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Application of Neural Network and Structural Model in AI Educational Performance Analysis

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In this study, we examine the effects of AI on education, specifically on students' cognitive and motivational factors and behaviors. Artificial neural networks (ANNs), including recurrent and deep neural networks, are used to analyze critical elements of educational training. Our research involves training ANNs and using Smart partial least squares regression (Smart PLS) for deep learning analysis. The findings indicate a high accuracy rate of 94% in factor analysis by ANNs, indicating a positive effect of AI on educational training. Smart PLS results show that each dimension positively affects student behavior. The study shows that AI technology can effectively increase learning efficiency in education, benefiting student education and training. The integration of ANN and Smart-PLS analyses supports the conclusion that AI technology can increase learning efficiency in education.

1. Introduction

AI now accompanies students in their digital learning journey. Virtual assistants like Siri and Google Assistant have gradually extended their AI technology into various fields such as healthcare, automotive, education, social media, entertainment, and robotics.(1) AI is recognized for its capability to address scientific and engineering challenges through innovations such as machine learning and neural networks. AI represents the convergence of science, technology, engineering, and mathematics (STEM), which poses significant educational challenges for students. These challenges include (1) explaining the importance of AI in early education,(2) (2) identifying suitable resources for students to learn fundamental AI concepts, and (3) creating engaging and enjoyable experiences that help children grasp basic AI principles.(2) We integrate these concepts to enhance students' motivation for AI education and investigate their motivation and behavior when learning about AI.

AI education enhances learning by merging various disciplines and technologies. It has been shown to boost creativity, emotional intelligence, collaboration, and literacy in students through

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interactions with AI via gestures, touch, and speech.[3,4] Despite its benefits, there is a gap in research on effective AI teaching methods and their impact on student development.[3] In this study, we examine how students' expectations, social influences, and available resources affect their intention to use AI for learning, as well as the link between their intentions and the actual AI usage, to better understand their motivation and learning outcomes.

Artificial neural networks (ANNs) are computational models inspired by the human brain, characterized by their capability to learn from data through adjustable connections, process information in parallel across multiple nodes and layers, and perform nonlinear mapping owing to their complex architectures and activation functions. In this study, we employ ANNs and structural equation modeling to assess the effect and effectiveness of AI educational software on student usage behavior.

ANNs exhibit formidable learning capabilities. This implies that they can autonomously extract features and patterns from vast datasets. This capability renders them highly efficient in dealing with complex problems and big data.[5] Furthermore, ANNs can handle nonlinear relationships[6] and adapt to such nonlinear data.[7,8] Currently, some studies have focused on neural network learning.[9,10]

Many researchers believe that ANNs can be utilized for the automatic assessment of student's learning progress and performance, and hence provide real-time feedback. This automated assessment system can assist teachers to better understand the individual needs of each student and thereby adjust teaching strategies.[9,10] ANNs can establish real-time interactive teaching environments, making the teaching process more lively and engaging.[11] Through this approach, students can actively participate in the learning process, which will enhance their engagement and interest. Therefore, we employ ANNs to comprehend the willingness to learn among students during the learning process.

The main contribution of this study is the investigation of whether or not students may become motivated to learn AI, using many factors, including performance expectancy, effort expectancy, social influence, and facilitating conditions and whether or not this motivation results in actual learning behaviors. The use of ANN techniques to forecast student learning outcomes, which are subsequently assessed using AI technologies, is the second significant contribution of this study. The results of this study emphasize how crucial it is for educators to balance equitable rewards and student learning success, adding that social pressure can significantly increase students' desire to learn.

2. Methodology

By this research, we seek to understand college students' acceptance of AI products by employing a questionnaire survey to gather and analyze relevant data. We aim to identify the key factors affecting college students' receptivity to AI products. We also examine the application and experiential behavior related to AI educational products in higher education, utilizing ANNs and the unified theory of acceptance and use of technology (UTAUT) as analytical frameworks.

2.1 Artificial neural network

In this study, a multilayer perceptron (MLP) is used in a multilayer perceptron architecture. Neurons are sorted by layer, and the output value of the neurons in the upper layer is the input value of the next layer, including the first and last layers as the input and output layers, respectively. Thus, there are a total of three layers where the middle is the hidden layer. ANNs compute the weighted sum of input values for each of the nodes. The main principle of the MLP mode is to multiply the input value by the relevant weight (w) and compare it with the threshold (θ), where a threshold value exists on each neuron. If the received signal value is greater than the defined threshold after weight calculation, the neuron will be triggered. During training, the error difference can be used to adjust the weight and assignment, so that the difference between the final simulated value and the predicted value can be directly minimized.

In the MLP network, the output layer arranges neurons into a matrix in a one-dimensional or two-dimensional space and adjusts the key value vector in accordance with the input vector. The neurons in the final output layer are output in the space with a meaningful topological structure following the "shape" of the input factor, including the input layer $x = [x_1, x_2, x_3, \ldots x_n]$, the output layer $y = [y_1, y_2, y_3, \ldots y_n]$, and the key value vector $w_j = [w_{j1}, w_{j2}, w_{j3}, \ldots w_{jp}]$, where $j = 1, 2, 3, \ldots$ p represents the dimension of the input data and n represents the number of neurons. This algorithm uses feature mapping to project information of any dimension onto a one-dimensional or two-dimensional map. The detailed steps are as follows.

Step 1: Initialization: Initialize the key value vector $w_j = [w_{j1}, w_{j2}, w_{j3}, \ldots w_{jp}]$, $j = 1, 2, 3, \ldots n$ in a random manner. All key value vectors must be different.

Step 2: Input of data: Randomly select a piece of data from the training data and input it into this network.

Step 3: Calculation of the winning neurons: Use the minimum Euclidean distance to identify the winning neuron j^*.

$$\left\|\underline{x} - \underline{w}j^*\right\| - b_{j^*} = \min_j \left(\left\|\underline{x}\right\| - \underline{w}j\right) - b_j, \quad j = 1, 2, 3, \ldots n \tag{1}$$

Step 4: Conscience mechanism: j_p is the probability value of the jth winning neural network.

$$P_j^{new} = P_j^{old} + \beta\left(Q_j - P_j^{old}\right)$$
$$Q_j = \begin{cases} 1, & j^* \\ 0, & j \neq j^* \end{cases} \tag{2}$$

$0 < \beta < 1$, where the initial value of P_j is set to 0.

Step 5: Find the winning neurons again and use the new mechanism to find the winner j^*.

$$\left\|\underline{x} - \underline{w}j^*\right\| - b_{j^*} = \min_{j}\left(\left\|\underline{x}\right\| - \underline{w}j\right) - b_j \tag{3}$$

b_j is the correction offset defined as

$$b_j = c\left(\frac{1}{n} - P_j^{new}\right). \tag{4}$$

Step 6: Adjust the key value vector as shown below.

$$\underline{w}_j(t+1) = \begin{cases} \underline{w}_j(t) + \eta(t)\pi_{j^*j^*}(t)\left[x(t) - \underline{w}_j(n)\right] & j \in \wedge j^*(t) \\ \underline{w}_j(t) & , \; j \notin \wedge j^*(t) \end{cases} \tag{5}$$

The framework includes the $\eta(t)$ learning rate function, the adjacent area functioning as the winning function, and the adjacent area of the victorious neuron j^*. All three of these elements are integral as functions of time (t).

Step 7: Examine the termination criteria and loop back to step 2, continuing this process until the learning phase concludes.

2.2 Research framework and hypothesis development

We employ UTAUT to investigate the adoption and user experience of AI educational products in higher education. By questionnaire analysis, we seek to identify the factors that affect students' use of these technologies. According to UTAUT, a learner's use of technology is affected by performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intention. The aim is to elucidate the factors that drive college students' intentions to use AI educational products and to understand the interplay among these variables.

Data collection and literature review have been utilized to create a conceptual framework, which is illustrated in Fig. 1.

Considering the research purpose and conceptual framework, the research hypotheses proposed in this study are as follows.

H1: Performance expectancy has a positive effect on behavioral intention.
H2: Effort expectancy has a positive effect on behavioral intention.
H3: Social influence has a positive effect on behavioral intention.
H4: Facilitating conditions have a positive effect on behavioral intention.
H5: Behavioral intention has a positive effect on usage behavior.

2.3 Research proposed

School curriculum planning raises questions of personal value, and educators possess a range of ideas concerning the educational content needed to match the requirements of their schools

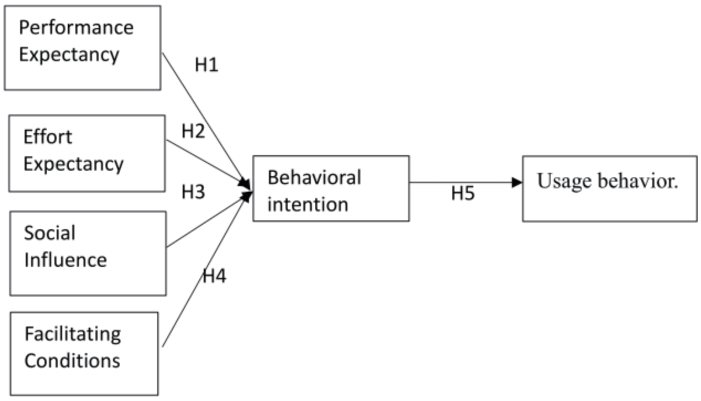

Fig. 1. Conceptual framework.

and students. Therefore, we used a purposive sampling technique to ensure qualified participation. Specifically, we enlisted four teachers experienced in AI-related teaching and four students to examine and amend the problematic questionnaire items. Before participating in the study, all participants were subjected to an informed consent procedure. The study population consisted of students in Taiwan who were also the subjects of the study. Strict adherence to ethical frameworks was ensured throughout the study. We used convenience sampling and administered an online questionnaire to gather data.

2.4 Research design

The research instrument in this study is a questionnaire designed to assess students' acceptance and usage experience of AI educational products. It is structured as two sections: the first collects basic demographic information such as gender, age, and willingness to pay for advanced features. The second part consists of a series of statements rated on a seven-point Likert scale, reflecting the degree of agreement from 1 (strongly disagree) to 7 (strongly agree). This section is organized into five dimensions, each with a set of items: three items each for performance expectancy, effort expectancy, social influence, and facilitating conditions, four items for behavioral intention, and three items for actual behavior.

3. Research Result

Data analysis and discussion were carried out using the results of the questionnaire survey. We adopted the purposive survey method and created an online questionnaire to collect data on the students' usage of AI educational products in school. The subjects of this study, who also make up the population of this study, are students in Taiwan. After the formal distribution of the questionnaire, a total of 858 valid samples were collected. In this section, we present the analysis and organization of the data collected after the distribution of the questionnaire in accordance with the aforementioned research framework, research purpose, and research questions. IBM SPSS Statistics 22 and Smart-PLS statistical software were used as analysis tools for data processing, statistical analysis, and descriptive analysis.

3.1 Samples and data collection

We followed rigorous procedures to ensure the reliability and validity of our survey instrument. We developed an English version of the questionnaire based on relevant guidelines and performed a double-blind back-translation with four independent bilingual experts.(12,13) We conducted two rounds of sorting with eight doctoral students in marketing and international business to assess the construct validity of our measures. We also pretested the questionnaire with 50 MBA students and interviewed 20 more users in Taiwan to evaluate the content validity and clarity of our items. We made minor revisions to some items on the basis of the feedback from these processes.

The explanation in this section is based on the data from the 858 valid samples. The first part of the questionnaire is the sample demographics, and the descriptive statistical analysis and discussion are carried out accordingly.

Here, we explain the descriptive statistics of the samples in this study. The male-to-female ratio of the sample is 600 to 258, which is about 2.33:1. As for the age distribution, a total of 67 respondents are under the age of 18 (7.81%), 716 respondents are between 23 and 30 years old (35.78%), 63 respondents are 31 to 42 years old (47.67%), and 12 respondents are between 43 and 53 years old. Nineteen respondents have high school degrees (2.21%), 321 respondents have junior college degrees (37.41%), 432 respondents have college degrees (50.35%), and 86 respondents have master's degrees (10.02%). Four hundred thirty-one respondents learn through AI robots at least 41–50 times a month (50.23%), 312 respondents at least 31–40 times a month (36.36%), 90 respondents at least 21–30 times a month (10.49%), and 2.91% of the total respondents at least 0–20 times a month.

3.2 Multilayer perceptron

The MLP mode is a neural network like forward propagation (forward transmission), but uses backward propagation (reverse transmission) to achieve the supervised learning of this model. The transmission process is simple. At the beginning, all weights are randomly assigned, and the predicted value is compared with the expected output value. If the predicted value is different from the expected output value, its error signal will also be sent back to the upper layer to correct it and the weight will be adjusted. These actions will be repeated until the output error reaches the minimum value.

Figure 2 and Table 1 show the neural network weight ratios. This study is divided into parts and testing. The grouping process is divided into 70% training and 30% testing.

In Table 1, it can be seen that training is between 0.161 and 1.165 and testing is between 0.105 and 1.042. The study's input parameters include performance expectancy, effort expectancy, social influence, facilitating conditions, behavior, and behavioral intention. These parameters are crucial in determining the success of the study. These results show that the training performance can be improved during group training. Figure 3 shows that each group of factors tends to approach 1.

During the training of ANNs, the effects of various factors on the network's performance can vary. ANNs adjust to variations through their learning process, which involves automatically

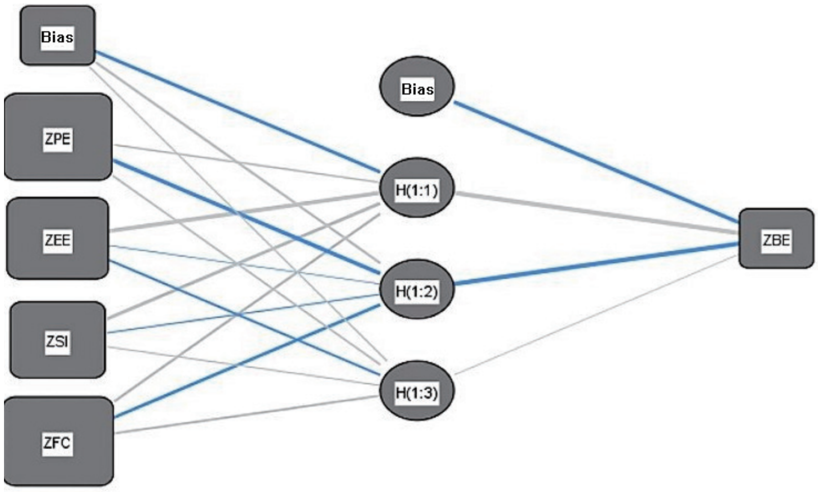

Fig. 2. (Color online) Schematic of ANN.

Table 1
Neural network validation results.

	ANN1	ANN2	ANN3	ANN4	ANN5	ANN6	ANN7	ANN8	ANN9	ANN10	Average	S.D.
Training	0.145	0.122	0.161	0.154	0.123	0.114	0.165	0.142	0.121	0.019	0.138	0.019
Testing	0.116	0.142	0.121	0.145	0.136	0.112	0.105	0.132	0.142	0.128	0.128	0.015

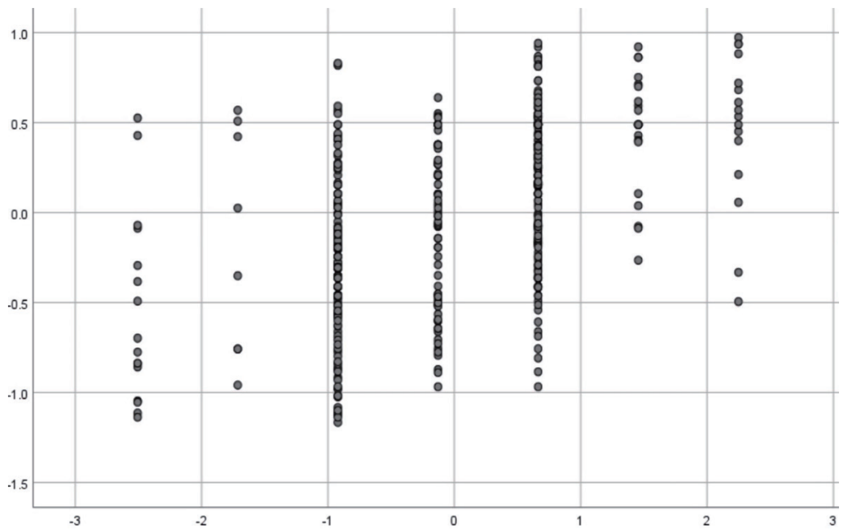

Fig. 3. ANN forecast.

tuning the connections (weights) between nodes (neurons) based on the data they process. This adaptability allows ANNs to make comparisons of local conditions and to learn from different situations, thereby enhancing its capability to solve complex problems. The network's capability to discern and adapt to the intricate relationships between different factors is a key aspect of its problem solving capability.

ANNs can reason and generate systems that are capable of automatic recognition. Unlike learning methods based on symbolic systems, ANNs also exhibit reasoning capabilities. Symbolic systems rely on logical algorithms. In other words, the capability of ANNs to reason stems from their own set of reasoning algorithms. Through the training process, the ANN algorithm is refined to better align with students' learning outcomes

In this study, the performance expectancy is 0.247, the effort expectancy is 0.21, the social influence is 0.179, and facilitating conditions is 0.364. These results show that in the training process of ANNs, the corresponding performance values of each factor group are 0.247, 0.210, 0.179, and 0.364, which all indicate high performance (see Table 2).

3.3 Measurement

Cronbach's alpha was employed to assess the reliability and construct validity of the research framework. All values exceed the recommended threshold of 0.80, indicating a reliable framework. The validity of convergence is confirmed through three criteria: factor loading above 0.70, a composite reliability score above 0.8, and an average variance extracted (AVE) above 0.5. All these values suggest a high convergent validity (see Table 3).(14)

Discriminant validity is evaluated by ensuring that the square root of AVE for each dimension is greater than the interconstruct correlations,(15) which is confirmed by the data in the study (see Table 4). Factor loadings on all dimensions exceed the 0.5 threshold (see Table 5), further supporting the model's validity. The heterotrait-to-monotrait ratio (HTMT) analysis is used as a variance-based estimator for discriminant validity,(16) with values ranging between 0.169 and 0.481, well below the 0.90 cutoff,(8) thus affirming the discriminant validity (see Table 6).

In the absence of comprehensive goodness-of-fit (GoF) indices for partial least squares structural equation modeling, R^2 is often used as the primary measure for assessing the

Table 2
ANN performance model.

	Performance of ANN model	Normalized value
Performance expectancy	0.247	67.9%
Effort expectancy	0.210	57.8%
Social influence	0.179	49.1%
Facilitating conditions	0.364	100.0%

Table 3
Construct reliability and validity.

	Cronbach's Alpha	rho_A	Composite reliability	Average variance extracted (AVE)
Behavioral	0.764	0.768	0.864	0.679
Behavioral intention	0.829	0.831	0.886	0.660
Effort expectancy	0.758	0.766	0.861	0.67
Facilitating conditions	0.819	0.841	0.891	0.731
Performance expectancy	0.737	0.758	0.851	0.656
Social influence	0.756	0.761	0.860	0.672

Table 4
Fornell–Larcker criterion.

	Behavioral	Behavioral intention	Effort expectancy	Facilitating conditions	Performance expectancy	Social influence
Behavioral	0.824					
Behavioral intention	0.319	0.813				
Effort expectancy	0.160	0.240	0.821			
Facilitating conditions	0.225	0.195	0.053	0.855		
Performance expectancy	0.279	0.380	0.224	0.176	0.810	
Social influence	0.226	0.284	0.184	0.130	0.287	0.820

Table 5
Cross-loading.

	Behavioral	Behavioral intention	Effort expectancy	Facilitating conditions	Performance expectancy	Social influence
BE1	**0.840**	0.284	0.125	0.192	0.230	0.177
BE2	**0.819**	0.259	0.138	0.199	0.244	0.195
BE3	**0.813**	0.243	0.133	0.165	0.215	0.187
BI1	0.260	**0.806**	0.180	0.189	0.280	0.210
BI2	0.278	**0.819**	0.214	0.152	0.335	0.259
BI3	0.275	**0.824**	0.195	0.174	0.308	0.225
BI4	0.219	**0.802**	0.189	0.117	0.310	0.226
EE1	0.119	0.191	**0.813**	0.070	0.161	0.165
EE2	0.139	0.179	**0.798**	0.022	0.198	0.152
EE3	0.135	0.218	**0.850**	0.040	0.193	0.138
FC1	0.203	0.126	0.022	**0.820**	0.132	0.138
FC2	0.195	0.177	0.043	**0.874**	0.179	0.140
FC3	0.185	0.186	0.065	**0.870**	0.137	0.066
PE1	0.241	0.252	0.174	0.194	**0.734**	0.230
PE2	0.222	0.318	0.171	0.121	**0.809**	0.230
PE3	0.222	0.345	0.199	0.128	**0.880**	0.240
SI1	0.213	0.245	0.139	0.142	0.249	**0.815**
SI2	0.172	0.243	0.192	0.083	0.223	**0.851**
SI3	0.168	0.208	0.115	0.092	0.234	**0.792**

Table 6
Heterotrait-to-monotrait ratio.

	Behavioral	Behavioral intention	Effort expectancy	Facilitating conditions	Performance expectancy
Behavioral intention	0.397				
Effort expectancy	0.210	0.301			
Facilitating conditions	0.286	0.230	0.064		
Performance expectancy	0.376	0.481	0.300	0.233	
Social influence	0.296	0.356	0.241	0.169	0.386

explanatory power of a model. Hair *et al.*[17] introduced GoF indices for PLS-SEM, providing an alternative means of model evaluation. Akter *et al.*[14] further defined thresholds for these GoF indices, categorizing them as small (0.12), medium (0.31), and large (0.42) to assess the model's fit.

The research GoF index is reported to be 0.621, which not only surpasses the threshold for a large GoF but also suggests an excellent fit according to the criteria set by Akter *et al.*[14] This high GoF index implies that the model is both efficient and plausible, indicating that the model is well-constructed and effectively captures the relationships between the constructs within the research framework.

3.4 Structural equation modeling

Structural models are used to test the hypotheses in the research model. First, the normalized path coefficients of the influencing paths and their statistical significance levels are estimated. Then, the coefficient of determination, R^2, for the endogenous variables was calculated to assess the predictive power of the research model. Figure 4 and Table 7 show the results for the structural model.

As shown in Fig. 4, performance expectancy shows a significant positive effect on behavioral intention ($\beta = 0.281$; $p < 001$), which supports H1. Effort expectancy shows a significant positive effect on behavioral intention ($\beta = 0.141$; $p < 001$), which supports H2. Social influence shows a significant positive effect on behavioral intention ($\beta = 0.162$; $p < 001$), thus supporting H3. Facilitating conditions shows a significant positive effect on behavioral intention ($\beta = 0.117$; $p < 001$), supporting H4. Behavioral intention shows a significant positive effect on actual behavior ($\beta = 0.319$; $p < 001$), supporting H5.

To evaluate the impact of the predicted latent variable on the R^2 value of the endogenous latent variable, we consider the estimated value of the path coefficient, its significance level, and the effect sample R^2 value.[17] From Table 7, the R^2 value falls between 0.030 and 0.087. The f^2 value from behavioral intention to usage behavior is 0.418, which is less than the threshold value of 0.350.[18]

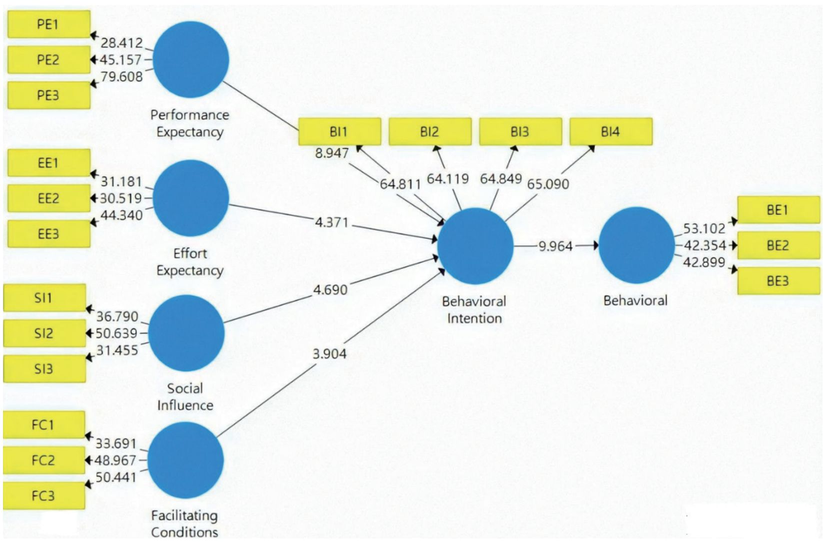

Fig. 4. (Color online) Research results.

Table 7
Structural equation modeling.

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	f^2
Behavioral Intention → Behavioral	0.319	0.322	0.030	10.558	0.113
Effort Expectancy → Behavioral Intention	0.141	0.143	0.032	4.373	0.024
Facilitating Conditions → Behavioral Intention	0.117	0.120	0.030	3.867	0.026
Performance Expectancy → Behavioral Intention	0.281	0.280	0.032	8.853	0.087
Social Influence → Behavioral Intention	0.162	0.164	0.034	4.729	0.030

In addition, the blindfolding-based cross-validation redundancy measure, Q^2 value, was used together with the coefficient of determination, R^2, to evaluate the predictive accuracy of the structural model.(19) The Q^2 values of behavioral intention and usage behavior are 0.287 and 0.292, respectively. These values show that the prediction correlation of the PLS structural model is at an average level.(17) Overall, the research model can correctly predict students' learning behavior (see Table 7).

4. Conclusions

Applying AI to educational tools increases students' motivation to adopt and use them. This underscores the importance of perceived effectiveness in AI adoption. When students accept that AI technology effectively supports their learning by providing accuracy and efficiency, they are more likely to incorporate it into their educational experience. The results of this research support the idea that the level of performance expectation is a critical factor in students' willingness to interact with AI technology for educational purposes.

Effort expectancy and social influence are key determinants of students' behavioral intentions to use AI products. Effort expectancy is based on how easily students can use the AI tool, making ease of using a strong predictor of adoption. Developers should thus prioritize user-friendly AI designs to boost this expectancy. Similarly, social influence, or how students' usage is affected by their peers and role models, also impacts their willingness to use AI. Observing others successfully using AI can encourage students to do the same; the results of studies confirm a significant link between social influence and the intention to use AI in learning.

Throughout the study, the ANNs underwent ten training cycles. Observations revealed a progressive concentration of weights, leading to reduced variance and increased accuracy as the ANNs learned patterns within the data. During the testing phase, the ANNs successfully classified or predicted new data without requiring further modifications. Consequently, after meticulous training and testing, we were able to precisely predict the learning states of the participants.

AI developers can enhance user behavioral intentions by integrating community features such as customer reviews into product guides to amplify social influence. Additionally, facilitating conditions such as accessible technology and support services are crucial. By offering technical assistance and training, developers can improve the user experience, which will encourage continued use. Ultimately, a positive behavioral intention leads to more frequent use and can be fostered by optimizing product performance, usability, social influence, and support, thereby nurturing sustained learning engagement with AI products.

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