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Enhancing Artificial Intelligence-Enabled Transformation Acceptance among Employees of Higher Education Institutions

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Abstract

This study aims to the direct relationship between perceived usefulness, perceived ease of use, technological innovativeness, and acceptance with self-efficacy as a mediator among employees in higher education institutions. To collect primary data, a thorough survey was designed and conducted based on previous research. Structural equation modeling, known for its ability to analyze complex interactions between variables, was used to analyze a comprehensive data set of 422 responses, and convergent and discriminant validity was confirmed. Evaluation of the structural model crucially confirmed the hypotheses and revealed nine direct relationships and four mediated relationships. The findings reveal that perceived usefulness, perceived ease of use, and technological innovativeness significantly influence artificial intelligence-enabled transformation acceptance, with attitude serving as a crucial mediator. Notably, perceived ease of use emerges as the most impactful factor, emphasizing the need for user-friendly interfaces and streamlined processes. The study demonstrates the relative importance of each latent variable in shaping acceptance, providing practical implications for HEIs. The results underscore the need for targeted interventions to enhance technological innovativeness and the cultivation of a positive attitude among employees. Moreover, the research contributes to theoretical frameworks by integrating attitude as a mediator, enriching our understanding of artificial intelligence-enabled transformation acceptance dynamics. Contextually, the study highlights the importance of organizational climate and culture in fostering a conducive environment for technological innovation. Future studies are suggested to adopt longitudinal designs, cross-cultural analyses, and intervention strategies, ensuring a comprehensive exploration of AI-ET acceptance and facilitating successful integration in the ever-evolving landscape of higher education.

Keywords: Perceived Usefulness, Perceived Ease of Use, Technological Innovativeness, Attitude, Acceptance

Introduction

The integration of artificial intelligence (AI) into online distance learning has gained wide acceptance among higher education professionals around the world. The use of AI technology improves teaching methods, personalizes learning experiences, and streamlines administrative tasks (George & Wooden, 2023). This transformation promotes efficiency, accessibility, and adaptability, and positively impacts educators and staff. As educational institutions harness the potential of AI, employees are recognizing their role in shaping the future of education and fostering a culture of innovation and collaboration that benefits students in online higher education (Cantú-Ortiz et al., 2020). Educators around the world are increasingly recognizing the benefits of AI in online distance learning. Seamless integration of AI tools improves instructional design, drives data-driven decision-making, and supports personalized student engagement (Okunlaya et al., 2022). This widespread adoption represents a major shift in the perception of AI, as educators realize the technology's transformative role in shaping the higher education landscape. Acceptance of artificial intelligence transformation refers to the willingness, awareness, and positive acceptance of the integration of artificial intelligence (AI) technology in a particular context or industry (Kuleto et al., 2021). In the context of higher education, this acceptance means that educators, staff, and other stakeholders adopt and leverage AI tools and technologies to bring about transformative changes in the way education is delivered, managed, and experienced. It suggests that you are positive about this (Jaiswal & Arun, 2021). In the Malaysian context, the adoption of artificial intelligence (AI) in online distance learning is gaining momentum among higher education personnel. Recognizing the potential for educational innovation, Malaysian educational institutions are increasingly incorporating AI into their teaching approaches (Ashaari et al., 2021). Technology's ability to personalize learning experiences, automate administrative tasks, and provide data-driven insights is resonating with faculty. This acceptance is supported by the recognition that AI can address the unique challenges of the Malaysian higher education environment, such as the diversity of the student population and the evolving needs of the industry (Chik & Ariokasamy, 2019). The introduction of AI will foster a culture of adaptability and technical competency in the workforce, putting Malaysia at the forefront of AI-powered education. The transformative power of AI has become an integral part of higher education in Malaysia, contributing to a dynamic and forward-thinking education ecosystem, as educators realize measurable improvements in student outcomes and institutional efficiency (Jamaludin et al., 2020).

Artificial intelligence (AI) integration in higher education institutions encounters resistance and acceptance challenges among employees, including faculty and administrative staff. One prominent issue is the fear of job displacement due to the misconception that AI will replace human roles (Jamaludin et al., 2020). This apprehension often leads to reluctance to embrace AI-enabled transformations, hindering realizing the technology's potential benefits. Moreover, there exists a significant skills gap among employees, with many lacking the necessary training and expertise to navigate and leverage AI tools effectively. The unfamiliarity with AI applications in teaching, research, and administrative tasks creates a barrier to acceptance, as employees may perceive AI as a threat rather than a valuable asset. Cultural factors within academic institutions also contribute to the resistance against AI adoption (Rosli & Saleh, 2023). Traditional approaches to teaching and research are deeply ingrained, and the shift towards AI-enabled methodologies requires a cultural shift that is often met with skepticism. The need for ongoing professional development and educational programs to enhance AI literacy becomes crucial to bridging this gap. To foster acceptance, higher education institutions must prioritize comprehensive training programs, establish a supportive organizational culture, and communicate the benefits of AI integration in improving efficiency, enhancing research capabilities, and advancing educational outcomes (Saidi et al., 2022). Addressing these challenges is pivotal to realizing the full potential of AI in higher education. This study demonstrates the direct relationship between perceived usefulness, perceived ease of use, technological innovativeness, and acceptance with self-efficacy as a mediator among employees in higher education institutions.

Literature Review

Underpinning Theory

The Technology Acceptance Model (TAM) provides a robust theoretical framework to underpin the study examining the acceptance of artificial intelligence (AI)-enabled transformation among employees in higher education institutions. Developed by Davis(1989), TAM posits that an individual's intention to use technology is determined by two key factors: perceived usefulness and perceived ease of use. In the context of AI-enabled transformation, perceived usefulness refers to the belief that utilizing AI technologies will enhance job performance, efficiency, or overall effectiveness in an academic setting. Perceived ease of use, on the other hand, relates to the individual's perception of the simplicity and user-friendliness of the AI applications. Additionally, TAM incorporates the crucial element of attitude towards technology use, reflecting an individual's overall positive or negative evaluation of adopting AI-enabled tools. Considering the multifaceted nature of your study, TAM's applicability extends to capturing the influence of self-efficacy, technological innovativeness, and adaptability to change on employees' acceptance of AI. By leveraging TAM, the study can systematically analyze how these factors interplay, providing valuable insights into the determinants of AI acceptance within the unique context of higher education institutions.

Relationship between Perceived Usefulness, Attitude, and Acceptance

In the realm of higher education, particularly in online distance learning institutions, the relationship between perceived usefulness, attitude, and acceptance of artificial intelligence (AI)-enabled transformation is complex and multifaceted (Tennakoon et al., 2023). Perceived usefulness refers to an individual's belief in the effectiveness of AI tools in enhancing educational processes (Keržič et al., 2019). A positive attitude toward these tools is pivotal, as it influences the overall acceptance of AI-enabled transformations. The direct relationship between perceived usefulness and acceptance is evident when individuals recognize the practical benefits AI brings to education—personalized learning, streamlined administrative tasks, and data-driven decision-making (Alkindi et al., 2022). A positive attitude towards AI fosters a smoother acceptance process. Educators who perceive AI as a valuable asset are more likely to embrace its integration into their teaching methodologies. When educators have a favorable view of AI's utility, this positive attitude becomes a driving force influencing their acceptance of AI-enabled transformations (Ajibade & Zaaidi, 2023). The interplay between these factors is crucial for successful implementation, as educators who perceive AI as useful and develop positive attitudes toward its role are more likely to integrate and accept these transformative technologies in higher education settings, particularly in the evolving landscape of online distance learning institutions (Kampa, 2023). Thus, the following hypotheses were proposed for this study:

H1: There is a relationship between perceived usefulness and attitude on acceptance among employees in higher education institutions
H2: There is a relationship between perceived usefulness and acceptance among employees in higher education institutions
H3: There is a mediating effect of attitude on the relationship between perceived usefulness and acceptance among employees in higher education institutions

Relationship between Perceived Ease of Use, Attitude, and Acceptance

The dynamic relationship between perceived ease of use, attitude, and the acceptance of artificial intelligence (AI)-)-enabled transformation is integral to the landscape of higher education, particularly within online distance learning institutions (Nuryakin et al., 2023). Perceived ease of use, representing an individual's perception of the simplicity and user-friendliness of AI tools, directly influences acceptance. A direct correlation exists between perceived ease of use and acceptance, as educators who find AI tools easy to use are more likely to embrace their integration into teaching practices (Tan et al., 2023). This positive correlation emphasizes the importance of user-friendly AI interfaces in fostering a smooth acceptance process. Additionally, there's an indirect relationship through the mediating factor of attitude. Positive attitudes toward AI act as a conduit between perceived ease of use and overall acceptance (Chahal & Rani, 2022). When educators perceive AI tools as easy to use, it positively shapes their attitude, contributing to a more favorable disposition towards the transformative potential of AI in education. Understanding these interconnected dynamics is essential for crafting effective strategies for AI implementation in higher education (Bansah & Darko Agyei, 2022). Ensuring the perceived ease of use of AI tools, coupled with cultivating positive attitudes, can collectively enhance the acceptance of AI-enabled transformations, particularly in the evolving landscape of online distance learning institutions. This nuanced approach supports a seamless integration of technology to enrich the educational experience (Saidi et al., 2022). Therefore, the following hypotheses were proposed for this study:

H4: There is a relationship between perceived ease of use and attitude toward acceptance among employees in higher education institutions
H5: There is a relationship between perceived ease of use and acceptance among employees in higher education institutions
H6: There is a mediating effect of attitude on the relationship between perceived Ease of use and acceptance among employees in higher education institutions

Relationship between Technological Innovativeness, Attitude, and Acceptance

The intricate relationship between technological innovativeness, attitude, and the acceptance of artificial intelligence (AI)-)-enabled transformation is crucial within higher education, especially in the realm of online distance learning institutions (Chahal & Rani, 2022). Technological innovativeness, representing one's inclination toward embracing new technologies, directly influences acceptance. Directly, a positive correlation exists between individual innovativeness and acceptance. Educators with a higher level of innovativeness are more likely to proactively accept and integrate AI tools into their teaching methodologies. This emphasizes the role of an individual's inherent innovative mindset in shaping their openness to technological transformations (Twum et al., 2022). Indirectly, technological innovativeness influences acceptance through the mediating factor of attitude. A positive attitude toward AI acts as a bridge between technological innovativeness and overall acceptance (Bubou & Job, 2022). Educators with a predisposition for innovation are more likely to develop positive attitudes toward the transformative potential of AI in education, fostering a more favorable disposition toward its acceptance (Salloum et al., 2023). Understanding these relationships is essential for crafting strategies that encourage the adoption of AI in higher education. Nurturing technological innovativeness, coupled with cultivating positive attitudes, contributes to a more seamless acceptance of AI-enabled transformations, particularly within the dynamic landscape of online distance learning institutions (Al-Adwan et al., 2023). This approach supports an environment where educators are not only open to change but actively seek innovative ways to enhance the educational experience through the integration of AI technologies (Awdziej, et al. 2023). Hence, the following hypotheses were proposed for this study:

H7: There is a relationship between technology innovativeness and attitude on acceptance among employees in higher education institutions
H8: There is a relationship between technology innovativeness and acceptance among employees in higher education institutions
H9: There is a relationship between attitude and acceptance among employees in higher education institutions
H10: There is a mediating effect of attitude on the relationship between technology innovativeness and acceptance among employees in higher education institutions

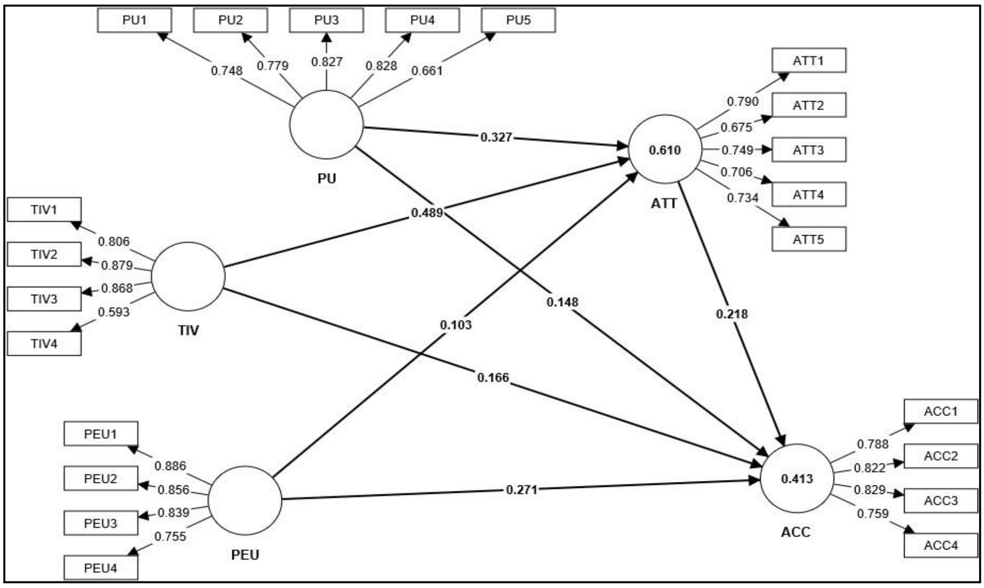

Figure 1: Research Model
Note: PU=Perceived Usefulness PEU=Perceived Ease of Use Technological Innovativeness ATT=Attitude ACC=Acceptance

Methodology
This research aimed to evaluate the performance of educators in public and private higher education institutions. To accomplish this goal, a survey was conducted to gather primary data, with a meticulous review of prior studies to identify reliable and valid metrics. The survey questionnaires were then sent via email to chosen participants, utilizing purposive

sampling due to the absence of a comprehensive population list. A total of 22 observed variables were examined, incorporating exogenous variables such as perceived usefulness (measured with 5 items) and perceived ease of use (measured with 4 items), both assessed by Shang et al (2011); and technological innovativeness, measured by 4 items (Son et al., 2019). The study's mediating variable, attitude, was assessed using 5 items according to Hair et al. (2019), while the dependent variable, acceptance, was appraised via 4 items based on (De Cannière et al., 2009). Each construct's elements were gauged using a Likert scale with five response choices, ranging from strongly disagree to strongly agree. Out of the 573 distributed surveys, 451 were collected, resulting in a response rate of 78.7%, deemed satisfactory for utilizing structural equation modeling (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 modeling (SEM) techniques. This choice was guided by the software's robust assessment capabilities and proficiency in handling multivariate data analysis, aligning seamlessly with the study's objectives and adhering to the guidelines outlined by (Ringle et al., 2022). Smartpls4 proved invaluable in effectively scrutinizing proposed hypotheses and conducting comprehensive multivariate data analysis, facilitating a thorough examination of both measurement and structural models. Table 1 depicts the profile of the respondents participate in this study.

Table 1
Respondents' Profiles

		Frequency	Percent
GENDER	MALE	259	61.4
	FEMALE	163	38.6
AGE	<30 YEARS OLD	30	7.1
	31 TO 40 YEARS OLD	99	23.5
	41 TO 50 YEARS OLD	172	40.8
	51 TO 60 YEARS OLD	84	19.9
	>60 YEARS OLD	37	8.8
YRSERV	<5 YEARS	25	5.9
	6-10 YEARS	57	13.5
	11-15 YEARS	128	30.3
	16-20 YEARS	121	28.7
	21-25 YEARS	50	11.8
	26-30 YEARS	20	4.7
	>30 YEARS	21	5.0
POSTLEVEL	ACADEMIC	339	80.3
	NON-ACADEMIC	83	19.7
EMPLOYER	PUBLIC HIGHER EDUCATION INSTITUTION	145	34.4
	PRIVATE HIGHER EDUCATION INSTITUTION	277	65.6
RECOMM	YES	415	98.3
	NO	7	1.7
	Total	422	100.0

Data Analysis

Common Method Bias

Kock (2015) introduced a comprehensive approach referred to as 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 common method bias concern within the model. 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. Table 2 illustrates that the VIFs resulting from the total collinearity evaluation were below 3.3, confirming the absence of any common method bias issue in the model (Kock, 2015; Kock & Lynn, 2012).

Table 2
Full Collinearity Test

	MACC	MPU	MATT	MTIV	MPEU
MACC		1.795	1.736	1.750	1.548
MPU	1.852		1.498	1.821	1.845
MATT	2.028	1.697		1.919	2.112
MTIV	1.769	1.784	1.661		1.759
MPEU	1.350	1.560	1.578	1.518	

Measurement Model
In this study, we adopted the methodology recommended by Hair et al (2017) to assess each measurement in both the first and second orders. This approach facilitates the identification of items with loadings falling below the 0.7 threshold. The analysis of construct reliability and validity unveiled that the Average Variance Extracted (AVE) for all constructs exhibited a range from 0.536 to 0.698, surpassing the 0.5 benchmark, thereby indicating well-established convergent validity Hair et al (2017) (Table 3). The composite reliability values for all constructs exceeded 0.7, ranging from 0.788 to 0.871. Furthermore, the Cronbach's alpha values for all constructs surpassed 0.7, ranging from 0.784 to 0.855 (refer to Table 3). To ensure discriminant validity, the initial step involved the assessment of cross-loadings to guarantee the appropriate representation and measurement of respective constructs (Table 3). Subsequently, the Hetrotrait-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). Table 4 provided the HTMT ratios, original sample, and 95% confidence intervals, confirming compliance with the HTMT threshold of 0.9. The bias-corrected and accelerated bootstrap confidence intervals were consistently below 1, reinforcing confidence in construct distinctiveness and their ability to measure distinct aspects of the phenomenon under scrutiny.

Table 3
Construct Reliability, Validity, Cross Loadings & HTMT

						HTMT			
Constructs	Indicators	ACC	CA	CR	AVE	ACC	ATT	PEU	PU
Acceptance	ACC1	0.788	0.813	0.818	0.64				
	ACC2	0.822							
	ACC3	0.829							
	ACC4	0.759							
Attitude	ATT1	0.790	0.784	0.788	0.536	0.676			
	ATT2	0.675							
	ATT3	0.749							
	ATT4	0.706							
	ATT5	0.734							
Perceived Ease of Use	PEU1	0.886	0.855	0.871	0.698	0.584	0.524		
	PEU2	0.856							
	PEU3	0.839							
	PEU4	0.755							
Perceived Usefulness	PU1	0.748	0.829	0.848	0.595	0.573	0.787	0.450	
	PU2	0.779							
	PU3	0.827							
	PU4	0.828							
	PU5	0.661							
Technological Innovativeness	TIV1	0.806	0.797	0.821	0.632	0.649	0.882	0.508	0.710
	TIV2	0.879							
	TIV3	0.868							
	TIV4	0.593							

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

Structural Model

In this study, the assessment of the structural model adhered to the methodology delineated by Hair et al (2017), concurrently examining pathway coefficients (β) and coefficients of determination (R2). The Partial Least Squares (PLS) method was applied, utilizing 5000 subsamples to establish the significance level of path coefficients. The outcomes of hypothesis tests, encompassing 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. For *H1*, the perceived usefulness significantly influences attitude (Beta = 0.327, T = 7.533, p = 0.000), supporting the hypothesis. Similarly, for *H2*, perceived usefulness positively impacts acceptance (Beta = 0.148, T = 2.427, p = 0.015), indicating support. *H3*, confirming attitude has a mediating effect on the relationship between perceived usefulness and acceptance, therefore the hypothesis is supported (Beta = 0.071, T = 2.905, p = 0.004). *H4* demonstrates that perceived ease of use influences attitude (Beta = 0.103, T = 2.502, p = 0.012), supporting the hypothesis. Additionally, *H5* indicates a significant positive impact of perceived ease of use on acceptance (Beta = 0.271, T = 5.447, p = 0.000). *H6*, confirming attitude has a mediating effect on the relationship between perceived ease of use and acceptance, therefore the hypothesis is supported (Beta = 0.023, T = 2.126, p = 0.034). *H7* reveals a substantial effect of technological innovativeness on attitude (Beta = 0.489, T = 11.298, p = 0.000), supporting the hypothesis. *H8* suggests a positive impact of technological innovativeness on acceptance (Beta = 0.166, T = 2.563, p = 0.010). *H9* demonstrates a significant influence of attitude on acceptance (Beta = 0.218, T = 3.210, p = 0.001). Finally, *H10*, confirming attitude has a mediating effect on the relationship between technological innovativeness and acceptance, therefore the hypothesis is supported (Beta = 0.107, T = 3.065, p = 0.002). Overall, the findings consistently support the formulated hypotheses, emphasizing the robust relationships among perceived usefulness, perceived ease of use, technological innovativeness, attitude, and acceptance.

Table 5 furnishes a comprehensive compilation of effect sizes and collinearity outcomes, encompassing effect sizes gauged 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 spanned from small (0.020) to large (0.382). Varied Value Inflation Factor (VIF) values, as detailed in Table 5, consistently remained below the more lenient threshold of 5, with the highest value recorded at 2.561. This level of collinearity facilitates meaningful comparisons of sizes and the interpretation of coefficients within the structural model. An appreciable degree of explained variance for the endogenous construct is discernible, with an R^2 value of 0.413 (refer to Figure 1). Regarding the mediator, the model elucidated approximately 61% of the variance in the structure, evidenced by an R^2 value of 0.610.

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 surpassing 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 seven out of nine instances, emphasizing 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 by conducting a CVPAT in conjunction 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 utilized 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. The outcomes, as detailed in Table 7, affirm that the average loss value of PLS-SEM was indeed lower than that of the benchmarks, manifested by the negative difference in average loss values, validating the model's enhanced predictive capacities.

Ringle and Sarstedt (2016); Hair et al (2018) propose the utilization of Importance Performance Analysis (IPMA) to evaluate the significance and effectiveness of latent variables in elucidating acceptance. The outcomes of this analysis are outlined in Table 8. Regarding overall impact, the most substantial influence on acceptance was associated with perceived ease of use (0.294), succeeded by technological innovativeness (0.272), perceived usefulness (0.219), and attitude (0.218). These values delineate the relative importance of each latent variable within the context of acceptance. In terms of performance scores, perceived ease of use garnered the highest score (66.533), while technological innovativeness recorded the lowest score (62.752) on a scale extending from 0 to 100. This implies that perceived ease of use exhibited relatively strong performance, whereas technological innovativeness achieved the lowest level of accomplishment. In light of these findings, it is recommended that working adults prioritize and accentuate endeavors aimed at enhancing their technological innovativeness. By concentrating on improving technological innovativeness, an overall enhancement in acceptance can be anticipated.

Table 4
Hypothesis Testing Results

Hypotheses	Beta	T statistics	P values	2.50%	97.50%	Decision
DecisionH1: PU -> ATT	0.327	7.533	0.000	0.240	0.410	*Supported*
H2: PU -> ACC	0.148	2.427	0.015	0.029	0.264	*Supported*
H3: PU -> ATT -> ACC	0.071	2.905	0.004	0.027	0.123	*Supported*
H4: PEU -> ATT	0.103	2.502	0.012	0.021	0.184	*Supported*
H5: PEU -> ACC	0.271	5.447	0.000	0.173	0.366	*Supported*
H6: PEU -> ATT -> ACC	0.023	2.126	0.034	0.006	0.049	*Supported*
H7: TIV -> ATT	0.489	11.298	0.000	0.400	0.572	*Supported*
H8: TIV -> ACC	0.166	2.563	0.010	0.039	0.296	*Supported*
H9: ATT -> ACC	0.218	3.210	0.001	0.081	0.346	*Supported*
H10: TIV -> ATT -> ACC	0.107	3.065	0.002	0.042	0.178	*Supported*

Table 5
Effect Size & VIF

Path	f^2	VIF
PU -> ATT	0.176	1.557
PU -> ACC	0.020	1.831
PEU -> ATT	0.022	1.266
PEU -> ACC	0.097	1.293
TIV -> ATT	0.382	1.602
TIV -> ACC	0.021	2.214
ATT -> ACC	0.032	2.561

Table 6
PLSpredicts

Indicator	Q^2predict	PLS-RMSE	LM_RMSE	PLS-LM
ACC1	0.271	0.622	0.594	0.028
ACC2	0.250	0.607	0.609	-0.002
ACC3	0.273	0.683	0.692	-0.009
ACC4	0.153	0.729	0.731	-0.002
ATT1	0.326	0.606	0.608	-0.002
ATT2	0.198	0.610	0.616	-0.006
ATT3	0.225	0.596	0.599	-0.003
ATT4	0.321	0.611	0.617	-0.006
ATT5	0.469	0.602	0.523	0.079

Table 7
Cross Validated Predictive Ability Test (CVPAT)

	Average loss difference	t-value	p-value
ACC	-0.137	6.043	0.000
ATT	-0.174	9.547	0.000
Overall	-0.158	9.501	0.000

Table 8
Importance-Performance Map Analysis

	Total Effect	Performance
ATT	0.218	65.774
PEU	0.294	66.533
PU	0.219	66.482
TIV	0.272	62.752

Discussion & Conclusion

The study's findings shed light on the intricate dynamics influencing the acceptance of artificial intelligence-enabled transformation among employees in Higher Education Institutions, emphasizing the crucial roles of perceived usefulness, perceived ease of use, and technological innovativeness, with attitude serving as a mediator. Perceived usefulness, a fundamental determinant, emerges as a significant driver with a coefficient of 0.219. This implies that when employees perceive artificial intelligence-enabled transformation as beneficial to their tasks and objectives, they are more likely to embrace the transformation. The study underscores the importance of emphasizing the practical advantages of artificial intelligence-enabled transformation to elicit positive perceptions among employees. Moreover, the impact of perceived ease of use cannot be overstated, as it exerts the most substantial influence on acceptance, with a coefficient of 0.294. This highlights the need for intuitive and user-friendly interfaces, streamlined processes, and comprehensive training to enhance employees' comfort and proficiency in engaging with artificial intelligence-enabled transformation tools. Creating an environment that fosters ease of use is pivotal for overcoming resistance and fostering a culture of acceptance. Technological innovativeness, although slightly lower in impact with a coefficient of 0.272, remains a critical factor. This underscores the importance of showcasing the innovative aspects of artificial intelligence-enabled transformation initiatives, stimulating curiosity and a forward-looking mindset among employees. Investments in training programs, workshops, and technological upskilling opportunities can contribute significantly to bolstering the perception of technological innovativeness. Crucially, the study identifies attitude as a mediator, emphasizing the role of employees' overall disposition in shaping their acceptance. A positive attitude, cultivated through effective communication, change management strategies, and addressing concerns, acts as a catalyst, smoothing the transition and fostering a more favorable outlook toward artificial intelligence-enabled transformation. In conclusion, a holistic approach that integrates perceived usefulness, ease of use, and technological innovativeness, with a focus on cultivating a positive attitude, can efficiently propel the acceptance of artificial intelligence-enabled transformation among employees in Higher Education Institutions.

Theoretical Implications

The theoretical implications derived from the aforementioned study are substantial, offering valuable insights into the dynamics of artificial intelligence-enabled transformation artificial intelligence-enabled transformation acceptance among employees in Higher Education Institutions. The identification of perceived usefulness, perceived ease of use, and technological innovativeness as pivotal factors aligns with the Technology Acceptance Model (TAM) and the Innovation Diffusion Theory (IDT). The study expands on these theoretical foundations by highlighting the nuanced interplay of these factors within the context of higher education. The prominence of perceived ease of use, emphasizing user-friendly interfaces and streamlined processes, resonates with the TAM's emphasis on perceived ease of use as a key predictor of technology adoption. The study's findings also contribute to the burgeoning literature on technology acceptance by incorporating the mediator role of attitude. The theoretical implications underscore the significance of cultivating a positive attitude toward artificial intelligence-enabled transformation initiatives to facilitate a more seamless acceptance process. In essence, the study enriches theoretical frameworks by refining our understanding of artificial intelligence-enabled transformation acceptance factors, offering a nuanced perspective on their interrelationships, and introducing attitude as a critical mediator. This not only advances theoretical discourse but also provides a comprehensive foundation for future research and strategic initiatives aiming to navigate the transformative landscape of artificial intelligence-enabled transformation in higher education.

Contextual Implications

The contextual implications stemming from the study hold significant relevance for Higher Education Institutions (HEIs) embarking on Artificial Intelligence-Enabled Transformation (AI-ET) initiatives. Understanding the interplay of perceived usefulness, perceived ease of use, technological innovativeness, and the mediating role of attitude provides practical insights for institutional leaders and policymakers. Firstly, the emphasis on perceived ease of use implies that HEIs should prioritize user-friendly interfaces, intuitive systems, and comprehensive training programs. This highlights the need for strategic investments in enhancing the user experience to overcome potential resistance and promote the seamless integration of AI-ET tools into daily operations. Secondly, acknowledging the role of technological innovativeness underscores the importance of cultivating a culture of innovation within HEIs. Encouraging a forward-looking mindset, fostering a technologically adept workforce, and showcasing the innovative aspects of AI-ET initiatives can contribute to a more positive reception among employees. Additionally, recognizing attitude as a mediator highlights the significance of change management strategies. Clear communication, addressing concerns, and fostering a positive organizational culture can facilitate a favorable attitude toward AI-ET, ultimately influencing its successful acceptance. In practical terms, HEIs should consider tailor-made training programs, communication strategies, and organizational policies that align with the identified factors influencing AI-ET acceptance. These contextual implications offer practical guidance for institutions navigating the complexities of incorporating artificial intelligence in higher education contexts.

Suggestions for Future Studies

Future studies in the realm of artificial intelligence-enabled transformation acceptance among employees in Higher Education Institutions (HEIs) could delve into several promising avenues. Longitudinal research designs would enhance our understanding of the temporal

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evolution of acceptance, tracking changes over time. Comparative analyses across different educational levels within HEIs could uncover nuanced differences in attitudes and perceptions. Cross-cultural studies would provide insights into how cultural factors influence artificial intelligence-enabled transformation acceptance. Exploring the impact of educational interventions and training programs on perceived ease of use and acceptance can guide institutions in addressing potential barriers. Investigating factors contributing to resistance against artificial intelligence-enabled transformation, integrating principles from Human-Computer Interaction (HCI), and exploring ethical considerations would contribute to a comprehensive understanding of acceptance dynamics. Additionally, focusing on the development and testing of intervention strategies, incorporating user feedback mechanisms, and evaluating the actual impact of artificial intelligence-enabled transformation on educational outcomes can inform evidence-based decision-making and foster successful AI integration in the higher education landscape.

Conclusion

The study provides valuable insights into the acceptance of artificial intelligence-enabled transformation among employees in Higher Education Institutions. Guided by established frameworks, the research emphasizes the pivotal roles of perceived usefulness, perceived ease of use, and technological innovativeness, with attitude serving as a mediator. The findings underscore the significance of fostering a positive attitude and cultivating a user-friendly environment to enhance intelligence-enabled transformation acceptance. The theoretical and contextual implications contribute to our understanding of technology adoption in educational settings.

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