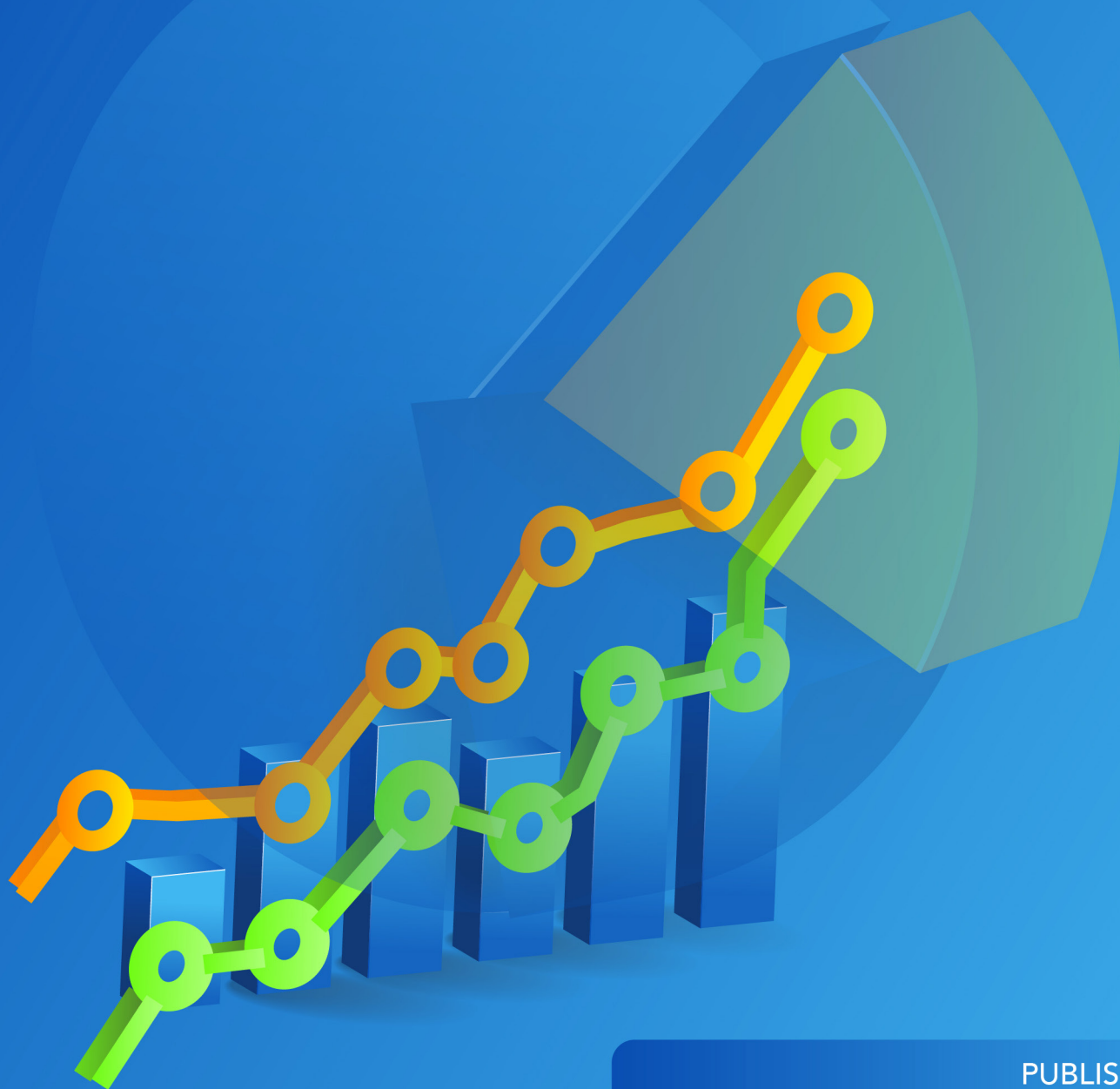


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## Analyzing University Students' Attitude and Behavior Toward AI Using the Extended Unified Theory of Acceptance and Use of Technology Model

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### ABSTRACT

This quantitative study using Partial Least Square Structural Equation Modeling (PLS-SEM) examined a structural model of the attitudes and behaviors of university students toward AI in higher education. The results obtained using SmartPLS 4.0 indicate that the constructs exhibit validity and reliability ( $\lambda \geq 0.708$ ,  $\alpha=0.767-0.948$ ,  $AVE=0.584-0.777$ ,  $HTMT=< 3.3$ ). Further, the analysis of the hypothesized extended Unified Theory of Acceptance and Use (UTAUT) model reveals that AI Awareness significantly impacts Attitude toward AI ( $\beta = 0.156$ ,  $p = 0.003$ ) and Behavioral Intention to Use AI (BIU) ( $\beta = 0.337$ ,  $p < 0.001$ ). AI Trust also significantly influences Attitude toward AI ( $\beta = 0.366$ ,  $p < 0.001$ ) and BIU-AI ( $\beta = 0.173$ ,  $p = 0.007$ ). Additionally, Attitude toward AI is a strong predictor of BIU-AI ( $\beta = 0.457$ ,  $p < 0.001$ ). Social Influence significantly affects Attitude toward AI ( $\beta = 0.21$ ,  $p < 0.001$ ), while Effort Expectancy and Performance Expectancy do not show significant effects in this context. The link between Facilitating Conditions and BIU-AI is also insignificant. The model explained a substantial portion of the variance in attitude ( $R^2 = 0.612$ ) and behavior ( $R^2 = 0.710$ ). Fit indices indicate good model fit, and predictive relevance metrics were satisfactory.

### INTRODUCTION

Artificial Intelligence (AI), which automates tasks and emulates human intelligence (Geetha & Bhanu Sree Reddy, 2018; Jarrett & Choo, 2021; Khanagar *et al.*, 2021; Saravanan *et al.*, 2017), is rapidly growing (Barton *et al.*, 2017; Beig & Qasim, 2023; Hassani *et al.*, 2020; Hilale, 2021; Olhede & Wolfe, 2018). It has now become an important technology that benefits society and the economy (Cockburn *et al.*, 2018; Hall & Pesenti, 2017; Lu *et al.*, 2018) and pervades many aspects of people's daily lives (Hilale, 2021; Loble *et al.*, 2017; Mintz & Brodie, 2019; Olhede & Wolfe, 2018; Tahiru, 2021). As AI has been prominent in various sectors (Berdiyeva *et al.*, 2021; Hall & Pesenti, 2017; Jindal *et al.*, 2021; Paul *et al.*, 2021), this technology has also been integrated into the field of higher education (Crompton & Burke, 2023; Pedro *et al.*, 2019; Zawacki-Richter *et al.*, 2019; Zhang & Aslan, 2021). The use of Artificial Intelligence (AI) has been implemented in language learning to improve instruction and address the learners' needs (Chen, 2021), facilitate interaction between instructors and learners (Seo *et al.*, 2021), and foster learners' educational experience (Alam, 2021; Kavitha & Lohani, 2018). Although artificial intelligence is thriving (Shao *et al.*, 2020; Tan & Ran, 2022; Zhou *et al.*, 2019), it is also seen as a threat to education (Humble & Mozelius, 2022; Xie & Wang, 2023). Some college students were concerned with ethical issues (Farhi *et al.*, 2023; Ghotbi *et al.*, 2022) and were wary of an unnatural learning environment (Kushmar *et al.*, 2022). The majority of college students have no intention of using AI to complete assignments or exams

in the near future (Welding, 2023), and according to Skeat and Ziebell (2023), a significant number of students still strongly oppose such technology utilization. In a similar study, it was also revealed that although the respondents understand the essence of AI technology and how it benefits their daily lives, they are not entirely clear about the benefits of incorporating artificial intelligence-enhanced technologies in learning and teaching (Slavov *et al.*, 2023).

Prior studies explored people's attitudes toward and behavioral intention to use artificial intelligence. In the study of Yadrovskaia *et al.* (2023), the respondents have a positive attitude towards the use of AI despite not fully grasping the fundamentals of these technologies. Additionally, some students believe that AI will positively benefit the field of education (Kairu, 2020; Marrone *et al.*, 2022), and they also have a positive attitude toward using it because it engages students and accommodates their varying cognitive levels (Obenza *et al.*, 2023b; Pande *et al.*, 2020). These attitudes regarding AI affect people's level of trust in AI technology (Liehner *et al.*, 2023). Moreover, artificial intelligence, such as chatbots, is found appealing to language learners since they can use them without the teachers' assistance, which helps them develop into independent learners (Mohamed & Alian, 2023). According to Chen *et al.* (2021), students' behavioral intention to study a language was positively correlated with their knowledge of AI-enabled language applications, attitude to use AI, perceived ease of use, subjective norm, and behavioral intention. Romero-Rodriguez *et al.* (2023) used the Unified Theory of

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Acceptance and Use of Technology (UTAUT) model for technology adoption to find that university students accept artificial intelligence like ChatGPT because they think it could help them learn. Usefulness, performance expectancy, hedonic motivation, private value, and habits also affect students' AI chatbot prototype use.

Kim (2017) found using the UTAUT model that expectation, social influence, work usefulness, and anxiety significantly affected healthcare university students' intention to use AI technology. Kim (2017) found that the use intention factor partially mediated the direct effect of the anxiety factor on the attitude factor and the task's usefulness factor on the attitude factor after verifying the indirect effect. Kaya *et al.* (2022) also reported that AI anxiety is a problem that can hinder the adoption, use, or acceptance of technology and can cause people to underestimate the usefulness of AI technology, fail to recognize its simplicity and fail to recognize its benefits. Moreover, in the study of Gado *et al.* (2022), the perceived usefulness of AI, attitude towards AI, perceived social norm regarding AI, and AI literacy proved to be significant indicators of students' intent to use artificial intelligence. Additionally, Alzahrani (2023) discovered that while students' attitudes were adversely affected by perceived risk, their behavioral intention to utilize AI in education was significantly influenced by performance expectancy and facilitating conditions. Additionally, the results indicate that effort expectancy has no substantial effect on attitudes toward the use of AI in higher education. In light of the empirical investigations delineated within extant literature, the pivotal function of AI literacy in shaping attitudes towards artificial intelligence (AI) emerges prominently. In a recent study conducted by Obenza *et al.* (2024), it was discerned that the cultivation of cognitive absorption among students represents a viable strategy for enhancing AI literacy, given its established status as a significant predictor thereof.

In addition to the above studies, UTAUT model has been used to study students' adoption of artificial intelligence-enabled e-learning systems (Lin *et al.*, 2021), intelligence-based robots (Roy *et al.*, 2022), and AI-powered web-based English writing assistance software (Intiser *et al.*, 2023). However, despite studies and existing literature concerning people's attitudes and behavioral intention to use AI, a particular study using UTAUT delving into AI trust and AI awareness in explaining and creating the structural model of college students' attitudes and behavior towards AI has been none. Therefore, this study is conducted to address this research gap. The results of this study can contribute specifically to academic sectors that are progressively integrating artificial intelligence in pedagogical approaches, as well as aid the technology sectors in enhancing AI tools that increase people's positive view and adoption of AI. This can also benefit future researchers in further in-depth exploration of factors influencing the students' attitude and behavioral intention to use artificial intelligence.

## MATERIALS AND METHODS

This study utilized a quantitative research design, and more specifically, the non-experimental correlational approach was utilized all throughout the research process. In accordance with the definition provided by Creswell and Creswell (2023), quantitative studies make use of inquiry methodologies such as surveys and experiments, and the data collected is gathered on predetermined instruments that generate statistical measurements.

Researchers distributed Google Forms survey questionnaires to random participants. A stratified random sampling method was utilized to select participants for the study. Utilizing this method allowed for the study variables to be represented in an equitable manner. For latent variable path models, the estimation of complex cause-effect relationships can be accomplished through the use of partial least squares path modeling (PLS-PM) or structural equation modeling (PLS-EM). As PLS-SEM gains popularity, more researchers are using it (Hair *et al.*, 2019a; Hair *et al.*, 2017b; Ringle *et al.*, 2015; Sarstedt *et al.*, 2019b). Using PLS-SEM, researchers are able to estimate large models that contain multiple constructs, indicator variables, and structural paths without making any assumptions about distributional relationships. More importantly, PLS-SEM emphasizes prediction in statistical model estimation and is designed to explain causality (Wold, 1982; Sarstedt *et al.*, 2017a). This partial data analysis method allows for smaller sample sizes. For the purpose of extrapolating sample results to the relevant population, larger sample sizes should be used whenever possible. (Hair *et al.*, 2022b; Kock & Hadaya, 2018).

The researchers used adapted questionnaires in the form of 5-point Likert Scales to gather the data. The attitude toward AI scale (Suh & Ahn, 2022), facilitating condition, performance expectancy, effort expectancy, and behavioral intention to use scales (Chatterjee & Bhattacharjee, 2020), social influence scale (Kandath & Shekhar, 2022), AI awareness scale (Isaac *et al.*, 2017), and AI trust scale (Choung *et al.*, 2022).

The study applied the 10-times rule proposed by Hair *et al.* (2011) to determine the total number of samples gathered. This method is commonly utilized in PLS-SEM to determine the minimal sample size. This strategy relies on the premise that the sample size must exceed ten times the highest number of inner or outer model linkages directed at any latent variable in the model (Hair *et al.*, 2017). The minimal sample size computed based on this criteria is 90. The study selected 322 college students from different universities in Region XI by stratified random sampling, exceeding the recommended sample size to ensure accurate results, particularly as we are suggesting a concise model.

A further evaluation of the validity and reliability of the measurement model was carried out using Cronbach's alpha. The method known as the Average Variance Extracted (AVE) was utilized in order to assess the convergent validity of the model. On the other hand, the Hetero-Monotrait Ratio (HTMT) method was

utilized in order to assess the discriminant validity of the model. The VIF was also utilized in this process. For the purpose of evaluating the hypothesized structural model, the bootstrapping standardized algorithm was utilized through the SmartPLS 4.0 software.

## RESULTS AND DISCUSSION

### Assessment of Measurement Model

Cronbach alpha and composite reliability are the two measurements that are most frequently used to determine internal consistency. These measurements determine reliability based on the interrelationship of the variables that are observed in the items (Hamid *et al.*, 2017). The reliability of the instruments that were utilized in the research is presented in Table 1. It was determined that Cronbach's alpha was the most reliable method for evaluating the instruments. Cronbach's alpha values for the questionnaires are as follows: 0.854 for AI Awareness (AI-A), 0.937 for AI Trust (AI-T), 0.951 for Attitude towards AI (At-AI), 0.904 for Behavioral Intention to Use (BIU), 0.767 for Effort Expectancy (EE), 0.864

for Facilitating Conditions (FC), 0.873 for Performance Expectancy (PE), and 0.896 for Social Influence. These values indicate that the questionnaires have a high degree of internal consistency (SI). Composite reliability and Cronbach alpha values that fall within the range of 0.60 to 0.70 are considered acceptable; however, in the more advanced stage, the value absolutely must be greater than 0.70. (Hair *et al.*, 2014).

The evaluation of the instruments' convergent validity was conducted by calculating the AVE. Convergent validity is the degree of agreement regarding the correlation between multiple indicators of the same construct (Hamid *et al.*, 2017). BIU (0.777), AI-A (0.696), AI-T (0.613), SI (0.766), EE (0.682), FC (0.647), and PE (0.664) all had AVE values that surpassed the 0.5 threshold. This is deemed acceptable in light of the fact that an acceptable minimum acceptable AVE is 0.50. An AVE value of 0.50 or greater signifies that the construct accounts for a minimum of 50 percent of the variance exhibited by the items comprising the construct (Bagozzi & Yi, 1988; Fornell & Larcker, 1981; Hair *et al.*, 2014; Henseler *et al.*, 2009).

**Table 1:** Construct Reliability and Validity

	Cronbach's Alpha	Composite Reliability (rho_a)	Average Variance Extracted (AVE)
AI-A	0.854	0.855	0.696
AI-T	0.937	0.937	0.613
At-AI	0.951	0.952	0.584
BIU	0.904	0.906	0.777
EE	0.767	0.767	0.682
FC	0.864	0.869	0.647
PE	0.873	0.878	0.664
SI	0.896	0.899	0.766

The next test employed was the HTMT values. This test evaluated the discriminant validity of the scales which pertains to the extent to which the items discriminate from one another empirically (Hamid *et al.*, 2017). The HTMT ratios of the constructs spans between 0.50 to 0.60 in the following construct pairs: AI-A and AI-T (0.723), AI-T and At-AI (0.742), At-AI and BIU (0.834), BIU and EE (0.611), EE to FC (0.570), FC and PE (0.725), PE and SI (0.654), AI-A and At-AI (0.691), AI-T and BIU (0.762), At-AI and EE (0.645), BIU and FC (0.497), EE and PE (0.823), FC and SI (0.570), AI-A and BIU (0.824), AI-T

and EE (0.573), BIU and PE (0.650), EE and SI (0.662), AI-A and EE (0.709), AI-T and FC (0.517), At-AI and PE (0.662), BIU and SI (0.668), AI-A and FC (0.519), AI-T and PE (0.638), At-AI and SI (0.682), AI-A and PE (0.682), AI-T and SI (0.649), and AI-A and SI (0.623). The fact that all ratios are lower than the threshold of 0.85 demonstrates that there is strong discriminant validity between the constructs (Kline, 2011). Additionally, Gold *et al.* (2001) suggested that a value of 0.90 should be proposed as the threshold.

**Table 2:** Heterotrait-Monotrait Ratio (HTMT)

	AI-A	AI-T	At-AI	BIU	EE	FC	PE	SI
AI-A								
AI-T	0.723							
At-AI	0.691	0.742						
BIU	0.824	0.762	0.834					
EE	0.709	0.573	0.645	0.611				
FC	0.519	0.517	0.566	0.497	0.570			
PE	0.682	0.638	0.662	0.650	0.823	0.725		
SI	0.623	0.649	0.682	0.668	0.662	0.570	0.654	

Prior to evaluating the structural relationships, it is necessary to investigate the collinearity in order to guarantee that it does not introduce any bias into the regression results. VIF values that are greater than five are indicative of probable collinearity issues among the predictor constructs, as stated by Hair *et al.* (2019). However, collinearity issues can also occur at lower VIF values, which range from three to five (Mason & Perreault, 1991; Becker *et al.*, 2014). In an ideal situation, the values of the VIF should be close to three or lower. The creation of higher-order models that are capable of being supported by theory is a common solution that is utilized in situations where collinearity is a problem (Hair *et al.*, 2017b).

**Table 3:** Variance Inflation Factor (VIF)

	VIF
AI Awareness -> Attitude toward AI	2.107
AI Awareness -> Behavioral Intention to Use	1.959
AI Trust -> AI Awareness	1.000
AI Trust -> Attitude toward AI	2.114
AI Trust -> Behavioral Intention to Use	2.342
Attitude toward AI -> Behavioral Intention to Use	2.343
Effort Expectancy -> Attitude toward AI	2.096
Facilitating Conditions -> Behavioral Intention to Use	1.441
Performance Expectancy -> Attitude toward AI	2.329
Social Influence -> Attitude toward AI	1.891

**Assessment of Structural Model**

Examining the path from AI-Awareness to Attitude toward AI, the coefficient of 0.156 indicates a positive relationship. This suggests that as students’ awareness of AI increases, their attitude toward AI tends to become more positive.

These findings indicate that as students’ knowledge of AI grows, their perception of AI tends to become more favorable. The statistical analysis reveals a significant connection ( $T = 3.004$ ,  $p = 0.003$ ), emphasizing its significance. Similarly, the association between AI Awareness and Behavioral Intention to Use is larger, with a value of 0.337.

This implies that higher levels of AI awareness among students are associated with a greater intention to use AI technology. This relationship is not only statistically significant but also notably stronger ( $T = 6.009$ ,  $p = 0.000$ ). This corroborates the findings of Marrone *et al.* (2022), who discovered that students with a greater comprehension of AI expressed more favorable attitudes toward incorporating AI into their educational environments. Students with limited comprehension of AI exhibited a tendency to experience apprehension towards AI.

Moving on to AI Trust, the results indicate a positive

association both with Attitude toward AI (coefficient = 0.366) and Behavioral Intention to Use (coefficient = 0.173). These findings suggest that as students’ trust in AI increases, so does their favorable attitude toward it, as well as their inclination to use AI technology. These relationships are statistically significant, underscoring the significance of trust in shaping attitudes and intentions toward AI adoption ( $T = 5.621$ ,  $p = 0.000$  and  $T = 2.679$ ,  $p = 0.007$ , respectively). The results of this study lend credence to the findings of Obenza *et al.* (2023a), which indicated that trust in artificial intelligence had a significant impact on attitudes toward AI.

The findings are also consistent with the assertions made by Choung *et al.* (2022), who stated that trust acts as a precursor to positive attitudes, which in turn affects usage intentions. The level of trust that an individual has in artificial intelligence (AI) is a significant factor in determining their attitude toward AI technology as well as their willingness to interact with it, as stated by Schepman and Rodway (2023). Furthermore, the findings of the research carried out by Emon *et al.* (2023) and Cook (2023) demonstrated that trust in artificial intelligence (AI) plays a significant part in determining whether or not an individual intends to make use of using it.

The path from Attitude toward AI to Behavioral Intention to Use exhibits a robust positive relationship (coefficient = 0.457). This implies that a positive attitude toward AI among students significantly influences their intention to use it. This relationship is highly significant ( $T = 8.597$ ,  $p = 0.000$ ), indicating its substantial impact. These findings are consistent with multiple research that have demonstrated a substantial correlation between attitude toward AI and the intention to employ it (Hasan Emon, 2023; Saxena, 2023).

However, the paths from Effort Expectancy to Attitude toward AI and from Facilitating Conditions to Behavioral Intention to Use demonstrate weaker relationships, as evidenced by their non-significant p-values ( $p > 0.05$ ). The results of this study suggest that the students’ perceptions of the amount of effort required to use artificial intelligence and the presence of favorable conditions do not significantly impact the attitudes and intentions of the students regarding the adoption of AI in this particular environment. These findings are in direct opposition to the findings of other research such those of Hasan Emon and Alzahrani (2023) that have demonstrated that enabling environments have an effect on the intention to engage in certain behaviors.

Similarly, while Performance Expectancy exhibits a positive relationship with Attitude toward AI, the relationship is not statistically significant ( $T = 1.711$ ,  $p = 0.087$ ), indicating that perceptions regarding the performance benefits of AI may not strongly influence attitudes toward AI among university students. According to Alzahrani (2023), performance expectancy significantly influences students’ attitudes toward AI.

Finally, Social Influence proves to be a substantial indicator of Attitude towards AI, with a coefficient of

0.21. Consequently, the impact of classmates, professors, or societal norms is crucial in molding students' attitudes toward AI. The statistical analysis reveals a significant

association ( $T = 4.051, p = 0.000$ ), indicating that social variables play a crucial role in shaping attitudes towards the adoption of AI.

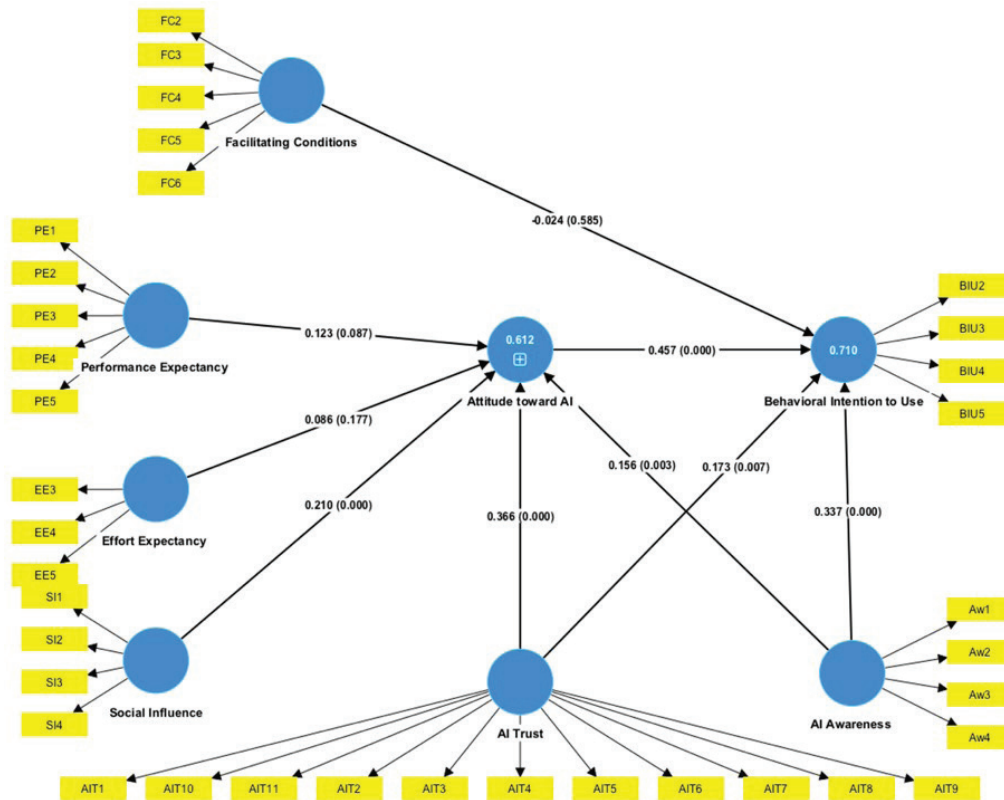


Figure 1: Partial least squares structural equation modeling (PLS-SEM) Results using Smart PLS 4.0

Table 3 presents various statistical measures used to evaluate the fit and predictive power of a structural equation model (SEM) that aims to analyze university students' attitudes and behavior toward AI using the UTAUT model. The Bayesian Information Criterion (BIC) values of both endogenous variables, 'At-AI' and 'BIU,' have negative BIC values, suggesting a good fit. Lower and Negative BIC values can occur and generally indicate a very strong model according to the likelihood function.

The R-squared ( $R^2$ ) and Adjusted  $R^2$  values represent the proportion of variance explained by the model. For At-AI, 61.2% of the variance is explained, and for BIU, 71.0% is explained. The high values of both  $R^2$  and adjusted  $R^2$  indicate a strong model. The Predictive Relevance ( $Q^2$ ) value shows the model's predictive relevance. A value larger than zero suggests the model has predictive relevance for the construct. Both of both endogenous variables, At-AI and BIU, show values well above zero, indicating good predictive power.

The Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are measurements of the average error that occurs between the predicted and observed values. Lower values are preferable because they demonstrate that the model's predictions are relatively close to the values that actually occur. Because the values of the model are

relatively low, it appears that the model is able to make accurate predictions. The Standardized Root Mean Square Residual (SRMR) is a measure of fit used in structural equation models. Values less than 0.08 are generally considered good. The model shows SRMR values close to this threshold, suggesting an acceptable fit.

The Unweighted Least Squares discrepancy ( $d_{ULS}$ ) and Geodesic discrepancy ( $d_G$ ) are discrepancy functions based on unweighted least squares and geodesic distances. The smaller these values, the better the model fit. Based on the fact that the values of the saturated model, which is the most complex model, and the estimated model, which is the proposed model, are relatively close to one another, it is possible to draw the conclusion that the proposed model fits almost as well as the most complex model that is possible. Utilizing the Chi-square statistic, one can perform an analysis of the disparity that exists between the covariance matrices that were observed and those that were anticipated. However, a lower value indicates a better fit between the data and the model. The chi-square value is sensitive to the sample size; yet, a lower value indicates a better fit. However, this should be interpreted in the context of other fit indices and sample sizes. The model has a high chi-square value, which may indicate that it does not fit the data well. However, this should be taken into consideration.

To determine how well the estimated model fits the data, the Normed Fit Index (NFI) compares it to a null model. This comparison is made in order to determine how well the model fits the data. A more satisfactory fit is indicated by values that are closer to the number one. Each of the

models has an NFI of approximately 0.72, which is lower than the threshold of 0.95 that is typically recommended. This indicates that there is room for improvement in the model.

**Table 4:** Model Fit

Endogenous Variables	BIC	R <sup>2</sup>	Adjusted R <sup>2</sup>	Q <sup>2</sup> predict	RMSE	MAE
Attitude toward AI	-271.195	0.612	0.606	0.588	0.646	0.450
Behavioral Intention to Use	-370.864	0.710	0.706	0.622	0.619	0.432
	Saturated model	Estimated model				
SRMR	0.059	0.061				
d_ULS	5.221	5.308				
d_G	2.501	2.506				
Chi-square	4293.77	4300.13				
NFI	0.723	0.722				

### CONCLUSION

Based on the UTAUT model and actual results, this study's theoretical implications reveal a complex understanding of university students' views and behavior toward artificial intelligence (AI). This section examines how the findings correlate with and extend the UTAUT model, providing insights into the elements that influence AI adoption in an academic setting. The positive relationship between AI awareness and students' attitudes and behavioral intentions to use AI underscores the critical role of knowledge and exposure in shaping perceptions of technology. This finding is consistent with the UTAUT model's emphasis on performance expectancy and effort expectancy as significant factors of technology adoption, suggesting that improved awareness can reduce perceived efforts and improve performance expectations (Venkatesh *et al.*, 2016). Furthermore, the significant impact of AI trust on both attitude and behavioral intention emphasizes the importance of credibility and reliability in the adoption process, which is consistent with the model's suggestion that social influence and enabling conditions are critical in technology acceptance.

However, the weaker/non-significant connections between effort expectancy and facilitating conditions with attitude and behavioral intention, respectively, call into question the UTAUT model's assertions about student AI adoption. This shows that other factors, presumably related to AI technology, such as ethical issues or the type of AI applications, may have a greater impact on students' views and intents. The robust association between attitude toward AI and behavioral intention to utilize AI further reinforces the main premise of the UTAUT model: good attitudes toward technology greatly contribute to its acceptance and utilization (Venkatesh & Davis, 2000; Venkatesh *et al.*, 2003). This suggests a direct channel for educators and policymakers to influence AI adoption by instilling a positive attitude towards AI in students. The significant predictive power of social influence on attitude toward AI emphasizes the model's assertion

that social factors are crucial in technology adoption (Venkatesh *et al.*, 2003). This underscores the need for educational institutions to foster a culture that supports and encourages AI learning and exploration. In light of these findings, this study expands upon the UTAUT model by highlighting the subtle impacts of AI awareness, trust, and social influence on university students' views and actions toward AI. It implies that although the basic elements of the UTAUT model are still applicable, the distinct features of AI technology and its specific usage in educational environments require modifications to the model in order to understand the process of AI adoption in educational settings comprehensively.

### RECOMMENDATIONS

The findings initiate a discourse regarding the strategic emphasis of educational programs and interventions. The primary focus of efforts to improve AI acceptance should be on establishing trust and promoting awareness while also creating an environment that supports good social influence. Future research should investigate the specific reasons why performance and effort expectancy are not significant and further examine how social influence works in the acceptability of technology in educational contexts. The correlation between AI Awareness and the inclination to utilize AI indicates a pressing requirement for educational initiatives focused on enhancing AI literacy among students. This entails instructing not only the technical facets of AI but also its ethical, social, and practical ramifications. Integrating AI subjects into the curriculum, covering fundamental principles to sophisticated applications, can cultivate a better-informed and favorable disposition towards AI technologies. The impact of AI Trust on attitude, while not directly on behavioral intention, suggests that trust plays a crucial role in shaping favorable views, but it may not be enough to solely drive actual usage. Hence, establishing confidence should be a comprehensive undertaking, encompassing not just the dependability and openness

of AI but also addressing students' apprehensions and misunderstandings around AI. Given the increasing importance of AI across different industries, providing students with education on AI equips them with the necessary skills for future employment. Gaining proficiency in AI will be an essential aptitude, and early familiarity can provide pupils with a distinct advantage.

### LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Although this study offers valuable information, it does have limits. Further inquiry is needed to explore additional moderating or mediating variables due to the lack of a significant association between most dimensions of the UTAUT model and At-AI and BIU. Subsequent investigations could examine how elements such as AI efficacy, aspects of TAM (Technology Acceptance Model), AI ethics, or specific AI features influence students' attitudes and behavioral intentions. The swift advancement of AI technology may surpass the conclusions of the study, thus requiring ongoing research. Furthermore, longitudinal studies have the potential to offer a more profound comprehension of the progression of students' perspectives and intentions as they acquire increased familiarity with AI technologies. Subsequent investigations ought to overcome these constraints by broadening the range of participants, consistently incorporating the most recent advancements in artificial intelligence, and potentially integrating supplementary constructs, theories, and methodologies to enhance comprehension of students' attitudes and behaviors toward technology acceptance.

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