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Artificial Intelligence Usage in Higher Education: Academicians' Perspective

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Abstract

Artificial intelligence (AI) has risen as a transformative catalyst in higher education, heralding substantial potential for the academic domain. By leveraging AI's capabilities, scholars access advanced tools for intricate tasks like data analysis, predictive modeling, and revolutionary insights. The present study delves deeply into the intricate nexus of relationships encompassing attitude, perceived behavioral control, trust, intention, and AI application within academia. The research framework integrates three distinct variables: attitude, perceived behavioral control, and trust, with intention serving as a mediating factor and AI usage as the outcome variable. A meticulous survey, thoughtfully adapted from prior research, was employed to collect primary data. Employing structural equation modeling,

which is adept at dissecting intricate variable interactions, the analysis was performed on 362 comprehensive datasets to confirm convergent and discriminant validity. The assessment of the structural model decisively validated the hypotheses, unveiling seven direct relationships and two intermediary connections. These findings underline the profound import of these factors in sculpting users' intentions and facilitating the efficacious incorporation of AI within the academic realm. Theoretical implications extend beyond these empirical discoveries, underscoring the pivotal roles played by attitude, perceived behavioral control, and trust in shaping intentions and consequent behaviors regarding AI integration. As educators worldwide grapple with the integration of AI, the significance of this study extends to actionable insights that can inform policy-making, training curricula, and the evolution of educational paradigms. By furthering our understanding of these underlying dynamics, this research contributes to optimizing AI's integration into higher education. It empowers educators to harness AI's potential, thus engendering innovative and enriching educational experiences that equip students for the demands of the modern world.
Keywords: Attitude, Perceived Behavioral Control, Trust, Intention, Usage

Introduction

In an increasingly interconnected world, the integration of artificial intelligence (AI) tools among academicians within higher education institutions is a burgeoning global phenomenon (He et al., 2019). This trend signifies a pivotal shift in teaching paradigms, harnessing AI's capabilities to enhance learning experiences, foster innovation, and equip educators with cutting-edge resources (Kaplan & Haenlein, 2019). Across diverse cultures and regions, this transformative technology is reshaping academia, ushering in a new era of collaborative, data-driven, and globally relevant pedagogy (Chatterjee & Bhattacharjee, 2020). Amidst Malaysia's higher education landscape, academicians' rapid usage of artificial intelligence (AI) is gaining momentum. This technological advancement holds the potential to revolutionize teaching methods, enrich personalized learning experiences, and spur innovation in research (Okunlaya et al., 2020). As Malaysia positions itself as a regional education hub, the integration of AI underscores the nation's commitment to cultivating a technologically empowered academic environment (Lee & Tajudeen, 2020). This dedication ensures that students are well-prepared for the challenges of the digital era, contributing to Malaysia's academic excellence on a global scale. The promising integration of artificial intelligence (AI) in Malaysian higher education institutions confronts a tapestry of intricate challenges. Disparities in awareness and unequal access to technology pose barriers to uniform AI usage across the educational spectrum (Khalid, 2020). Faculty hesitancy and reluctance add layers of complexity to implementation efforts. Overcoming these hurdles necessitates a united endeavor, encompassing meticulous faculty empowerment programs, all-encompassing training endeavors, and strategic collaborations (Ashaari et al., 2021). This collaborative approach ensures that AI becomes a potent catalyst, invigorating teaching methodologies and fostering an enriched academic journey for learners within the distinctive tapestry of Malaysia's higher education panorama (Ahmed et al., 2022). This study's significance lies in its exploration of artificial intelligence (AI) usage among academicians in higher education institutions. By delving into the complexities of AI integration, it contributes valuable insights into the evolving educational landscape. The findings have the potential to inform policy decisions, shape effective faculty training programs, and foster a deeper understanding of the role AI plays in advancing teaching methods, enhancing student engagement, and preparing educators for the future of education. This research endeavors to comprehensively analyze the intricate network of relationships within the realm of artificial intelligence (AI) usage for teaching among academicians in higher education institutions. The integration of artificial intelligence (AI) in higher education is a rapidly growing field with potential to revolutionize the way students learn and educators teach. Understanding academicians' perspectives on AI usage in higher education is crucial for developing effective and efficient AI-based educational tools and systems. The study's primary goal is to evaluate both the direct and indirect links connecting attitude, perceived behavioral control, trust, and intention with the usage of AI among academicians in higher education institutions. By investigating these interconnections, the research aims to provide a comprehensive understanding of how these constructs collectively shape the integration of AI in educational settings. This exploration will illuminate the multifaceted dynamics that influence AI usage, shedding light on the nuanced interplay between these variables and their combined impact on teaching practices in higher education.

Literature Review

Underpinning Theory

The Theory of Planned Behavior (TPB) (Ajzen, 1985) provides a comprehensive framework for analyzing the direct and indirect relationships linking attitude, perceived behavioral control, trust, and intentions. According to the TPB, academics' attitudes toward AI, particularly how positively or negatively they perceive it impact on their work and educational environments, directly affect their intentions to use AI. In addition, the theory suggests that perceived behavioral control, which reflects individuals' intentions; and their perception of their ability to use AI effectively plays a direct role in shaping their intentions. Trust in both the technology itself and the institutions implementing it is a key factor that indirectly influences attitudes and intentions. The more an academic trust the AI system and the institutions that use it, the more likely they are to have a positive attitude towards AI and with it a greater intention to use it. In addition, trust can influence perceived behavioral control, as greater trust in AI can increase trust in and ability to use it. Overall, the TPB framework provides a systematic lens through which to examine these interrelated constructs and provide insight into the determinants of AI usage in higher education.

Relationship of Trust, Intention, and Usage

The study investigates the mediating role of intention in the relationship between trust and the utilization of artificial intelligence (AI) in teaching among academicians in higher education institutions (Chatterjee& Bhattacharjee, 2020). Trust is a crucial factor in the acceptance and usage of new technologies, including AI, in educational settings. It reflects the extent to which academicians believe in the reliability, credibility, and effectiveness of AI tools for teaching (Bilquise et al., 2023). The mediating variable, intention, represents the willingness and motivation of academicians to employ AI in their teaching practices. It acts as a bridge between trust and the actual usage of AI in the classroom (Ofosu-Ampong et al., 2023). Higher levels of trust are expected to positively influence the intention to use AI in teaching, which, in turn, is expected to lead to higher AI usage (Ragheb et al., 2022). Understanding this mediating effect is pivotal for educators, institutions, and policymakers aiming to promote the effective integration of AI in education (Khan et al., 2023). It provides insights into the psychological processes that underpin technology usage and helps design interventions to enhance trust and intention, ultimately fostering the successful utilization of AI in higher education teaching practices (Rahim et al., 2022). This study contributes to the broader field of educational technology by shedding light on the intricate relationships between trust, intention, and AI usage, furthering our understanding of how these variables interact within the academic community.

Relationship of Attitude, Intention, and Usage

This study delves into the mediating effect of intention in the relationship between attitude and the utilization of artificial intelligence (AI) in teaching among academicians in higher education institutions (Andrews et al., 2021). In this context, attitude signifies the academic community's general disposition toward AI as an instructional tool. It reflects their beliefs, perceptions, and overall sentiment concerning the incorporation of AI into the teaching and learning processes (Gupta & Yadav, 2022). The mediating variable, intention, represents the willingness and motivation of academicians to integrate AI into their teaching practices (Masa'deh et al., 2022). It serves as a bridge between their attitudes toward AI and their actual usage of this technology. The hypothesis posits that a positive attitude toward AI will lead to a stronger intention to incorporate AI in teaching, which, in turn, will predict higher AI usage in academic contexts (Rahman et al., 2021). Understanding this mediating effect is paramount for educational institutions and policymakers aiming to drive successful AI integration in higher education. By identifying the interplay between attitude, intention, and AI usage, it provides insights into the psychological mechanisms behind technology usage (Wang et al., 2023). This knowledge can guide the development of targeted interventions to foster positive attitudes, enhance intention, and promote the effective incorporation of AI into teaching practices (Rahman et al., 2021). In essence, this research contributes to the broader field of educational technology by unraveling the intricate relationships that underlie the usage of AI in higher education institutions, ultimately offering a pathway for enhancing AI's role in academic settings (Srivastava et al., 2021).

Relationship of Perceived Behavioural Control, Intention, and Usage

This study investigates the mediating effect of intention in the relationship between perceived behavioral control and the utilization of artificial intelligence (AI) in teaching among academicians in higher education institutions (Malhotra & Ramalingam, 2023). Perceived behavioral control represents the academicians' beliefs in their ability to effectively use AI in teaching, reflecting their confidence and perceived competence in leveraging AI tools for educational purposes (Ahmad et al., 2022). The mediating variable, intention, signifies the academicians' willingness and motivation to incorporate AI into their teaching practices. It bridges their perceived behavioral control and the actual usage of AI in the academic environment. The hypothesis suggests that higher levels of perceived behavioral control will positively influence the intention to use AI in teaching, which, in turn, will lead to a higher level of AI utilization in higher education (Wang et al., 2023). Understanding this mediating effect is crucial for institutions and policymakers aiming to promote the effective integration of AI in education. It provides insights into the psychological processes that underlie technology usage and helps design interventions to enhance perceived behavioral control and intention, ultimately fostering successful AI utilization in higher education teaching practices (Chanda et al., 2023). This research contributes to the broader field of educational technology by shedding light on the intricate relationships between perceived behavioral control, intention, and AI usage, furthering our understanding of how these variables interact within the academic community Srivastava et al., 2023).

Based on the above hypotheses' development, the following hypotheses were proposed for this study

H1: There is a relationship between trust and intention to use artificial intelligence in teaching among academicians of higher education institutions

H2: There is a relationship between attitude and intention to use artificial intelligence in teaching among academicians of higher education institutions

H3: There is a relationship between perceived behavioral control and the intention to use artificial intelligence in teaching among academicians of higher education institutions

H4: There is a relationship between trust and the usage of artificial intelligence in teaching among academicians of higher education institutions

H5: There is a relationship between attitude and usage of artificial intelligence in teaching among academicians of higher education institutions

H6: There is a relationship between perceived behavioral control and the usage of artificial intelligence in teaching among academicians of higher education institutions

H7: There is a relationship between the intention and usage of artificial intelligence in teaching among academicians of 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 of 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 of higher education institutions

H10: There is a mediating effect of intention on the relationship between perceived behavioral control and the usage of artificial intelligence in teaching among academicians of higher education institutions

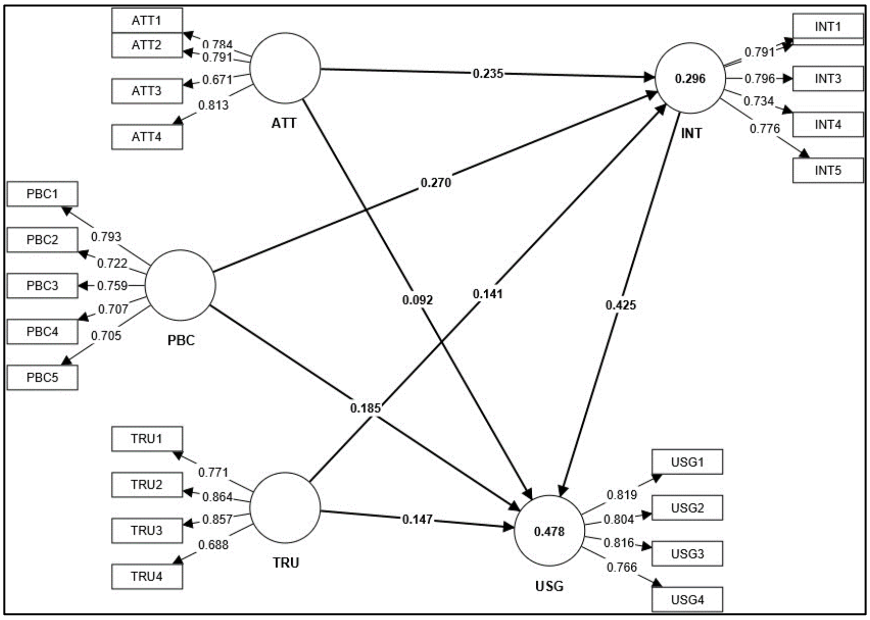

Figure 1: Research Model
Note: ATT=Attitude PBC=Perceived Behavioral Control TRU=Trust INT=Intention USG=Usage

Methodology

This study aimed to assess academics in both public and private higher education institutions. To achieve this goal, the researchers conducted a survey to collect primary data. In order to ensure the survey's efficacy, they meticulously examined previous research and selected reliable and valid measurements. The survey questionnaires were subsequently emailed to the selected participants, employing purposive sampling due to the unavailability of a comprehensive population list. A total of 22 variables were scrutinized in this investigation, encompassing exogenous variables like attitude, gauged using a 4-item scale (Hair et al., 2019); perceived behavioral control, assessed with 5 items (Li et al., 2020); and trust, evaluated through 4 items from Jasielska et al. (2021). The study's mediating factor was intention, measured with 5 items (Shang et al., 2011), while the dependent variable was usage, appraised via 5 items (De Cannière et al., 2009). For this study, a Likert scale featuring five response choices ranging from strongly disagree to strongly agree was employed to gauge the elements within each construct. Out of the 495 surveys disseminated, 381 were collected, yielding a response rate of 76.9%, which was deemed satisfactory for employing structural equation modeling (SEM) in data analysis. From the collected surveys, 362 were identified as clean and suitable for analysis. Table 1 offers a detailed overview of the profile of the online distance-learning student participants included in the sample. For data analysis and hypothesis testing, researchers selected the Smartpls4 software, renowned for its utilization of structural equation modeling (SEM) techniques. This decision was driven by the software's robust assessment capabilities and its proficiency in handling multivariate data analysis. Adhering to the guidelines outlined by Ringle et al. (2022), the researchers employed Smartpls4 to facilitate the evaluation procedures for both model measurement and structural assessment. This software proved indispensable in effectively scrutinizing the proposed hypotheses and conducting comprehensive multivariate data analysis. Its extensive array of features facilitated a thorough examination of both measurement and structural models, seamlessly aligning with the study's objectives.

Data Analysis

Respondents' Profiles

The table offers an extensive examination of survey data pertaining to diverse demographic factors and viewpoints within an academic or educational context. The gender distribution discloses that 59.1% of participants are male, while 40.9% are female, indicating a minor gender disparity within the sample. Analyzing age distribution, the majority fall into the 41 to 50 years old bracket (40.9%), followed by 22.9% in the 31 to 40 years old range, indicating a varied age range with a substantial representation of middle-aged individuals. Concerning years of service, most respondents (30.1%) have served between 11 to 15 years, indicating a seasoned cohort with considerable tenure in their roles. Regarding position hierarchy, the majority of respondents are in the role of Senior Lecturer (76.5%), followed by Associate Professor (19.9%), and Professor (2.5%), suggesting a prevalence of mid-level academic professionals. When examining employers, a higher percentage of participants (68.0%) are employed in private higher education institutions, while 32.0% are affiliated with public institutions, highlighting a greater presence of the private sector. Overall, the survey's tone is positive, with a vast majority of respondents (95.9%) offering positive recommendations, and only a minority (4.1%) expressing negative viewpoints.

Common Method Bias

When engaging in management research, a persistent challenge often encountered is the potential for common method bias, which can lead to the study's variability erroneously reflecting the measurement technique rather than the actual underlying structure. To tackle this issue, the researchers in this investigation utilized Harman's one-factor test method to evaluate the measurement points. The outcomes demonstrated that the primary factor only accounted for 38.2% of the variability, indicating that overall method bias was not a notable concern in this study. This discovery is in accordance with the notion put forth by Podsakoff & Organ (1986) that bias becomes less troublesome when the principal components elucidate less than 50% of the variability. By adopting this strategy, the study's findings gained enhanced robustness and validity, as the potential influence of common method bias on the results was effectively mitigated.

Outer Model Measurement

This study adopted a technique proposed by Hair et al. (2017) to comprehensively evaluate both first-order and second-order measurements. This approach was employed to identify items that exhibited loadings falling below the established threshold of 0.7. Initially, the specified model was introduced, and the evaluation of construct reliability and validity indicated that the Average Variance Extracted (AVE) did not meet the prescribed threshold of 0.5. Consequently, item 2 of the trust construct, with low loading, was removed, leading to the subsequent introduction of a re-specified model. The assessment of construct reliability and validity for the re-specified model demonstrated that all constructs exhibited Average Variance Extracted (AVE) values exceeding 0.5, ranging from 0.544 to 0.642 (Table 1). This result signified the successful establishment of convergent validity, as per Hair et al. (2017). Additionally, the composite reliability of all constructs surpassed 0.7, with values ranging from 0.850 to 0.888, while Cronbach's alpha values were also above 0.7, ranging from 0.764 to 0.842 (Table 1). To ascertain discriminant validity, the researchers initially evaluated cross-loadings to ensure that each item effectively represented and measured its designated construct (Table 1). 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, along with the original sample and corresponding two-tailed 95% confidence intervals, were presented in Table 1. It was observed that the HTMT values remained below the established threshold of 0.9, thereby confirming compliance with discriminant validity.

Table 1
Construct Reliability and Validity, Cross Loadings & Hetrotrait-Monotrait Ratio

						HTMT			
Constructs	Items	Loadings	CA	CR	AVE	**ATT**	**INT**	**PBC**	**TRU**
Attitude	ATT1	0.784	0.764	0.850	0.588				
	ATT2	0.791							
	ATT3	0.671							
	ATT4	0.813							
Intention	INT1	0.791	0.842	0.888	0.613	**0.537**			
	INT2	0.817							
	INT3	0.796							
	INT4	0.734							
	INT5	0.776							
Perceived Behavioral Control	PBC1	0.793	0.791	0.856	0.544	**0.627**	**0.584**		
	PBC2	0.722							
	PBC3	0.759							
	PBC4	0.707							
	PBC5	0.705							
Trust	TRU1	0.771							
	TRU2	0.864	0.808	0.875	0.638	**0.596**	**0.529**	**0.878**	
	TRU3	0.857							
	TRU4	0.688							
Usage	USG1	0.819	0.815	0.878	0.642	**0.547**	**0.74**	**0.658**	**0.615**
	USG2	0.804							
	USG3	0.816							
	USG4	0.766							

Note: CA=Cronbach Alpha CR=Composite Reliability AVE=Average Variance Extracted HTMT=Hetrotrait-Monotrait Ratio

Structural Model
The evaluation of the structural model within this research encompassed the concurrent appraisal of pathway coefficients (β) and coefficients of determination (R2), employing the approach detailed by Hair et al. (2017). The Partial Least Squares (PLS) technique was utilized, involving the use of 5000 subsamples to establish the significance level of path coefficients. The outcomes of hypothesis tests for confidence intervals, inclusive of the path coefficients (beta), corresponding t-statistics, and p-values, are delineated in Table 2. This comprehensive examination furnishes insights into the import and robustness of the relationships among the

variables embedded within the structural model. H1: TRU -> INT - This hypothesis examines the relationship between Trust (TRU) and Intention (INT). The analysis reveals a positive beta coefficient of 0.141, which indicates that an increase in Trust is associated with a corresponding increase in Intention. The substantial T statistic of 2.124 indicates that this relationship is statistically significant. The p-value of 0.034 further supports the significance. Therefore, the study provides evidence to support H1. H2: ATT -> INT - This hypothesis explores the impact of Attitude (ATT) on Intention (INT). The beta coefficient of 0.235 implies that a positive change in Attitude corresponds to a notable positive change in Intention. The high T statistic of 4.441 highlights the statistical significance of this relationship. The extremely low p-value of 0.000 reinforces the robustness of the findings. Hence, the analysis supports H2, indicating that Attitude significantly influences Intention in the studied scenario. H3: PBC -> INT - This hypothesis investigates the association between Perceived Behavioral Control (PBC) and Intention (INT). The analysis reveals a substantial beta coefficient of 0.270, suggesting that an increase in Perceived Behavioral Control leads to a significant increase in Intention. The T statistic of 4.069 underscores the statistical significance of this relationship. The p-value of 0.000 further strengthens the argument. Therefore, the findings lend strong support to H3, indicating a significant impact of Perceived Behavioral Control on Intention. H4: TRU -> USG - This hypothesis examines the effect of Trust (TRU) on Usage (USG). The beta coefficient of 0.147 indicates that an increase in Trust is linked to a moderate increase in Usage. The T statistic of 2.323 signifies the statistical significance of this relationship. With a p-value of 0.020, the analysis supports the notion that this relationship is unlikely to be attributed to random chance. Hence, H4 is supported, suggesting a significant influence of Trust on Usage in the context of the study. H5: ATT -> USG - This hypothesis explores the influence of Attitude (ATT) on Usage (USG). The beta coefficient of 0.092 suggests that changes in Attitude result in a modest change in Usage. The T statistic of 1.764 indicates some level of significance, though not as pronounced as in other cases. The p-value of 0.078 suggests a higher possibility of chance influencing this relationship. Therefore, the study does not support H5, indicating that Attitude does not have a statistically significant impact on Usage. H6: PBC -> USG - This hypothesis investigates the impact of Perceived Behavioral Control (PBC) on Usage (USG). The analysis reveals a substantial beta coefficient of 0.185, indicating that changes in Perceived Behavioral Control correspond to a meaningful change in Usage. The high T-statistic of 3.198 underscores the statistical significance of this relationship. With a low p-value of 0.001, the analysis strongly supports H6, highlighting the significant influence of Perceived Behavioral Control on Usage. H7: INT -> USG - This hypothesis examines the relationship between Intention (INT) and Usage (USG). The beta coefficient of 0.425 suggests that changes in Intention have a pronounced effect on Usage. The remarkably high T statistic of 8.181 indicates a very strong statistical significance. The p-value of 0.000 further reinforces this. Therefore, H7 is strongly supported, indicating a substantial impact of Intention on Usage. H8: TRU -> INT -> USG - This hypothesis explores a sequential relationship, suggesting that Trust (TRU) affects Intention (INT), which subsequently affects Usage (USG). The beta coefficient of 0.060 indicates that Trust's influence on Intention has a modest effect on the overall sequence. The T statistic of 2.040 suggests statistical significance, while the p-value of 0.041 indicates support for this relationship being more than a random occurrence. Hence, H8 is supported, indicating a meaningful mediating influence from Trust to Intention and then to Usage. H9: ATT -> INT -> USG - This hypothesis examines a similar sequential relationship, where Attitude (ATT) affects Intention (INT), which then impacts Usage (USG). The beta coefficient of 0.100 suggests that

Attitude's effect on Intention contributes to the overall sequence. The high T statistic of 3.668 and the low p-value of 0.000 provide strong evidence of statistical significance, indicating that this sequence is unlikely to be a chance result. Consequently, H9 is supported, highlighting a significant mediating influence from Attitude to Intention and subsequently to Usage. H10: PBC -> INT -> USG - This hypothesis investigates the sequential impact of Perceived Behavioral Control (PBC) on Intention (INT) and Usage (USG). The beta coefficient of 0.115 indicates that the influence of Perceived Behavioral Control on Intention contributes to the overall sequence. The considerable T statistic of 3.670 and the low p-value of 0.000 emphasize the statistical significance. Thus, H10 is supported, suggesting a substantial mediating influence from Perceived Behavioral Control to Intention and then to Usage.

The analysis conducted in this study furnished significant substantiation for the majority of the hypotheses, affirming the established connections among the variables scrutinized. A comprehensive overview of the outcomes from hypothesis testing, accompanied by the assessment of effect size (f2), is displayed in Table 2. Effect sizes were appraised using the framework introduced by Cohen (1992) and categorized as small (0.020 to 0.150), medium (0.150 to 0.350), or large (0.350 or greater). The identified effect sizes within this investigation spanned from minor (0.014) to substantial (0.243). To ensure the dependability of the structural model, the inherent value inflation factor (VIF) values were assessed, all of which were found to be beneath the generous threshold of 5, with the highest value recorded at 2.204 (Table 2). This minimal level of collinearity facilitates meaningful comparisons of magnitudes and the interpretation of coefficients within the model. The endogenous construct exhibited a noteworthy degree of explicated variance, displaying an R^2 value of 0.478 (Figure 1). Regarding the mediator, the model elucidated around 29.6% of the variability in the framework, as evidenced by an R^2 value of 0.296. To assess the model's capacity for drawing conclusions and offering managerial recommendations, an out-of-sample predictive analysis was carried out employing the PLSpredict technique, following the methodology expounded by Shmueli et al. (2016, 2019). Table 3 illustrates the Q^2 forecasts, where values surpassing 0 indicate that the forecasts generated by PLS-SEM exceeded 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 six out of the nine instances, underscoring the predictive capability of the proposed model (Table 3). These findings additionally substantiate the efficacy of the structural model in producing precise forecasts and offering valuable insights for managerial decision-making. Hair et al. (2022) introduced the Cross-Validated Predictive Ability Test (CVPAT) to assess PLS-SEM model predictions. Liengaard et al. (2021) applied CVPAT alongside PLSpredicts for evaluation. CVPAT uses out-of-sample predictions, comparing average loss values to benchmarks: indicator averages (IA) and linear model (LM). Lower PLS-SEM loss values indicate better prediction. CVPAT aims to show if PLS-SEM outperforms benchmarks, with a significantly negative difference indicating enhanced predictive ability. Table 4 presents results, confirming PLS-SEM superiority; its lower average loss values strongly support its robust predictive performance. Importance Performance Analysis (IPMA), proposed by Ringle and Sarstedt (2016) and Hair et al. (2018), was employed to assess the significance and effectiveness of latent variables in elucidating acceptance. The outcomes of this assessment are showcased in Table 5. Concerning the overall impact on usage, intention exhibited the most substantial influence (0.423), trailed by perceived behavioral control (0.30), trust (0.207), and attitude (0.192). These figures signify the relative importance of each latent variable within the usage context. In terms of performance scores, attitude attained the highest score (66.768) on a scale spanning 0 to 100, signifying its relatively robust performance. In contrast, intention garnered the lowest score (60.528), indicating a lower level of accomplishment. Interestingly, despite being pivotal for usage, intention displayed the weakest performance. In light of these findings, higher education institutions' top management should prioritize and accentuate efforts aimed at enhancing academicians' intentions. By concentrating on elevating intention, overall performance can consequently be elevated as well.

Table 2
Hypotheses Testing Results, f2 & Inner VIF

Hypotheses	Beta	T statistics	P values	f2	Inner VIF	Decision
H1: TRU -> INT	0.141	2.124	0.034	0.014	2.059	*Supported*
H2: ATT -> INT	0.235	4.441	0.000	0.057	1.376	*Supported*
H3: PBC -> INT	0.270	4.069	0.000	0.049	2.100	*Supported*
H4: TRU -> USG	0.147	2.323	0.020	0.020	2.088	*Supported*
H5: ATT -> USG	0.092	1.764	0.078	0.011	1.455	*Not Supported*
H6: PBC -> USG	0.185	3.198	0.001	0.030	2.204	*Supported*
H7: INT -> USG	0.425	8.181	0.000	0.243	1.420	*Supported*
H8: TRU -> INT -> USG	0.060	2.040	0.041			*Supported*
H9: ATT -> INT -> USG	0.100	3.668	0.000			*Supported*
H10: PBC -> INT -> USG	0.115	3.670	0.000			*Supported*

Table 3
PLSpredict

	Q^2predict	PLS RMSE	LM RMSE	PLS-LM
INT1	0.210	0.617	0.610	0.007
INT2	0.190	0.612	0.623	-0.011
INT3	0.140	0.664	0.660	0.004
INT4	0.130	0.684	0.697	-0.013
INT5	0.182	0.614	0.621	-0.007
USG1	0.279	0.617	0.616	0.001
USG2	0.205	0.619	0.626	-0.007
USG3	0.219	0.678	0.694	-0.016
USG4	0.144	0.722	0.726	-0.004

Table 4
Cross-Validated Predictive Ability Test (CVPAT)

	Average loss difference	t value	p-value
INT	-0.083	4.593	0.000
USG	-0.116	5.510	0.000
Overall	-0.097	5.919	0.000

Table 5
Importance-Performance Map Analysis

	Total Effect	Performance
ATT	0.192	66.768
INT	0.425	60.528
PBC	0.300	65.773
TRU	0.207	63.705

Discussion & Conclusion

The utilization of artificial intelligence (AI) has garnered substantial interest in the realm of education, particularly in higher education institutions, where it holds significant potential to transform teaching methodologies. This discussion delves into the intricate strategy by which attitude, perceived behavioral control, and trust, channelled through intention, can exert both direct and indirect influences on the usage of AI among academicians in higher education teaching. At the heart of this strategy lies attitude, reflecting individuals' overall positive or negative assessment of AI integration in teaching. A positive attitude can foster openness and enthusiasm toward adopting AI tools, directly influencing academicians to embrace AI in their teaching practices. However, the connection is not solely unmediated. Perceived behavioral control, encompassing perceived ease of use and self-efficacy in AI implementation, acts as a crucial bridge. A favorable attitude coupled with a high perceived behavioral control fosters a direct inclination to utilize AI tools. Thus, academicians who view AI as beneficial and believe in their ability to effectively employ it are more likely to engage in its usage. Trust plays a pivotal role in amplifying these effects. Trust in AI, rooted in reliability and competency perceptions, both directly and indirectly reinforces the usage of AI among academicians. A direct pathway implies that higher levels of trust lead to greater willingness to utilize AI tools, as the perception of AI as a dependable and capable assistant engenders a sense of comfort. Indirectly, the trust operates through intention. The mediating role of intention signifies that higher levels of trust enhance the intention to use AI, and this intention, in turn, fuels actual usage. This cascading effect underscores the importance of fostering trust in AI systems, as it not only shapes intention but also propels concrete usage. The interplay between these variables elucidates a comprehensive strategy for encouraging AI integration in higher education teaching. A positive attitude, buttressed by perceived behavioral control and trust, forms the foundational construct of intention. The subsequent influence of intention on usage completes the nexus. This intricate web of connections emphasizes the significance of fostering not only a positive attitude but also perceived behavioral control and trust to catalyze AI's effective usage. Institutions aiming to enhance AI utilization should design interventions that address these elements collectively. In conclusion, the strategy outlined here underscores the interwoven roles of attitude, perceived behavioral control, trust, and intention in steering the utilization of AI among academicians in higher education teaching, providing a holistic framework for comprehensive intervention and strategic planning.

Theoretical Implications

The theoretical implications of the interplay between attitude, perceived behavioral control, trust, and intention in shaping the usage of artificial intelligence (AI) among academicians in higher education institutions are profound and multifaceted. Firstly, this conceptual framework underscores the significance of cognitive factors in technology usage within educational settings. It extends the Theory of Planned Behavior by illuminating the crucial mediating role of intention, highlighting that intention serves as a bridge between attitudinal factors and actual usage. This contributes to a deeper understanding of the psychological mechanisms underlying technology acceptance. The model enriches the literature on trust and AI integration by emphasizing trust's dual role as both a direct enabler and an indirect influencer. Trust is established as a pivotal factor that not only instills a sense of confidence in AI's capabilities but also amplifies individuals' willingness to engage with AI tools through the lens of intention. This dual function of trust contributes to a more nuanced comprehension of its role in technology usage. Furthermore, this framework underscores the necessity of considering perceived behavioral control as a significant determinant of AI usage. By demonstrating its mediating effect on the relationship between attitude and intention, it highlights the practical importance of ensuring that individuals perceive AI as accessible and manageable, thereby enhancing their confidence in utilizing it effectively.

Practical Implications

The practical implications stemming from the interplay of attitude, perceived behavioral control, trust, and intention in shaping the usage of artificial intelligence (AI) among academicians in higher education institutions offer valuable insights for educators, administrators, and policymakers. Firstly, understanding the pivotal role of attitude underscores the importance of fostering positive perceptions of AI technology. To promote AI integration, institutions can design targeted awareness campaigns and training programs to enhance academicians' positive attitudes, emphasizing the benefits and advantages AI can offer in teaching. Recognizing the mediating role of perceived behavioral control highlights the need for comprehensive support mechanisms. Institutions should provide accessible and user-friendly AI tools, along with training and technical assistance, to bolster academicians' confidence in utilizing AI effectively. By addressing perceived barriers and enhancing perceived control, institutions can facilitate a smoother transition to AI-enhanced teaching.

Moreover, the emphasis on trust underscores the significance of ensuring AI systems are reliable, transparent, and ethically sound. Transparent communication about AI processes and outcomes, coupled with regular updates and improvements, can enhance trust and confidence among academicians. Additionally, fostering a sense of collaboration between AI and educators can build trust by showcasing AI as a supportive tool rather than a replacement.

Suggestions for Future Studies

Future studies in this domain could explore the moderating effects of individual characteristics, such as technological proficiency and personality traits, on the relationships between attitude, perceived behavioral control, trust, intention, and AI usage. Additionally, investigating the impact of contextual factors, such as institutional support, on these relationships could provide a deeper understanding of the broader ecosystem influencing technology usage. Longitudinal studies could capture the dynamics of attitude, trust, and intention over time, offering insights into how these factors evolve and interact throughout the usage process. Furthermore, qualitative research could delve into the nuances of academicians' experiences, shedding light on the emotional and cognitive dimensions underlying AI integration. Overall, a multifaceted approach considering individual, contextual, and temporal dimensions could enrich our understanding and inform more targeted strategies for promoting AI usage in higher education teaching.

Conclusion

This study sheds light on the intricate dynamics of attitude, perceived behavioral control, trust, intention, and their collective influence on the usage of artificial intelligence among academicians in higher education. The findings emphasize the pivotal role of intention as a mediating factor and the dual significance of trust as both a direct enabler and an indirect influencer. By comprehensively examining these interconnected factors, this study provides a nuanced framework for fostering successful AI integration. The insights gleaned offer valuable guidance for educators, administrators, and policymakers, aiding in the effective implementation of AI technology to enhance teaching practices in higher education institutions. Further research, incorporating individual characteristics and contextual factors, promises to enrich our understanding and refine strategies for advancing AI usage in educational settings.

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