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# Deciphering Academicians' Usage of Artificial Intelligence among Academicians in Higher Education Institutions

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**Abstract**
Artificial intelligence (AI) has emerged as a transformative technology in higher education, holding immense significance for academicians. By harnessing the power of AI, researchers are empowered with advanced capabilities for data analysis, trend prediction, and innovative insights. This study aims to explore the direct correlation between attitude, perceived usefulness, perceived ease of use, and perceived behavioral control with intention and the subsequent usage of AI in the academic setting. The research model integrates three independent variables: attitude, perceived usefulness, perceived ease of use, and perceived behavioral control, with intention acting as a mediator and usage as the dependent variable. Primary data were collected through a well-structured survey questionnaire, which was thoughtfully adopted and adapted from previous studies. The study diligently analyzed 362 clean datasets using the structural equation modeling technique, which is well-suited for assessing complex relationships among variables. In the initial stages of analysis, the measurement model's convergent validity was evaluated by assessing construct reliability and validity. Subsequently, the discriminant validity was assessed and confirmed through cross-loading and Hetrotrait-Monotrait (HTMT) ratios, ensuring that each construct is distinct

and not redundant with others. Upon evaluating the structural model, the hypotheses testing yielded significant results. It revealed that attitude, perceived usefulness, perceived ease of use, and perceived behavioral control have a positive and significant influence on intention. Moreover, the study established that intention strongly affects AI usage among academicians. These findings reaffirm the importance of these factors in shaping users' intention to embrace AI technology and subsequently utilize it effectively in their academic pursuits. Theoretical implications derived from this study highlight the critical role of attitude, perceived usefulness, perceived ease of use, and perceived behavioral control in shaping users' intentions and their subsequent behavior toward AI usage.

**Keywords:** Attitude, Perceived Usefulness, Perceived Ease of use, Perceived Behavioral Control, Intention, Usage

## Introduction

The increasing usage of artificial intelligence (AI) among academicians has sparked a paradigm shift in the learning landscape, empowering teaching, research, and administrative processes (Al-Sartawi et al., 2021). AI's versatility extends from personalized learning experiences, tailoring education to individual needs, to data-driven decision-making, and optimizing academic practices for enhanced outcomes (Mohamad et al., 2023). This introduction delves deeper into AI's growing significance in higher education, meticulously evaluating its profound impact on educators and students, while concurrently shaping academia's global future (lić et al., 2021). Harnessing AI capabilities, academicians gain access to valuable insights, leading to elevated student engagement and more efficient administrative workflows (Rangel-de Lázaro & Deart, 2023). Embracing AI's boundless potential becomes a strategic imperative for higher education institutions to spearhead innovation and effectively cater to the diverse needs of learners in today's ever-evolving educational landscape. This transformative journey stands paramount in sustaining a position at the forefront of educational excellence in the digital age. The use of artificial intelligence (AI) by academicians in Malaysian higher education institutions has experienced significant growth. Malaysia's focus on technological advancement and educational excellence has led to the transformation of the academic landscape through AI integration (Alhumaid et al., 2023). This introduction delves into the application of AI among Malaysian educators, analyzing its effects on teaching methodologies, research, and administrative processes. By examining specific AI initiatives in academia, the study aims to understand how this cutting-edge technology is reshaping the learning experience and fostering innovation in the country's higher education sector (Barakina et al., 2021). Embracing AI, academicians in Malaysia personalize learning, optimize course content, and provide adaptive assessments to students. AI-driven research tools facilitate data analysis, leading to ground-breaking discoveries, while AI-powered systems streamline administrative tasks, improving resource management and student services (Yu & Nazzir, 2021). This exploration contributes to Malaysia's global competitiveness in education while addressing unique challenges, shedding light on AI's transformative impact and its integration with academic excellence and innovation (Abid et al., 2021). The challenge of incorporating artificial intelligence (AI) in teaching among academicians in Malaysia stems from various factors. Primarily, educators may lack awareness and training on effective AI integration (Alhumaid et al., 2023). Moreover, concerns about job security and AI's complexity deter some academicians from adopting AI. Additionally, the cost and availability of AI tools hinder widespread implementation. Addressing these obstacles is crucial to fully exploit AI's potential in enhancing teaching practices (Rahim et al., 2022). This study's significance lies in its implications for policymakers, higher education institutions, and students. Policymakers can utilize research findings to craft policies promoting AI in education, bolstering technological advancement and global academic competitiveness. Higher education institutions can benefit from insights into AI-driven teaching methods, enhancing student learning experiences and academic achievements, thus improving institutional reputation and student satisfaction (Mohamad et al., 2023). Ultimately, students gain from personalized learning and increased access to educational resources, acquiring essential skills for future job markets. The driving force behind this study is the accelerating adoption of artificial intelligence in the realm of education. This study seeks to delve deeper into how educators within higher education institutions embrace AI technologies, aiming to unravel the nuances of its utilization, potential transformative effects, prevalent obstacles, and the imperative for well-informed AI integration strategies. By investigating this domain, we aim to provide valuable insights into the evolving landscape of AI in academia. The study examines the direct correlation between attitude, perceived usefulness, perceived ease of use, and perceived behavioral control with intention and the subsequent usage of AI among academicians in Malaysia's higher education institutions.

## Literature Review

*Relationship between Attitude and Intention*

Attitudes of academicians toward AI can have a significant impact on their teaching practices. Attitude toward using technology has a direct effect on the intention to use technology among student-teachers (Luik & Taimalu, 2021, Ayanwale et al., 2022). Positive attitudes can lead to the integration of AI-based teaching and learning solutions into their classrooms, resulting in personalized and innovative teaching experiences (Gupta & Bhaskar, 2020). In the context of experienced academicians, attitude toward E-learning use was found to be a significant factor in predicting the intention to use E-learning in teaching (Mailizar et al., 2021). Additionally, attitude toward AI for social good was found to be a powerful predictor of students' behavioural intention to engage in AI learning (Chai et al., 2020). These findings suggest that a positive attitude towards technology and AI can contribute to the intention to use them in teaching. Academicians' attitudes toward AI are influenced by several factors. According to Sjoden (2020), teachers need support in making ethically informed decisions about educational interventions and strategies when using AI systems. Trust and institutional support are important factors that influence academicians' adoption of AI-based educational technology (Nazaretsky et al., 2021; and Gupta & Bhaskar, 2020). Furthermore, the advancement of AI methods and techniques can create a gap between researchers and academicians, making it more difficult for academicians to accept AI systems in education (Khlaif, 2018). On the other hand, scepticism or rejection of AI can hinder its adoption in education. According to Nazaretsky et al. (2021), teachers are reluctant to accept AI-based recommendations when it contradicts their previous knowledge about their students and they expect AI to be absolutely correct even in situations that absolute truth may not exist. Vazhayil (2019) mentioned that teachers have a poor belief state in the potential of AI and face challenges in policy communication, infrastructure, pedagogy, content delivery, and cultural influence. It is important for teachers to have adequate support from their institutions, including resources, time, and recognition, to willingly embrace AI-based methodologies (Lindner & Berges, 2020). Academicians perceived the integration of AI technology positively due to its dynamic characteristics and effectiveness, despite facing various challenges, such as lack of training, technical support, and resources, resulting in disadvantages associated with its use (Zulkarnain & Md Yunus, 2023). Polak (2022) found that teachers have a positive attitude towards AI education and are motivated to introduce AI-related content in their classrooms, even with a basic level of digital skills and low AI-related skills. Overall, the attitudes of academicians toward AI can shape their willingness to adopt and effectively utilize AI-based teaching methods in thclasseslass. Thus, it can be hypothesized that:

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

*Relationship between Perceived Behavioural Control and Intention*

The belief that one can carry out an activity is known as perceived behavioral control (PBC). Along with attitude and subjective norm, it is one of the three elements of the theory of planned behaviour (TPB), which was developed by Ajzen in 1985. PBC has been demonstrated to be an important predictor of intention and behavior in a number of scenarios, including the application of artificial intelligence (AI) in education. The connection between perceived behavioral control and the intention to employ AI in education has been the subject of numerous studies. Perceived behavioral control is a strong predictor of intention to employ AI in education, according to these researches. For instance, a study by Roy et al. (2022) and Chai et al. (2020) indicated that perceived behavioral control was the best predictor of both science teachers' and students' intentions to employ AI in the educational setting. The availability of resources (Gado et al., 2022), the degree of training (Wu et al., 2022), and the perceived usability of AI (Yan et al., 2014) are only a few examples of the variables that can affect perceived behavioral control. Academics are more likely to plan to use artificial intelligence (AI) in their teaching when they feel they have the tools, education, and expertise to do so. The results of this research indicate that in order to boost academicians' intentions to employ AI in teaching, it is critical to address their perceived behavioral control. This can be accomplished by providing them with the resources, training, and assistance they require to properly employ AI effectively. Therefore, it can be hypothesized that:

*H2: There is a relationship between perceived behavioural control and intention to use artificial intelligence in teaching among academicians in higher education institutions.*

*Relationship between Perceived Ease of Use and Intention*

Perceived ease of use is an important determinant of use of technology or systems (Davis, 1989, 1993; Davis, Bagozzi, & Warshaw 1992; Mathieson, 1991). The importance of perceived ease of use has been highlighted in TAM because of the impact a poor user interface has on rejection of IT technology (Venkatesh & Davis, 1996). Perceived ease of use in TAM is "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989, p.320). The findings by Abdulla Al Darayseh (2023) and Osman et al. (2023) revealed that science teachers have a high level of acceptance for using AI applications in their classrooms. Ease of use and attitudes toward AI applications have the greatest influence on teachers' behavioural intention toward AI applications. Besides, teachers' perceived ease of use of AI further influences their perceived usefulness as well as their behavior of employing AI to support teaching. Lee et al. (2005), perceived ease of use influenced student intention to use Internet-based learning indirectly through perceived usefulness and perceived enjoyment. Findings suggested that perceived ease of use has a significant effect on students' attitudes and perceived usefulness simultaneously. Research conducted by Anouze, AL, and Alamro, AS (2020), proved that there is an effect of perceived ease of use on the intention to use the mobile banking application. Prior researchers by H.Y. Kim, Lee, Mu,n and Johnson (2017) found that perceived ease of use is a significant factor in determining the adoption of smart retail technologies, and Brill (2018) indicated that improved consumer satisfaction will result if digital assistants can meet consumers' expectations. In view of the above, it is hypothesized that:

*H3: There is a relationship between perceived ease of use and intention to use artificial intelligence in teaching among academicians in higher education institutions.*

*Relationship between Perceived Usefulness and Intention*

The study found that AI-powered tools and technologies can have a positive effect on teaching and learning. A study by Chen, et al. (2018), for example, found that academics who use AI are more likely to report that they are satisfied with their teaching. Similarly, the study by Alghamdi et al. (2020) found that AI-powered tools can improve student learning outcomes. Chen and Alghamdi also found that there was a positive correlation between perceptions of usefulness and intentions to use AI in teaching, that is; academics who used artificial intelligence were more likely to report that they were satisfied with their teaching (Chen, et al., 2018; Osman et al., 2023). While Alghamdi et al. (2020) also found that AI can help improve student learning outcomes. This is corroborated by Zulkarnain, N.S, Yunus, M (2023) who found that teachers' perceptions influence teachers' intentions to continue using AI technology. There is no doubt that there are positive and negative effects on the relationship between intelligence and learning by using AI (Bali, M.M E, I, Kumalasani, M.P, Yunilasari, D, 2022), but the use of AI in higher education does not affect the attitude of higher education students. AI-powered tools can only be effective if they are used thoughtfully and deliberately. Academics must be trained in how to use AI tools effectively and be willing to experiment with new technologies. Thus, it is hypothesized that:

*H4: There is a relationship between perceived usefulness and intention to use artificial intelligence in teaching among academicians in higher education institutions.*

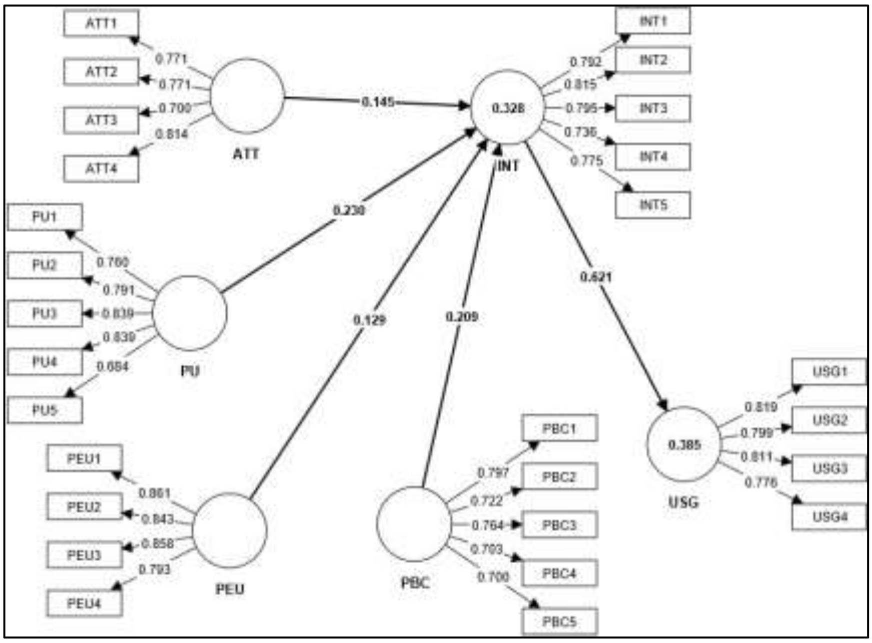
*Relationship between Intention and Usage*

The intricate connection between AI intention and usage in higher education pedagogy is multifaceted (Shahzad et al., 2021). Intention concerns AI's purpose in education, while usage involves its tangible application (Holmes, 2021). Scholarly inquiries suggest varied factors shape AI adoption inclinations (Kebah et al., 2019). Crucially, perceived AI benefits, such as personalized learning, adaptable teaching, and instant feedback, influence intent (Molnar, 2019). Additionally, institutional support for AI integration influences adoption (Tondeur et al., 2019; Kebah et al., 2019). Institutions prioritizing AI tend to have stronger intentions for integration. However, the intention-usage relationship isn't consistently direct (Ayanwale et al., 2022; Connie et al., 2022). Despite well-meaning intent, obstacles like faculty resistance, inadequate training, and ethical concerns can hinder AI's practical usage (Molnar, 2019). Successful AI integration requires careful planning, collaboration, and ongoing evaluation (Tondeur et al., 2019). Ertmer and Ottenbreit-Leftwich's 2013 study underscores educators' attitudes shaping AI intent. This aligns with the Technology Acceptance Model (TAM), suggesting perceived usefulness and ease of impact on technology intent (Davis, 1989).

Educators perceive AI's value in enhancing teaching efficiency, personalized learning, and timely feedback (Samarakoon & Naidu, 2017; Osman et al., 2023)). Moreover, the interplay between intention and actual AI usage in education has been investigated across contexts. Wang and Hannafin's 2005 study explores the intention-behavior gap among university instructors. Despite positive intent, barriers like limited training and technical support hinder actual usage (Wang & Hannafin, 2005). In higher education, where teaching practices are diverse, factors like institutional policies, technology infrastructure, and educator familiarity can influence the intent-usage relationship (Siemens, 2013). Scholars emphasize professional development to bridge this gap (Siemens, 2013).
Therefore, it is hypothesized that:

*H5: There is a relationship between the intention and usage of artificial intelligence in teaching among academicians in higher education institutions.*

Figure 1: Research Model



Note: ATT=Attitude PU=Perceived Usefulness PEU=Perceived Ease of Use
PBC=Perceived behavioural Control INT=Intention USG=Usage

**Methodology**

The main objective of this research was to examine academicians from both public and private higher education institutions. The researchers gathered primary data for their study by conducting a survey. To ensure the survey's effectiveness, they carefully reviewed past studies and selected appropriate measurements that were reliable and valid. The survey questionnaires were then distributed via email to the chosen participants, utilizing purposive sampling as a data collection method since a comprehensive list of the entire population was not available. A total of 27 variables were observed in this study, including exogenous variables, mediating variable, and endogenous variable. The exogenous variables comprised the attitude construct, which was measured using 4 items (Hair et al., 2019); the perceived usefulness construct, which was measured using 5 items (Shang et al., 2011); the perceived ease of use construct, which was measured using 4 items (Shang et al., 2011); and the perceived behavioral control construct, which was measured using 5 items (Li et al., 2020).

The mediating variable in this study was the intention, which was measured using 5 items (Shang et al., 2011), while the dependent variable was the usage, which was measured using 5 items (De Cannière et al., 2009). In this study, a Likert scale with five response options ranging from strongly disagree to strongly agree was used to measure the items for each construct. Out of the 495 questionnaires distributed, 381 were returned, resulting in a response rate of 76.9%. This response rate was considered sufficient for conducting data analysis using structural equation modeling (SEM). Among the returned questionnaires, 362 were determined to be clean and suitable for analysis. In Table 1, a comprehensive summary of the profile of the online distance-learning student respondents included in the sample is presented. In conducting data analysis and hypothesis testing, researchers opted for the Smartpls4 software, which employs structural equation modeling (SEM) techniques. This choice was motivated by the software's robust evaluation capabilities and its aptitude for handling multivariate data analysis. Following the guidelines suggested by Ringle et al. (2022), the researchers utilized Smartpls4 to facilitate the assessment procedures for model measurement and structural evaluation. This software proved invaluable in effectively testing the proposed hypotheses and conducting comprehensive multivariate data analysis. Its extensive features enabled a thorough evaluation of both the measurement and structural models, aligning seamlessly with the study's objectives.

Table 1

*Respondents' Profiles*

| | | Frequency | Percent |
|---|---|---|---|
| Gender | Male | 214 | 59.1 |
| | Female | 148 | 40.9 |
| Age | <30 years old | 27 | 7.5 |
| | 31 to 40 years old | 83 | 22.9 |
| | 41 TO 50 years old | 148 | 40.9 |
| | 51 TO 60 years old | 73 | 20.2 |
| | >60 years old | 31 | 8.6 |
| Year Service | <5 years | 20 | 5.5 |
| | 6-10 years | 48 | 13.3 |
| | 11-15 years | 109 | 30.1 |
| | 16-20 years | 106 | 29.3 |
| | 21-25 years | 46 | 12.7 |
| | 26-30 years | 16 | 4.4 |
| | >30 years | 17 | 4.7 |
| Position Level | Lecturer | 4 | 1.1 |
| | Senior Lecturer | 277 | 76.5 |
| | Associate Professor | 72 | 19.9 |
| | Professor | 9 | 2.5 |
| Employer | Public Higher Education Institution | 116 | 32.0 |
| | Private Higher Education Institution | 246 | 68.0 |
| Recommendation | Yes | 347 | 95.9 |
| | No | 15 | 4.1 |
| | Total | 362 | 100.0 |

**Data Analysis**

*Common Method Bias*

Conducting management research often faces the challenge of common method bias, where study variance may mistakenly reflect the measurement method rather than the actual structure. To address this concern, the investigators in this study employed Harman's one-factor test method to assess the measurement points. The results revealed that the main factor accounted for only 36.9% of the variance, indicating that general method bias was not a significant concern in this study. This finding aligns with the suggestion by Podsakoff & Organ (1986) that bias becomes less problematic if the principal components explain less than 50% of the variance. By adopting this approach, the study's results were rendered more robust and valid, as the potential impact of common method bias on the outcomes was effectively minimized.

*Reflective Model Measurement*

This study adopted a technique proposed by Hair et al. (2017) to evaluate the measurements in both first-order and second-order. This approach aimed at identifying items with loadings below the threshold of 0.7. The examination of construct reliability and validity revealed that all constructs had Average Variance Extracted (AVE) values greater than 0.5, ranging from 0.545 to 0.704 (Table 2), signifying the establishment of convergent validity (Hair et al., 2017). Moreover, the composite reliability for all constructs exceeded 0.7, ranging from 0.849 to 0.905, and Cronbach's alpha values were greater than 0.7, ranging from 0.775 to 0.857 (Table 2). To establish discriminant validity, the researchers initially assessed cross-loadings to ensure that all items effectively represented and measured their respective constructs (Table 2). Subsequently, they utilized the Hetrotrait-Monotrait (HTMT) ratio, a recommended criterion for evaluating discriminant validity in Variance-Based Structural Equation Modeling (VB-SEM) (Henseler, Ringle & Sarstedt, 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 analysis further strengthened the confidence in the constructs' distinctiveness and ability to effectively measure different aspects of the phenomenon under investigation.

Table 2

*Construct Reliability & Validity & Cross Loadings*

| Constructs | Items | Loadings | CA | CR | AVE |
|---|---|---|---|---|---|
| Attitude | ATT1 | 0.771 | 0.764 | 0.849 | 0.585 |
| | ATT2 | 0.771 | | | |
| | ATT3 | 0.700 | | | |
| | ATT4 | 0.814 | | | |
| Intention | INT1 | 0.792 | 0.842 | 0.888 | 0.613 |
| | INT2 | 0.815 | | | |
| | INT3 | 0.795 | | | |
| | INT4 | 0.736 | | | |
| | INT5 | 0.775 | | | |
| Perceived Behavioral Control | PBC1 | 0.797 | 0.791 | 0.856 | 0.545 |
| | PBC2 | 0.722 | | | |
| | PBC3 | 0.764 | | | |
| | PBC4 | 0.703 | | | |
| | PBC5 | 0.700 | | | |
| Perceived Ease of Use | PEU1 | 0.861 | 0.860 | 0.905 | 0.704 |
| | PEU2 | 0.843 | | | |
| | PEU3 | 0.858 | | | |
| | PEU4 | 0.793 | | | |
| Perceived Usefulness | PU1 | 0.760 | 0.844 | 0.888 | 0.616 |
| | PU2 | 0.791 | | | |
| | PU3 | 0.839 | | | |
| | PU4 | 0.839 | | | |
| | PU5 | 0.684 | | | |
| Usage | USG1 | 0.819 | 0.815 | 0.878 | 0.642 |
| | USG2 | 0.799 | | | |
| | USG3 | 0.811 | | | |
| | USG4 | 0.776 | | | |

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

Table 3
*Hetrotrait-Monotrait (HTMT) Ratios*

| | ATT | INT | PBC | PEU | PU |
|---|---|---|---|---|---|
| INT | 0.537 | | | | |
| PBC | 0.627 | 0.584 | | | |
| PEU | 0.467 | 0.418 | 0.489 | | |
| PU | 0.751 | 0.587 | 0.792 | 0.454 | |
| USG | 0.547 | 0.740 | 0.658 | 0.546 | 0.599 |

*Structural Model*

The structural model evaluation in this study involved the simultaneous assessment of pathway coefficients (β) and coefficients of determination ($R^2$), following the methodology outlined by Hair et al. (2017). The Partial Least Squares (PLS) method was employed, utilizing 5000 subsamples to determine the significance level of path coefficients. The results of hypothesis tests for confidence intervals, including the path coefficients (beta), corresponding t-statistics, and p-values, are presented in Table 4. This comprehensive analysis provides insights into the significance and strength of the relationships among the variables in the structural model. The first hypothesis examines the relationship between attitudes (ATT) and intention to use (INT). The coefficient of 0.145 indicates a positive association between the two variables. This means that favorable attitudes towards the technology are related to a stronger intention to use it. The t-value of 2.497 is statistically significant (p-value = 0.013), with a relatively low $f^2$ (0.018). The second hypothesis investigates how perceived behavioral control (PBC) affects intention to use (INT). The coefficient of 0.209 suggests a positive relationship between PBC and INT. Individuals who perceive greater control over using the technology are more likely to have a higher intention to use it. The t-value of 3.558 (p-value = 0.000) indicates the significance of this relationship with a relatively low $f^2$ of 0.035. The third hypothesis explores the impact of perceived ease of use (PEU) on intention to use (INT). With a coefficient of 0.129, this relationship is also positive. It suggests that individuals who perceive the technology as easy to use are more likely to have a stronger intention to use it. The t-value of 2.578 (p-value = 0.010) supports the statistical significance of this relationship, with a low $f^2$ of 0.019. The fourth hypothesis examines the relationship between perceived usefulness (PU) and intention to use (INT). The coefficient of 0.230 indicates a positive association. Individuals who perceive the technology as useful are more likely to have a higher intention to use it. The t-value of 3.373 (p-value = 0.001) confirms the statistical significance of this relationship with a relatively low $f^2$ of 0.036. The fifth hypothesis investigates the impact of intention to use (INT) on usage (USG). With a coefficient of 0.621, this relationship is highly positive and indicates that a stronger intention to use leads to greater ultimate system usage. The t-value of 17.724 (p-value = 0.000) signifies the high statistical significance of this relationship with a large $f^2$ of 0.626.

The study's analysis provided substantial evidence supporting the majority of the hypotheses, confirming the relationships among the variables under investigation. A comprehensive summary of the hypothesis testing results, along with the effect size, is presented in Table 4. Effect sizes were evaluated using Cohen's criteria (1992) and classified 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 ranged from small (0.003) to large (0.231). To ensure the reliability of the structural model, the intrinsic value inflation factor (VIF) values were examined, with all values below the lenient threshold of 5, and the highest value being 2.214. This low level of collinearity allows for meaningful comparisons of sizes and interpretation of coefficients in the model. The endogenous construct showed a significant degree of explained variance, with an $R^2$ value of 0.385 (Figure 1). As for the mediator, the model accounted for approximately 32.8% of the variance in the structure, as indicated by an $R^2$ value of 0.328. To evaluate the model's ability to make inferences and provide management suggestions, an out-of-sample predictive analysis was conducted using the PLSpredict method, following the approach described by Shmueli et al. (2016, 2019). Table 5 presents the Q2 predictions, where values higher than 0 indicate that the predictions made by PLS-SEM outperformed the standard naive mean prediction results. Additionally, the root mean square error (RMSE) values of the PLS-SEM predictions were lower than those of the linear model (LM) prediction benchmark in six out

of nine instances, demonstrating the predictive power of the proposed model (Table 5). These results further validate the effectiveness of the structural model in generating accurate predictions and providing valuable insights for managerial decision-making.
Ringle and Sarstedt (2016) and Hair et al. (2018) proposed the use of Importance Performance Analysis (IPMA) to evaluate the significance and effectiveness of latent variables in explaining acceptance. The results of this analysis are presented in Table 7. In terms of overall impact on adoption, intention exhibited the strongest influence (0.621), followed by perceived usefulness (0.143), perceived behavioral control (0.130), attitude (0.090), and perceived ease of use (0.080). These values signify the relative importance of each latent variable in the context of usage. Regarding performance scores, perceived ease of use obtained the highest score (66.860) on a scale ranging from 0 to 100, indicating its relatively strong performance. Conversely, intention received the lowest score (60.555), suggesting the lowest level of achievement. Interestingly, despite being the most crucial factor for usage, intention displayed the lowest performance level. Based on these findings, it is advisable for top management in higher education institutions to prioritize and emphasize activities aimed at improving employees' intentions. By focusing on enhancing intention, overall performance can be enhanced as well.

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

| Hypotheses | Beta | T statistics | P values | $f^2$ | Inner VIF | Decision |
|---|---|---|---|---|---|---|
| H1: ATT -> INT | 0.145 | 2.497 | 0.013 | 0.018 | 1.702 | *Supported* |
| H2: PBC -> INT | 0.209 | 3.558 | 0.000 | 0.035 | 1.869 | *Supported* |
| H3: PEU -> INT | 0.129 | 2.578 | 0.010 | 0.019 | 1.274 | *Supported* |
| H4: PU -> INT | 0.230 | 3.373 | 0.001 | 0.036 | 2.214 | *Supported* |
| H5: INT -> USG | 0.621 | 17.724 | 0.000 | 0.626 | 1.203 | *Supported* |

Table 5
*PLSpredict*

| | $Q^2$predict | PLS-SEM RMSE | LM RMSE | PLS - LM |
|---|---|---|---|---|
| INT1 | 0.238 | 0.606 | 0.616 | -0.010 |
| INT2 | 0.197 | 0.61 | 0.629 | -0.019 |
| INT3 | 0.152 | 0.66 | 0.669 | -0.009 |
| INT4 | 0.153 | 0.675 | 0.697 | -0.022 |
| INT5 | 0.192 | 0.61 | 0.629 | -0.019 |
| USG1 | 0.242 | 0.632 | 0.611 | 0.021 |
| USG2 | 0.191 | 0.624 | 0.624 | 0.000 |
| USG3 | 0.199 | 0.687 | 0.692 | -0.005 |
| USG4 | 0.144 | 0.722 | 0.721 | 0.001 |

Table 6
*Cross-Validated Predictive Ability Test (CVPAT)*

| | Average loss difference | t-value | p-value |
|---|---|---|---|
| INT | -0.091 | 4.761 | 0.000 |
| USG | -0.106 | 7.983 | 0.000 |
| Overall | -0.098 | 6.786 | 0.000 |

Table 7
*Importance-Performance Map Analysis*

| | Total Effect | Performance |
|---|---|---|
| ATT | 0.090 | 66.775 |
| INT | 0.621 | 60.555 |
| PBC | 0.130 | 65.842 |
| PEU | 0.080 | 66.860 |
| PU | 0.143 | 66.513 |

**Discussion & Conclusion**

This study aims to investigate the influence of attitude, perceived behavioral control, perceived ease of use, and perceived usefulness on intention, as well as the impact of intention on the usage of artificial intelligence among academicians in higher education institutions. The attitudes of academicians towards AI technology play a pivotal role in determining their intention to adopt it. Positive attitudes create a stronger willingness to incorporate AI tools into teaching and research practices. Higher education institutions can foster positive attitudes by organizing workshops, seminars, and training programs that showcase the benefits and potential of AI in improving work efficiency and student learning outcomes. Additionally, sharing successful case studies of AI integration can contribute to dispelling any negative perceptions. The level of perceived behavioral control influences academicians' intention to adopt AI tools. Providing support and resources, such as technical assistance, training, and user-friendly interfaces, can enhance the perceived control over using AI. Encouraging a culture that fosters experimentation and autonomy further boosts academicians' confidence in adopting AI technology, thus increasing their intention to incorporate it into their academic activities. Perceived ease of use is a significant factor impacting academicians' intention to use AI tools. Higher education institutions can focus on user interface design, offering clear and intuitive instructions to reduce perceived complexity. Initiating trial periods and pilot projects allows academicians to experience the ease of AI technology first hand, encouraging them to integrate it more willingly into their academic workflows. Moreover, the perceived usefulness of AI tools influences academicians' adoption decisions. Institutions can highlight the ways AI enhances teaching, research, and administrative tasks, increasing the perceived usefulness of AI technology and thus positively influencing intention. Higher education institutions can conduct needs assessments to identify specific challenges and pain points faced by academicians, customizing AI solutions to address these needs effectively. Demonstrating how AI streamlines administrative tasks, enhances data analysis, and personalizes learning experiences can enhance the perceived usefulness of AI technology, influencing academicians' intention to adopt it. On the other hand, academicians' intention to use AI technology also significantly impacts its actual usage. To optimize AI adoption, institutions can implement comprehensive training and ongoing support to help academicians build their skills and confidence in using AI tools effectively. Workshops, webinars, and online resources can be employed to address any barriers or uncertainties related to AI usage. Furthermore, higher education institutions can provide incentives or recognition for academicians who successfully integrate AI into their academic practices. Celebrating successful AI implementations can inspire others to follow suit, promoting a culture of AI adoption within the institution. Fostering a collaborative and supportive community is also crucial in encouraging AI adoption. Institutions can facilitate peer support and the exchange of ideas among academicians, creating a positive environment for exploring and implementing AI solutions. Continuous assessment and evaluation of the impact of AI technology on academic practices and student outcomes are vital. Using feedback from users, institutions can continuously improve AI tools, addressing any shortcomings and ensuring that AI remains relevant and beneficial to academicians and their students. By incorporating these strategies, higher education institutions can successfully promote AI adoption among academicians, leading to enhanced teaching, research, and administrative practices, ultimately benefiting both the faculty and the students.

*Theoretical implications*

Theoretical implications derived from the study contribute to the existing knowledge on technology adoption in higher education institutions. The findings shed light on the crucial role of attitude, perceived behavioral control, perceived ease of use, and perceived usefulness as determinants of academicians' intention to adopt artificial intelligence (AI) technology. Positive attitudes were found to be instrumental in shaping intention, underscoring the importance of addressing negative perceptions through awareness-building initiatives and successful case studies. Perceived behavioral control emerged as a significant predictor of AI adoption intention, highlighting the need for providing ample support, resources, and a conducive environment to enhance academicians' perceived control over using AI effectively. The study further accentuates the role of perceived ease of use in influencing intention to adopt AI. Institutions can promote higher adoption rates by emphasizing user-friendly interfaces and intuitive designs, reducing perceived complexity. Additionally, the perceived usefulness of AI significantly impacts intention, advocating the showcasing of tangible benefits in teaching, research, and administrative tasks to drive usage.

*Managerial Implications*

The study's managerial implications provide valuable guidance to higher education institutions on effectively integrating artificial intelligence (AI) technology among academicians. To promote AI adoption, institutions should create a positive and supportive environment, organizing workshops and training programs to showcase successful AI implementations and dispel apprehensions. Offering comprehensive support and resources, such as technical assistance and user-friendly interfaces, will enhance perceived behavioral control, empowering faculty members to confidently use AI tools. Prioritizing user experience through intuitive interfaces and clear instructions will motivate greater AI adoption. Highlighting the perceived usefulness of AI in enhancing teaching, research, and administrative tasks can drive adoption. Fostering a collaborative community where academicians can share AI experiences and best practices will encourage exploration and adoption. Continuous evaluation and feedback collection will help institutions improve AI tools and address challenges, ensuring AI technology remains relevant and beneficial to both faculty and students. In summary, the managerial implications emphasize creating a positive and supportive environment, providing comprehensive support, prioritizing user experience, showcasing the usefulness of AI, fostering a collaborative community, and implementing continuous evaluation to effectively integrate AI technology in higher education institutions.

*Suggestions for Future Study*

Future studies in this area can build upon the findings of this study by exploring additional factors that may influence the intention to adopt artificial intelligence (AI) technology among academicians. Investigating the role of organizational culture, leadership support, and faculty training in the context of AI adoption can provide deeper insights. Moreover, longitudinal studies can assess the long-term impact of AI integration on academic practices and student outcomes. Comparing AI adoption patterns across different disciplines or educational institutions can offer a broader perspective. Additionally, research can focus on the challenges and strategies for scaling up AI adoption in higher education settings, considering the evolving technological landscape.

## Conclusion

In conclusion, this study delved into the factors influencing the intention to adopt artificial intelligence (AI) technology among academicians in higher education institutions. The findings highlight the significant roles of attitude, perceived behavioral control, perceived ease of use, and perceived usefulness in shaping the intention to adopt AI. Positive attitudes, comprehensive support, user-friendly interfaces, and showcasing AI benefits were identified as key drivers of AI adoption intention. The study underscores the importance of fostering a supportive environment and a collaborative community to encourage faculty members' exploration and integration of AI technology. Moreover, the research provides valuable managerial implications for institutions seeking to promote AI adoption effectively. Future studies can further explore additional variables and longitudinal impacts, enabling a deeper understanding of AI adoption in academia and its long-term implications on academic practices and student outcomes.

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