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Optimizing Artificial Intelligence Usage among Academicians in Higher Education Institutions

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Abstract

Artificial Intelligence (AI) is becoming a transformative force in higher education and offers tremendous potential to reshape the academic landscape. With the power of artificial intelligence, educators and researchers can use advanced tools to perform complex tasks such as data analysis, predictive modeling, and breakthrough insights. This study delves into the complex relationships between attitudes, perceived usefulness, perceived ease of use, trust, intentions, and AI usage in academia. The research framework is based on four different variables: attitude, perceived usefulness, perceived ease of use, and trust, with intention as the mediator and AI use as the outcome variable. 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 362 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. Notably, seven of the nine direct hypotheses and all four mediating hypotheses were supported. These results highlight the profound importance of these factors in shaping user intentions and facilitating the effective integration of AI into academia. In addition to the empirical findings, this study

contains very important theoretical implications, highlighting the central role that attitudes, perceived usefulness, perceived ease of use, and trust play in influencing intentions and subsequent behavior related to AI integration. As educators around the world work to integrate artificial intelligence into their teaching and research, the relevance of this research extends to actionable insights that can inform policymaking, curriculum development, and the development of educational paradigms.
Keywords: Attitudes, Perceived Usefulness, Perceived Ease of Use, Trust, Intentions, Usage

Introduction
Artificial intelligence (AI) has enormous potential to transform higher education, but its practical implementation among academics presents several challenges. One major problem is the lack of awareness and understanding of AI technologies (Chen et al., 2020). Many academics do not know the usage and benefits of artificial intelligence, which prevents its use in their teaching and research activities (Bearman et al., 2023). The limited availability of AI infrastructure and resources in higher education institutions is also a problem (Alam, 2022). The high costs associated with AI technologies and the need for specialized technical expertise make it difficult for academics to use AI tools effectively (Bhattacharjee, 2019). In addition, there are concerns about the ethical implications of using artificial intelligence in higher education. Issues such as data protection, algorithmic bias, and impact on teacher employability must be carefully addressed (Gurung and Ashmita, 2023). In addition to practical challenges, there is also resistance among researchers to changes regarding the adoption of artificial intelligence in their teaching practice (Jokhan et al., 2022). Many teachers are used to traditional teaching methods and may be hesitant to incorporate AI technologies into their classrooms (Kuleto et. al., 2021). In addition, the lack of standard guidelines and practices for the use of AI in higher education makes its implementation more difficult. The lack of clear regulations and frameworks can lead to inconsistencies in the implementation of AI and possible misuse of the technology (Chauhdry and Kazim, 2022). Addressing these practical issues requires collaboration between higher education institutions, policymakers, and AI developers to provide appropriate training, resources, and ethical guidelines for the successful integration of AI into higher education (Wang et., 2023). The issue of using artificial intelligence (AI) among teaching staff in Malaysian higher education institutions is multifaceted. First, although AI has the potential to revolutionize learning, research, and management processes, its use and implementation across countries and higher education settings is inconsistent (Rahim et al., 2022). Many educational institutions in Malaysia have yet to fully exploit the potential of AI and lack the ability to provide more innovative and engaging learning. This lack of widespread integration of AI challenges the Malaysian academic community to meet the changing needs of students and remain competitive in the global arena (Khalid, 2020). In addition, there are significant problems in faculty training and the development of skills related to artificial intelligence. Many academies may not have the necessary expertise to effectively incorporate AI tools and techniques into their teaching methods or research projects (Sinniah et al., 2022). This knowledge gap must be addressed to ensure that educators are prepared to harness the potential of AI to improve pedagogical and research outcomes. Infrastructure and resource allocation also emerge as critical issues (Ahmed et al., 2022). Malaysian HEIs may have limitations related to the technological infrastructure and financial resources required for a successful AI integration strategy. Without proper support, institutions may struggle to fully embrace the transformative capabilities of AI (Ahmad et al., 2021). In light of these challenges,

the study aims to delve into the specific barriers and bottlenecks that prevent the widespread use of AI in Malaysian HEIs (Mohanachandran et al., 2021). It aims to identify the root causes of these problems and find possible solutions. This research can inform policy decision-making, guide institutional investment, and facilitate faculty development, ultimately contributing to a stronger AI ecosystem in Malaysian academia. This in turn improves the quality of education, research, and administrative processes and makes Malaysian higher education institutions more competitive on the global stage (Ashaari et al., 2021Studying AI use in academia is vital for education's future. It offers insights into AI's impact on teaching, research, and management, aiding informed decisions to enhance quality and competitiveness. Tailored AI integration strategies drive innovation and adaptability in a tech-driven landscape. This research is pivotal for shaping education and effective AI utilization in higher learning. The purpose of this study is to assess the relationship between attitude, perceived ease of use, trust in perceived usefulness, and usage with intention as a mediator among higher education institutions academicians.

Literature Review

Underpinning Theory

The underpinning theory for this study is grounded in the Technology Acceptance Model (TAM) and its extensions. TAM, originally proposed by Davis(1989), provides a comprehensive framework to understand users' acceptance of technology by examining the interplay between their attitudes, perceived ease of use, perceived usefulness, and usage intentions. In the context of higher education institutions and academicians, where the integration of technology is pivotal, TAM serves as an ideal theoretical foundation. According to TAM, individuals form positive attitudes toward technology when they perceive it as easy to use and valuable in achieving specific goals. Perceived ease of use and perceived usefulness, therefore, become critical factors influencing users' attitudes and subsequently impacting their intention to use technology. In this study, the inclusion of trust in perceived usefulness adds a nuanced layer, recognizing the importance of trust in shaping users' perceptions. Furthermore, the study introduces the concept of usage intention as a mediator, acknowledging that the influence of attitudes and perceptions on actual technology usage is not direct but mediated by the intention to use. This nuanced exploration within the TAM framework aligns with the complex dynamics of technology adoption among higher education institutions academicians, providing a robust theoretical foundation for investigating these relationships.

Relationship between Attitude, Intention & Usage

The relationship between attitude, intention, and the usage of artificial intelligence (AI) among academicians in higher education institutions is a multifaceted and critical aspect in the era of digital transformation (Wang et al., 2021). Attitudes toward AI in academia significantly shape an individual's intention to incorporate AI tools into their teaching, research, or administrative roles. These attitudes are influenced by factors such as perceived usefulness, ease of use, and compatibility with existing practices (Andrews et al., 2021). A positive attitude generally correlates with a stronger intention to adopt AI technologies for academic purposes. However, the transition from intention to actual AI usage is influenced by various elements (Rahim et al., 2022). Organizational factors, such as institutional support, access to AI resources, and training opportunities, can either facilitate or hinder the adoption process. Additionally, an academician's own technological proficiency and self-efficacy in implementing AI effectively play a crucial role (Gupta & Yadav, 2022). External influences, including government policies and the evolving landscape of educational technology, can also impact an academician's attitude, intention, and readiness to embrace AI. Understanding these intricate relationships is pivotal for educational institutions and policymakers (Wang et al., 2023). It enables the design of targeted interventions and strategies that bridge potential gaps between attitudes, intentions, and AI usage, ultimately fostering a seamless integration of AI for the enhancement of educational quality, efficiency, and competitiveness within higher education institutions (Chiu & Chai, 2020). Therefore, the following hypotheses were proposed:

H1: There is a relationship between attitude and intention to use artificial intelligence among Academicians in higher education institutions
H2: There is a relationship between attitude and usage of artificial intelligence among Academicians in higher education institutions
H3: There is a mediating effect of intention on the relationship between attitude and usage of artificial intelligence among academician's in higher education institutions

Relationship between Perceived Ease of Use, Intention & Usage
The relationship between perceived ease of use, intention, and the actual usage of artificial intelligence (AI) among academicians in higher education institutions is a fundamental aspect of AI adoption in the academic landscape (Wang et al., 2021). Perceived ease of use is a crucial determinant of an academician's intention to incorporate AI technologies into their educational, research, or administrative activities. When academicians believe that using AI tools is straightforward and user-friendly, they are more inclined to form a positive intention to embrace AI (Chatterjee & Bhattacharjee, 2020). However, the transition from intention to actual AI usage hinges on various factors. The availability of adequate training and support resources, both at the individual and institutional levels, significantly influences the ability to effectively use AI tools (Gupta & Yadav, 2022). Institutions that offer training programs and ensure easy access to AI resources are more likely to witness successful AI implementation. Furthermore, an academician's own technological proficiency and familiarity with AI play a critical role (Zhang et al., 2023). Those who possess the requisite skills and self-efficacy are more likely to transform their intentions into practical AI utilization. Understanding the interplay between these factors is vital for fostering the successful integration of AI in higher education institutions (An et al., 2023). It guides the development of targeted strategies and interventions that enhance the perceived ease of use, align intentions, and facilitate the effective utilization of AI. Ultimately, this integration can lead to improved educational quality, efficiency, and competitiveness within the higher education sector (Gupta & Yadav, 2022). Given the above, the following hypotheses were proposed:

H4: There is a relationship between perceived ease of use and intention to use artificial intelligence among academicians in higher education institutions
H5: There is a relationship between perceived ease of use and usage of artificial intelligence among academicians in higher education institutions
H6: There is a mediating effect of intention on the relationship between perceived ease of use and usage of artificial intelligence among academicians in higher education institutions

Relationship between Perceived Usefulness, Intention & Usage

The relationship between perceived usefulness, intention, and actual usage of artificial intelligence (AI) among academicians in higher education institutions is a pivotal factor in the successful usage of AI technology in academia (Chatterjee & Bhattacharjee, 2020). Perceived usefulness refers to an academician's belief in the benefits (Davis, 1989) and advantages that AI tools can bring to their teaching, research, or administrative tasks. When academicians perceive AI as beneficial, they are more likely to form a positive intention to integrate AI into their work (Chatterjee & Bhattacharjee, 2020). However, the translation of intention into practical AI usage depends on several critical factors. Institutional support and resource allocation play a significant role, as institutions that provide the necessary infrastructure, training, and incentives for AI adoption are more likely to see successful implementation (An et al., 2023). Additionally, the individual's own technological proficiency and confidence in using AI tools can greatly influence the execution of their intention. Understanding this relationship is essential for higher education institutions and policymakers (Kashive et al, 2020). It enables the development of targeted strategies to enhance the perceived usefulness of AI, align intentions with actual usage, and ultimately facilitate the effective integration of AI in academia. This integration, when successful, can lead to improved educational quality, increased efficiency, and enhanced competitiveness within the higher education sector (Lew et al., 2019). Therefore, the following hypotheses were proposed:

H7: There is a relationship between perceived usefulness and intention to use artificial intelligence among academicians in higher education institutions
H8: There is a relationship between perceived usefulness and usage of artificial intelligence among academicians in higher education institutions
H9: There is a mediating effect of intention on the relationship between perceived usefulness and usage of artificial intelligence among academicians in higher education institutions

Relationship between Trust, Intention & Usage

The relationship between trust, intention, and the usage of artificial intelligence (AI) among academicians in higher education institutions is a complex and crucial aspect of AI adoption in academia (Chatterjee & Bhattacharjee, 2020). Trust in AI systems and technologies significantly influences an academician's intention to utilize AI in their teaching, research, or administrative roles. When academicians have confidence in the reliability, security, and ethical use of AI, they are more likely to form a positive intention to adopt AI solutions Qin et al., 2020). However, the translation of intention into actual AI usage depends on several critical factors. Institutional support and policies that promote trust in AI systems are essential (Choi et al., 2023). Institutions that prioritize data security, ethical AI use, and transparency are more likely to encourage academicians to implement AI in their work. Furthermore, the academician's trust in their ability to use AI effectively, coupled with the accessibility of training and resources, plays a crucial role (Sánchez-Prieto et al., 2020). Understanding this relationship is vital for educational institutions and policymakers. It informs the development of strategies and interventions that build trust in AI, align intentions with usage, and ultimately facilitate the successful integration of AI in higher education (Sharawy, 2023). When trust is established and intention is translated into effective usage, it can lead to improved educational quality, efficiency, and competitiveness within the higher education sector (Pisica et., 2023). Given the above, the following hypotheses were proposed:

H10: There is a relationship between trust and intention to use artificial intelligence among Academicians in higher education institutions
H11: There is a relationship between trust and the usage of artificial intelligence among Academicians in higher education institutions
H12: There is a relationship between intention and the usage of artificial intelligence among Academicians in higher education institutions
H13: There is a mediating effect of intention on the relationship between trust and usage of artificial intelligence among academicians in higher education institutions

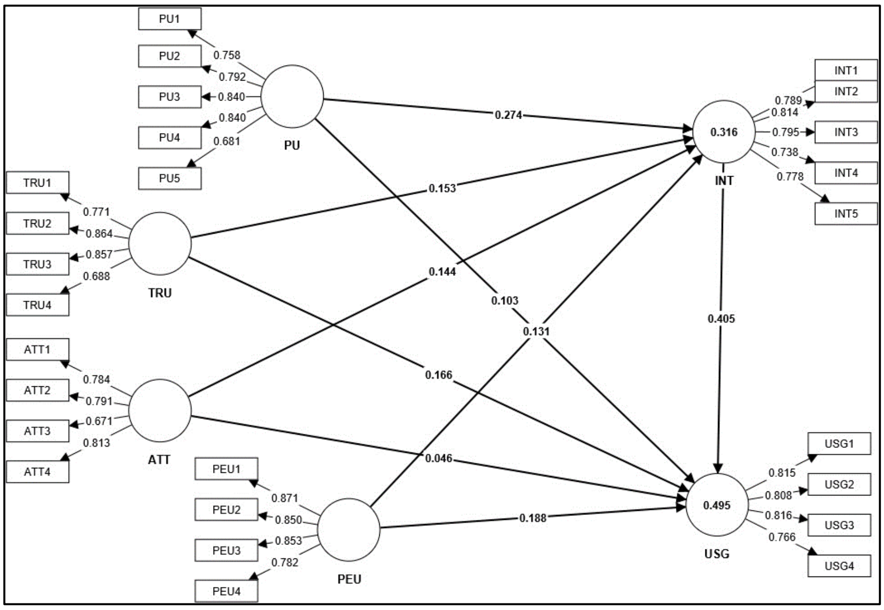

Figure 1: Research Model
Notes: PU=Perceived Usefulness TRU=Trust ATT=Attitude PEU=Perceived Ease of Use INT=Intention USG=Usage

Methodology

This study sought to assess academics in both public and private higher education institutions. To achieve this objective, researchers conducted a survey to collect primary data, meticulously examining previous research to select reliable and valid measurements. The survey questionnaires were then emailed to selected participants, utilizing purposive sampling due to the unavailability of a comprehensive population list. A total of 25 observed variables were scrutinized, including exogenous variables such as attitude, gauged using a 4-item scale (Hair et al., 2019); perceived usefulness, assessed with 4 items (Li et al., 2020); trust, evaluated through 4 items from Jasielska et al (2021); and perceived ease of use measured by 4 items (Shang et al., 2011). The study's mediating factor was intention, measured with 5 items Shang et al (2011), while the dependent variable was usage, appraised via 4 items (De Cannière et al., 2009). A Likert scale featuring five response choices, ranging from strongly disagree to strongly agree, was employed to gauge elements within each construct. Out of 495 surveys disseminated, 381 were collected, resulting in a response rate of 76.9%, considered satisfactory for employing structural equation modeling (SEM) in data analysis. Of the collected surveys, 362 were identified as clean and suitable for analysis. For data analysis and hypothesis testing, researchers selected the Smartpls4 software, known for its use of structural equation modeling (SEM) techniques. This choice was driven 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 indispensable in effectively scrutinizing proposed hypotheses and conducting comprehensive multivariate data analysis, facilitating a thorough examination of both measurement and structural models.

Respondents' Profile
The gender distribution among respondents indicates a notable majority of males, constituting 59.1% of the sample, while females account for 40.9%. This gender representation reflects potential disparities in the participation of male and female academicians, prompting further exploration into gender dynamics within the study. The highest percentage falls within the 41 to 50-year-old category (40.9%), suggesting a substantial representation of mid-career professionals. The inclusion of participants across various age brackets, including those under 30 and over 60 years old, contributes to a comprehensive understanding of technology adoption across different career stages. The data on years of service illustrate a varied level of experience among respondents. A substantial portion, 59.4%, has served between 11 and 20 years, indicating a cohort with moderate experience. The majority of respondents hold the position of Senior Lecturer (76.5%), indicating a concentration of experienced academics. There is a minimal representation of Lecturers (1.1%) and a notable presence of Associate Professors (19.9%) and Professors (2.5%). This distribution highlights the seniority and diversity in the academic hierarchy among the participants. The categorization based on the employer type reveals a balance between respondents affiliated with public and private higher education institutions. Public Higher Education Institution employees constitute 32.0%, while those from Private Higher Education Institutions represent 68.0%. The respondents overwhelmingly express a positive stance toward recommending technology adoption, with 95.9% endorsing it, while 4.1% indicate otherwise. This high recommendation rate suggests a general positive disposition among the surveyed academicians toward adopting technological advancements in their academic practices.

Data Analysis
Common Method Bias
Kock (2015) proposed that a variance inflation factor (VIF) exceeding 3.3 indicates the presence of common method bias. Common method bias arises when variations in respondents' responses are attributed to the measurement instrument rather than the respondents' actual predispositions that the instrument aims to uncover. To assess the presence of collinearity and common method bias, a comprehensive collinearity test was performed. As indicated in Table 1, the results of the factor-level analysis from the full collinearity test revealed that all variance inflation factors (VIF) were below 3.3. This confirms that the model did not encounter any common method bias issues.

Table 1
Full Collinearity

	USG	INT	PU	PEU	ATT	TRU
USG		1.586	1.929	1.848	1.936	1.887
INT	1.444		1.725	1.802	1.75	1.764
PU	2.018	2.071		2.126	1.827	1.839
PEU	1.31	1.379	1.377		1.357	1.353
ATT	1.683	1.671	1.453	1.661		1.677
TRU	1.737	1.784	1.549	1.755	1.777	

Notes: PU=Perceived Usefulness TRU=Trust ATT=Attitude
PEU=Perceived Ease of Use INT=Intention USG=Usage

Measurement Model

This study employed the measurement evaluation technique proposed by Hair et al (2017) to assess both first-order and second-order measurements. The primary objective was to identify items with loadings below the 0.7 threshold. The examination of construct reliability and validity indicated that all constructs exhibited Average Variance Extracted (AVE) values exceeding 0.5, ranging from 0.588 to 0.705 (refer to Table 2), demonstrating the establishment of convergent validity (Hair et al., 2017). Additionally, composite reliability for all constructs surpassed 0.7, ranging from 0.850 to 0.905, and Cronbach's alpha values were greater than 0.7, ranging from 0.764 to 0.860 (see Table 2). To ascertain discriminant validity, the researchers initially evaluated cross-loadings to ensure the effective representation and measurement of each construct by its respective items (Table 3). Subsequently, the Heterotrait-Monotrait (HTMT) ratio, a recommended criterion for assessing discriminant validity in Variance-Based Structural Equation Modeling (VB-SEM) (Henseler, Ringle & Sarstedt, 2015), was employed. The HTMT ratios for the constructs, alongside the original sample, are presented in Table 4. These values were below the 0.85 threshold, and the bias-corrected and accelerated bootstrap confidence intervals remained below 1, affirming adherence to discriminant validity. This analysis further bolstered confidence in the distinctiveness of the constructs and their ability to effectively measure various aspects of the phenomenon under investigation.

Table 2
Construct Reliability & Validity

	CA	CR	AVE
ATT	0.764	0.85	0.588
INT	0.842	0.888	0.614
PEU	0.860	0.905	0.705
PU	0.844	0.888	0.615
TRU	0.808	0.875	0.638
USG	0.815	0.878	0.643

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

Table 3
Cross Loadings

	ATT	INT	PEU	PU	TRU	USG
ATT1	**0.784**	0.329	0.337	0.443	0.342	0.349
ATT2	**0.791**	0.271	0.275	0.391	0.306	0.338
ATT3	**0.671**	0.362	0.241	0.464	0.367	0.285
ATT4	**0.813**	0.363	0.314	0.562	0.428	0.362
INT1	0.386	**0.789**	0.310	0.438	0.335	0.544
INT2	0.357	**0.814**	0.254	0.412	0.365	0.487
INT3	0.336	**0.795**	0.275	0.345	0.302	0.448
INT4	0.300	**0.738**	0.273	0.373	0.318	0.472
INT5	0.315	**0.778**	0.285	0.410	0.410	0.461
PEU1	0.350	0.295	**0.871**	0.383	0.385	0.429
PEU2	0.291	0.281	**0.850**	0.365	0.338	0.390
PEU3	0.283	0.289	**0.853**	0.261	0.262	0.331
PEU4	0.352	0.332	**0.782**	0.313	0.383	0.385
PU1	0.463	0.324	0.271	**0.758**	0.467	0.318
PU2	0.424	0.388	0.322	**0.792**	0.513	0.397
PU3	0.586	0.502	0.372	**0.840**	0.487	0.509
PU4	0.463	0.406	0.329	**0.840**	0.518	0.427
PU5	0.444	0.329	0.235	**0.681**	0.413	0.318
TRU1	0.346	0.296	0.304	0.435	**0.771**	0.340
TRU2	0.383	0.318	0.369	0.522	**0.864**	0.380
TRU3	0.435	0.391	0.334	0.526	**0.857**	0.475
TRU4	0.334	0.387	0.303	0.454	**0.688**	0.401
USG1	0.418	0.562	0.382	0.484	0.434	**0.815**
USG2	0.359	0.447	0.376	0.421	0.433	**0.808**
USG3	0.343	0.479	0.365	0.426	0.425	**0.816**
USG4	0.267	0.486	0.351	0.299	0.331	**0.766**

Notes: ATT=Attitude INR=Intention PEU=Perceived Ease of Use PU=Perceived Usefulness TRU=Trust USG=Usage

Table 4
Hetrotrait-Monotrait Ratio (HTMT)

	ATT	INT	PEU	PU	TRU
INT	0.537				
PEU	0.467	0.418			
PU	0.751	0.587	0.454		
TRU	0.596	0.529	0.489	0.737	
USG	0.547	0.74	0.546	0.599	0.615

Structural Model

Within this study, the assessment of the structural model involved a concurrent examination of pathway coefficients (β) and coefficients of determination (R^2) using the methodology outlined by (Hair et al., 2017). The Partial Least Squares (PLS) technique was employed, utilizing 5000 subsamples to establish the significance level of path coefficients. The results of hypothesis tests, encompassing confidence intervals, path coefficients (beta), associated t-statistics, and p-values, are presented in Table 5. This thorough analysis provides valuable insights into the significance and robustness of relationships among the variables integrated into the structural model. H1 proposed that attitude has a relationship with intention. The beta coefficient for attitude (ATT) influencing intention to use (INT) is 0.144, with a t-statistic of 2.434 and a p-value of 0.015. The positive beta suggests a positive relationship between attitude and intention. The t-statistic indicates that the relationship is significant ($p < 0.05$), supporting rejecting the null hypothesis. This implies that users' attitudes significantly influence their intention to use the system. Therefore, H1 was supported. For H2, it was proposed that a relationship between attitude and usage exists. The statistical result showed the relationship between attitude (ATT) and artificial intelligence usage (USG) and the beta is 0.046, the t-statistic is 0.841, and the p-value is 0.401. The low beta and non-significant t-statistic suggest a weak and non-significant relationship between attitude and artificial intelligence usage, leading to the acceptance of the null hypothesis. In this context, attitude may not significantly predict actual system usage. Hence, H2 was not supported. H3 proposed that intention mediates the relationship between intention and usage. The statistical result showed that indirect beta coefficients are 0.058 (ATT -> INT -> USG), with corresponding t-statistics of 2.239 and p-values of 0.025. The t-statistic and p-value were significant. This suggests that intention mediated the relationship between attitudes and artificial intelligence usage. Given that, H3 was supported H4 suggested that there was a relationship between perceived ease of use and intention. The statistical data analysis showed that the beta is 0.131, the t-statistic is 2.451, and the p-value is 0.014. The positive beta and significant t-statistic and p-value indicated that perceived ease of use significantly influences users' intention to use the system. Therefore, H4 was supported. H5 suggested that there was a relationship between perceived ease of use and usage. The statistical analysis showed that the relationship between perceived ease of use (PEU) and artificial intelligence usage (USG), the beta is 0.188, the t-statistic is 3.449, and the p-value is 0.001. The positive beta and significant t-statistic suggest that perceived ease of use has a significant and positive impact on actual system usage. Therefore, H5 was supported. H6 proposed intention mediated the relationship between perceived ease of use and usage. The mediating statistical analysis result showed that the indirect beta coefficients are 0.053 with corresponding t-statistics of 2.326 and p-values of 0.020 and 0.001. Both the t-statistics and p-value were significant, supporting the rejection of the null hypothesis. This implies that intention significantly mediated the relationship between perceived ease of use and artificial intelligence usage. Hence, H6 was supported. H7 suggested that there was a relationship between perceived usefulness and intention. The statistical analysis result showed a beta of 0.274, a t-statistic of 4.262, and a p-value of 0.000. The high positive beta and significant t-statistic indicate a strong and significant relationship. Therefore, H7 was supported. H8 suggested that there was a relationship between perceived usefulness and usage. The statistical data analysis showed that the relationship between perceived usefulness (PU) and artificial intelligence usage (USG), the beta is 0.103, the t-statistic is 1.657, and the p-value is 0.098. The lower beta and non-significant t-statistic suggest a weaker and non-significant relationship between perceived usefulness and artificial intelligence usage. Hence, H8 was not supported. H9 proposed that intention mediated the relationship between perceived usefulness and usage. The statistical analysis result showed that the indirect beta coefficient was 0.111 with corresponding t-statistics of 3.687 and p-values of 0.000. Both the t-statistics and p-value are significant. This implies that there was a mediating effect of intention on the relationship between perceived usefulness and artificial intelligence usage. Therefore, H9 was supported.

H10 suggested there was a relationship between trust and intention. The statistical data analysis indicated that the beta is 0.153, the t-statistic is 2.596, and the p-value is 0.009. The positive beta and significant t-statistic suggest that trust significantly influences users' intention to use artificial intelligence. Hence, H10 was supported. H11 proposed that there was a relationship between trust and the usage of artificial intelligence.: The statistical data analysis showed that the beta is 0.166, the t-statistic is 2.734, and the p-value is 0.006. The positive beta and significant t-statistic suggest that trust has a significant and positive impact on actual system usage. Hence, H11 was supported. H12 suggested that there was a relationship between intention and usage. The result of statistical data analysis revealed that the beta is 0.405, the t-statistic is 8.027, and the p-value is 0.000. The high positive beta and highly significant t-statistic indicate a strong and highly significant relationship. Users' intention to use significantly predicts their artificial intelligence usage. Therefore, H12 was supported. H13 suggested that intention mediated the relationship between trust and usage. The mediating statistical analysis result revealed that the indirect beta coefficient was 0.062 with corresponding t-statistics of 2.451 and p-values of 0.014. Both t-statistics and p-value were significant. This implies that intention mediated the relationship between trust and artificial intelligence usage. Therefore, H13 was supported.

The conducted analysis in this research provided robust evidence supporting the majority of the hypotheses, confirming the established connections among the scrutinized variables. To ensure the reliability of the structural model, we assessed the inherent Value Inflation Factor (VIF) values, all of which were found to be below the generous threshold of 5, with the highest value recorded at 2.204 (Table 6). This minimal level of collinearity facilitates meaningful comparisons of magnitudes and the interpretation of coefficients within the model. The endogenous construct demonstrated a noteworthy degree of explicated variance, with an R^2 value of 0.495 (as depicted in Figure 1). Regarding the mediator, the model elucidated approximately 31.6% of the variability in the framework, as evidenced by an R^2 value of 0.316. To evaluate the model's capacity for drawing conclusions and offering managerial recommendations, an out-of-sample predictive analysis was conducted using the PLSpredict technique, following the methodology outlined by Shmueli et al (2016, 2019). Table 7 illustrates the Q^2 forecasts, where values exceeding 0 indicate that the predictions generated by PLS-SEM surpassed the outcomes of standard naive mean predictions. Furthermore, the Root Mean Square Error (RMSE) values associated with the PLS-SEM predictions demonstrated lower values than those derived from the Linear Model (LM) prediction benchmark in seven out of the nine instances, underscoring the predictive capability of the proposed model (refer to Table 7). These findings further substantiate the efficacy of the structural model in producing precise forecasts and offering valuable insights for managerial decision-making. The introduction of the Cross-Validated Predictive Ability Test (CVPAT) by Hair et al (2022) and its application alongside PLSpredicts for evaluation by Liengaard et al (2021) are noteworthy contributions to the ongoing assessment of PLS-SEM model predictions. CVPAT utilizes out-of-sample predictions, comparing average loss values to two benchmarks: indicator averages (IA) and linear model (LM). Lower PLS-SEM loss values indicate superior predictive ability. The objective of CVPAT is to demonstrate whether PLS-SEM surpasses benchmarks, with a significantly negative difference indicating enhanced predictive performance. The results in Table 8 confirm the superiority of PLS-SEM, as its lower average loss values strongly support robust predictive performance. Importance Performance Analysis (IPMA), proposed by Ringle and Sarstedt (2016); Hair et al (2018), was employed to assess the significance and effectiveness of latent variables in elucidating acceptance. The outcomes presented in Table 9 reveal that concerning the overall impact on usage, intention exhibits the most substantial influence (0.405), followed by perceived ease of use (0.241), trust (0.228), perceived usefulness (0.214), and attitude (0.105). These figures signify the relative importance of each latent variable within the usage context. Regarding performance, perceived ease of use achieved the highest score (66.858) on a scale spanning 0 to 100, indicating relatively robust performance. In contrast, intention garnered the lowest score (60.562), signifying a lower level of accomplishment. Notably, despite its pivotal role in usage, intention displayed the weakest performance. In light of these findings, top management in higher education institutions should prioritize and emphasize efforts aimed at enhancing academicians' intentions, as elevating intention can consequently enhance overall performance.

Table 5
Hypotheses Testing Results

	Beta	T statistics	P values	2.50%	97.50%	Results
H1: ATT -> INT	0.144	2.434	0.015	0.022	0.254	*Accepted*
H2: ATT -> USG	0.046	0.841	0.401	-0.059	0.157	***Rejected***
H3: ATT -> INT -> USG	0.058	2.239	0.025	0.010	0.112	*Accepted*
H4: PEU -> INT	0.131	2.451	0.014	0.025	0.235	*Accepted*
H5: PEU -> USG	0.188	3.449	0.001	0.074	0.289	*Accepted*
H6: PEU -> INT -> USG	0.053	2.326	0.020	0.011	0.101	*Accepted*
H7: PU -> INT	0.274	4.262	0.000	0.143	0.395	*Accepted*
H8: PU -> USG	0.103	1.657	0.098	-0.018	0.226	***Rejected***
H9: PU -> INT -> USG	0.111	3.687	0.000	0.056	0.175	*Accepted*
H10: TRU -> INT	0.153	2.596	0.009	0.036	0.267	*Accepted*
H11: TRU -> USG	0.166	2.734	0.006	0.050	0.286	*Accepted*
H12: INT -> USG	0.405	8.027	0.000	0.303	0.501	*Accepted*
H13: TRU -> INT -> USG	0.062	2.451	0.014	0.015	0.115	*Accepted*

Table 6
Inner VIF

	INT	USG
ATT	1.685	1.715
INT		1.463
PEU	1.288	1.313
PU	2.054	2.164
TRU	1.713	1.747

Table 7
PLSpredicts

	Q^2predict	PLS-RMSE	LM_RMSE	PLS - LM
INT1	0.213	0.616	0.615	0.001
INT2	0.190	0.612	0.628	-0.016
INT3	0.145	0.662	0.665	-0.003
INT4	0.155	0.674	0.694	-0.020
INT5	0.198	0.608	0.614	-0.006
USG1	0.284	0.615	0.612	0.003
USG2	0.248	0.602	0.611	-0.009
USG3	0.240	0.669	0.687	-0.018
USG4	0.148	0.720	0.727	-0.007

Table 8
Cross Validated Predictive Ability Test (CVPAT)

	Average loss difference	t value	p-value
INT	-0.088	4.583	0.000
USG	-0.125	5.728	0.000
Overall	-0.104	6.145	0.000

Table 9
Importance-Performance Map Analysis

	Total Effect	Performance
ATT	0.105	66.768
INT	0.405	60.562
PEU	0.241	66.858
PU	0.214	66.542
TRU	0.228	63.704

Discussion & Conclusion

The robust relationships uncovered in the study offer valuable insights that can guide strategic interventions aimed at optimizing AI utilization in educational settings. The positive association between attitude and intention to use AI underscores the significance of cultivating a positive attitude among academicians. Institutions can implement targeted initiatives such as training programs, workshops, and awareness campaigns to foster a positive perception of AI technology. Emphasizing the benefits and relevance of AI in academia can contribute to shaping favorable attitudes, consequently bolstering the intention to integrate AI tools into teaching and research practices. The influential role of perceived ease of use on both intention and actual usage highlights the importance of simplifying the user experience with AI systems. Higher education institutions should focus on user-friendly design, intuitive interfaces, and comprehensive training programs to enhance the ease with which academicians can navigate and utilize AI tools. This approach not only directly influences the intention to use but also catalyzes actualizing AI adoption. The demonstrated impact of perceived usefulness on intention and usage suggests that emphasizing the practical benefits of AI in academia is crucial. Institutions should provide clear evidence of how AI can enhance teaching effectiveness, streamline administrative tasks, and contribute to cutting-edge research. By aligning AI applications with the specific needs and goals of academicians, perceived usefulness can be maximized, driving both intention and actual usage. Moreover, trust emerges as a critical factor influencing both the intention and actual usage of AI. To build trust, institutions must prioritize transparent communication regarding AI systems' reliability, security, and ethical considerations. Establishing governance structures, ensuring data privacy, and fostering a culture of openness around AI implementation can contribute to building and sustaining trust among academicians. Considering intention as a moderator adds a layer to the strategic framework. Recognizing the pivotal role of academicians' intentions in the adoption process, institutions should tailor interventions to specifically address factors influencing intention, such as attitude, perceived ease of use, perceived usefulness, and trust. A comprehensive strategy for enhancing AI usage among academicians in higher education institutions involves cultivating positive attitudes, ensuring ease of use, emphasizing usefulness, building trust, and strategically addressing intention as a moderator. By strategically implementing interventions across these dimensions, institutions can pave the way for a successful and sustainable integration of AI in the academic landscape.

Theoretical Implications

The theoretical implications of the above study are multifaceted, contributing significantly to the existing body of knowledge in the field of technology adoption, particularly within the context of higher education. Firstly, the study advances our understanding of the factors influencing the adoption of artificial intelligence (AI) among academicians. The identified relationships among attitude, perceived ease of use, perceived usefulness, trust, and intention offer a nuanced perspective on the intricate dynamics involved in the decision-making process related to AI utilization. The incorporation of intention as a mediator in the theoretical framework adds depth to current models of technology adoption, emphasizing the pivotal role of individuals' intentions in shaping actual behavior. This nuanced approach acknowledges that intention serves not only as an antecedent to adoption but also as a critical factor influencing the relationship between various determinants and the ultimate adoption outcome. Furthermore, the study underscores the importance of considering the unique context of higher education institutions when examining technology adoption. The academic environment introduces specific challenges and opportunities that influence the perceptions and attitudes of academicians toward AI. Theoretical frameworks and models developed within this study can serve as a foundation for future research endeavors, providing a more tailored and contextually relevant understanding of technology adoption processes in educational settings. In essence, the study contributes theoretical insights that can inform and guide further investigations into the complex interplay of factors influencing the integration of AI in higher education.

Practical Implications

The practical implications of the above study carry substantial value for higher education institutions aiming to strategically integrate artificial intelligence (AI) into their academic landscapes. Firstly, the findings emphasize the need for targeted interventions to shape positive attitudes among academicians towards AI. Educational institutions can design awareness programs, training sessions, and forums to familiarize faculty with the benefits and relevance of AI, fostering a positive perception that positively influences their intention to use it. Practical strategies should also focus on enhancing the perceived ease of use of AI systems. User-friendly interfaces, accessible training programs, and ongoing support mechanisms can reduce barriers, making it more convenient for academicians to adopt and incorporate AI tools into their teaching and research practices. To capitalize on the perceived usefulness of AI, institutions can tailor implementations to align with specific academic needs and goals. Demonstrating the practical benefits, such as increased efficiency in administrative tasks or improved research capabilities, can further motivate academicians to embrace AI technologies. Building and maintaining trust emerge as practical imperatives. Establishing transparent communication channels about AI system reliability, data security, and ethical considerations is crucial. Higher education institutions must invest in governance structures and privacy safeguards to foster a culture of trust around AI adoption. In practice, recognizing the significance of intention as a mediator prompts institutions to develop targeted strategies specifically addressing factors influencing intention. Prioritizing efforts to elevate academicians' intention to use AI, perhaps through incentives, recognition, or tailored support, becomes paramount in translating positive attitudes and perceptions into actual utilization.

Suggestions for Future Studies

Future studies could delve into the nuanced dynamics of AI adoption in diverse educational contexts, considering cultural and institutional variations. Investigating the impact of extended interventions, such as long-term training programs, on sustained AI adoption and examining the role of organizational culture in shaping attitudes and intentions would provide valuable insights. Additionally, exploring the potential influence of external factors, like policy changes or technological advancements, on AI adoption in higher education could contribute to a comprehensive understanding. Comparative studies across various academic disciplines and institutions may also shed light on discipline-specific variations in AI acceptance and utilization.

Conclusion

This study offers a comprehensive exploration of the factors influencing the adoption of artificial intelligence (AI) among academicians in higher education institutions. The intricate relationships between attitude, perceived ease of use, perceived usefulness, trust, and intention provide a nuanced understanding of the decision-making processes associated with AI utilization. The strategic framework outlined underscores the importance of cultivating positive attitudes, ensuring usability, emphasizing usefulness, building trust, and addressing intention as a key moderator. The theoretical implications contribute to the evolving discourse on technology adoption, while the practical implications provide actionable insights for institutions seeking to integrate AI successfully. Suggestions for future studies encourage further exploration of cultural, contextual, and organizational influences on AI adoption, offering avenues for continued research in this dynamic and evolving field. Ultimately, this study equips academia and institutions with valuable insights to navigate the complexities of AI integration, fostering informed decision-making and advancing the educational landscape.

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