between perceived ease of use and acceptance (Shao et al., 2024). Educators with high self-efficacy are likelier to perceive AI tools as easy to use, leading to a positive attitude and increased acceptance of these technologies (Chahal & Rani, 2022). Understanding and optimising this relationship is essential for enhancing the acceptance of AI-enabled transformations in higher education institutions (Nguyen et al., 2025). By fostering self-efficacy through training and support programs, alongside prioritising user-friendly interfaces, institutions can effectively navigate the challenges associated with AI adoption and maximise the transformative potential of these tools in the educational landscape (Lai et al., 2023). Therefore, the following hypotheses were proposed for this study:

H1: There is a relationship between perceived ease of use and acceptance of artificial intelligence-enabled transformation among employees *in digital higher educationinstitutions*.

H2: There is a relationship between perceived ease of use and self-efficacy in the acceptance of artificial intelligence-enabled transformation among employees *in digitalhigher education institutions*.

H3: There is a relationship between perceived ease of use and perceived usefulness in theacceptance of artificial intelligence-enabled transformation among employees *in digital higher education institutions*.

H4: There is a relationship between self-efficacy and acceptance of artificial intelligence-enabled transformation among employees *in digital higher education institutions*.
H5: There is a mediating effect of self-efficacy on the relationship between perceived ease of use and acceptance of artificial intelligence-enabled transformation among employees *in digital higher education institutions*.

Relationship between Perceived Ease of Use, Attitude & Acceptance

The relationship between perceived ease of use and acceptance of artificial intelligence-enabled transformation in higher education institutions, with attitude as a mediator, is a pivotal factor influencing the successful integration of AI technologies. Perceived ease of use, reflecting individuals' perceptions of the simplicity and user-friendliness of AI tools, directly impacts their acceptance (Rahman & Kodokal, 2024). Educators who find AI tools easy to use are more likely to embrace their incorporation into teaching practices, underscoring the importance of user-friendly interfaces in facilitating acceptance (Tan et al., 2023). This direct correlation highlights the significance of ensuring that AI technologies are intuitive and accessible to users, promoting a smoother adoption process (AlGerafi et al., 2023). Furthermore, attitude is crucial in the relationship between perceived ease of use and acceptance (Kebah et al., 2019). Positive attitudes toward AI bridge perceived ease of use and acceptance (Chahal & Rani, 2022). When educators perceive AI tools as easy to use, it positively influences their attitude toward these technologies, fostering a more favourable disposition and enhancing acceptance in the educational context (Habes et al., 2024). Understanding and optimising this interconnected dynamic between perceived ease of use, attitude, and acceptance are essential for crafting effective strategies for AI implementation in higher education (Bansah & Darko Agyei, 2022). By prioritising user-friendly interfaces, cultivating positive attitudes, and emphasising the practical benefits of AI technologies, institutions can navigate the challenges associated with AI adoption and maximise the transformative potential of these tools in the educational landscape (Lalicic & Weismayer, 2021). Hence, the following hypotheses were proposed for this study:

H6: There is a relationship between perceived ease of use and attitude in the acceptance of artificial intelligence-enabled transformation among employees *in digital higher education institutions*.
H7: There is a relationship between attitude and acceptance of artificial intelligence-enabled transformation among employees *in digital higher education institutions*.
H8: There is a mediating effect of attitude on the relationship between the perceived ease of use and acceptance of artificial intelligence-enabled transformation among employees *in digital higher education institutions*.

Relationship between Perceived Usefulness, Self-Efficacy & Acceptance

The relationship between perceived usefulness and acceptance of artificial intelligence-enabled transformation in higher education, with self-efficacy as a mediator, is a critical aspect that influences the successful integration of AI technologies (Gosh & Bhattacharyya, 2021). Perceived usefulness, reflecting individuals' beliefs about the benefits and advantages of AI tools, directly impacts their acceptance. Educators who perceive AI tools as applicable are more likely to embrace their incorporation into teaching practices, highlighting the importance of recognising the practical benefits of AI technologies (Chen et al., 2023). Self-efficacy, individuals' confidence in their ability to effectively utilise AI tools, plays a mediating role in this relationship (Sadriwala & Sadriwala, 2022). Educators with high self-efficacy are more inclined to perceive AI tools as applicable, leading to a positive attitude and increased acceptance of these technologies (Ofosu-Ampong et al., 2021). This indirect relationship underscores the significance of fostering educators' confidence to leverage AI tools effectively (Li et al., 2020). Understanding and optimising the interconnected dynamic between perceived usefulness, self-efficacy, and acceptance are essential for enhancing the acceptance of AI-enabled transformations in higher education institutions (Alshare & Mousa, 2024). By empowering educators with the necessary skills and confidence through training programs and support initiatives, institutions can cultivate a positive attitude towards AI tools, facilitating a smoother adoption process and maximising the transformative potential of these technologies in the educational landscape (Vedapradha et al., 2024). Thus, the following hypotheses were proposed for this study:

H9: There is a relationship between perceived usefulness and acceptance of artificial intelligence-enabled transformation among employees *in digital higher education institutions*.
H10: There is a relationship between perceived usefulness and self-efficacy in the acceptance of artificial intelligence-enabled transformation among employees *in digital higher education institutions*.
H11: There is a mediating effect of self-efficacy on the relationship between perceived usefulness and acceptance of artificial intelligence-enabled transformation among employees *in digital higher education institutions*.

Relationship between Perceived Usefulness, Attitude & Acceptance
The relationship between perceived usefulness and acceptance of artificial intelligence-enabled transformation in higher education, with attitude as a mediator, is a critical aspect that influences the successful integration of AI technologies (Rahman & Kodikal, 2024). Perceived usefulness, reflecting individuals' beliefs about the benefits and advantages of AI tools, directly impacts their acceptance (Li et al., 2022). Educators who perceive AI tools as applicable are more likely to embrace their incorporation into teaching practices, highlighting the importance of recognising the practical benefits of AI technologies (Osman et al., 2018). Attitude is crucial in this relationship (Malodia et al., 2021). Positive attitudes toward AI serve as a bridge between perceived usefulness and overall acceptance. When educators perceive AI tools as applicable, it positively influences their attitude toward these technologies, fostering a more favourable disposition and enhancing acceptance in the educational context (Alnaser et al., 2023; Mohamad & Osman, 2025). Understanding and optimising the interconnected dynamic between perceived usefulness, attitude, and acceptance are essential for enhancing the acceptance of AI-enabled transformations in higher education institutions (Cheng et al., 2022). Institutions can cultivate a positive attitude toward AI tools by showcasing the innovative aspects of AI-enabled transformation initiatives, stimulating curiosity and a forward-looking mindset among educators (Hernandez et al., 2023). Investments in training programs, workshops, and technological upskilling opportunities can contribute significantly to bolstering the perception of technological innovativeness, further enhancing the perceived usefulness of AI tools (Lai et al., 2023). Therefore, the following hypotheses were proposed for this study:

H12: There is a relationship between perceived usefulness and attitude in the acceptance of artificial intelligence-enabled transformation among employees *in digital higher education institutions*.

H13: There is a mediating effect of attitude on the relationship between perceived usefulness and acceptance of artificial intelligence-enabled transformation among employees *in digital higher education institutions*.

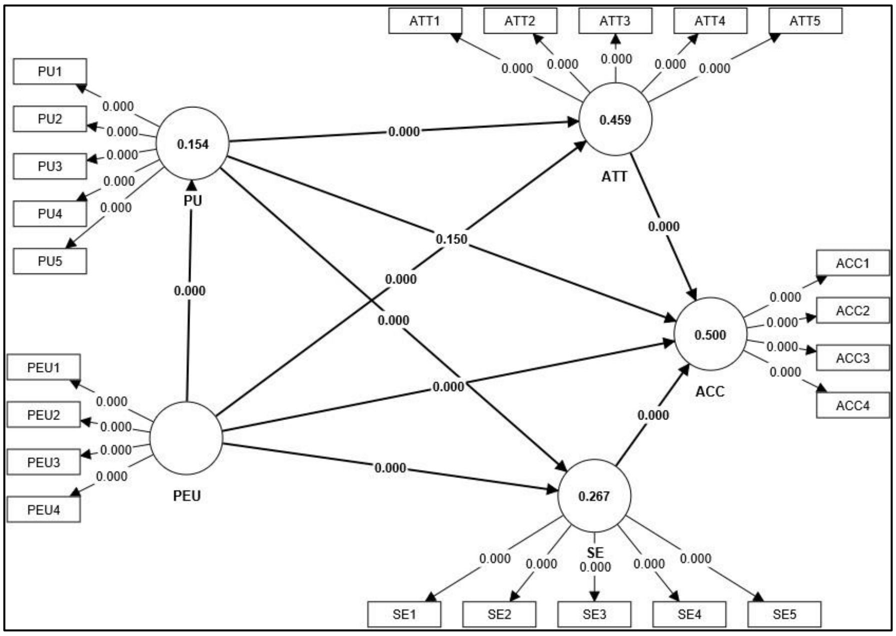

Figure 1: Research Framework

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

Methodology

This study thoroughly examined the direct and indirect relationships between perceived usefulness, perceived ease of use, and acceptance, with self-efficacy and attitude serving as mediators among employees in digital 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), perceived ease of use (4 items), the mediating variables of self-efficacy (5 items), and attitude (5 items), and the dependent variable, acceptance (4 items). 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 revealed several key insights about the sample. Regarding gender, most participants were male, comprising 61.4% of the total, while females accounted for 38.6%. This gender imbalance suggests that the sample may not fully represent the broader population. Examining the age distribution, the largest group was the 41 to 50-year-old cohort, making up 40.8% of respondents. The largest groups were the 31 to 40 (23.5%) and 51 to 60 (19.9%) categories. Only 7.1% were under 30 years old, and 8.8% were over 60 years old. This age profile indicates the sample was heavily weighted towards middle-aged individuals, with the 41-50 and 31-40 age groups accounting for 64.3% of participants. In terms of years of service, the largest group had 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%). Only 5.9% had less than five years of service, while 5% had over 30 years. This suggests the sample was dominated by more experienced employees, with 59% having 11 to 20 years of service. Regarding post level, most respondents (80.3%) held academic positions, while 19.7% were in non-academic roles. This indicates that the sample was heavily skewed towards academic staff compared to administrative or support personnel.

The employer breakdown showed that 65.6% of participants worked at private higher education institutions, while 34.4% were employed at public institutions. This suggests that the sample had more excellent representation from the private sector. Finally, 98.3% of respondents indicated they would recommend artificial intelligence-enabled transformation, while only 1.7% would not. This indicates a high willingness among the sample to endorse artificial intelligence-enabled transformation.

Common Method Bias

Kock (2015) introduced a comprehensive approach called the collinearity test, while Kock and Lynn (2012) further elaborated on this method. The collinearity test is designed to evaluate both vertical and horizontal collinearity. Pathological collinearity is identified based on variance inflation factors (VIFs) exceeding 3.3, indicating a significant standard method bias concern within the model (Kock, 2015; Kock & Lynn, 2012). Therefore, if the VIFs derived from the overall collinearity assessment are below 3.3, it can be concluded that the model is not influenced by common method bias. A full collinearity test was conducted to assess the presence of common method bias in the current study. The results in Table 1 illustrate that the VIFs resulting from the total collinearity evaluation were well below the conservative threshold of 3.3 (Kock, 2015; Kock & Lynn, 2012). Specifically, the VIFs ranged from 1.000 to 1.736, with an average VIF of 1.368. These findings confirm the model's absence of a significant standard method bias issue. The low VIF values indicate that the relationships between the latent variables are not inflated due to standard method variance. This suggests that the observed correlations between the constructs are not solely attributable to the measurement method but rather reflect genuine relationships between the variables of interest. The results provide empirical support for the validity and reliability of the measures used in the study. By conducting a rigorous collinearity test and reporting the VIF values, this study adheres to the recommendations of Kock (2015) and Kock and Lynn (2012). The findings demonstrate a robust approach to assessing and mitigating common method bias, a critical consideration in survey-based research. The low VIF values instil confidence in the integrity of the data and the validity of the conclusions drawn from the analysis.

Table 1
Full Collinearity Test

	ACC	PU	ATT	SE	PEU
ACC		1.775	1.766	1.630	1.539
PU	1.758		1.468	1.631	1.832
ATT	2.034	1.694		1.828	2.121
MS	1.669	1.884	1.578		1.803
PEU	1.450	1.571	1.668	1.741	

Measurement Model
In this study, we followed the methodology advocated by Hair et al. (2017) to evaluate each measurement in both the first and second orders, enabling the identification of items with loadings below the 0.7 threshold. The construct reliability and validity analysis revealed that all constructs' Average Variance Extracted (AVE) ranged from 0.538 to 0.698, surpassing the 0.5 benchmark, indicating robust convergent validity (Hair et al., 2017). The composite reliability values for all constructs exceeded 0.7, ranging from 0.786 to 0.864. Additionally, the Cronbach's alpha values for all constructs were above 0.7, ranging from 0.784 to 0.855. To ensure discriminant validity, the initial step involved assessing cross-loadings to accurately represent and measure the respective constructs. Subsequently, the Heterotrait-Monotrait (HTMT) ratio was utilised for further evaluation, aligning with the recommended criterion for scrutinising discriminant validity in Variance-Based Structural Equation Modeling (VB-SEM) (Henseler et al., 2015). The HTMT ratios, original sample, and 95% confidence intervals presented in Table 4 confirmed adherence to the HTMT threshold of 0.9. The bias-corrected and accelerated bootstrap confidence intervals consistently remained below 1, reinforcing confidence in the constructs' distinctiveness and ability to measure unique aspects of the phenomenon under investigation.

Table 3
Construct Reliability and Validity & Cross Loadings

Constructs	Items	Loadings	CA	CR	AVE	Sources
Acceptance	ACC1	0.793	0.813	0.816	0.640	De Cannière et al. (2009)
	ACC2	0.815				
	ACC3	0.819				
	ACC4	0.772				
Attitude	ATT1	0.800	0.784	0.786	0.538	Hair et al. (2019)
	ATT2	0.690				
	ATT3	0.763				
	ATT4	0.701				
	ATT5	0.706				
Perceived Ease of Use	PEU1	0.882	0.855	0.864	0.698	Shang et al. (2011)
	PEU2	0.853				
	PEU3	0.840				
	PEU4	0.763				
Perceived Usefulness	PU1	0.748	0.829	0.852	0.594	Shang et al. (2011)
	PU2	0.783				
	PU3	0.832				
	PU4	0.823				
	PU5	0.655				
Self-Efficacy	SE1	0.795	0.838	0.842	0.608	Son et al. (2019)
	SE2	0.805				
	SE3	0.782				
	SE4	0.724				
	SE5	0.789				

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

Table 3
Hetrotrait-Monotrait (HTMT) Ratios

	ACC	ATT	PEU	PU
ATT	0.676			
PEU	0.584	0.524		
PU	0.573	0.787	0.45	
SE	0.725	0.591	0.436	0.549

Structural Model

In this study, the assessment of the structural model was conducted using the methodology outlined by Hair et al. (2017), simultaneously examining pathway coefficients (β) and coefficients of determination (R^2). The Partial Least Squares (PLS) method was employed, utilising 5000 subsamples to establish the significance level of path coefficients. The outcomes of hypothesis tests, including confidence intervals, path coefficients (beta), associated t-statistics, and p-values, are meticulously presented in Table 4. This comprehensive scrutiny provides valuable insights into the significance and robustness of the relationships among the variables within the structural model (Hair et al., 2017). The analysis of hypotheses reveals significant findings, underscoring the importance of each pathway in the model. The path coefficients (β) and coefficients of determination (R^2) are crucial in understanding the strength and direction of the relationships between the constructs. The t-statistics and p-values provide a statistical basis for evaluating the significance of each pathway. At the same time, the confidence intervals offer a range of values within which the proper population parameter is likely to lie. By presenting these outcomes in a detailed and transparent manner, this study adheres to the highest standards of academic rigour and facilitates a thorough understanding of the structural model's dynamics.

For *H1, t*he analysis reveals a significant positive relationship between perceived ease of use and acceptance, with a beta coefficient of 0.226, a t-statistic of 4.753, and a p-value of 0.000. This result supports the hypothesis that acceptance increases as perceived ease of use increases. The 95% confidence interval of 0.130 to 0.314 further reinforces the strength of this relationship. For *H2, t*he results indicate a significant positive relationship between perceived ease of use and self-efficacy, with a beta coefficient of 0.218, a t-statistic of 4.372, and a p-value of 0.000. This finding supports the hypothesis that self-efficacy increases as perceived ease of use increases. The 95% confidence interval of 0.117 to 0.315 provides additional evidence for the robustness of this relationship. For *H3, t*he analysis demonstrates a significant positive relationship between perceived ease of use and perceived usefulness, with a beta coefficient of 0.392, a t-statistic of 7.663, and a p-value of 0.000. This result supports the hypothesis that as perceived ease of use increases, perceived usefulness also increases. The 95% confidence interval of 0.288 to 0.487 further strengthens the confidence in this relationship. For *H4, t*he results indicate a significant positive relationship between self-efficacy and acceptance, with a beta coefficient of 0.380, a t-statistic of 8.843, and a p-value of 0.000. This finding supports the hypothesis that as self-efficacy increases, acceptance also increases. The 95% confidence interval of 0.294 to 0.463 provides additional evidence for the strength of this relationship. For *H5, t*he analysis reveals a significant indirect relationship between perceived ease of use and acceptance through self-efficacy, with a beta coefficient of 0.083, a t-statistic of 3.950, and a p-value of 0.000. This result supports the hypothesis that self-efficacy mediates the relationship between perceived ease of use and acceptance. The 95% confidence interval of 0.045 to 0.128 further reinforces the significance of this indirect relationship.

For *H6, t*he results indicate a significant positive relationship between perceived ease of use and attitude, with a beta coefficient of 0.213, a t-statistic of 4.658, and a p-value of 0.000. This finding supports the hypothesis that as perceived ease of use increases, attitude also improves. The 95% confidence interval of 0.123 to 0.302 provides additional evidence for the strength of this relationship. For *H7, t*he analysis demonstrates a significant positive relationship between attitude and acceptance, with a beta coefficient of 0.214, a t-statistic of 3.616, and a p-value of 0.000. This result supports the hypothesis that as attitude improves, acceptance also increases. The 95% confidence interval of 0.096 to 0.330 further strengthens the confidence in this relationship. For *H8, t*he results reveal a significant indirect relationship between perceived ease of use and acceptance through attitude, with a beta coefficient of 0.046, a t-statistic of 3.210, and a p-value of 0.001. This finding supports the hypothesis that attitude mediates the relationship between perceived ease of use and acceptance. The 95% confidence interval of 0.022 to 0.078 provides additional evidence for the significance of this indirect relationship. For *H9, t*he analysis does not support a significant direct relationship between perceived usefulness and acceptance, with a beta coefficient of 0.082, a t-statistic of 1.440, and a p-value of 0.150. This result leads to the rejection of the hypothesis that as perceived usefulness increases, acceptance also increases. The 95% confidence interval of -0.029 to 0.192 confirms the lack of a significant direct relationship between these variables. For *H10, t*he results indicate a significant positive relationship between perceived usefulness and self-efficacy, with a beta coefficient of 0.390, a t-statistic of 7.925, and a p-value of 0.000. This finding supports the hypothesis that as perceived usefulness increases, self-efficacy also improves. The 95% confidence interval of 0.288 to 0.480 provides additional evidence for the strength of this relationship.

For *H11, t*he analysis reveals a significant indirect relationship between perceived usefulness and acceptance through self-efficacy, with a beta coefficient of 0.148, a t-statistic of 5.597, and a p-value of 0.000. This result supports the hypothesis that self-efficacy mediates the relationship between perceived usefulness and acceptance. The 95% confidence interval of 0.100 to 0.203 further reinforces the significance of this indirect relationship. For *H12, t*he results indicate a significant positive relationship between perceived usefulness and attitude, with a beta coefficient of 0.565, a t-statistic of 14.643, and a p-value of 0.000. This finding supports the hypothesis that as perceived usefulness increases, attitude also improves. The 95% confidence interval of 0.482 to 0.635 provides additional evidence for the strength of this relationship. For *H13, t*he analysis reveals a significant indirect relationship between perceived usefulness and acceptance through attitude, with a beta coefficient of 0.121, a t-statistic of 3.416, and a p-value of 0.001. This result supports the hypothesis that attitude mediates the relationship between perceived usefulness and acceptance. The 95% confidence interval of 0.053 to 0.192 further reinforces the significance of this indirect relationship.

Table 4
Hypotheses Testing Results

Hypotheses	Beta	T statistics	P values	2.5%	97.5%	Decision
H1: PEU -> ACC	0.226	4.753	0.000	0.130	0.314	*Accepted*
H2: PEU -> SE	0.218	4.372	0.000	0.117	0.315	*Accepted*
H3: PEU -> PU	0.392	7.663	0.000	0.288	0.487	*Accepted*
H4: SE -> ACC	0.380	8.843	0.000	0.294	0.463	*Accepted*
H5: PEU -> SE -> ACC	0.083	3.950	0.000	0.045	0.128	*Accepted*
H6: PEU -> ATT	0.213	4.658	0.000	0.123	0.302	*Accepted*
H7: ATT -> ACC	0.214	3.616	0.000	0.096	0.330	*Accepted*
H8: PEU -> ATT -> ACC	0.046	3.210	0.001	0.022	0.078	*Accepted*
H9: PU -> ACC	0.082	1.440	0.150	-0.029	0.192	*Rejected*
H10: PU -> SE	0.390	7.925	0.000	0.288	0.480	*Accepted*
H11: PU -> SE -> ACC	0.148	5.597	0.000	0.100	0.203	*Accepted*
H12: PU -> ATT	0.565	14.643	0.000	0.482	0.635	*Accepted*
H13: PU -> ATT -> ACC	0.121	3.416	0.001	0.053	0.192	*Accepted*

Table 5 provides a comprehensive summary of effect sizes and collinearity outcomes, with effect sizes measured independently of sample size according to Cohen's criteria (1992): small (0.020 to 0.150), medium (0.150 to 0.350), or large (0.350 or greater). The observed effect sizes ranged from small (0.007) to large (0.499), indicating varying degrees of practical significance. Variance Inflation Factor (VIF) values, as detailed in Table 5, consistently remained below the more lenient threshold of 5, with the highest value recorded at 1.943. This level of collinearity facilitates meaningful comparisons of effect sizes and the interpretation of coefficients within the structural model, as multicollinearity is not a concern. The model demonstrates an appreciable degree of explained variance for the endogenous construct, with an R^2 value of 0.500 (refer to Figure 1). This suggests that the exogenous variables in the model account for approximately 50.0% of the variance in the dependent variable. The model explains a substantial portion of the variance for the mediator constructs, with R^2 values of 0.459 for self-efficacy and 0.267 for attitude. These R^2 values indicate that the model explains 45.9% and 26.7% of the variance in self-efficacy and attitude, respectively.

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

	f^2				VIF			
	ACC	ATT	PEU	SE	ACC	ATT	PEU	SE
ATT	0.047				1.943			
PEU	0.078	0.071		0.055	1.304	1.182		1.182
PU	0.007	0.499	0.182	0.175	1.858	1.182	1.163	1.182
SE	0.201				1.433			

The model's ability to make inferences and provide managerial insights was evaluated using the PLSpredict method, as outlined by Shmueli et al. (2016, 2019). Table 6 illustrates the results of out-of-sample predictive analysis, where Q^2 predictions exceeding 0 indicate superior performance compared to standard naive mean predictions. Furthermore, the root mean square error (RMSE) values for PLS-SEM predictions consistently outperformed those of the linear model (LM) prediction benchmark in eleven out of fifteen instances, emphasising the predictive effectiveness of the proposed model (Table 6). Hair et al. (2022) introduced the Cross-Validated Predictive Ability Test (CVPAT) as a crucial element in assessing the predictive prowess of PLS-SEM outcomes. Liengaard et al. (2021) evaluated the model's predictive performance using a CVPAT with PLSpredict analysis. The CVPAT employed an out-of-sample prediction method, gauging the model's prediction error and computing the average loss value. Two benchmarks were utilised for comparison: the average loss value of predictions using indicator averages (IA) as a straightforward benchmark and the average loss value of a linear model (LM) forecast as a more conservative benchmark. To establish the model's superior predictive capabilities over the benchmarks, the average loss value of PLS-SEM should be lower, resulting in a negative difference in average loss values. The objective of the CVPAT was to ascertain whether the difference in average loss values between PLS-SEM and the benchmarks significantly fell below zero. As detailed in Table 7, the outcomes affirm that the average loss value of PLS-SEM was lower than that of the benchmarks, manifested by the negative difference in average loss values, validating the model's enhanced predictive capacities.

Table 6
PLSpredicts

Indicators	Q^2predict	PLS-RMSE	LM-RMSE	PLS-LM
ACC1	0.138	0.672	0.676	-0.004
ACC2	0.153	0.661	0.652	0.009
ACC3	0.178	0.727	0.731	-0.004
ACC4	0.13	0.752	0.747	0.005
ATT1	0.09	0.704	0.706	-0.002
ATT2	0.066	0.658	0.661	-0.003
ATT3	0.111	0.639	0.643	-0.004
ATT4	0.109	0.699	0.702	-0.003
ATT5	0.103	0.783	0.785	-0.002
PU1	0.059	0.797	0.801	-0.004
PU2	0.101	0.778	0.782	-0.004
PU3	0.137	0.739	0.745	-0.006
PU4	0.089	0.851	0.855	-0.004
PU5	0.036	0.747	0.748	-0.001
SE1	0.101	0.664	0.667	-0.003
SE2	0.054	0.66	0.662	-0.002
SE3	0.064	0.686	0.685	0.001
SE4	0.092	0.684	0.681	0.003
SE5	0.081	0.657	0.663	-0.006

Table 7
Cross-Validated Predictive Ability Test (CVPAT)

Constructs	Average loss difference	t-value	p-value
ACC	-0.088	4.33	0.000
ATT	-0.052	3.984	0.000
PU	-0.057	3.372	0.001
SE	-0.038	3.202	0.001
Overall	-0.057	4.721	0.000

Ringle and Sarstedt (2016) and Hair et al. (2018) advocate for the application of Importance Performance Analysis (IPMA) to assess the significance and effectiveness of latent variables in explaining acceptance. The results of this analysis are detailed in Table 8. In terms of the overall impact on acceptance, perceived ease of use demonstrated the most substantial influence (0.492), followed by self-efficacy (0.380), perceived usefulness (0.351), and attitude (0.214). These values provide insights into the relative importance of each latent variable in the context of acceptance. When considering performance scores, perceived usefulness achieved the highest (66.539), while self-efficacy obtained the lowest (60.676) on a scale ranging from 0 to 100. This suggests that perceived usefulness exhibited relatively strong performance, whereas self-efficacy showed the lowest level of achievement. Based on these findings, it is recommended that employees prioritise efforts to enhance their self-efficacy. An overall enhancement in acceptance levels can be expected by improving self-efficacy.

Table 8
Importance-Performance Map Analysis

Constructs	Total Effect	Performance
ATT	0.214	65.888
PEU	0.492	66.534
PU	0.351	66.539
SE	0.380	60.676

Discussion

Digital higher education institutions can formulate strategies to ensure the practical impact of perceived ease of use and perceived usefulness on acceptance of artificial intelligence-enabled transformation among employees by focusing on self-efficacy and attitude as mediators. The research findings suggest that perceived ease of use and usefulness influence the acceptance of AI-enabled transformation. To enhance perceived ease of use, institutions can provide training programs and online support to familiarise employees with AI technologies, making them more user-friendly and accessible. This can include clear instructions, easy-to-use interfaces, and the ability to load and upload information efficiently (Rahman & Kodikal, 2024). Institutions can also emphasise the perceived usefulness of AI technologies by highlighting their benefits, such as increased efficiency, improved accuracy, and enhanced decision-making capabilities. This can be achieved through demonstrations, workshops, and success stories that showcase AI's practical applications and advantages in the educational setting. Self-efficacy plays a significant role in mediating the relationship between perceived ease of use and perceived usefulness and acceptance. Institutions can foster self-efficacy by providing opportunities for employees to develop their skills and abilities in using AI technologies. This can include mentorship programs, online tutorials, and hands-on experience with AI tools. By building employees' confidence in their ability to use AI, institutions can increase their willingness to adopt and utilise these technologies (Zwacki-Ritcher et al., 2019). Attitude is another critical mediator that can influence the acceptance of AI-enabled transformation. Institutions can shape a positive attitude towards AI by promoting a culture of innovation and experimentation. This can involve recognising and rewarding employees who successfully integrate AI into their work and providing a supportive environment that encourages exploration and learning. In conclusion, by focusing on self-efficacy and attitude as mediators, digital higher education institutions can ensure the practical impact of perceived ease of use and perceived usefulness on acceptance of AI-enabled transformation. By providing training and support, highlighting the benefits of AI, fostering self-efficacy, and promoting a positive attitude, institutions can increase the adoption and utilisation of AI technologies among employees, ultimately enhancing the overall effectiveness of AI-enabled transformation.

Theoretical Implications

The theoretical implications of the studies highlighted in the provided sources offer valuable insights into the dynamics of artificial intelligence-enabled transformation acceptance among employees in Higher Education Institutions (HEIs), particularly about the Technology Acceptance Model (TAM). Identifying perceived usefulness, perceived ease of use, and technological innovativeness as pivotal factors aligns with the TAM's core tenets, emphasising these constructs' importance in predicting technology adoption. By expanding on these theoretical foundations, the studies shed light on the nuanced interplay of these factors within the context of higher education, providing a deeper understanding of how these variables influence the acceptance of AI-enabled transformation. The prominence of perceived ease of use, which underscores the significance of user-friendly interfaces and streamlined processes, resonates with the TAM's emphasis on perceived ease of use as a critical determinant of technology adoption. Additionally, introducing attitude as a mediator in the acceptance process further enriches the TAM framework by highlighting the role of employees' overall disposition in shaping their acceptance of AI-enabled transformation initiatives. This inclusion of attitude as a mediator aligns with the TAM's focus on the influence of external variables on technology acceptance. In essence, these theoretical implications advance our understanding of artificial intelligence-enabled transformation acceptance and contribute to the refinement and application of the Technology Acceptance Model in the context of higher education institutions. By elucidating the interrelationships between perceived usefulness, ease of use, technological innovativeness, and attitude, these studies provide a comprehensive foundation for future research and strategic initiatives to navigate the transformative landscape of artificial intelligence-enabled transformation in higher education.

Practical Implications

The practical implications of the studies on artificial intelligence-enabled transformation acceptance among employees in Higher Education Institutions (HEIs) offer valuable insights for institutional leaders and policymakers. The findings underscore the importance of addressing perceived ease of use, perceived usefulness, and technological innovativeness to foster successful AI adoption. Institutions can enhance perceived ease of use by providing comprehensive training programs and online support, ensuring employees have the necessary skills and knowledge to navigate AI technologies effectively. This can involve creating user-friendly interfaces, offering clear instructions, and facilitating efficient data management processes. To emphasise the perceived usefulness of AI, institutions should highlight the tangible benefits of these technologies, such as improved efficiency, enhanced decision-making, and increased accuracy. Showcasing real-world success stories and organising demonstrations can help employees visualise the practical applications of AI in their daily work. Fostering self-efficacy is another crucial aspect, as it directly influences employees' willingness to adopt AI. Mentorship programs, online tutorials, and hands-on experience can boost employees' confidence in AI tools, ultimately increasing their acceptance of AI-enabled transformation. Lastly, institutions should promote a positive attitude towards AI by creating a culture of innovation and experimentation. This can be achieved by recognising and rewarding employees who successfully integrate AI into their work while providing a supportive environment that encourages exploration and learning. By addressing these practical implications, HEIs can effectively navigate the challenges associated with AI adoption and maximise the transformative potential of these technologies in the educational landscape.

Suggestions for Future Study

Building on the study's findings on artificial intelligence-enabled transformation acceptance in Higher Education Institutions (HEIs), future research could explore the longitudinal effects of interventions to enhance perceived ease of use, perceived usefulness, self-efficacy, and attitude towards AI technologies. Long-term studies could provide valuable insights into the sustainability of these interventions and their impact on employees' acceptance of AI-enabled transformation over time. Additionally, investigating the role of organisational culture, leadership support, and change management strategies in facilitating AI adoption in HEIs could offer a comprehensive understanding of the contextual factors influencing technology acceptance. Exploring the perspectives of different stakeholders, such as students, administrators, and IT professionals, could also provide a more holistic view of the challenges and opportunities associated with AI implementation in higher education settings.

Conclusion

The study on artificial intelligence-enabled transformation acceptance among employees in Higher Education Institutions (HEIs) highlights the critical role of perceived ease of use, usefulness, self-efficacy, and attitude in shaping the successful adoption of AI technologies. By addressing these factors through targeted interventions, such as providing comprehensive training, emphasising the benefits of AI, fostering self-efficacy, and promoting a positive attitude towards innovation, HEIs can enhance the acceptance and utilisation of AI-enabled transformation initiatives. The findings of this study offer valuable insights for institutional leaders and policymakers, guiding them in navigating the challenges and opportunities associated with integrating artificial intelligence in higher education settings.

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