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Drivers of Artificial Intelligence Usage in Teaching Among Academicians in Higher Education Institutions

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Abstract

Artificial intelligence (AI) has emerged as a revolutionary influence within higher education, presenting substantial potential for educators. Through harnessing AI's capabilities, researchers acquire advanced tools for tasks such as data analysis, predicting trends, and generating innovative insights. This investigation undertakes a comprehensive exploration of the intricate relationships between attitude, perceived utility, trust, intention, and AI utilization in the academic sphere. The research framework encompasses three distinct variables: attitude, perceived usefulness, and trust. Intention functions as an intermediary among these factors, while usage stands as the dependent variable, reflecting the practical integration of AI in educational practices. To achieve a comprehensive perspective, primary data was meticulously gathered using a survey method informed by established research paradigms. Employing structural equation modeling on a robust dataset of 362 responses, intricate associations were analyzed to ensure a thorough evaluation. Via this rigorous methodology, the study not only substantiated the convergence and differentiation validity of the constructs but also corroborated hypotheses, revealing seven direct relationships and

two mediating connections. These empirical discoveries underscore the central importance of attitude, perceived utility, and trust in shaping educators' intentions to adopt AI and subsequently employ it effectively within their teaching approaches. The theoretical implications stretch beyond immediate findings, emphasizing the foundational roles played by these elements in steering intentions and behaviors concerning AI usage. As the academic realm grapples with AI integration, this research provides actionable insights to guide policy decisions, training initiatives, and curriculum adaptations. By advancing our comprehension of the underlying dynamics, this study contributes to optimizing AI integration in higher education, empowering educators to harness technology's potential in cultivating enriching and innovative learning experiences.
Keywords: Attitude, Perceived Usefulness, Trust, Intention, Usage

Introduction

In the realm of higher education, Artificial Intelligence (AI) is progressively permeating teaching methodologies on a global scale. Academicians are embracing AI-powered tools to individualize learning experiences, analyze intricate data sets, and automate evaluative processes (Vlasova et al., 2019). This integration enhances pedagogical efficiency and offers profound insights into student progress. Despite apprehensions regarding data privacy and the irreplaceable human element, the growing presence of AI in academia highlights a transformative trend toward data-responsive, adaptable, and streamlined teaching approaches (Gupta & Yadav, 2022). As higher education institutions worldwide navigate the evolving landscape, harnessing AI's potential stands as a pivotal development, poised to redefine the future of learning and instruction (Chen et al., 2020). In the context of Malaysia's higher education institutions, the utilization of Artificial Intelligence (AI) in teaching practices is gaining momentum. Academicians are increasingly harnessing AI-driven tools to enhance the learning journey. These applications encompass personalized learning pathways, data-driven insights, and automated assessment processes. The country's multicultural and diverse student body benefits from tailored approaches that cater to individual needs. While concerns around technological proficiency and cultural sensitivities exist, AI's integration has the potential to address these challenges, fostering inclusive education. Striking a balance between AI-driven advancements and the preservation of traditional teaching values is pivotal as Malaysia's academic landscape evolves. AI's role in Malaysian academia exemplifies an innovative stride toward cultivating globally competitive graduates (An et al., 2023). In Malaysia's higher education institutions, the usage of Artificial Intelligence (AI) in teaching presents challenges. While AI offers personalized learning and efficiency, there's a concern of overreliance on technology, potentially overshadowing the vital role of educators (Khalid, 2020). Issues of equitable access to AI tools across diverse socioeconomic backgrounds and the need for culturally sensitive content also arise. Moreover, there's a necessity for comprehensive training to equip academicians with AI competencies (Bujang et al., 2020). Striking a balance between AI integration and preserving effective human interaction is imperative, ensuring that the benefits of AI align with Malaysia's unique educational landscape while addressing these multifaceted challenges. The study of Artificial Intelligence (AI) usage in teaching among academicians in Malaysian higher education institutions holds paramount importance. This research is significant to policymakers, academia, and students. Policymakers can use its findings to develop educational strategies for integrating AI to improve the quality and accessibility of education. Higher education institutions can use research to optimize the implementation of artificial intelligence and promote innovative teaching methods. Students benefit from enhanced learning experiences and greater access to cutting-edge technology, improving their readiness for the rapidly evolving job market. This research bridges the gap between academia and technology and advances education in the digital age. It offers insights into optimizing pedagogical practices by integrating AI tools, fostering personalized learning experiences, and improving educational outcomes (Khalid, 2020). This research provides a framework to address challenges unique to Malaysia's multicultural context, ensuring equitable AI usage and culturally relevant content. Additionally, understanding the implications of AI in education informs policy decisions, faculty training, and curriculum development, ensuring a balanced blend of technological innovation and human interaction. Ultimately, this study paves the way for a progressive and globally competitive higher education landscape in Malaysia. The central aim of this research is to comprehensively examine the intricate network of direct and indirect connections that exist within the realm of perceived usefulness, trust, attitude, intention, and the practical application of artificial intelligence in the educational practices of academicians within Malaysia's higher education institutions. By delving into these interrelationships, the study seeks to shed light on the complex dynamics that influence how educators perceive the usefulness of AI tools, the level of trust they place in these technologies, their overall attitude towards AI integration, their intention to adopt AI-driven teaching methodologies, and the actual utilization of AI in their instructional approaches. Through this in-depth investigation, valuable insights will emerge, contributing to a nuanced understanding of the factors that shape the successful integration of artificial intelligence in teaching within the Malaysian higher education context.

Literature Review

Relationship between Perceived Usefulness, Intention, and Usage

The study by Tiza et al (2023) revealed a positive correlation between privacy concerns, perceived ease of use and usefulness utility, and institutional support for adaptation to artificial intelligence among Kurdish university students. A study by S. Yadav et al., (2022) shows that perceived usefulness and perceived ease of use have a positive significant relationship on the attitude and behavioral intention of the students of higher educational institutions of Delhi NCR to use ICT tools and its usage by the students is a must in the current scenario where online tools, virtual education and LMS are in high demand. An earlier study by Liu and Cavanaugh (2012) investigated whether there is a correlation between the usage of artificial intelligence by high school pupils, specifically in online classes, and their algebra scores. The research results suggested that implementing the technology, i.e., AI, improves student performance, indicating that adopting technology is perceived as beneficial by students. When academicians perceive AI as useful for enhancing their teaching, it positively influences their intention to adopt AI-driven tools. This intention, in turn, predicts their actual usage of AI in the educational setting (An et al., 2023). Therefore, recognizing and promoting the perceived usefulness of AI can serve as a significant driver for its integration into higher education, helping educators harness its potential for improved teaching and learning experiences (Ayanwale et al., 2022). Perceived usefulness is a linchpin in the usage of AI in education. When academicians recognize that AI technologies can streamline administrative tasks, provide personalized learning experiences, and improve educational outcomes, their intention to incorporate AI into their teaching practices is bolstered (Al-Rahmi et al., 2019). This intention is a crucial predictor of actual usage, as educators are more likely to explore and implement AI-driven solutions when they believe in their utility. To foster AI usage in higher education, institutions must emphasize and demonstrate the tangible benefits of AI, aligning perceived usefulness, intention, and usage to maximize the potential of these innovative tools in the classroom (Albelbesi & Yusop, 2020).

Relationship between trust, Intention, and Usage

The relationship between trust, intention, and usage of artificial intelligence (AI) in teaching among academicians in higher education institutions is a complex and evolving field of research. Trust plays a crucial role in the acceptance and usage of AI technologies in education. When academicians trust AI systems, they are more likely to have positive intentions toward using them in their teaching practices. Research by Adiguzel et al (2023) found that trust in AI systems positively influences the intention to use AI in teaching. This suggests that academicians who trust AI technologies are more likely to have a favorable attitude toward incorporating AI tools into their teaching practices. Additionally, a study by Liu et al (2020) revealed that trust in AI-based educational systems positively affects the perceived usefulness and ease of use of these systems. However, trust in AI is not solely based on the technology itself. Factors such as transparency, explainability, and accountability of AI algorithms also play a significant role in building trust among academicians. Research by Zhang et al (2021) emphasized the importance of algorithmic transparency and interpretability in fostering trust in AI systems in education. Furthermore, the intention to use AI in teaching is influenced by various factors, including perceived usefulness, perceived ease of use, and personal innovativeness. A study by Alzahrani and Goodwin (2020) found that perceived usefulness and ease of use significantly impact the intention to use AI in teaching among academicians. In conclusion, trust is a crucial factor in the intention and usage of AI in teaching among academicians in higher education institutions. Trust in AI systems positively influences the intention to use AI in teaching, while factors such as transparency and interpretability of AI algorithms also contribute to building trust. Additionally, perceived usefulness and ease of use are important determinants of the intention to use AI in teaching. Further research is needed to explore the dynamics of trust, intention, and usage of AI in teaching, considering the rapid advancements in AI technologies and their implications for higher education.

Relationship of Attitude, Intention, and Usage

The relationship between attitude, intention, and usage of artificial intelligence (AI) in teaching among academicians in higher education institutions is a topic of growing interest and research. Attitude plays a significant role in shaping the intention and subsequent usage of AI technologies in educational settings (Saleem et al., 2023). When academicians have a positive attitude towards AI in teaching, they are more likely to have the intention to use it in their instructional practices. Recent research by Li and Liang (2021) found a positive relationship between attitude and intention to use AI in teaching among academicians. The study highlighted that a favorable attitude towards AI technologies, such as perceiving them as beneficial and effective tools, increases the likelihood of academicians intending to incorporate AI in their teaching practices. Similarly, a study by Chen and Wang (2021) revealed that a positive attitude towards AI-based educational systems positively influences the intention to use AI in teaching. Furthermore, the intention to use AI in teaching is influenced by various factors, including perceived usefulness, ease of use, and self-efficacy. Research by Zhang and Liu (2020) found that a positive attitude toward AI technologies enhances the perceived usefulness and ease of use of these systems, thereby increasing the intention to use AI in teaching among academicians. In conclusion, a positive attitude towards AI in teaching is a significant predictor of the intention to use AI among academicians in higher education institutions. When academicians perceive AI as beneficial and effective, they are more likely to have the intention to incorporate AI technologies into their instructional practices. Factors such as perceived usefulness, ease of use, and self-efficacy further influence the intention to use AI in teaching. Future research should continue to explore the dynamics of attitude, intention, and usage of AI in teaching, considering the evolving nature of AI technologies and their implications for higher education (Gupta & Yadav, 2022).

The following hypotheses were proposed for this study based on the above conceptual development

H1: There is a relationship between attitude and intention to use artificial intelligence in teaching among academicians in higher education institutions.
H2: There is a relationship between attitude and usage of artificial intelligence in teaching among academicians in higher education institutions.
H3: There is a relationship between the intention and usage of artificial intelligence in teaching among academicians in higher education institutions.
H4: There is a relationship between perceived usefulness and intention to use artificial intelligence in teaching among academicians in higher education institutions.
H5: There is a relationship between perceived usefulness and usage of artificial intelligence in teaching among academicians in higher education institutions.
H6: There is a relationship between trust and intention to use artificial intelligence in teaching among academicians in higher education institutions.
H7: There is a relationship between trust and the usage of artificial intelligence in teaching among academicians in higher education institutions.
H8: There is a mediating effect of intention on the relationship between trust and the usage of artificial intelligence in teaching among academicians in higher education institutions.
H9: There is a mediating effect of intention on the relationship between attitude and the usage of artificial intelligence in teaching among academicians in higher education institutions.
H10: There is a mediating effect of intention on the relationship between perceived usefulness and the usage of artificial intelligence in teaching among academicians in higher education institutions.

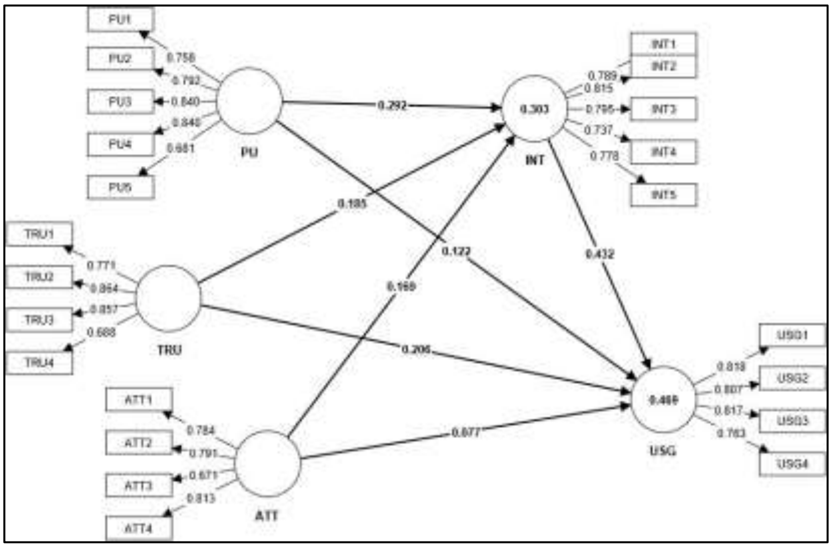

Figure 1: Research Model
Note: ATT=Attitude PU=Perceived Usefulness TRU=Trust INT=Intention USG=Usage

Methodology
The primary aim of this study was to investigate the usage of artificial intelligence in teaching among academicians working in both public and private higher education institutions. To gather relevant data, the researchers designed a survey, ensuring its effectiveness by carefully reviewing previous studies and selecting reliable and valid measurements. To achieve this goal, a quantitative approach is taken The survey questionnaires were distributed via email to the selected participants, using purposive sampling as the data collection method due to the unavailability of a comprehensive list of the entire population. The study observed a total of 22 variables, encompassing exogenous, mediating, and endogenous variables to comprehensively analyze the research subject. In this study, several constructs were examined using established measurements from existing literature. The exogenous variables included the attitude construct, measured with 4 items from Hair et al (2019); the perceived usefulness construct, measured using 5 items from Shang et al. (2011); and the trust construct, measured with 4 items from (Jasielska et al., 2021). The mediating variable, intention, was assessed using 5 items from Shang et al (2011), while the dependent variable, usage, was measured using 4 items from (De Cannière et al., 2009). Each construct's items were measured on a Likert scale with five response options ranging from strongly disagree to strongly agree. A total of 495 questionnaires were distributed, and 381 responses were received, resulting in a response rate of 76.9%, which was deemed sufficient for conducting data analysis through structural equation modeling (SEM). Out of the questionnaires received, 362 were identified as clean and suitable for analysis. To perform data analysis and hypothesis testing, researchers selected Smartpls4 software, which utilizes structural equation modeling (SEM) techniques. The choice was influenced by the software's robust evaluation capabilities and its suitability for handling multivariate data analysis. Adhering to the guidelines provided by Ringle et al (2022), the researchers used Smartpls4 to facilitate model measurement and structural evaluation processes. The software's comprehensive features proved invaluable in effectively testing the proposed hypotheses and conducting thorough multivariate data analysis, aligning seamlessly with the study's objectives.

Data Analysis

Respondents Profile

The table provides a comprehensive analysis of survey data based on various demographic factors and opinions within an academic or educational context. The gender distribution shows that 59.1% of the respondents are male, while 40.9% are female, indicating a slight gender imbalance in the sample. Looking at the age distribution, the majority falls within the 41 to 50 years old range (40.9%), followed by 22.9% in the 31 to 40 years old range, reflecting a diverse age group with a significant representation of middle-aged individuals. In terms of years of service, the data reveals that the majority (30.1%) have served for 11 to 15 years, suggesting an experienced group with substantial time spent in their positions. Regarding position level, the respondents mainly hold the position of Senior Lecturer (76.5%), followed by Associate Professor (19.9%), and Professor (2.5%), indicating a sample dominated by mid-level academic professionals. When considering employers, a higher percentage of respondents (68.0%) work in private higher education institutions compared to public ones (32.0%), showcasing a higher representation of the private sector. The survey's overall sentiment is positive, as an overwhelming majority of respondents (95.9%) give positive recommendations, with only a small portion (4.1%) offering negative ones.

Common Method Bias

In management research, addressing common method bias is crucial as it can lead to study variance being influenced by the measurement method rather than the actual structure being studied. In this study, the investigators tackled this challenge by employing Harman's one-factor test method to assess the measurement points. The results indicated that the main factor accounted for only 39.3% of the variance, suggesting that general method bias was not a significant concern in this research. This finding aligns with Podsakoff & Organ's (1986) suggestion that bias becomes less problematic when the principal components explain less than 50% of the variance. By adopting this approach, the study's results were rendered more robust and valid, effectively minimizing the potential impact of common method bias on the outcomes.

Outer Model Measurement

In this study, the evaluation of measurements in both first-order and second-order utilized a technique proposed by (Hair et al., 2017). The aim was to identify items with loadings below the threshold of 0.7. The examination of construct reliability and validity indicated that all constructs achieved Average Variance Extracted (AVE) values greater than 0.5, ranging from 0.588 to 0.642 (Table 1), confirming the establishment of convergent validity (Hair et al., 2017). Additionally, composite reliability for all constructs exceeded 0.7, ranging from 0.850 to 0.888, and Cronbach's alpha values were also greater than 0.7, ranging from 0.764 to 0.844 (Table 1), indicating high internal consistency and reliability. To establish discriminant validity, the researchers first assessed cross-loadings to ensure that each item effectively represented and measured its respective construct (Table 2). Subsequently, they employed the Hetrotrait-Monotrait (HTMT) ratio, a recommended criterion for evaluating discriminant validity in Variance-Based Structural Equation Modeling (VB-SEM) (Henseler et al., 2015). The HTMT ratios for the constructs, along with the original sample and 95% confidence intervals (two-tailed), were presented in Table 3. The HTMT values were below the threshold of 0.85, and the bias-corrected and accelerated bootstrap confidence intervals remained below 1, confirming compliance with discriminant validity. This comprehensive analysis further bolstered confidence in the constructs' distinctiveness and their ability to effectively measure different aspects of the phenomenon under investigation. Overall, the robust evaluation of measurements and validity in this study provides a solid foundation for the subsequent data analysis and interpretation.

Table 1
Construct Reliability & Validity

	Cronbach Alpha	Composite Reliability	Average variance Extracted (AVE)
ATT	0.764(0.716, 0.806)	0.850(0.824, 0.874)	0.588(0.538, 0.636)
INT	0.842(0.808, 0.867)	0.888(0.867, 0.904)	0.614(0.566, 0.653)
PU	0.844(0.808, 0.870)	0.888(0.866, 0.906)	0.615(0.567, 0.659)
TRU	0.808 (0.760, 0.845)	0.875(0.848, 0.896)	0.638(0.584, 0.685)
USG	0.815(0.773, 0.842)	0.878(0.854, 0.893)	0.642(0.592, 0.676)

Note: *Note: CI* 95% bootstrap confidence interval ATT=Attitude INT=Intention PU=Perceived Usefulness TRU=Trust USG=Usage

Table 2
Cross Loadings

	ATT	INT	PU	TRU	USG
ATT1	**0.784**	0.329	0.443	0.342	0.349
ATT2	**0.791**	0.271	0.391	0.306	0.339
ATT3	**0.671**	0.362	0.464	0.367	0.285
ATT4	**0.813**	0.363	0.562	0.428	0.363
INT1	0.386	**0.789**	0.438	0.335	0.545
INT2	0.357	**0.815**	0.412	0.365	0.488
INT3	0.336	**0.795**	0.345	0.302	0.448
INT4	0.300	**0.737**	0.373	0.318	0.472
INT5	0.315	**0.778**	0.410	0.410	0.461
PU1	0.463	0.324	**0.758**	0.467	0.318
PU2	0.424	0.388	**0.792**	0.513	0.398
PU3	0.586	0.502	**0.840**	0.487	0.509
PU4	0.463	0.406	**0.840**	0.518	0.427
PU5	0.444	0.329	**0.681**	0.413	0.318
TRU1	0.346	0.296	0.435	**0.771**	0.340
TRU2	0.383	0.318	0.522	**0.864**	0.381
TRU3	0.435	0.391	0.526	**0.857**	0.475
TRU4	0.334	0.387	0.454	**0.688**	0.401
USG1	0.418	0.562	0.484	0.434	**0.818**
USG2	0.359	0.447	0.421	0.433	**0.807**
USG3	0.343	0.479	0.426	0.425	**0.817**
USG4	0.267	0.486	0.299	0.331	**0.763**

Note: ATT=Attitude INT=Intention PU=Perceived Usefulness TRU=Trust USG=Usage

Table 3
Hetrotrait-Monotrait(HTMT) Ratio

	ATT	INT	PU	TRU
INT	0.537(0.426, 0.644)			
PU	0.751(0.674, 0.830)	0.587(0.483, 0.687)		
TRU	0.596(0.482, 0.717)	0.529(0.412, 0.632)	0.737(0.647, 0.820)	
USG	0.547(0.425, 0.666)	0.740(0.661, 0.818)	0.599(0.510, 0.681)	0.615(0.510, 0.726)

Note: CI 95% bootstrap confidence interval, ATT=Attitude INT=Intention PU=Perceived Usefulness TRU=Trust USG=Usage

Inner Model

In this study, the structural model evaluation entailed the concurrent assessment of pathway coefficients (β) and coefficients of determination (R2), following the methodology outlined by (Hair et al., 2017). The Partial Least Squares (PLS) method was utilized, employing 5000 subsamples to determine the significance level of path coefficients. The results of hypothesis tests, including confidence intervals, path coefficients (beta), corresponding t-statistics, and p-values, are presented in Table 4. This extensive analysis offers valuable insights into the significance and strength of the relationships among the variables in the structural model.

Hypothesis 1 tests a direct relationship between Attitude (ATT) and Intention (INT). The significant beta value of 0.169, the t-statistic of 2.815, and the low p-value of 0.005 indicate that Attitude has a positive and statistically significant effect on Intention. This finding supports the notion that a favorable attitude towards a particular behavior or action can lead to a higher intention to engage in that behavior or action. Hence, hypothesis 1 is supported. Hypothesis 2 examines the direct relationship between Attitude (ATT) and Usage (USG). However, the results show a non-significant beta value of 0.077, a t-statistic of 1.355, and a relatively high p-value of 0.175. Therefore, the hypothesis is not supported, suggesting that Attitude alone may not have a significant effect on Usage in this context. Therefore the hypothesis is not supported. Hypothesis 3 explores the direct relationship between Intention (INT) and Usage (USG). The significant beta value of 0.432, the high t-statistic of 8.338, and the very low p-value of 0.000 indicate a strong and statistically significant positive relationship between Intention and Usage. This finding suggests that a higher intention to perform a specific behavior is associated with an increased level of actual usage. Hence hypothesis 3 is supported. Hypothesis 4 tests the direct relationship between Perceived Usefulness (PU) and Intention (INT). The results show a significant beta value of 0.292, a t-statistic of 4.415, and a p-value of 0.000, indicating that Perceived Usefulness has a positive and statistically significant impact on Intention. It implies that if individuals perceive a particular action or behavior to be useful, they are more likely to intend to engage in it. Therefore hypothesis 4 is supported. Hypothesis 5 investigates the direct relationship between Perceived Usefulness (PU) and Usage (USG). However, the non-significant beta value of 0.122, the t-statistic of 1.830, and the p-value of 0.067 suggest that Perceived Usefulness does not have a significant effect on Usage in this specific context. Therefore, hypothesis 5 is not supported. Hypothesis 6 examines the direct relationship between Trust (TRU) and Intention (INT). The results reveal a significant beta value of 0.185, a t-statistic of 3.066, and a p-value of 0.002, indicating a positive and statistically significant relationship between Trust and Intention. This finding suggests that higher levels of trust in a specific context may lead to a stronger intention to engage in the associated behavior or action. Hence, hypothesis 6 is supported. Hypothesis 7 tests the direct relationship between Trust (TRU) and Usage (USG). The significant beta value of 0.206, the t-statistic of 3.276, and the p-value of 0.001 indicate a positive and statistically significant effect of Trust on Usage. This implies that higher levels of trust in a particular context are associated with increased levels of actual usage. Hence, hypothesis 7 is supported. Hypothesis 8 explores a mediating relationship between Trust (TRU), Intention (INT), and Usage (USG). The significant beta value of 0.080, the t-statistic of 2.862, and the p-value of 0.004 suggest that Trust influences Intention, which, in turn, influences Usage. This supported hypothesis reveals the importance of Trust as an intermediate factor that affects both Intention and Usage. Hence, hypothesis 8 is supported. Similar to H8, hypothesis 9 examines a mediating relationship, but involving Attitude (ATT), Intention (INT), and Usage (USG). The significant beta value of 0.073, the t-statistic of 2.568, and the p-value of 0.010 indicate that Attitude influences Intention, which then influences Usage. This finding highlights the significance of Attitude as a precursor to Intention, which subsequently impacts Usage. Hence, hypothesis 9 is supported. Hypothesis 10 also explores a mediating relationship between Perceived Usefulness (PU), Intention (INT), and Usage (USG). The significant beta value of 0.126, the t-statistic of 3.788, and the p-value of 0.000 suggest that Perceived Usefulness influences Intention, which, in turn, influences Usage. This supported hypothesis indicates that the perceived usefulness of a particular behavior influences individuals' intention to engage in that behavior, ultimately impacting actual usage. Therefore, hypothesis 10 is supported.

The study's analysis yielded substantial evidence in favor of the majority of the hypotheses, confirming the relationships among the variables under investigation. A detailed overview of the hypothesis testing results, including the effect size, is presented in Table 4. Effect sizes were assessed using Cohen's criteria (1992) and categorized as small (0.020 to 0.150), medium (0.150 to 0.350), or large (0.350 or greater). The observed effect sizes in this study spanned from small (0.003) to large (0.231). These effect size measurements provide valuable insights into the magnitude and practical significance of the relationships observed in the research, helping to interpret the impact of the variables more comprehensively. To ensure the structural model's reliability, the intrinsic value inflation factor (VIF) values were examined, all of which were found to be below the lenient threshold of 5, with the highest value being 2.152. This low level of collinearity ensures that meaningful comparisons of sizes and interpretation of coefficients in the model can be made without concern. The endogenous construct exhibited a substantial degree of explained variance, with an R2 value of 0.469 (Figure 1). Regarding the mediator, the model accounted for approximately 30.3% of the variance in the structure, as evidenced by an R2 value of 0.303. These R2 values provide valuable insights into the amount of variance explained by the model and its ability to predict the observed outcomes. To assess the model's ability to draw inferences and offer management recommendations, an out-of-sample predictive analysis was carried out using the PLSpredict method, following the approach outlined by (Shmueli et al., 2016; 2019). The predictive analysis results, presented in Table 5, include Q^2 predictions, with values above 0 indicating that the predictions made by PLS-SEM surpassed the standard naive mean prediction outcomes. Moreover, in six out of nine instances, the root mean square error (RMSE) values of the PLS-SEM predictions were lower than those of the linear model (LM) prediction benchmark, highlighting the superior predictive power of the proposed model (Table 5). These findings serve as additional evidence supporting the effectiveness of the structural model in generating precise predictions and offering valuable insights for managerial decision-making. Hair et al (2022) introduced the Cross-Validated Predictive Ability Test (CVPAT) as an assessment tool for evaluating the predictive capabilities of PLS-SEM models. In their study, Liengaard et al (2021) applied the CVPAT alongside the PLSpredicts analysis to evaluate the model's predictive performance. The CVPAT involved an out-of-sample prediction method to measure the model's prediction error and compute the average loss value. Two benchmarks were used for comparison: the average loss value of predictions using indicator averages (IA) as a simple 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 compared to the benchmarks, the average loss value of PLS-SEM should be lower, resulting in a negative difference in the average loss values. The CVPAT aimed to assess whether the difference in average loss values between PLS-SEM and the benchmarks was significantly below zero. A significantly negative difference would indicate that the model exhibited enhanced predictive abilities. The results of the CVPAT, presented in Table 6, confirmed the model's superiority. The average loss value of PLS-SEM was indeed lower than that of the benchmarks, as evidenced by the negative difference in the average loss values. This provides compelling evidence of the model's robust and superior predictive capabilities compared to the benchmarks.

Ringle and Sarstedt (2016); Hair et al (2018) introduced the application of Importance Performance Analysis (IPMA) as a robust approach to assessing the significance and effectiveness of latent variables in explaining acceptance. The outcomes of this comprehensive analysis are thoughtfully presented in Table 7. Among the latent variables studied, intention emerged as the most influential factor (0.432) concerning the overall impact on usage, followed by trust (0.143), perceived behavioral control (0.286), perceived usefulness (0.248), and attitude (0.150). These values elucidate the relative importance of each latent variable within the context of usage. Additionally, in terms of performance scores, attitude demonstrated the highest score (66.768) on a 0 to 100 scale, indicating its relatively robust performance. Conversely, intention received the lowest score (60.555), suggesting the lowest level of achievement. Intriguingly, despite its utmost significance in determining usage, intention exhibited the lowest performance level. Drawing on these noteworthy findings, we recommend that top management in higher education institutions prioritize and accentuate endeavors aimed at improving employees' intentions. By strategically focusing on enhancing intention, the overall usage of artificial intelligence can be significantly enhanced, leading to more effective and beneficial outcomes for the institutions and their stakeholders.

Table 4
Hypotheses Testing Results, f^2 & Inner VIF

Hypotheses	Beta	T statistics	P values	f2	Inner VIF	Decision
H1: ATT -> INT	0.169	2.815	0.005	0.025	1.640	*Supported*
H2: ATT -> USG	0.077	1.355	0.175	0.007	1.681	*Not Supported*
H3: INT -> USG	0.432	8.338	0.000	0.245	1.435	*Supported*
H4: PU -> INT	0.292	4.415	0.000	0.006	2.030	*Supported*
H5: PU -> USG	0.122	1.830	0.067	0.013	2.152	*Not Supported*
H6: TRU -> INT	0.185	3.066	0.002	0.030	1.638	*Supported*
H7: TRU -> USG	0.206	3.276	0.001	0.047	1.687	*Supported*
H8: TRU -> INT -> USG	0.080	2.862	0.004			*Supported*
H9: ATT -> INT -> USG	0.073	2.568	0.010			*Supported*
H10: PU -> INT -> USG	0.126	3.788	0.000			*Supported*

Table 5
PLSpredict

	Q^2predict	PLS RMSE	LM RMSE	PLS - LM
INT1	0.203	0.620	0.616	0.004
INT2	0.192	0.612	0.621	-0.009
INT3	0.136	0.666	0.665	0.001
INT4	0.146	0.678	0.693	-0.015
INT5	0.193	0.610	0.612	-0.002
USG1	0.262	0.624	0.623	0.001
USG2	0.222	0.612	0.621	-0.009
USG3	0.217	0.679	0.686	-0.007
USG4	0.109	0.736	0.738	-0.002

Table 6
Cross-Validated Predictive Ability Test (CVPAT)

	Average loss difference	t value	p-value
INT	-0.085	4.482	0.000
USG	-0.11	5.399	0.000
Overall	-0.096	5.809	0.000

Table 7
Importance-Performance Map Analysis

	Total Effect	Performance
ATT	0.150	66.768
INT	0.432	60.555
PU	0.248	66.541
TRU	0.286	63.704

Discussion

The research findings highlight the significance of perceived usefulness, attitude, trust, and intention in driving the usage of artificial intelligence (AI) by academicians in higher education institutions. To ensure widespread and effective utilization of AI technologies, institutions can adopt specific strategies targeting each of these critical factors. Higher education institutions should focus on promoting the perceived usefulness of AI among academicians. This can be achieved through targeted communication and training programs that showcase the practical benefits of AI in academic activities. Demonstrating how AI can streamline research processes, enhance data analysis, and improve teaching methods can effectively increase the perceived usefulness of AI, encouraging academicians to embrace its usage. Creating a positive attitude towards AI is vital for its successful integration. Institutions can organize workshops and seminars to address any misconceptions or fears associated with AI. Moreover, highlighting success stories of academicians who have effectively utilized AI in their work can inspire others and foster a more positive attitude towards AI usage. Building trust in AI technologies is essential for academicians to feel confident in using them. Higher education institutions can establish transparent processes for data privacy and security in AI applications. Implementing rigorous quality control measures in AI algorithms and ensuring ethical guidelines are followed in AI research can enhance the trustworthiness of AI systems and boost academicians' trust in using them. Intention plays a critical role in driving the actual usage of AI. Institutions can facilitate intention by providing the necessary resources and technical support for AI integration. Offering incentives or recognition for academicians who actively engage with AI technologies can also reinforce positive intention and encourage greater usage. Moreover, incorporating AI-related training and development opportunities in faculty development programs can equip academicians with the skills and knowledge needed to integrate AI effectively into their academic practices. By addressing perceived usefulness, attitude, trust, and intention through these targeted strategies, higher education institutions can create an enabling environment that encourages academicians to embrace AI technologies confidently and optimally.

Theoretical Implications

The findings of the above study have significant theoretical implications, making noteworthy contributions to the existing knowledge on AI usage and usage in higher education institutions. The study sheds light on the crucial role of various factors, including perceived usefulness, attitude, trust, and intention, in influencing the usage of artificial intelligence by academicians. These implications offer valuable insights for researchers and practitioners in the field of technology usage and organizational behavior. The study's reinforcement of the importance of the Technology Acceptance Model (TAM) in understanding AI usage in higher education is notable. By incorporating perceived usefulness, attitude, and intention as key determinants, the study aligns with the core constructs of TAM, thereby validating its relevance in predicting the usage of AI technologies in academic settings. Another significant implication arises from the study's emphasis on the role of trust in AI usage. Trust in technology is an emerging area of research, and the study contributes to this domain by demonstrating its impact on academicians' intention to use AI. This finding underscores the importance of building trust in AI systems and the need for transparent and ethical AI practices to foster greater trust among users. The study's focus on intention as a critical factor influencing AI usage provides valuable theoretical insights into the motivational aspects of technology usage. Understanding the determinants of intention can guide future research on intervention strategies aimed at enhancing intention and, in turn, encouraging higher usage of AI in academic contexts. Moreover, the examination of perceived usefulness and its impact on intention and usage adds to the ongoing discourse on user perceptions of technology. The study's findings suggest that academicians' perceptions of AI's usefulness significantly shape their intention to use it, extending our theoretical understanding of how user perceptions influence technology usage decisions. Furthermore, the study's use of Importance Performance Analysis (IPMA) offers a novel perspective on the evaluation of latent variables in technology usage. By assessing the relative importance and performance of each variable, the study provides a comprehensive understanding of their role in determining AI usage outcomes. This methodological contribution can inspire further research on assessing the significance and effectiveness of variables in other technology usage contexts.

Managerial Implications

The research findings presented in this study carry significant managerial implications for higher education institutions aiming to effectively implement and encourage the usage of artificial intelligence (AI) among their academicians. These implications offer practical guidance and actionable strategies that institutional leaders and managers can employ to harness the full potential of AI technologies in the academic setting. A primary focus for managers should be to cultivate a supportive and innovative culture within the institution. Nurturing an environment that fosters experimentation and promotes AI-related learning will empower academicians to explore and embrace AI tools in their research, teaching, and administrative tasks. Institutional leaders should actively endorse AI-related workshops, training programs, and knowledge-sharing sessions, enabling academicians to gain the essential skills and confidence for AI usage. Addressing concerns related to trust in AI systems is crucial for managers. Implementing robust data privacy and security measures, adhering to ethical guidelines in AI research, and ensuring transparency in AI practices will foster trust among academicians and other stakeholders. Clear and effective communication regarding the benefits and responsible use of AI can dispel any skepticism and encourage wider acceptance of AI technologies. Higher education institutions must actively support and recognize academicians who integrate AI into their work. Establishing incentive programs, grants, or awards for AI adopters can act as motivational tools, encouraging broader participation in AI usage. Managers should publicly acknowledge and celebrate successful AI usage stories, inspiring others and fostering a positive culture around AI usage. Additionally, managers should proactively identify and address any barriers hindering the intention to use AI among academicians. Conducting regular assessments and gathering feedback from users can aid in identifying specific challenges and tailoring intervention strategies accordingly. Managers should offer technical assistance and continuous support to facilitate the smooth integration of AI into academic practices. Furthermore, encouraging collaboration between academic departments and industry partners can play a pivotal role in promoting AI usage. Managers should actively foster interdisciplinary collaborations and forge partnerships with technology companies to explore innovative AI solutions and applications. Such collaborations can enhance the relevance and real-world impact of AI usage in academic research and teaching. Lastly, ensuring the integration of AI-related training and development opportunities into faculty development programs is essential. Equipping academicians with the necessary AI skills and knowledge will pave the way for a future-ready workforce that confidently and competently embraces AI technologies.

Suggestions for Future Studies

The study suggests several future research avenues to advance our understanding of AI usage in higher education. Firstly, exploring individual differences like technological self-efficacy and innovativeness in influencing AI usage among academicians can provide valuable insights into technology usage behaviors. Investigating how these factors interact with perceived usefulness, attitude, trust, and intention can shed light on the complexities of AI usage. Secondly, examining the impact of institutional-level factors, such as organizational culture and leadership support, on AI usage is crucial. Longitudinal studies tracking AI usage trends over time can offer insights into the long-term effects and evolution of AI usage in higher education. Comparative studies across different types of institutions can reveal how contextual differences influence AI usage strategies and outcomes. Lastly, studying the impact of AI usage on academic outcomes like research productivity and student engagement can provide evidence of AI's effectiveness in enhancing higher education. These future studies can contribute to a comprehensive understanding of AI usage, benefiting institutional leaders, researchers, and policymakers.

Conclusion

In conclusion, the research provides valuable insights into the usage of artificial intelligence (AI) by academicians in higher education institutions. The study identifies key factors, including perceived usefulness, attitude, trust, and intention, that significantly influence AI usage. The findings reinforce the relevance of the Technology Acceptance Model (TAM) in understanding AI usage in academic settings. Additionally, the study highlights the importance of fostering a supportive and innovative culture, addressing trust concerns, and providing recognition for AI users to encourage wider participation and acceptance. Furthermore, the research emphasizes the significance of interdisciplinary collaborations and industry partnerships in promoting AI usage. The study's implications for managerial strategies offer practical guidance for institutions to effectively integrate AI and unlock its transformative potential in teaching, research, and administrative practices. Looking ahead, future research exploring individual differences, institutional-level factors, longitudinal trends, and academic outcomes can further enrich our understanding of AI usage in higher education. Overall, this study contributes to the ongoing discourse on technology usage and lays the foundation for a future-ready academic ecosystem embracing AI technologies.

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