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Factors affecting the intent to adopt artificial intelligence in learning: An empirical study

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Abstract
The upsurge of artificial intelligence (AI) has left a substantial mark in education — reshaping the ways, students obtain knowledge and interact with digital tools. Gaining insight into the psychological and perceptual elements that influence this shift is vital for understanding learning environments that effectively integrate AI. The present study examines the factors that influence students' intent to embrace AI know-hows namely attitude, perceived usefulness, perceived ease of use, and performance expectancy. Collection of data was done from 163 students representing numerous academic levels within North Bengal. Employing multiple regression analysis, the research found out that perceived usefulness, performance expectancy, and attitude significantly predicted students' intent to adopt AI-based tools, whereas perceived ease of use's effect on behavioral intention to adopt AI-based tools was found insignificant. The results suggest that students' motivation to incorporate AI into their academic activities are mainly due to the perceived advantages of AI and their attitude towards the technology rather than its simplicity of use. The findings highlight the significance of improving AI literacy for educational institutions and underline its advantages to encourage meaningful and sustained adoption.

Keywords: Artificial intelligence; Behavioral intention; Technology acceptance; Students; Perceived usefulness

1. Introduction

The term AI denotes a technology that is able to imitate certain characteristics of human cognition (Korteling et al. 2021). Owing to the advancement of science and technology, AI has seen humongous progress, with it being incessantly updated and extensively used across numerous fields (Huang et al. 2021). AI has rapidly evolved into a major driver of change in education, communication, and innovation (Guan et al. 2020). With AI tools increasingly embedded in classrooms and digital learning environments, students are engaging with systems that enhance understanding, creativity, and problem-solving (Albakry et al. 2025). Yet, how deeply they comprehend and accept AI remains insufficiently explored, especially in developing countries. By combining existing theories of acceptance such as Technology Acceptance Model - TAM (Davis, 1989), Theory of Planned Behavior – TPB (Ajzen, 1991), and the Unified Theory of Acceptance and Use of Technology – UTAUT (Venkatesh et al., 2003), with modern views on digital literacy, the current research offers acumens into the affective and cognitive developments that impact the uptake of AI knowhows among students.

In semi-urban and rural areas of India, AI is gradually entering classrooms through digital platforms and online learning tools (Jeyakumaran et al. 2025). Limited awareness, uneven infrastructure, and varying digital competence influence how students engage with these technologies. This research examines how measures like perception of expectancy, usefulness, and ease of use, and attitude cumulatively determine students' behavioral intention and entrepreneurial mindset in adopting AI. By analyzing responses from different educational levels in North Bengal, the research offers insights to support effective and inclusive AI adoption in education.

2. Literature Review

Research on technology acceptance consistently emphasizes the psychological and perceptual factors shaping users' adoption of new technologies. Foundational frameworks such as TAM, TPB, and UTAUT explain how individuals assess and engage with innovations. Collectively, these models highlight that attitude, perceived usefulness (PU) and perceived ease of use (PEOU) are significant factors of behavioural intention (BI), which further predicts actual technology adoption.

2.1. Behavioural intention towards AI

Behavioural intention toward AI reflects inclination to adopt and utilize AI technologies. Behavioural intention is a subjective likelihood as to how an individual executes a behaviour (Ajzen and Fishbein, 1980). It is the degree to which a person has constructed thoughtful tactics whether to execute or not certain imminent behaviour (Verplanken and Orbell, 2022). Generally, students who have greater intent to engage in a specific behaviour are in more likelihood to learn the related knowledge and skills (Chai et al. 2020). Students' intentions to use AI appear to be primarily perception-driven, shaped by their overall outlook toward technology (Chai et al. 2020). This is line with Davis (1989) and Venkatesh et al. (2003), who emphasized the significance of perceived usefulness in technology adoption. Similarly, studies have found that positive attitudes and performance-related beliefs significantly enhance behavioral intention (Dwivedi et al. 2023; Vamvaka et al. 2020; Liñán and Chen, 2009). These factors collectively propose a rising acceptance of AI in educational surroundings and innovation.

2.2. Attitude

Attitude signifies an individual's overall affirmative or adverse assessment of executing the behaviour. It entails a person's judgment that executing a behaviour is adequate or inadequate, and a general assessment that a person is willing or unwilling to execute the behaviour (Ajzen, 1980). Davis (1989) is his research found that technology usage is influenced by behavioural intention, and also attitude plays a significant role in modelling behavioral intention. This also aligns with findings of the research of Ajzen (1991), which identified attitude as a key variable impacting intention. Similarly, Venkatesh et al. (2003) demonstrated that favourable perceptions of technology directly enhance users' intention to adopt it. Liñán and Chen (2009) further observed that attitude mediates the effect of cognitive factors on intention in entrepreneurial contexts. Thus, fostering positive attitudes toward AI through awareness and skill development is vital for encouraging meaningful adoption among students. Therefore, it is posited that:

H_1: Attitude [ATT] positively impacts the intent to use AI among students.

2.3. Perceived Ease of Use

PEOU is the level that an individual finds a technology and its interface effortless to access and operate (Moslehpour et al. 2018). TAM stated that technologies viewed as simple and convenient are in more probability to be adopted. Likewise, Venkatesh and Davis (2000) demonstrated that PEOU influences BI indirectly through perceived usefulness. In educational settings, Al-Emran et al. (2018) found that students' perceptions of the ease of employing digital tools substantially enhances their intention to accept learning technologies. Therefore, simplifying AI interfaces and offering structured exposure can strengthen students' readiness to amalgamate AI into academic and entrepreneurial activities. Hence, it is hypothesized that:

H_2: Perceived ease of use [PEOU] favourably impacts intent to adopt AI among students.

2.4. Performance Expectancy

Performance expectancy is the utility and advantages than can assist customers in their actions owing to the employment of the digital systems (Venkatesh et al. 2003). It is a participant's confidence that the employment of a technology will assist in the execution of a task (Cimperman et al. 2016). UTAUT identified PE as the strongest factor of behavioural intention. Similarly in educational environments, it was found that perceived performance advantages significantly predict technology adoption. It was also established that when individuals view AI as a means to improve productivity and innovation, their intention to adopt it increases (Chatterjee et al. 2020). Therefore, performance-related advantages are key motivators for students' adoption of AI. Hence, it is posited that:

H_3: Performance expectancy [PE] positively influences the intent to employ AI among students.

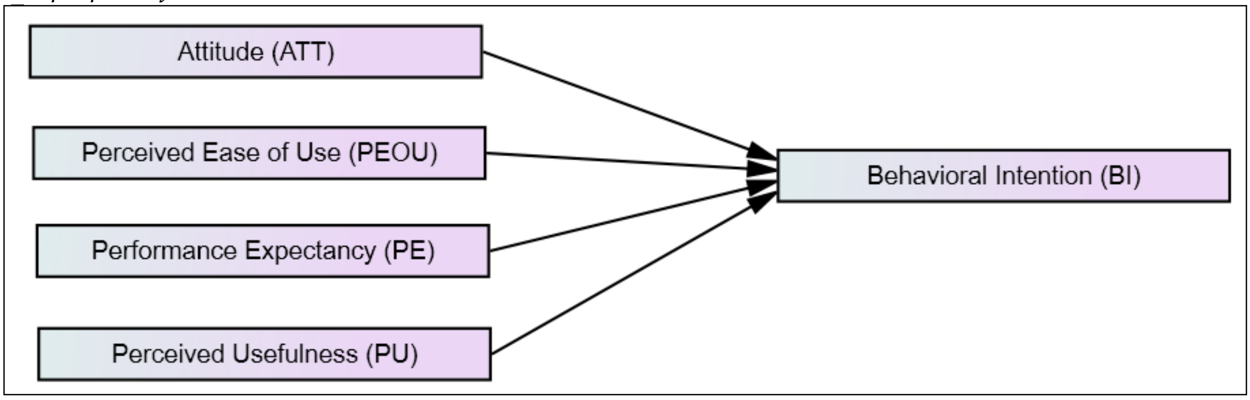
2.5. Perceived Usefulness

Perceived usefulness denotes the level to which people believe that embracing a technology will augment their activities, and the greater the consumer interest, greater the access of these technologies (Arta and Azizah, 2020). Davis (1989) identified PU as a core determinant of technology acceptance in the TAM. Likewise, Venkatesh and Davis (2000) confirmed that PU directly impacts users' intentto adopt new technologies by reinforcing expected performance improvements. Al-Gahtani (2016) further demonstrated that individuals' perception of a technology's usefulness strongly predicts their adoption behaviour. Therefore, increasing awareness of AI's practical value is essential for strengthening students' behavioural intention to integrate intelligent systems into learning and innovation. Hence, it is hypothesized that:

H_4: PU has an affirmative impact on the purpose of adopting AI among students.

The proposed research framework illustrated in Figure 1.

Figure 1
The proposed framework



The framework identifies BI to adopt AI in learning, as the dependent construct. ATT, PEOU, PE, and PU serve as independent constructs used to predict the dependent construct.

3. Method

3.1. Research Design

The present study adopts a quantitative, cross-sectional survey design grounded in established technology acceptance theories (TAM, TPB, UTAUT). A structured questionnaire was used to collect data on students' perceptions of AI in learning and their behavioral intention to adopt AI tools.

Multiple regression analysis was employed to examine the influence of ATT, PEOU, PE, and PU on BI. Assumptions of multiple regression, including reliability, normality, multicollinearity, and autocorrelation, were tested prior to hypothesis testing.

3.2. Participants

Data were collected from students in North Bengal, located in West Bengal, India, covering secondary, higher secondary, and college levels. A total of 163 students participated in the study, and all responses were valid and included in the final analysis. Sampling was conducted using a snowball sampling technique, and the researcher personally administered the questionnaires to ensure completeness and correctness of responses. Data collection took place between October 16 and October 26, 2025. The demographic profile of the participants is summarized in Table 1.

Table 1
Characteristics of participants

Variables	*Frequency*	*Percentage*
Gender		
Male	73	44.8%
Female	90	55.2%
Age Group (in the year)		
13-15	6	3.7%
16-18	85	52.1%
19-21	72	44.2%
Present Education Level		
8-10 (School)	9	5.5%
11-12 (School)	40	24.5%
College	114	70%
Time Frame of applying AI Tools		
Above 1 year	61	37.4%
Above 2 years	46	28.2%
Above 3 years and more	36	22.1%
Never used	20	12.3%

3.3. Instrument

The study used a structured questionnaire to measure five main constructs related to students' adoption of AI in learning. Attitude (ATT) was measured with two items (ATT1 and ATT2) adapted from Ajzen (1991) and Liñán and Chen (2009), which assessed students' affective evaluations of AI use, such as how helpful and desirable they perceive AI tools to be. Perceived Ease of Use (PEOU) was measured with three items (PEOU1–PEOU3) adapted from Davis (1989) and Venkatesh and Davis (2000), focusing on how easy students believe AI tools are to use and understand. Performance Expectancy (PE) consisted of three items (PE1–PE3) derived from Venkatesh et al. (2003), examining students' beliefs about AI's ability to improve their performance, productivity, and effectiveness in work or study tasks. Perceived Usefulness (PU) was also measured with three items (PU1–PU3) adapted from Davis (1989) and Al-Gahtani (2016), evaluating the extent to which students believe AI enhances learning outcomes and academic achievement. Behavioral Intention (BI) was measured using four items (BI1–BI4) drawn from Venkatesh et al. (2003) and Dwivedi et al. (2019), capturing students' future intentions to use AI tools, expected frequency of use, willingness to recommend AI to others, and their adoption decisions. In total, 15 items were adapted and partially modified to suit the objectives of the present study.

The reliability of these scales was examined using Cronbach's alpha (α). The BI scale yielded an alpha of 0.838 for its four items, indicating good internal consistency. The ATT scale, with two items, had an alpha of 0.690, while the PEOU scale, with three items, showed an alpha of 0.625. Performance Expectancy (PE) achieved an alpha of 0.836, and Perceived Usefulness (PU) demonstrated very high reliability with an alpha of 0.897. Overall, the alpha values ranging from 0.625 to 0.897 indicate acceptable to high internal consistency for all constructs, in line with the guidelines discussed by Taber (2018).

3.4. Data Analysis

Data analysis was carried out using SPSS, following several structured analytical procedures. First, descriptive statistics were calculated to summarize the demographic characteristics of the participants using frequencies and percentages. Reliability analysis was then conducted for each construct using Cronbach's alpha to determine the internal consistency of the measurement scales. To evaluate whether the dependent variable, Behavioral Intention (BI), satisfied the assumptions of normality, the study examined its mean, standard deviation, skewness, and kurtosis, supplemented by visual inspections such as the histogram, Normal P–P plot, and scatterplot.

Skewness and kurtosis values were interpreted according to the criteria proposed by Kline (2011), which indicate acceptable normality when skewness is below ±3 and kurtosis is below 10.

The analysis also included diagnostics for multicollinearity among the independent variables—Attitude (ATT), Perceived Ease of Use (PEOU), Performance Expectancy (PE), and Perceived Usefulness (PU). This was done using Tolerance and Variance Inflation Factor (VIF) values, with thresholds based on O'Brien (2007), where VIF values exceeding 5–10 or Tolerance values below 0.20–0.10 signal problematic multicollinearity. Autocorrelation of residuals was assessed using the Durbin–Watson statistic, with values close to 2 indicating the absence of serious autocorrelation issues.

Finally, multiple regression analysis was employed to test the study's hypotheses and to determine the extent to which ATT, PEOU, PE, and PU predicted Behavioral Intention. The regression model was specified as: $Y = \beta_0 + 0.300(PU) + 0.299(PE) + 0.213(ATT) + 0.118(PEOU)$ (see Table 5) where Y represents Behavioral Intention (BI). This model allowed the researchers to quantify the individual and combined effects of the independent variables on students' intention to adopt AI tools in learning.

4. Results

The study employed multiple regression analysis to weigh the effect of various AI learning factors — ATT, PEOU, PE, and PU—on BI. Table 2 displays the multiple regression coefficient results.

Table 2
Multiple regression coefficient result

Hypothesis	*Regression weights*	*Beta coefficient*	*R^2*	*F*	*t-value*	*p*	*Remarks*
H_1	ATT→BI	0.213	0.520	42.713	3.522	0.000***	Supported
H_2	PEoU→ BI	0.118			1.868	0.064*	Not Supported
H_3	PE→ BI	0.299			3.501	0.001**	Supported
H_4	PU→ BI	0.300			3.859	0.001**	Supported

Note: * $p < .05$; ** $p < .01$; *** $p < .001$.

Based on the regression results, the model can be expressed as follows:

$$\text{Let } Y = \beta_0 + \beta_1{*}X1 + \beta_2{*}X2 + \beta_3{*}X3 + \beta_4{*}X4$$

or

$$Y = \beta_0 + 0.300{*}(PU) + 0.299{*}(PE) + 0.213{*}(ATT) + 0.118{*}(PEOU)$$

where Y represents students' behavioral intention to employ AI in their learning. β_0 (Constant) represents the expected value of Behavioral Intention (BI) when other constructs are absent (i.e., all equal zero). β_1 (ATT) indicates the expected change in BI when attitude increases by one unit, holding PEOU, PE, and PU constant. β_2 (PEOU) indicates the expected change in BI when Perceived Ease of Use increases by one unit, holding ATT, PE, and PU constant. β_3 (PE) denotes the expected change in BI when performance expectancy increases by one unit, holding ATT, PEOU, and PU constant. β_4 (PU) signifies the expected change in BI when Perceived Usefulness increases by one unit, holding ATT, PEOU, and PE constant.

4.1. Hypothesis 1

Hypothesis H_1 examines whether the learning parameter Attitude (ATT) has a substantial impact on BI to adopt AI. To test this hypothesis, Behavioral Intention (BI) was regressed on Attitude (ATT) as the predictor variable. The results reveal that attitude significant impact on students' intent to use AI, with $\beta = 0.213$ and $p < 0.001$, indicating that favorable perceptions substantially enhance students' readiness to engage with AI-based learning (see Table 5 and Figure 2). The findings confirm an affirmative association between attitude and behavioral intention. Thus, H_1 is accepted.

4.2. Hypothesis 2

Hypothesis H_2 examines whether PEOU significantly influences BI to adopt artificial intelligence. The results of the analysis demonstrate that PEOU has an insignificant effect on BI, with $\beta = 0.118$ and $p > .05$, indicating that PEOU does not shape students' intent to adopt AI (see Table 5 and Figure 2). Therefore, H_2 is rejected.

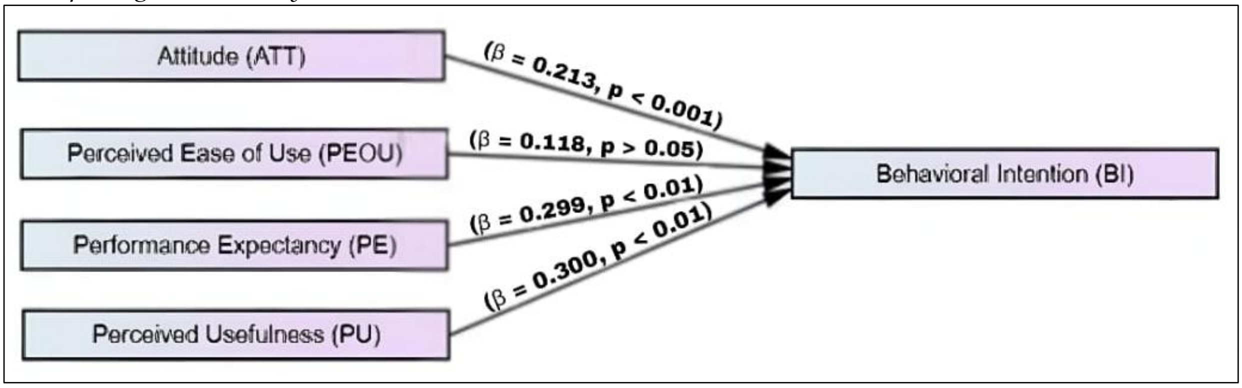
4.3. Hypothesis 3

Hypothesis H_3 assesses whether performance expectancy significantly impacts BI to embrace AI. The analysis displayed that PE has a substantial influence on BI, with $\beta = 0.299$ and $p < .01$, indicating that students' intent to adopt AI is largely driven by their perception of enhanced learning consequences and performance through its use (see Table 5 and Figure 2). Hence, the results confirm an affirmative and substantial impact of PE on BI. Thus, H3 is accepted.

4.4. Hypothesis 4

Hypothesis H_4 examines whether PU significantly affects BI to adopt AI. The analysis show that PU has a significant impact on behavioral intention, with $\beta = 0.300$ and $p < .01$, suggesting that students are highly inclined to embrace AI when they perceive clear academic or professional benefits from its use (see Table 5 and Figure 2). Therefore, the results confirm a positive link between PU and BI. Thus, H4 is accepted. Figure 2 displays the Multiple Regression analysis's results.

Figure 2
Multiple regression analysis results



Moreover, the proposed model for predicting BI to adopt AI in learning yielded an R^2 value of 0.520. This signifies that about 52.0% of the variance in students' behavioral intention toward adopting AI in learning is elucidated by the antecedents included in the model.

4.5. Major Research Findings

Students' intention to adopt AI represents a key determinant that could transform the future landscape of education and innovation. The results suggested that behavioral intention to adopt AI is shaped by multiple psychological and perceptual constructs. Perceived Usefulness arose as the most significant antecedent determining students' intention to adopt AI, reflecting that learners are more inclined to use AI when they recognize its potential to augment academic performance and output. Attitude (ATT) and Performance Expectancy (PE) also demonstrated strong positive effects on behavioral intention, indicating that favorable insights of AI's ability to improve efficiency play a vital role in motivating adoption. However, results revealed that PEOU does motivate adoption.

The findings suggest that educational institutions should focus on promoting AI literacy and awareness, highlighting the practical applications and performance advantages of AI to foster positive attitudes and encourage meaningful adoption among students.

5. Discussion

The study focused on the role of factors influencing students' behavioral intention to use AI in learning, drawing on established technology acceptance theories such as TAM (Davis, 1989), TPB (Ajzen, 1991), and UTAUT (Venkatesh et al., 2003). The results indicated that PU, PE, and ATT were significant predictors of BI, whereas PEOU was not. The findings both support and extend prior research within the AI and educational technology domains.

This strong impact of PU on BI is also very much consistent with the foundational TAM model, which identifies usefulness as the primary driver of technology acceptance (Davis, 1989; Venkatesh & Davis, 2000). Similarly, Al-Gahtani (2016) concluded that learners adopt digital and e-learning technologies when they perceive meaningful improvements in academic performance. In the context of AI tools, as echoed in Albakry et al. (2025) and Jeyakumaran et al. (2025), students prefer AI because such tools are believed to enhance creativity, problem-solving, and personalized learning. The present study extends these insights and suggests that students in North Bengal are motivated to adopt AI primarily because they recognize its capacity to raise learning outcomes and efficiency.

The second strong predictor was performance expectancy, which also affirms the UTAUT framework; usually, PE is the strongest indicator of intention to use technology, according to Venkatesh et al. (2003). Various previous research related to enhanced learning environments using technology, for example, Chatterjee et al. (2020) and Cimperman et al. (2016), likewise indicated that perceived improvements in performance are closely linked to the willingness to adopt intelligent systems. Current results also show that students are more likely to use AI when they believe that this innovative technology will allow them to work smarter, be more effective, and make everyday learning processes easier:

Attitude was another strong determinant of intention, which reflects the centrality of evaluative beliefs discussed under TPB (Ajzen, 1991) and found by Kim et al. (2009). More favorable affective perceptions-that is, finding AI desirable, beneficial, or relevant-lead to greater adoption. This finding is further supported by Chai et al. (2020), who concluded that favorable attitudes make a significant difference in motivating students to continue AI learning. Beyond functionality, therefore, how students "feel" about AI appears to assume great psychological importance in shaping their adoption behavior.

In contrast, perceived ease of use failed to exhibit a significant influence on behavioral intention. Although PEOU is considered traditionally important in TAM (Davis, 1989), more recent research, such as Al-Emran et al. (2018), asserts that in today's learning environment, students with digital experience may no longer consider the usability aspect as an issue. Most present-day students, including those in North Bengal, have been informally exposed to AI-enabled tools in everyday applications and do not perceive the use of AI as difficult. Hence, usefulness and performance benefits overshadow ease of use. Similar observations were made in the case of studies like Dwivedi et al. (2019), where the performance-related constructs were greater influencers of behavioral intention than usability factors. Taken together, these findings reinforce the importance of improving AI literacy and awareness in schools. Institutions that emphasize concrete advantages of AI—enhanced performances, efficiency, creativity, and learning support—are likely to sustain more positive attitudes and higher adoption rates. In literature coming out on AI in Indian classrooms, as works by Jeyakumaran et al. (2025) demonstrate, effective adoption requires not only accessible tools but also student confidence and value recognition.

6. Conclusions

The research revealed that PU, PE, and attitude has significant influence on behavioural intention, while PEOU was found to be an insignificant antecedent. This suggests that students' intention to employ AI is mostly motivated by the perceived utility and optimistic attitude toward technology more than the ease of use. The research highlights the necessity for augmented AI literacy, showcasing the practical value of AI tools, and the development of positive attitudes in order to trigger massive AI adoption across educational environments. Future research can be undertaken in various regions and fields of study.

7. Limitations

The research was confined to students in North Bengal, and their attitudes or intentions may not represent those of students from other regions. Consequently, the findings may have limited generalizability to broader populations. Secondly, cross-sectional design of the research, captured students' perceptions and intent. Thus, the potential to infer long-term causal relationships or to observe potential changes in behavioural intention is restricted, as AI technologies evolve or as students gain more exposure to them.

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Appendix 1. Adoption of AI in learning constructs with their respective measurement items

Constructs and Items	*Descriptions*	*Adopted from*
Attitude (ATT)		
ATT1	Use of AI tools in everyday life would be useful.	Rahman et al., 2017, Venkatesh et al. (2003)
ATT2	Use of AI tools in everyday life would be desirable.	
Perceived Ease of Use (PEoU)		
PEoU1	Using AI tools would be easy.	Venkatesh and Davis, 2000
PEoU2	Interaction with AI tools would be clear and understandable.	
PEoU3	I would find it easy to get AI tools to do what I want them to do.	
Performance Expectancy (PE)		
PE1	Using AI tools would improve my work performance.	Venkatesh et al., 2003
PE2	Using AI tools would be helpful in my work.	
PE3	Using AI tools would enhance the effectiveness of my work.	
Perceived Usefulness (PU)		
PU1	Using AI tools would improve my daily learning performance.	Venkatesh and Davis, 2000
PU2	Using AI tools would help my everyday learning.	
PU3	Using AI tools would enhance the effectiveness of my daily learning.	
Behavioral Intention (BI)		
BI1	I intend to use AI tools in the future.	Rahman et al., 2017
BI2	I intend to use AI tools frequently.	
BI3	I intend to recommend that other people use AI tools.	
BI4	I intend to buy AI tools in the future.	

Appendix 2. Histogram, Normal P-P Plot and Scatterplot of dependent variable Behavioral Intention in adoption of AI in learning among students