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University Students' Willingness to Accept AI-Assisted Learning Environments in Bangladesh: Moderating Role of AI Awareness

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Abstract

This research examines the predictors of university students' willingness to accept AI-assisted learning environments in Bangladesh. This study particularly observes the moderating role of AI awareness (AIA) based on the Unified Theory of Acceptance and Use of Technology (UTAUT) and Perceived Risk Theory. This study used structured survey questionnaire for collecting data from 499 university students across various faculties i.e. Business, Science, and Social Sciences and analyzed the collected data using Structural Equation Modeling (PLS-SEM). For data analysis, this study applied Smart PLS version. The measurement model shown its fitness well to proceed further and the structural model also illustrated a robust fit (CFI = 0.948, RMSEA = 0.056) and explained 50.5% of the variance in Behavioral Intention to Use (R-square = 0.505). The results shows that the most influential determinant of AI adoption in education is performance expectancy, followed by social influence and effort expectancy. Conversely, there are some risk factors which affect this adoption negatively. Of them, functional risk played the most significant role along with psychological and social risks. This study also uniquely found the moderating effect of AI Awareness, which substantially amplifies the positive impacts of performance expectancy, effort expectancy, and social influence on the students' use intention of AI-assisted learning environment. This study proposed an integrated model including AI awareness as moderator for understanding AI adoption in education at tertiary level, and suggested that, for AI-assisted learning to be successfully implemented in Bangladesh, institutional strategies must move beyond infrastructure provision to focus on AI literacy and risk-mitigation protocols.

1. Introduction

The global rise of technology is a broader and transformative trend that goes beyond the computing capacities of the new intelligent machines. In recent years, especially- the growth of Artificial intelligence (AI) technologies has been fueling a revolution in various aspects of our lives. Artificial Intelligence in Education (AIED) at Higher Education Institutions (HEI) are not any exception beyond that line of influence, turning it as to be one of the currently emerging fields. In practice, the AI-based technologies are promising to revolutionize the traditional higher education teaching and learning methods by enhancing the teaching-learning effectiveness (Yadav, 2025; Sanders & Mukhari, 2024) and academic level diagnosis (Lourenço et al., 2025), fostering inclusivity and enhancing human-machine collaboration (Alif Hd & Mariyono, 2025; Zhai et al., 2021; Lim, 2020). Previous studies have also shown that the amalgamation of AI in higher education holds significance in increasing academic performance (Zhou, 2023) through strengthening academic motivation (Yilmaz & Yilmaz, 2023) with developed self-directed learning skills (Lasfeto & Ulfa, 2023) and problem-solving skills (Zhang & Zhu, 2022); cumulatively enhancing the students' learning experiences (Ouyang & Jiao, 2021) at HEIs. However, the prompt development of AI at HEIs raises questions about its technical feasibility, sustainability, educational equity, and ethical considerations. The growing dependence on AIED at HEI pose significant challenges through reduced interaction between academicians and students, digital divide (Doğan & Arslan, 2025), facilitating plagiarism, undermining critical thinking (Pikhart & Al-Obaydi, 2025) often bypassing the unique human aspects of teaching- the emotional engagement and personalized instructions (Gammoh,

2024). Amidst such dualities of both the prospects and challenges, the adaptation of AIED is expected to rise, pushing HEIs to invest more in the infrastructure and resources to support their AI-driven systems.

Acting as the active participants of learning process, the students in addition realize the potential of AIED and its prospective impact on their learning support, brainstorming assistance, research and analysis capabilities (Chan & HU,2023). However, research works have indicated that the successful integration of AIED lies in a multifaceted process influenced by several factors, including technical infrastructures (Matsika & Zhou, 2021), governmental policies (Cheng & Wang, 2022), and teaching methods (Chan, 2023). Studies have constantly shown that intra-personal attitude (Ma et al., 2024) and perceptions (Akinoso, 2023; Zulaiha & Triana, 2023) also play important role in successive AIED. Further studies have confirmed that the changes in attitudes among students significantly influences the successive AIED. Positive attitude enhances respective desire to improve learning experiences (Linardatos & Apostolou, 2023) where negative attitude hinders the AIED incorporation indeed (Y. Wang, 2023). Therefore, it is built that examining students' perspectives in AIED at HEIs is a crucial step towards the understanding of dynamic relationship between AI and Education. Where regionality significantly affects, building a difference amidst west and the rest. As research works have proved that cultural differences influence AI adaptation as well, which may seem vocal in terms of AIED. Digital divide and differential AI literacy results in distinct styles of technological interactions, economic standings and many more (Vargo et al., 2021). It is evident that numerous studies have explored the dynamics of AIED at HEIs, predominantly focusing on developed west, often ignoring the global south. AIED at HEI, the landscape in global south is merely observed with the absence of comprehensive guidelines, uncertainty, over-reliance on AI-assisted tools by students and resistance among academics (Henadirage & Gunarathne, 2024) but how they are built or why they act like such is a matter of query till date. There is a "black box" between the AIED and its actual adoption in global south. Indeed, technology adoption is not just about perceived benefits but also about a conscious evaluation of potential risks. So, to consider the risk factors as critical elements, this study is expected to elaborate on the functional, psychological and social factors to investigate the underlying factors, influencing the behavioral intention to use AI among HEI students from the south global. Hereby, the study sets its aim towards examining the extent to which the Performance Expectancy, Effort Expectancy, and Social Influence affect the behavioral intention towards AIED among the HEI level students and address the moderating risks associated with AI and behavioral intention.

2. Literature Review and Research Gap

Zhang et al., (2025) stated that the ease of use and usefulness of AI were found to be the primary determinants of teachers' acceptance rather than their trust in AI. Moreover, Teachers' trust in AI was negatively impacted by their privacy and safety risks concerns, especially those from rural areas. The study indicates that functional, simple, and transparent systems are key to wider acceptance of AI. There are urban–rural differences in attitudes. Rawashdeh et al., (2025) said that the positive attitude of students regarding Artificial Intelligence (AI) in auditing practices depends on their awareness of AI. The knowledge of awareness is greatly impacted by the level of education and the availability of reputable

information and a strong support system. Students who get to experience learning and authentic resources learn the value of AI better. Islam et al., (2025) found that AI tools like ChatGPT help students solve their problems without asking for help from others or depending on others. However, many people have opined that relying too much on AI may reduce students' creativity. In addition, many people worry about data privacy when using AI for research or other educational purposes. Overall, the study's findings urge policymakers, researchers, and students to use AI in balance with traditional teaching and learning methods. Klimova & Pikhart, (2025) stated that AI has a great impact on students' mental health, social life, and academic performance in different ways. Though in the educational sector, AI offers personalized learning and support, it sometimes causes digital fatigue, loneliness, and stress. When students depend too much on AI, it reduces a learner's emotional skills. Furthermore, there are also concerns about data privacy and job loss as AI grows in education. Tomczyk & Majkut, (2025) also said that that most students use AI for finding information. However, advanced-level uses of AI in the education sector are still not popular among students.

Ma et al., (2024) found that cultural background and prior technology experience play important roles in shaping students' perceptions of AI. Ma & Lei, (2024) reveled that educators are influenced by the impact of AI literacy on their AI implementation decisions. As a result, informing teachers about the usefulness of AI and its effectiveness in teaching can spur the usage of AI in digital learning to a greater extent. Sultana & Faruk, (2024) said that AI-related concepts, such as adaptive and personalized learning, greatly help improve educational sustainability as well as teaching evaluation and educational fairness in Bangladesh. But they were identified as critical obstacles to achieving this goal. Wang & Li, (2024) also shown that Students' continued use of AI tools is strongly influenced by positive emotions, digital skills, and overall satisfaction, with positive emotions playing the most critical role. Additionally, students with higher digital proficiency are more capable of autonomous learning and derive greater satisfaction from AI use. Parveen et al., (2024) found that that behavioral attention was the strongest and most motivating factor influencing the use of AI-generated software like ChatGPT. Hazaimeh & Al-Ansi, (2024) conducted a research in the Arab region shows that there are some factors that positively affect students to embrace AI in higher education. Among them, the prominent factors are digital competency, students' attitude, and openness to new experiences.

Dalalah & Dalalah, (2023) said that AI helps the students collect information from the diverse Dataset. Furthermore, when students instruct the AI to present information in a more human-like manner, the system is capable of doing so effectively. Although these activities of AI can normalize the plagiarism practice but if we can use AI ethically, then AI could be helpful for scientific research. Abbad, (2021) said that the students' intention to use Moodle was influenced strongly by their perceived usefulness and ease of use, but not by the opinions of others. The actual use of Moodle mainly reflects the users' intention to use, but also relies on the availability of supporting resources. Zhai et al., (2021) highlighted that though AI provides various opportunities in education, it also has some demerits, such as misuse of AI tools, shifting the roles of teacher-students, and emerging social and ethical issues. Ijaz et al., (2017) found that to become a digital citizen, students can use AI. However, the negative use of AI tools or

using them in the wrong way may bring particular risk for the students. Additionally, it can also harm their learning experience and lead to negative attitudes toward learning.

While these studies acknowledge AI's promise, empirical research focusing specifically on university students' willingness to accept AI-assisted learning environments in Bangladesh remains limited. More importantly, existing studies predominantly examine direct effects of technological, emotional, or skill-based factors, while the moderating role of AI awareness has received insufficient attention, particularly in developing-country contexts, especially among university students in Bangladesh. Addressing this gap, the present study positions AI awareness as a moderating variable to explain variations in students' willingness to accept AI-assisted learning environments within a developing-country higher education setting.

3. Theoretical Propositions and Hypotheses Developmen

3.1 The UTAUT Model and Application in Education:

When new technologies are introduced, it is necessary to consider user acceptance. Numerous models have previously been posited to explain the adoption of technology (Al-Momani et al., 2019). UTAUT is an extended TAM in which the eight prominent theoretical models are integrated (Venkatesh et al., 2003). Among the existing technology acceptance models, UTAUT is considered one of the most applied models. According to a survey in 2014, the UTAUT was used in nearly 743 journals during the period of 2003 to 2013 (Khechine et al., 2016). Besides, in previous research, UTAUT is deemed as a robust theory in order to investigate the determinants of technology acceptance in various contexts around the globe (Arif et al., 2018). The use of UTAUT model helps explain 70% usage behavior (Venkatesh et al., 2003) which is comparatively better than other models (Venkatesh et al., 2003). Besides, the model has also been used in several studies of user behavioral intention in education (Menant et al., 2021; Wu et al., 2022; Abbad, 2021). For this reason, the current study adopts the UTAUT model as the study's theoretical foundation. We chose three main dimensions as the variables, i.e., performance expectation, effort expectation, and Social Influence, in the UTAUT model which indicate willingness, and investigated their influence on students' WTA AI-supported learning environments.

Performance expectancy is the degree, perceived by the individuals, of the applications of technology, which enables them to accomplish their jobs more effectively(Milicevic et al., 2024). In light of several studies, performance expectancy (PE) has a remarkably positive impact on the willingness of students to seek AI technology in their academic domain (Li & Zhao, 2021; Parveen et al., 2024). Performance expectancy tends to influence the students' choice to integrate AI technology in their education, and the students who believe that AI can bring a positive impact on their educational performance are more tend to use AI tools in their learning endeavors (Abbad, 2021).

H1: Performance expectancy (PE) has a positive effect on students' intention to use AI in education

Effort expectancy (EE) refers to the level of effort an individual perceives as necessary to use a technology (Milicevic et al., 2024). Duong (2023), in his study, revealed the significant importance of EE on the willingness of students at the tertiary level to adopt AI tools such as ChatGPT, which encourages them to integrate this tool into their learning materials. Besides, the study also highlights that the negative perception regarding EE can remarkably lower both the in tention to integrate AI for educational purposes and its actual usage. A number of researchers opine that while a technology is found to be convenient and effective, people are more likely to rely on it (Wu et al., 2022; Abbad, 2021; Altalhi, 2021).

H2: Effort expectancy has a positive effect on behavioral intention to use AI

Social influence (SI) is defined to be the people's willingness and attitude towards using technology, shaped by the recommendations, opinions, expectations, and pressures of significant others, such as family, friends, colleagues, and society at large (Camilleri, 2024). Given the Indian perspective, SI has been considered to be a major factor that shapes people's acceptance and usage of technologies, as reported by the findings of Alvi (2021) and Hoang et al. (2022). Furthermore, when people receive positive reviews from peers and superiors regarding AI, they grow trust among themselves, leading them to embrace and use AI in their educational atmosphere (Venkatesh & Davis, 2000).

H3: Social influence has a positive effect on behavioral intention to use AI

3.2 Perceived Risk Theory (PRT):

Users' perceptions of risk have been regarded as a critical determinant of their inclination to adopt new technology (Wu et al., 2022). As Artificial Intelligence (AI) is being quickly introduced to education, a growing attention has also been paid to the potential risks when educators use AI system (Zhang et al., 2025). Wu et al. (2022) applied perceived risk theory to explore the determinants of students' adoption of an AI-aided learning environment as an innovative learning approach in their study. Perceived risk has been conceptualized as "individuals assessing the consequences of the behavior before the behavior occurs" (Bauer, 1960). It includes six types of risks: financial, functional, physical, psychological, social, and temporal risks (Jacoby & Kaplan, 1972. According to Chen et al. (2021), Hoo and Ibrahim (2019)Wu et al. (2022), learners may experience Functional, Psychological, and Social risk when using AI in the classroom, and these risks appear to be functions of the nature of AI technology. In the context of the traits of AI technology and referring to perceived risk theory, this paper aims to concentrate on functional, social, and psychological risk, including the impact of technology risk on students' usage of AI, excluding financial, physical, and time risks. Therefore, the following hypotheses were proposed:

H4: Functional risk (FR) negatively affects students' behavioral intention to use AI in education.

H5: Psychological risk (PR) negatively affects students' behavioral intention to use AI in education.

H6: Social risk (SR) negatively affects students' behavioral intention to use AI in education.

3.3 Moderating Role of AI Awareness:

Awareness is an individual's level of exposure to or knowledge of or consciousness about a given service or phenomenon (Crist et al., 2007). Besides the core UTAUT determinants of behavioral intention, this research also incorporated awareness as an external factor. Faruq and Ahmad (2013) assert that technology awareness has an important influence in the formation of behavioural intention, since it will either increase or decrease the role of comparative variable factors, for example, performance expectancy, effort expectancy, at an individual level of using technology. In addition, Chiemeke and Evwiekpaefe (2011) pointed out that when individuals perceive a technology as useful, they are motivated to explore its relevance to their work and integrate its use, while those who do not perceive anything good in a system may be reluctant about its use.

In a similar way, Daniali et al. (2022) found the moderating effects of awareness in the relations between PE, EE, social influence, and students' intentions to adopt 4.5G mobile phones in Malaysia. Another study (Al-Azizi et al., 2018) found that only performance expectancy, effort expectancy, and facilitating conditions positively influence Oman government employees' intention toward using mobile applications. In addition, awareness was shown to moderate the influence of these independent variables on behavioral intention. Milicevic et. al, (2024) also found the strong moderating effect of AI awareness in the usage of AI in education. On the basis of the above study, the following were hypothesized:

H7: AI awareness moderates the relationship between performance expectancy (PE) and students' intention to use AI in education.

H8: AI awareness moderates the relationship between effort expectancy (EE) and students' intention to use AI in education.

H9: AI awareness moderates the relationship between social influence (SI) and students' intention to use AI in education

Based on the above theoretical propositions, the following conceptual framework shown in Fig. 1 has been developed for this study.

4. Methodology

4.1 Sample and Procedures:

In order to empirically investigate the proposed relationships between the major constructs influencing university students' willingness to accept AI-Assisted learning environments in Bangladesh, this study used a cross sectional quantitative approach. Field data was collected using a structured survey questionnaire, allowing for statistical analysis using Structural Equation Modeling (PLS-SEM). The study was undertaken with a group of Bangladeshi university students who use online platforms for their educational purposes. A nonprobability convenience sampling strategy was implemented to circulate 600 questionnaires to undergraduate and postgraduate students interacting with online platforms. This

method is both economical and appropriate for research that needs input from a particular user group (Campbell et al., 2020; and Nur Ullah, & Biswas, 2024). The survey was administered through group interactions, inviting participants to contribute information by filling out a Google Form instead of providing a hard copy. Nevertheless, university students extensively use online platforms; researchers intend to ensure data is gathered from real online platform users. Accordingly, researchers ascertained the participants' involvement with online platforms pertinent to their academic pursuits before engaging in the study. With the assistance of academic experts from Bangladesh University of Professionals, the questionnaire items were translated from English to Bengali using the back-translation method (Brislin, 1970, 1986) to guarantee linguistic accuracy and cultural relevance.

A Google form containing the questions had been circulated, of which around 521 were regained after the questionnaires were distributed in November 2025. From this total, 499 questionnaires were deemed valid and were subsequently proceeded further for analysis. Cohen's (1988) rule states that a sample size that is at least ten times the number of hypotheses is necessary to achieve a strong effect size. 9 hypotheses were tested in this study, indicating a minimum sample size of 90. Memon et al. (2021) state that multivariate techniques like PLS-SEM and CB-SEM require a sample size of 160–300. This criterion is satisfied by the dataset, and is adequate for assessing the suggested relationships. For populations larger than 100,000, Yamane's (1967) formula for large populations suggests at least 400 respondents in order to reach a 95% confidence level. Consequently, 499 valid responses in the final sample guarantee both statistical power and analytical robustness.

4.2 Measures:

To ensure validity and reliability, the study's measurement tools and construct items (see Appendix 1) were modified from well-established literature. Through a multi-phase process that included initial drafting, expert consultation, pilot testing, and final refinement, a structured questionnaire was created. An online survey was used in a pilot study where 30 students participated and 24 responses were received in a week and incorporated into the analysis. The measurement items were slightly altered in light of the findings from this preliminary investigation. A five-point Likert scale, with 1 denoting "strongly disagree" and 5 denoting "strongly agree", was used to measure all latent constructs, including Performance Expectancy (PE); Effort expectancy (EE); Social Influence (SI), Functional Risk (FR); Social Risk (SR); Psychological Risk (PR); AI Awareness (AIA) and Behavioral Intention to Use (BIU). The items were taken from and adjusted from validated scales that were used in previous research on e-government services and technology adoption (Bhuasiri et al., 2016; Venkatesh et al., 2003; Gefen et al., 2003; and Yi & Gong, 2013). Cronbach's alpha and composite reliability were used to evaluate the constructs' reliability; all values were above the suggested cutoff point of 0.70, indicating strong internal consistency. The data gathered was robust and appropriate for structural equation modeling fits to this meticulous instrument design.

4.3 Data Analysis Tools and Applications:

This study used SPSS version 25 for analyzing descriptive statistics and applied Smart PLS version 4 for testing validity and reliability of data collected from the field. This study alongside used PLS-SEM using SPSS Amos and Hayes PROCESS-Macro for calculating Conformity Factor Analysis (CFA) and Structural Equation Modeling (SEM). These are the widely used and accepted software for theoretical model testing and validation. Additionally, in order to ensuring accuracy, suitability and precision of the parameters, this study adopted Partial Least Square (PLS) method. According to Anderson & Gerbing, (1988), PLS is the best suitable tool for checking the validity and reliability of the measurement model and its theoretical inferences and for analyzing high-quality data with a large sample size (Wong, 2013).

5. Results

5.1 Demographic Information of the Respondents:

The demographic information presented in Table 1 demonstrates a youthful and gender diverse sample of 499 respondents mainly dominated by university students aged 21–24 (76.0%), followed by those aged 17–20 (20.2%) and 25 and above (3.8%). In this study, the majority of the respondents are female students accounted for 56.7%, while males accounted for 43.3%, which indicates a balanced dataset. This balanced distribution across academic years is consistent, approximately 20% of total respondents participated from each year in this study. This balance extends to the academic faculties, where participation is nearly equal among the Faculty of Business Studies (35.2%), Arts and Social Science (33.0%), and Science and Technology (31.7%), ensuring the findings are not biased toward any specific discipline. Finally, in terms of practical application, ChatGPT is the most popular AI tool among students (48.2%), followed by Gemini (19.6%) and Deepseek (17.6%), highlighting a clear preference for generative AI platforms in the Bangladeshi academic landscape.

Table 1
Descriptive Statistics of Respondents (n = 499)

Variables	*Categories*	*Frequency (n)*	*Percentage (%)*
Age	17–20	101	20.2%
	21–24	379	76.0%
	≥ 25+	19	3.8%
Gender	Male	216	43.3%
	Female	283	56.7%
Education Level	First Year	97	19.4%
	Second Year	101	20.2%
	Third Year	93	18.6%
	Fourth Year	106	21.2%
	Fifth Year	102	20.4%
Faculty	Faculty of Arts and Social Science	165	33.0%
	Faculty of Business Studies	176	35.2%
	Faculty of Science and Technology	158	31.7%
AI Tools Used	ChatGPT	241	48.2%
	Deepseek	88	17.6%
	Gemini	98	19.6%
	Others	72	14.4%
Source: Author's Estimation (2026)			
Note: Fifth year means masters students			

5.2 Measurement model:

5.2.1 4.2.1 Factor loading, Reliability and Convergent Validity analysis:

To ensure the validity and reliability of the constructs used in this study, a comprehensive evaluation of the measurement model was conducted using Confirmatory Factor Analysis (CFA) and the statistics are presented in Table 2. Internal consistency was assessed using Cronbach's alpha and composite reliability (CR). With Cronbach's alpha values ranging from 0.876 to 0.936 and CR values between 0.886 and 0.983, the results showed good internal consistency across all constructs and both exceeded the

recommended criterion of 0.70 (Nunnally, 1978; and Hair et al., 2019). Convergent validity was confirmed using standardized factor loadings, which all exceeded 0.70 and ranged from 0.782 to 0.948. This suggests that each item significantly contributes to the corresponding construct. Additionally, the Average Variance Extracted (AVE) values, which varied from 0.730 to 0.878 and were significantly higher than the 0.50 benchmark (Hair et al., 2019), demonstrated that the constructs effectively capture the variance of their indicators.

Table 2
Item loading, convergent validity, and reliability

Variable	*Items*	*Loadings*	*CA*	*CR*	*AVE*
AIA	AIA1	0.910	0.936	0.970	0.837
	AIA2	0.914			
	AIA3	0.915			
	AIA4	0.921			
BIU	BIU1	0.898	0.876	0.886	0.730
	BIU2	0.863			
	BIU3	0.782			
	BIU4	0.870			
EE	EE1	0.910	0.928	0.940	0.776
	EE2	0.871			
	EE3	0.845			
	EE4	0.868			
	EE5	0.909			
FR	FR1	0.922	0.931	0.943	0.878
	FR2	0.940			
	FR3	0.948			
PE	PE1	0.884	0.931	0.934	0.829
	PE2	0.905			
	PE3	0.927			
	PE4	0.926			
PR	PR1	0.899	0.930	0.983	0.816
	PR2	0.926			
	PR3	0.863			
	PR4	0.922			
SI	SI1	0.916	0.917	0.917	0.800
Source: Author's Estimation (2026)					
Note: CA= Cronbach's alpha, CR= Composite reliability, and AVE= Average variance extracted					

Variable	*Items*	*Loadings*	*CA*	*CR*	*AVE*
	SI2	0.881			
	SI3	0.883			
	SI4	0.897			
SR	SR1	0.889	0.906	0.927	0.778
	SR2	0.868			
	SR3	0.876			
	SR4	0.895			
Source: Author's Estimation (2026)					
Note: CA= Cronbach's alpha, CR= Composite reliability, and AVE= Average variance extracted					

5.2.2 Discriminant Validity:

Discriminant validity was assessed using the Fornell-Larcker criterion and the Heterotrait–Monotrait ratio (HTMT). Table 3 presents the discriminant validity assessment results using the Fornell–Larcker criterion. The square root of the average variance extracted (AVE), shown on the diagonal, is higher than the corresponding inter-construct correlations for all constructs. This indicates that each construct shares more variance with its own indicators than with other constructs in the model. Discriminant validity was further supported by the HTMT values shown in Table 4, which were below the recommended cut-off of 0.90 (Henseler et al., 2015), demonstrate the differences between the constructs. Therefore, adequate discriminant validity among the constructs is established.

Table 3
Correlations among the constructs (Fornell and Larker Test)

AIA	AIA	BIU	EE	FR	PE	PR	SI	SR
	0.915							
BIU	0.048	**0.854**						
EE	0.073	0.284	**0.881**					
FR	-0.017	0.173	0.126	**0.937**				
PE	0.002	0.463	0.120	0.521	**0.911**			
PR	0.075	0.007	0.131	-0.057	0.160	**0.903**		
SI	0.034	0.352	0.266	0.158	0.171	0.082	**0.894**	
SR	-0.020	-0.205	-0.027	-0.124	-0.123	-0.004	-0.070	**0.882**
Source: Author's Estimation (2026)								
Note: The diagonal bold values represent the square root of the average variance extracted (AVE) of the corresponding construct								

Table 4
Heterotrait Monotrait (HTMT) Ratio

AIA	AIA	BIU	EE	FR	PE	PR	SI	SR
BIU	0.059							
EE	0.075	0.310						
FR	0.041	0.185	0.132					
PE	0.049	0.507	0.125	0.562				
PR	0.076	0.019	0.142	0.057	0.168			
SI	0.041	0.389	0.287	0.170	0.185	0.091		
SR	0.031	0.226	0.047	0.131	0.127	0.019	0.075	
Source: Author's Estimation (2026)								

5.2.3 Model Fitness and Its Explanatory Power:

To evaluate the fit between the proposed theoretical model and the empirical data, several goodness-of-fit indices were utilized, including RMSEA, GFI, AGFI, NFI, TLI, and CFI and the values of all the indices are presented in Table 5. The results of the confirmatory analysis indicate that the model demonstrates a

strong overall fit. Specifically, the Root Mean Square Error of Approximation (RMSEA) was 0.056, which is well below the 0.08 threshold, indicating a high level of parsimony and low residual error. The incremental fit indices all exceeded the recommended 0.90 benchmark for a Well fit: NFI (0.918), TLI (0.941), and CFI (0.948). These values suggest that the proposed model represents a significant improvement over the baseline null model. While the Goodness-of-Fit Index (GFI) and the Adjusted Goodness-of-Fit Index (AGFI) yielded values of 0.892 and 0.869 respectively, they fall comfortably within the Acceptable range (0.7–0.9). Given that these indices are often sensitive to sample size and model complexity, the collective evidence from the full suite of indices supports the conclusion that the model possesses a satisfactory level of fitness for further hypothesis testing.

Table 5
Model fitting results

The index name	The evaluation index		The actual index
	Well	Acceptable	
RMESA (Root Mean Square Residual)	< 0.08	0.08–0.1	0.056
GFI	> 0.9	0.7–0.9	0.892
AGFI	> 0.9	0.7–0.9	0.869
NFI	> 0.9	0.7–0.9	0.918
TLI	> 0.9	0.7–0.9	0.941
CFI	> 0.9	0.7–0.9	0.948
Source: Author’s Estimation (2026)			

5.3 Structural Model:

5.3.1 Direct Effect Analysis:

The structural model demonstrates significant explanatory power regarding students' willingness to accept AI. The calculated R-square is 0.505, meaning the combined influence of Performance Expectancy, Effort Expectancy, Social Influence, and the various risk factors explains 50.5% of the variance in Behavioral Intention to Use (BIU). After adjusting for the number of predictors, the Adjusted R-square remains high at 0.495, indicating a stable and parsimonious model.

The path analysis results shown in Table 6 and Fig. 2 confirm that the drivers of AI acceptance among Bangladeshi students are led by Performance Expectancy (PE), which shows the strongest positive impact ($\beta = 0.539$, $p < 0.001$). This implies that students prioritize the perceived academic utility and productivity gains of AI tools above all else. Social Influence (SI) ($\beta = 0.250$, $p < 0.001$) and Effort Expectancy (EE) ($\beta = 0.187$, $p < 0.001$) also play significant roles, suggesting that peer recommendations and the ease of navigating these AI environments are key motivators.

Conversely, the model highlights significant barriers. Functional Risk (FR) is the primary inhibitor (β = -0.235, $p < 0.001$), reflecting students' concerns regarding the technical reliability and accuracy of AI in an educational context. Psychological Risk (PR) (β = -0.179, $p < 0.01$) and Social Risk (SR) (β = -0.133, $p < 0.001$) further reduce the willingness to accept these tools, indicating that anxiety and social perceptions are critical hurdles.

Table 6
Direct Effect Results

Path	*Path Coefficient (β)*	*Standard deviation (STDEV)*	*T-statistic*	*P-value*	*Remarks*
PE -> BIU	0.539	0.051	10.524	0.000***	Supported
SI -> BIU	0.250	0.040	6.275	0.000***	Supported
EE -> BIU	0.187	0.039	4.757	0.000***	Supported
FR -> BIU	-0.235	0.044	5.348	0.000***	Supported
PR -> BIU	-0.179	0.054	3.307	0.001**	Supported
SR -> BIU	-0.133	0.033	3.974	0.000***	Supported
Source: Author's Estimation (2026)					
Note: *** $p < 0.001$, ** $p < 0.01$, R-square (0.505), and R-square adjusted (0.495)					

5.3.2 Moderating Effect Analysis:

The study further investigated the moderating role of AI Awareness (AIA) on the relationships between Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Behavioral Intention to Use (BIU). The results, summarized in the moderation analysis Table 7 and Fig. 3, 4, and 5 reveal that AI Awareness significantly and positively moderates all three paths ($p < 0.001$). The interaction between AI Awareness and Performance Expectancy yielded the strongest moderating effect (β = 0.192, t = 3.598, $p < 0.000$). This suggests that as students in Bangladesh become more aware of AI's functional capabilities, the influence of "usefulness" on their intention to adopt AI-assisted learning becomes even more pronounced. In other words, awareness amplifies the perceived value of AI tools. AI Awareness also significantly moderates the relationship between Social Influence and BIU (β = 0.173, t = 3.669, $p < 0.000$). This indicates that for students with high AI awareness, social pressure and peer recommendations have a stronger impact on their willingness to accept AI-assisted environments compared to those with lower awareness. The moderating effect of AIA on the relationship between Effort Expectancy and BIU was also confirmed (β = 0.162, t = 3.736, $p < 0.000$). This implies that when students are more aware of AI technology, the "ease of use" becomes a more critical factor in forming their intention to use it. Awareness likely helps students better navigate the interface, thereby making the perceived ease of use a more potent driver of acceptance.

Table 7
Moderating Effect Results

Path	*Path Coefficient (β)*	*Standard deviation (STDEV)*	*T-statistic*	*P-value*	*Remarks*
AIA x EE -> BIU	0.162	0.043	3.736	0.000***	Supported
AIA x PE -> BIU	0.192	0.053	3.598	0.000***	Supported
AIA x SI -> BIU	0.173	0.047	3.669	0.000***	Supported
Source: Author's Estimation (2026)					
Note: *** p < 0.001					

6. Discussion

The findings of this study unwrapped a comprehensive understanding of the factors which are influencing the acceptance of AI-assisted learning environments, among the students of universities in Bangladesh. The structural model demonstrates that it fits the data exceptionally well (CFI = 0.948, RMSEA = 0.056) and explains a substantial variability of the intention of the students (R square = 0.505). This indicates that the compilation of UTAUT constructs and perceived risks effectively captures the mindset of the students of Bangladesh regarding AI adoption. The key determinant of intention was Performance Expectancy (PE) (β = 0.539), followed by Social Influence (SI), and then Effort Expectancy (EE). Hereafter, the results show that the students of universities in Bangladesh are highly pragmatic, and their intention to use AI is largely dependent on their perceived enhancement in academic grades and productivity that can be ensured by these technologies. On the contrary, the dominant role of Social Influence reflects the collectivist nature of Bangladeshi society, in which opinions from friends and teachers play a very important role in deciding the use of any new technology. This findings are in line with the studies of Wu et al., (2022); Abbad, (2021); and Li & Zhao, (2021). However, all the risk factors acted as strong deterrents. Of these, Functional Risk (FR) had the highest negative impact on intention (β = -0.235), which highlights an important issue: Bangladeshi students are concerned that AI might provide incorrect information or fail in critical academic situations. This insights are supported by the previous studies of Wei et al., (2021); and Wu et al., (2022).Therefore, to reach the stage of acceptance in Bangladesh, AI-based learning should provide an assurance of the system's dependability to dispel concerns about technical failure.

A key contribution of this study is the confirmation of AI Awareness (AIA) as a strong moderator. The interaction effects of AIA on PE (AIA x PE), SI (AIA x SI), and EE (AIA x EE) are all positive and statistically significant. This result reveals that the intensity of the factors' influencing adoption is not fixed. Instead, it strengthens as students gain information. When students display high awareness of AI, the effect of Performance Expectancy on their intention strengthens (β = 0.192). In short, students' knowledge of AI improves its perceived benefits. Higher awareness helps students move from knowledge to using AI.

This is clear from the moderation of Effort Expectancy (β = 0.162). This findings are also supported by the previous studies from Milicevic et. al, (2024); and Alif & Mariyono, (2025). Informed students are expected to view AI tools as non-threatening and easy to use.The result shows that the adoption of AI-assisted learning in Bangladesh is dependent not only on the provision of the tool but also on literacy and awareness. Since awareness of AI strengthens every positive path to adoption, universities should introduce AI training programs and by increasing awareness, institutions can maximize the positive effects of perceived usefulness and ease of use while potentially mitigating the negative impact of perceived risks.

7. Research Implications

7.1 Theoretical Implications:

There are several important contributions of this research to the body of knowledge on technology adoption. In particular, this research advances the Unified Theory of Acceptance and Use of Technology (UTAUT) by introducing the concept of multi-dimensional risks (Functional, Psychological, and Social), and Artificial Intelligence Awareness. This research moves the literature from being primarily centered on “positive drivers”-to provide a more balanced view of the psychological tension between benefits and barriers of educational environment in the context of a developing country. Theoretically, this study establishes AI Awareness (AIA) as a critical moderator that amplifies the positive effects of Performance Expectancy, Social Influence, and Effort Expectancy. These results confirm that the acceptance of technology is not merely dependent on the properties of the technology but is also largely affected by the cognitive understanding of the technology on the part of the user. With an optimal fit of the model (CFI = 0.948) and an explained variance of 50.5%, this study validates that Western-origin technology models are highly applicable to the Bangladeshi educational context when these models are extended to incorporate context-specific determinants of technology adoption, such as social influence and functional reliability.

7.2 Practical Implications

For educational policymakers, university administrators, and AI developers in Bangladesh, the results provide several actionable implications. In light of the fact that AI Awareness has a significant positive impact on all positive paths to adoption, it is essential for the universities in Bangladeshi to devote its resources not only to the development of AI technology but also to AI Literacy Programs. Workshops and seminars that explain “how” and “why” AI works would increase the students’ awareness of productivity benefits (PE) and help them navigate tools more easily (EE). Functional Risk was found to be the strongest inhibitor for this study. To encourage adoption, developers and educators must ensure that AI-assisted platforms are reliable and accurate. The universities should provide “vetted” versions of these AI tools, which have been tested for academic accuracy to reduce students’ fear of getting incorrect information or experiencing technical failures. Since, Social Influence has been shown to have a positive effect with a value of β = 0.250, it is essential for Bangladeshi universities to adopt initiating “student

ambassador" programs or "peer study groups for AI technology." In the cultural context of Bangladesh, the students are more likely to adopt these AI-assisted learning platforms if they see their high-achieving peers and respected faculty members successfully using these tools. While Performance (PE) is the main goal, it is essential for university administrators to opt for AI tools with user-friendly interfaces. Additionally, in the light of the fact that AI Awareness moderates Effort Expectancy, it is essential for these AI tools to have a "low entry barrier," through simple user-friendly guides can help to bridge the gap for students with little knowledge of these AI platforms' technical complexities.

8. Limitations and Future Research Direction

Despite the importance of the findings of this study, there are a number of limitations that should be acknowledged. Firstly, while the study focused on university students within Bangladesh, there could be a degree of bias towards urban institutions with better internet access, which could mean that the university students within rural colleges with less access to resources could have different views on Effort Expectancy and Functional Risk. Secondly, this research employed a cross-sectional study design, capturing the students' intentions at a single moment, but since AI technology and AI Awareness (AIA) are evolving rapidly, a longitudinal study would be more effective at in observing how the students' willingness to adopt AI changes as they gain more hands-on experiences over a semester or degree program. Thirdly, the data were collected via self-reported surveys, which could be at risk of being subject to social desirability bias. This could mean that students might overstate their "AI Awareness" or their "Intention to Use" to appear more technologically savvy, which could potentially inflate the R-square values. Fourthly, although the model explained 50.5% of the variance, nearly half of the variance was still unaccounted for. Future studies could incorporate additional variables, such as- Cost of Access, Privacy Concerns, or Personal Innovativeness to gain a better understanding of the determining factors that affect the adoption of AI within developing countries. Finally, this study measured only the willingness (Behavioral Intention) to accept AI, rather than monitoring students' behavior. There is a well-documented gap within several studies on technology adoption models, a degree of disparity between user intentions and their long-term behavior. In consideration of this, this study encourages future researchers to explore this topic further.

9. Conclusion

This study intended to measure the predictors of the adoption of AI-assisted learning environments by university students in Bangladesh. This study comprehensively provides an integrated framework based on UTAUT and PRT along with the AI awareness as moderator for understanding the dynamics of emerging AI usage in education in context of Bangladeshi higher education. The findings of the study affirm that the proposed framework holds an acceptable significance in this developing context, predicting 50% variation in the AI usage willingness of university students. This study found that there are some factors that positively affects AI use intention of the students, while some other risk factors affecting the intention negatively and all the effects of that factors found statistically significant. The most significant predictor of university students' willingness towards AI usage is performance

expectancy, claiming that if the students perceive AI usage improves their academic performances, they are more approachable towards using AI-assisted learning environments. This use intention is also triggered by social influence and effort expectancy. However, this eagerness towards AI usage by university students is also affected by some risks factors i.e. Functional Risk, suggesting that if students do not trust the accuracy of AI-assisted platforms, they will lose their interests in the usage. This interest can be lost by the factors like psychological risk, and social risk also. It is evident that the crucial contribution of this study is the affirmation of moderating effect of AI awareness on the relation between PE, EE, SI and BIU. This study also confirms that when the students are more aware of the positive sides of using AI assisted learning platforms, the impacts of performance expectancy, effort expectancy and social influence on use intention positively increases. It indicates that the digital divide is not a matter of access to digital technology but a matter of cognitive awareness and literacy.

It can be suggested that, there is a need of dual strategy for AI-assisted learning to be successfully integrated into the Bangladeshi education system. Respective authority should provide high quality, reliable AI tools and take awareness building campaigns together. Bangladeshi universities can make a shift by transforming this AI tools from a misunderstood source of risk to a very effective engine for students' academic betterment.

Declarations

Conflict of Interest: There is no conflict of interest

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Ethical Statement: This study was conducted in strict adherence to established ethical guidelines to uphold academic integrity, transparency, and research credibility. Ethical clearance (Ref: 23.0.902.858.07.786.24/63) was granted by the Research Ethical Committee (REC) of Bangladesh University of Professionals (BUP), Dhaka, prior to the commencement of data collection. All necessary institutional permissions were obtained, and informed consent was secured from each participant, ensuring voluntary participation and the protection of confidentiality.

Data Availability Statement: Data can be shared upon request from the corresponding author.

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Figures

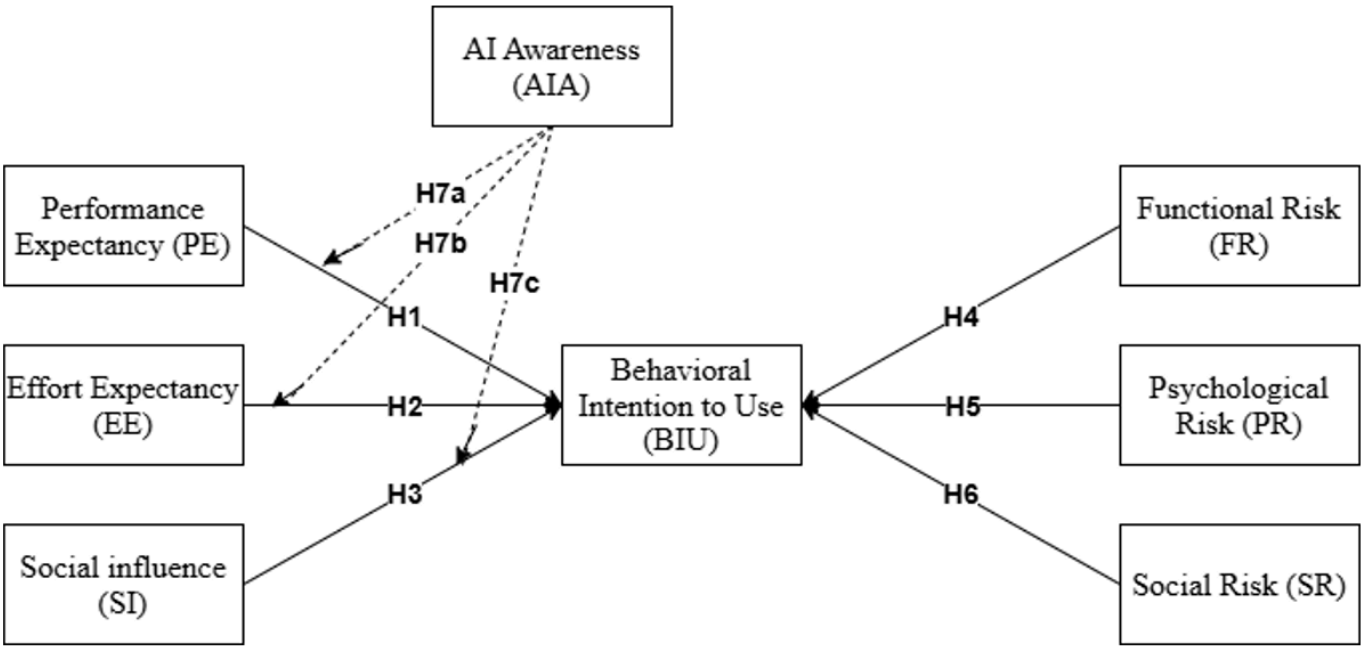


Figure 1

Conceptual Framework

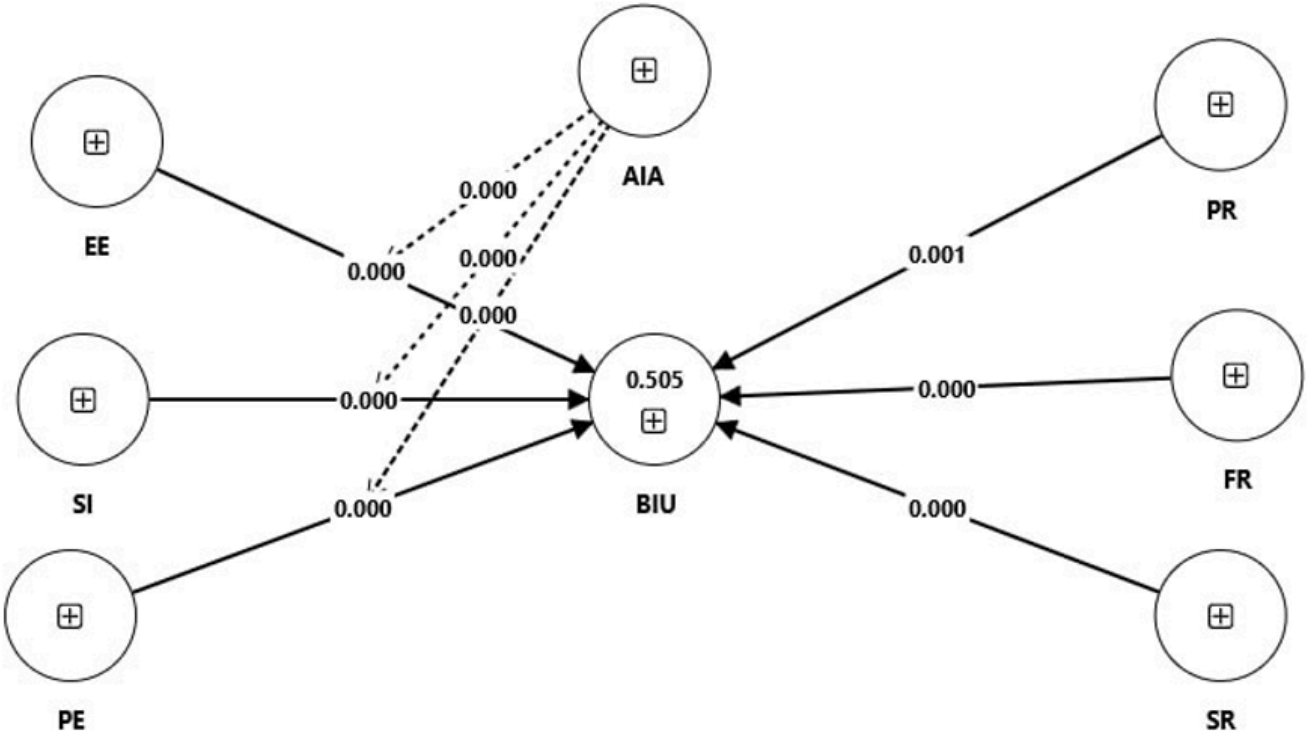


Figure 2

Structural Model with P-value

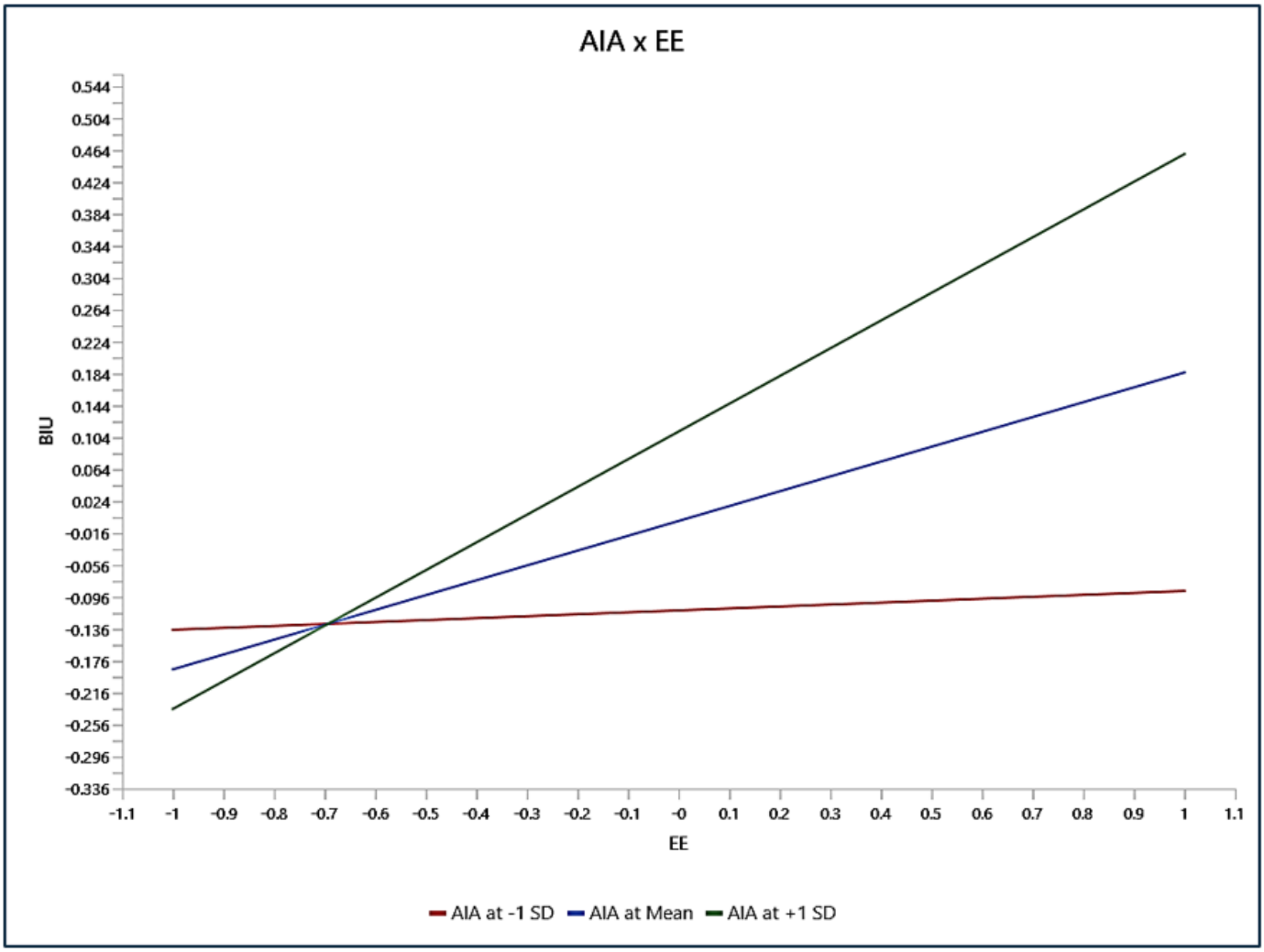


Figure 3

Moderating Effect of AIA (AIA x EE -> BIU)

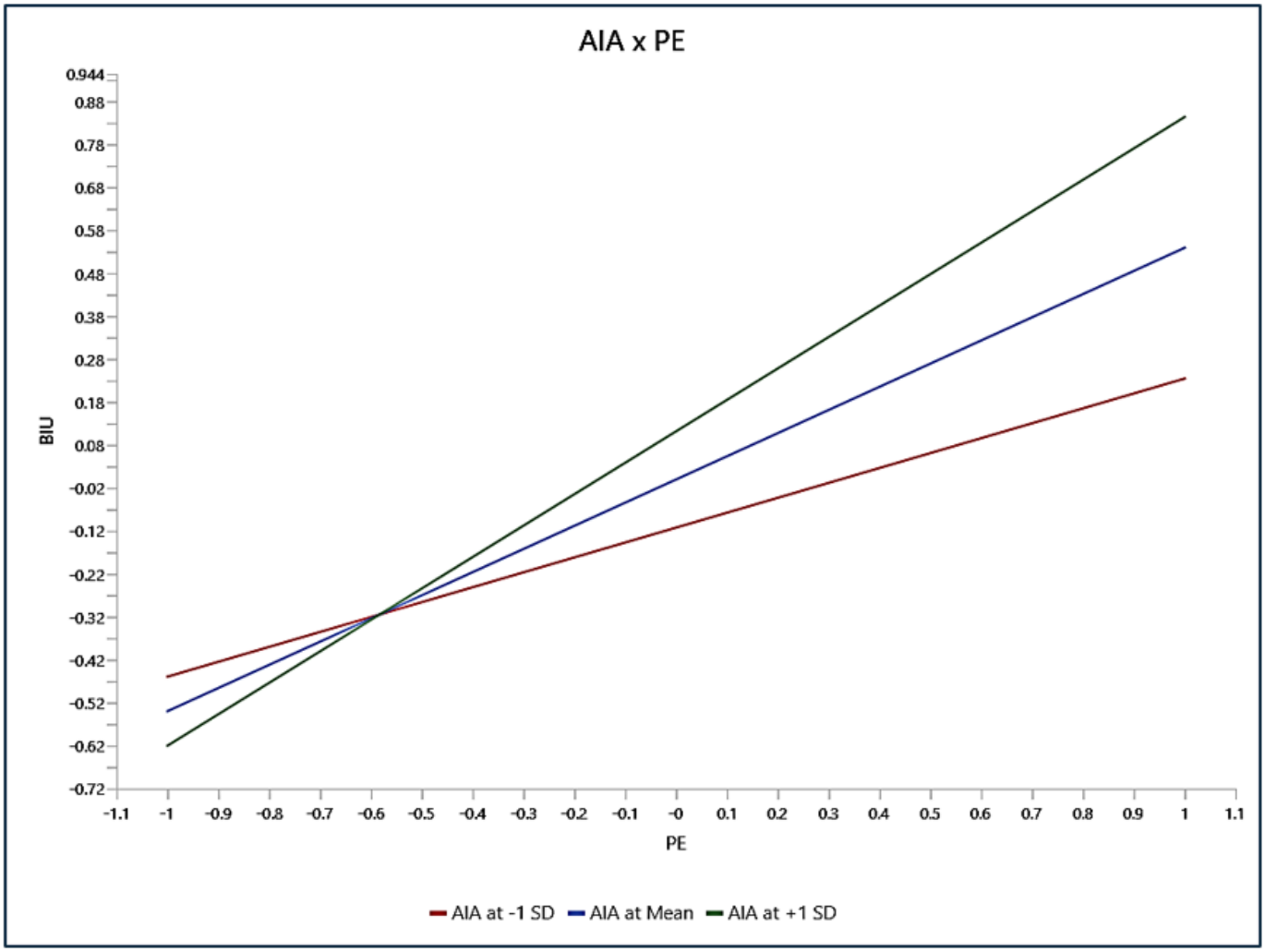


Figure 4

Moderating Effect of AIA (AIA x PE -> BIU)

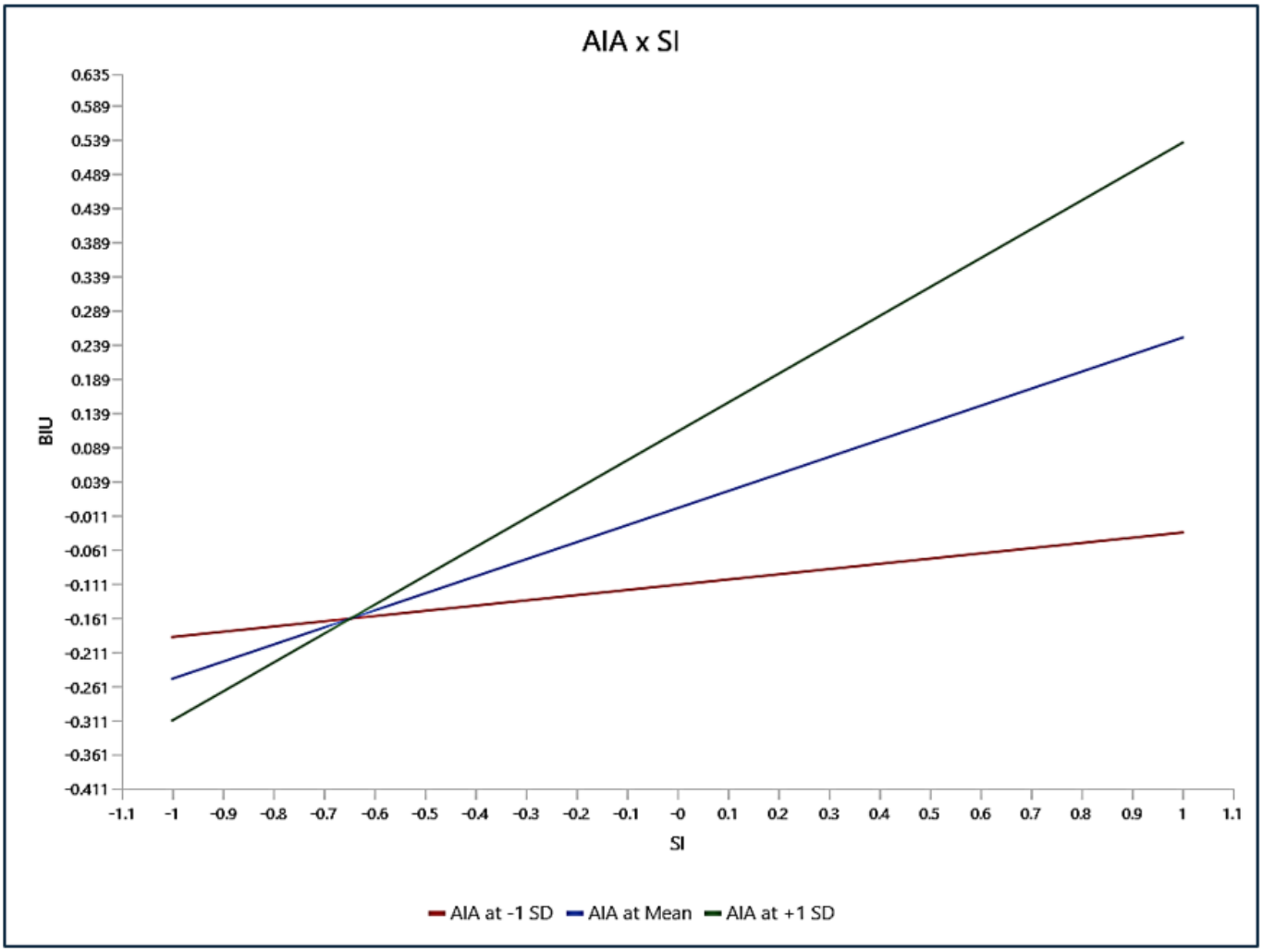


Figure 5

Moderating Effect of AIA (AIA x SI -> BIU)