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Enhancing the Willingness of Adopting AI in Education Using Back-propagation Neural Networks

Chien-Hung Wu,[1] Chih-Hsiang Hung,[2] Chih-Chien Shen,[3] and Jo-Hung Yu[4*]

[1]Department of Marine Recreation, National Penghu University of Science and Technology, Magong 880011, Taiwan
[2]Center for General Education, Taipei Medical University, Taipei 11031, Taiwan
[3]School of Physical Education, Hanjiang Normal University, Hubei 442000, China
[4]Department of Marine Leisure Management, National Kaohsiung University of Science and Technology, Kaohsiung 81157, Taiwan

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The use and application of artificial intelligence (AI) in Taiwanese higher education bring about new possibilities and challenges. Using AI will effectively change the entire internal structure of the Taiwan Institute of Higher Education; for instance, AI can be utilized in education to investigate how teachers enrich their knowledge, how students learn, and how higher education institutions make accurate and timely decisions. Timely responses are critical for higher education. Hence, AI applications in higher education are important from an educational perspective. In this research, we employ Statistical Package for the Social Sciences (SPSS) and smart partial least squares regression (Smart PLS) software as the primary analytics tools; the former is used to analyze fundamental statistics, whereas the latter is used to investigate the structural model. We also explore how stakeholders can adopt AI applications using back-propagation neural networks and structural equation modeling for analysis. A framework and model were developed for this study and 408 respondents analyzed, and we concluded that the model can explain the increase in the willingness to adopt AI in higher education.

1. Introduction

Over the past two decades, higher education in Taiwan has undergone dramatic development. Many researchers believe that the education system has transformed because of technological change, and many higher education systems have not kept up with the pace of technology, resulting in a gradual increase in the rigidity of the autonomy and flexibility of the university education system.(1) Therefore, there is an urgent demand to change the teaching context and administrative activities in Taiwan's higher education.(2) All aspects of higher education need updating;(3) in other words, special attention should be paid to some basic science and technology

*Corresponding author: e-mail: henry@nkust.edu.tw
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education to ensure a good quality of education.(4) Many researchers consider that Taiwanese higher education urgently needs to implement the latest technologies such as AI.(5)

AI technology enables the customization of learning, where the unique needs of diverse student groups are addressed. This approach ensures that each student benefits from an educational experience specifically tailored to their individual requirements.(6) In higher education, AI plays a pivotal role in enhancing learning experiences(7) by offering personalized and individualized learning strategies. Various AI applications are being developed to personalize these experiences,(8) although current AI technologies might need more time to fully adapt to these advanced requirements. In the interim, chatbots provide personalized support by addressing specific student issues with targeted solutions. As AI technology evolves, these chatbots will increasingly respond to individual student inquiries with greater accuracy,(9) extending support beyond traditional classroom settings. AI-driven systems also assist students in accessing admission information and navigating administrative processes. Furthermore, AI is instrumental in creating intelligent textual materials,(10) and thus contributes significantly to the advancement of higher education in numerous ways.(11)

As students face an increasing volume of homework and the need for updated learning skills, the application of modern technologies such as AI becomes crucial.(12) However, the effectiveness of AI in education hinges on its adoption by key stakeholders, including students, teaching staff, and nonteaching personnel such as administrative staff. Despite its importance, there is a noticeable scarcity of detailed research on AI adoption within the Taiwanese higher education sector.(13) In this study, we aim to identify the factors affecting the adoption of AI in higher education and will explore the following research questions in this context.

Structural equation modeling (SEM) can be used to process multiple variables simultaneously, allowing observational errors between arguments and variables; this method is particularly suitable for sociological and psychological studies involving analyses with multiple variables that cannot be measured accurately or directly. SEM can also be used to investigate various facets, latent variables, and the relationship between these facets and observed variables, including their direct and indirect effects, allowing researchers to understand the causation and interaction between different variables.

The back-propagation neural network (BPNN) is an AI technology that imitates the biological nervous system and solves complex problems through learning and self-adaptation.(14,15) In education, neural networks can be applied in adaptive learning, personalized learning, student assessment, learning analysis, and other fields, which are significant to education reform and teaching innovation.(14,16) Adaptive learning is a learning method that dynamically adjusts the learning process in accordance with the characteristics and needs of learners,(16) and BPNN can realize personalized learning recommendations and promote adjustments for learners by analyzing students' learning history, behaviors, hobbies, and other data,(17) which will not only improve the learning effect but also allow learners to participate more actively and autonomously in the learning process. On the other hand, personalized learning is a learning approach that addresses individual differences among learners,(18) where BPNN can implement personalized design and adjustment of learning content and methods by analyzing students' learning habits, styles, abilities, and other factors; this can better meet the needs of learners and improve learning effects.(14)

BPNN can also be used to evaluate students' learning ability and progress by analyzing students' learning histories, behaviors, results, and other data, allowing teachers to understand students' learning statuses more comprehensively and adjust teaching strategies and learning content accordingly to improve students' learning effects and motivations. When researchers expect to conduct an in-depth study involving complicated relationships between variables, they can use SEM to build theoretical frameworks and explore causation. Moreover, they can employ BPNN for practical data analysis and prediction. In social sciences, researchers can validate theoretical models using SEM and predict specific variable behaviors through BPNN. SEM is applicable for comparing appropriateness between different models, which helps in the investigation of various hypotheses and their correlations. With SEM, researchers can construct different models, test the models using BPNN, and confirm which model is most suitable for data interpretation. The objectives of this study are as follows: (1) to understand how AI applications will affect Taiwan's higher education system and (2) to understand the factors of learning behavior using AI by BPNN analysis.

2. Research Method

We rigorously tested educational concepts using neural networks and structural equation modeling. Our extensive study examined how college students behave when integrating AI technology into their learning experiences. To facilitate this, we developed questionnaires on the basis of expert opinions and the scale development method.[19] We focused on social influence, trust, innovation, resistance to change, and experience, with most questions addressing various facets of AI technology in higher education, especially in customizing educational content. This includes AI technology that responds to individual student queries outside the classroom. Additionally, the questionnaire explores the user-friendliness of AI technology, potential risks associated with its use in higher education (such as responding to student inquiries), and its application in admission processes. It also assesses the performance of AI technologies and the effort required from different higher education stakeholders to effectively utilize AI for their needs.

2.1 BPNN

BPNN, a prevalent model in neural networks, comprises three key components: input layer, hidden layer(s), and output layer. In this structure, while the input and output layers are singular, the hidden layer can range from one to multiple layers.[14,20] The input layer functions as the receptor of 'stimuli' akin to a biological neural network, the hidden layer is responsible for weight modulation and processing, and the output layer presents the final results. Each layer's neurons possess specific weights. Notably, the hidden layer's neurons utilize a sigmoid transfer function while those of the output layer employ a linear transfer function, enabling the network to approximate any function with a finite number of discontinuities.[21] In this multilayered setup, the output of each layer serves as the input for the subsequent layer. A standard BPNN employs the gradient descent algorithm, where the network's weight values are adjusted along the negative gradient of the performance function. This continuous updating of weight and bias values is aimed at minimizing the performance function.(22)

In the final step, the output value calculated is compared with the target output. If the discrepancy between them is less than the system's required error margin, the learning process ends. The weights established in the network at this point represent the acquired knowledge post-training.(23) The extended delta-bar-delta (EDBD) algorithm is designed to expedite the convergence of the energy function to its minimum. During network learning, the repeated alternation of the sign of the weight of a specific connection indicates a continuous mix of positive and negative differences between neurons at that point, which suggests that the optimal weight value, which minimizes the error function, has been overlooked. An increase in the error function value under these circumstances is referred to as a 'pop-out' phenomenon.(24)

To improve the above two phenomena, we used the EDBD algorithm proposed by Sutton(25) to improve the speed and accuracy of back-propagation network learning. The mathematical formula related to the EDBD algorithm is

$$\Delta W_{ij}\left(t\right)=-\varphi_{ij}\left(t\right)\frac{\partial E\left(t\right)}{\partial W_{ij}}+\alpha_{ij}\left(t\right)\Delta w_{ij}\left(t-1\right). \tag{1}$$

i: Number of the $n-1$–layer processing unit.
j: Processing unit number of this layer.
W: Weight on the link between the $(n-1)$th layer and the nth layer processing unit.
Δw_{ij}: Amount of change of the tth learning cycle of w_{ij}; the rest can be analogized.
$\alpha_{ij}(t)\Delta w_{ij}(t-1)$: Inertia term that improves the phenomenon of oscillation during the convergence, accelerating the convergence.
$\alpha_{ij}(t)$: Inertia factor that controls the ratio of the inertia term.

$$\varphi_{ij}\left(t+1\right)=\min\left[\varphi_{max},\varphi_{y}\left(t\right)+\Delta\varphi_{y}\left(t\right)\right], \tag{2}$$

where φ_{max} is the upper limit of the inertia factor.

The network learning method updates the weighted and threshold values every time a training example is loaded. A learning cycle is completed once all the training examples have been loaded. At the end of each learning cycle, the network calculates the mean-squared error (MSE) using the training and test examples:

$$MSE=\sqrt{\frac{\sum_{p}^{M}\sum_{j}^{N}\left(T_{j}^{p}-Y_{j}^{p}\right)^{2}}{M*N}}, \tag{3}$$

where T_j^p is the target output value of the jth output neuron of the Pth training (test) example, Y_j^p is the inferred output value of the jth output neuron of the Pth training (test) example, M is the number of training (testing) examples, and N is the number of neurons in the output layer.

Following each learning cycle, the model is utilized to compute the mean squared errors (*MSE*s) for both the learning and test examples, which serve as a measure to track the progress of online learning.

3. Research Design

3.1 Development of hypotheses and conceptual model

The Unified Theory of Acceptance and Use of Technology (UTAUT) synthesizes elements from eight theoretical frameworks: the theory of rational action (TRA), the technology acceptance model (TAM), the motivational model (MM), the theory of planned behavior (TPB), a combination of TAM and TPB, the model of PC utilization (MPCU), the innovation diffusion theory (IDT), and the social cognitive theory (SCT).(25) This integration results in a comprehensive model that encapsulates the primary factors influencing technology acceptance.(26) Given its holistic structure, UTAUT is particularly relevant for understanding human behaviors in adopting AI. Research in AI development has increasingly recognized the suitability of UTAUT for this purpose.(26) In this study, we focused on the adoption of AI in higher education (AAHE), examining external variables such as social influence, trust, innovation, resistance to change, and experience. We aim to elucidate these constructs individually, developing corresponding hypotheses and models. The following hypotheses are derived by this approach.

Hypothesis 1: Social influence has a positive and significant impact on AAHE.
Hypothesis 2: Trust has a positive and significant impact on AAHE.
Hypothesis 3: Innovation and resistance to change have a positive and significant impact on AAHE.
Hypothesis 4: Experience has a positive and significant impact on AAHE.

3.2 UTAUT

Venkatesh *et al.*(26) integrated various key factors and formed a comprehensive model based on the theories of the eight concepts mentioned above, namely, TRA, TAM, MM, TPB, combined TAM and TPB, MPCU, IDT, and SCT. The model variables consist of performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, and actual use behavior.

The BPNN proposed in this article is coded using SPSS 24.0. Traditional BPNN primarily explores the relationships between variables by predicting the values; thus, BPNN empowers researchers to understand a school's current educational status. In this research, we employed four indexes, namely, social influence, trust, innovation and resistance to change, and experience, to predict AAHE. Setting *MSE* as the fitness function, we obtained the BPNN structure's optimal goodness of fit through a series of experiments with different parameters. When the number of hidden neurons is ten, the test dataset's prediction error becomes minimal.

The four indexes above are set as the variables forming four input neurons. The mean absolute error works as a fitness function to enhance the model evaluation. Since optimizing the

BPNN structure requires a series of experiments, other experimental parameters remain the same apart from the number of hidden neurons. Hence, the results of these meticulous experiments have confirmed that ten neurons in the hidden layer result in the best prediction precision.

The repeated calculations and tests from published research provide sufficient parameters to form the BPNN structure's optimal goodness of fit. Meanwhile, we also set the following parameters.

Maximum training number: 1000
Learning rate: 0.001
Target error of training (*MSE*): 0.0001
Range of connection weights and thresholds: [1, 1]

3.3 Research process

The study is focused on creating a model using SEM for analysis and validation. The SEM-BPNN model construction is used for training. We propose a model for comprehensive evaluation (see Fig. 1).

4. Empirical Research

Data analysis and discussion were carried out using the questionnaire survey results. The questionnaire was distributed to members of randomly selected universities in Taiwan. We contacted university students, departments (faculty), and administrators. There were a total of

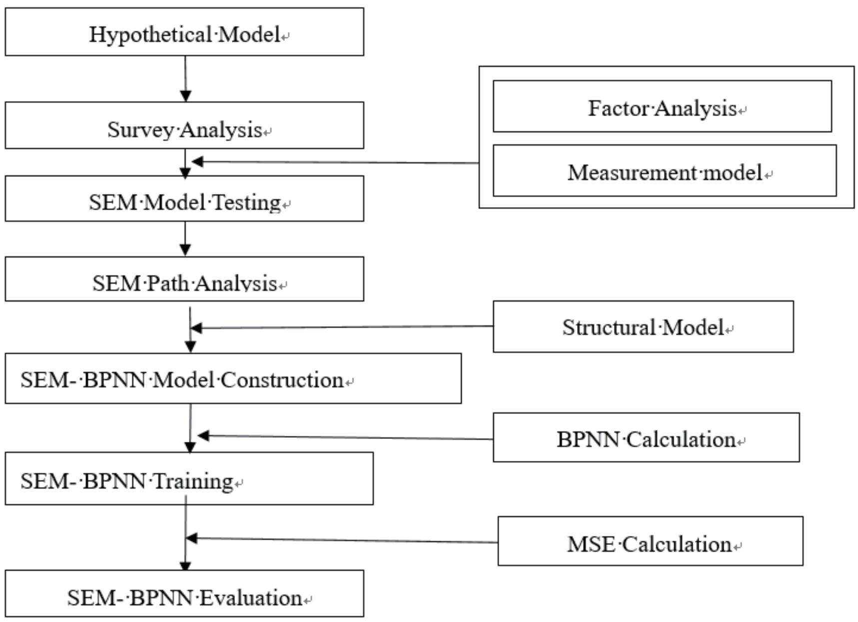

Fig. 1. Research process.

600 potential respondents, of which 480 consented to provide their feedback through questionnaires. We sent hard copies of the questionnaires from January to March 2023. The study received responses from 428 experts within the specified time period. Finally, 408 valid samples were analyzed.

4.1 BPNN

We employed both BPNN and the radial basis function neural network to forecast the inclination towards embracing AI. Zeng *et al.*[27] predicted energy consumption using BPNN and concluded that the training time of the proposed model is 30 s when α equals 0.8, and the total required time is 120 s for four repeated calculations. On the other hand, Wang *et al.*[28] combined BPNN to predict the monthly travel demand and showed that the training time is 43 s when α equals 0.4, and the total required time is 210 s for five repeated calculations. The SEM-BPNN proposed in this article showed that AI techniques increase students' willingness to learn and reduces the training time. Moreover, the proposed SEM-BPNN enhances accuracy effectively.

Figure 2 shows the structural neural network. In the BPNN training parameters, we utilized 428 samples as the training dataset, in which 16 samples were used as testing data. Model training was started after standardizing the input and output data. We set 0.1 as the learning rate, and the number of learning times as 2,000; the model stopped training after reaching the set number of learning times. Afterward, we further tested the trained model with the testing data. The output *MSE* and average results calculated using the model are shown in Table 1.

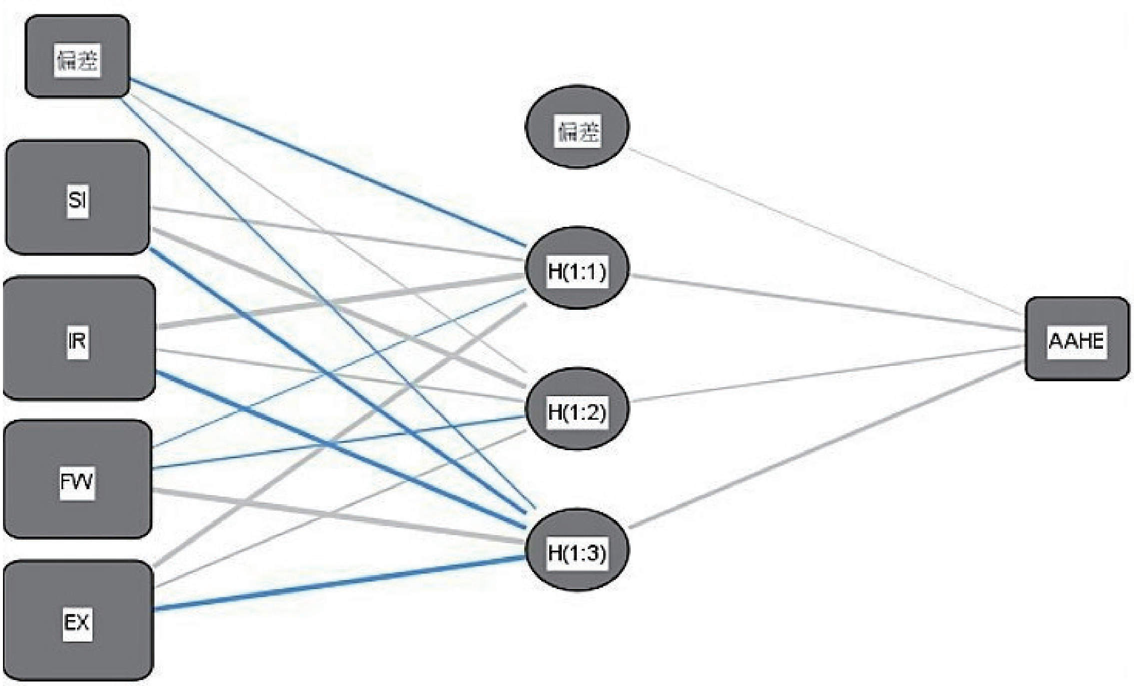

Fig. 2. (Color online) BPNN.

Table 1
Neural network validation results.

		ANN1	ANN2	ANN3	ANN4	ANN5	ANN6	ANN7	ANN8	ANN9	ANN10	Average	*MSE*
BPNN-SEM	Training	0.212	0.234	0.131	0.133	0.142	0.215	0.214	0.156	0.142	0.132	0.212	0.234
	Testing	0.214	0.150	0.164	0.136	0.146	0.164	0.143	0.131	0.123	0.134	0.214	0.150
BPNN	Training	0.112	0.124	0.122	0.144	0.121	0.145	0.144	0.124	0.132	0.122	0.145	0.240
	Testing	0.114	0.120	0.124	0.146	0.126	0.142	0.123	0.141	0.114	0.122	0.124	0.122

The learning ability of the BPNN can be adjusted to approximately align with the nonlinear system to achieve a higher prediction accuracy. The purpose of using the BPNN in this study is to improve the accuracy and reduce prediction error. The radial basis function neural network possesses outstanding mapping ability, and its advantage is that it significantly reduces the time required for learning and training. The purpose is to minimize the error.

In this study, we used two training models to compare the accuracies of BPNN and the radial basis function neural network. Figure 3 shows that the accuracies of the two are comparable when using all the data as the training condition. Using half of the data as the training condition to judge performance means the same as 30% as the training condition, and the accuracies of the two are similar.

However, when all the data in training is used in student learning outcomes, the radial basis function neural network takes all the trained input points as potential center points and then selects new center points from the potential center points one by one to reduce the error of the output as a benchmark. We select the input point with the smallest error as the center point until the error value reaches an acceptable level. The accuracy shown by the radial basis function neural network is better than that of the BPNN. In the following, we discuss the research results of the BPNN. The study results showed that students are highly willing to adopt trained and tested AI. Table 1 shows that after ten epochs of training and testing, the difference in *MSE* between the two models decreases and approaches the correct value. Table 1 reveals that the *MSE* values of all measurements in the testing dataset are close to 0.2 and smaller than in the training data. The maximum errors are also smaller than 0.2, proving that the model has obtained a better convergence after 2000 repetitions of learning. The result shows the model's optimal goodness of fit.

4.2 Structural equation model analysis

We conducted a comprehensive analysis of both the measurement and structural models, with a specific focus on the discriminant validity within the measurement model. According to the data presented in Table 2, the model demonstrates robust discriminant validity, as evidenced by the square root of each average variance extracted (AVE) value in the measurement model surpassing the correlation coefficients of the corresponding latent variables. Further validation is provided in Table 2, where the diagonal values consistently exceed the off-diagonal values in their respective rows and columns, indicating exceptional discriminant validity of the research model. Additionally, Table 2 substantiates the strong construct validity of each dimension within the model.

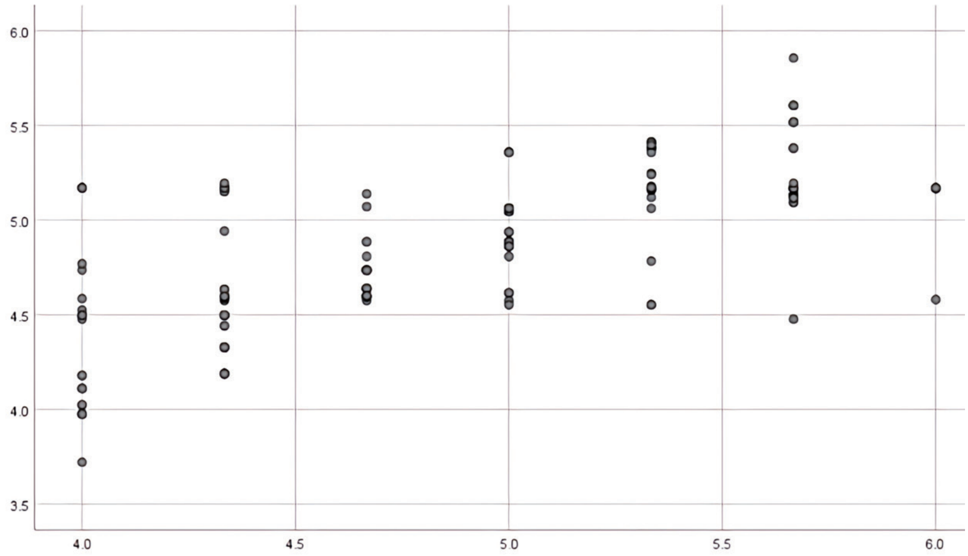

Fig. 3. Classification map forecast.

Table 2
Discriminant validity.

	AAHE	EX	IR	IRC	SI
AAHE	0.813				
EX	0.336	0.816			
IR	0.240	0.188	0.821		
IRC	0.284	0.184	0.184	0.820	
SI	0.380	0.238	0.224	0.287	0.810

Table 3 presents the results of the reliability and validity analyses of the study. Cronbach's Alpha values range from 0.737 to 0.829, comfortably exceeding the established reliability threshold of 0.7. Furthermore, the composite reliability scores, lying between 0.851 and 0.886, surpass the minimum standard of 0.6. The AVE values also align with the criteria set forth in the relevant literature, with a threshold exceeding 0.6. These results collectively affirm that the framework satisfactorily meets the standards for both reliability and validity in its analysis

We utilized Smart PLS software to analyze a robotics course, implementing an influential factor model that encompasses four external variables and a single outcome variable. The analysis within Smart PLS employs the maximum likelihood method to determine the model fitness index. Paths that failed to align with this fitness index were subsequently removed. A diagram illustrating the standardized regression coefficients was then constructed using Smart PLS, as illustrated in Fig. 4. The evidence presented in both Fig. 4 and Table 4 conclusively supports the acceptance of all the proposed hypotheses.

Table 3
Construct reliability and validity.

	α	η	CR	AVE
AAHE	0.829	0.830	0.886	0.660
EX	0.749	0.751	0.857	0.666
IR	0.758	0.766	0.861	0.673
IRC	0.756	0.761	0.860	0.672
SI	0.737	0.758	0.851	0.656

α: Cronbach's Alpha; η: rho_A; CR: Composite Reliability; AVE: Average Variance Extracted.

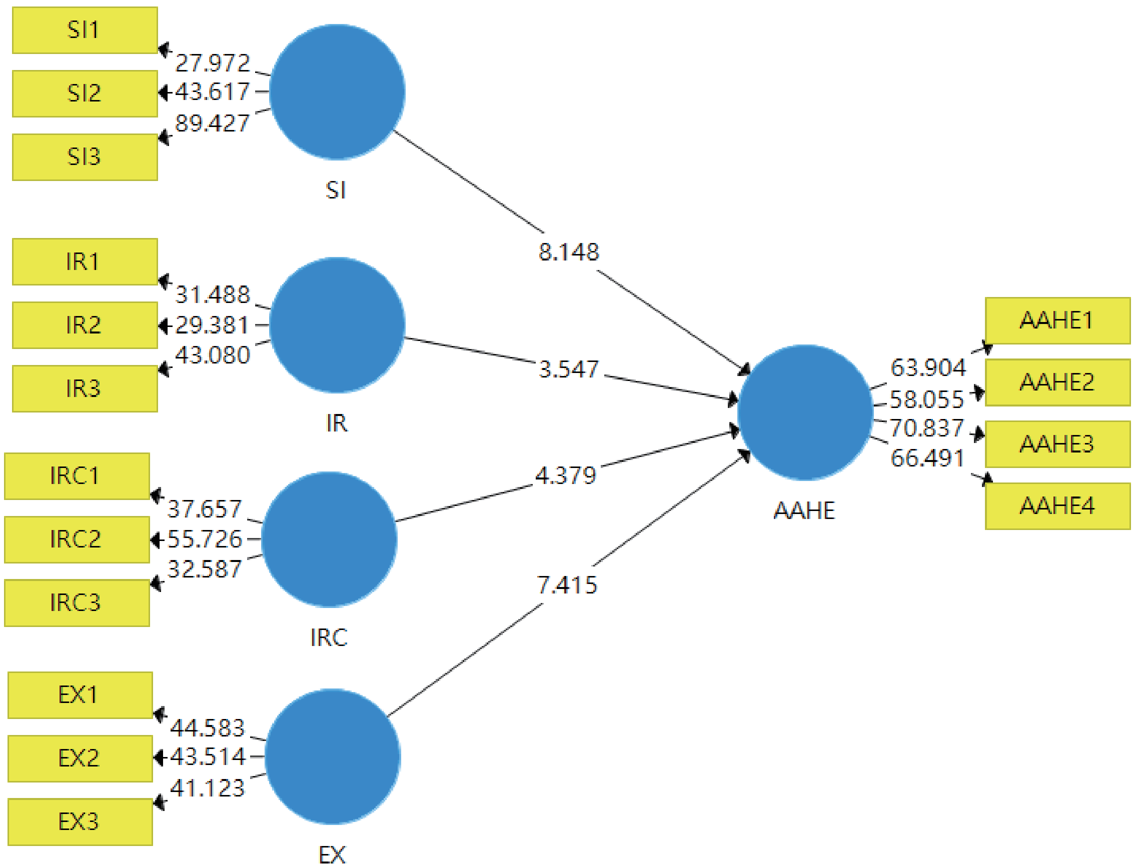

Fig. 4. (Color online) Path analysis.

Table 4
Path coefficients.

	β	M	SD	T value	Decision
EX → AAHE	0.227	0.228	0.031	7.415	Supported
IR → AAHE	0.113	0.113	0.032	3.547	Supported
IRC → AAHE	0.147	0.150	0.034	4.379	Supported
SI → AAHE	0.259	0.257	0.032	8.148	Supported

β: Original Sample; M: Sample Mean; SD: Standard Deviation.

5. Conclusions and Contribution

5.1 Conclusion

In this study, we used BPNN and radial basis function neural networks to establish a prediction model for AAHE to understand the four relationships affecting AAHE and proposed an integrated research framework. AI developers can predict AI development courses and software for the system, pre-adjust or correct them before listing, and reduce the number of testing techniques and costs. Customers can first use this system to obtain reference values for AAHE before making a choice and purchase.

AI technology can be applied in higher education. Other AI techniques can also be found in adaptive and personalized learning, providing students with a more effective and efficient learning experience. The analysis reveals that social influence has a positive relationship with AAHE; in other words, under the influence of society, the demand for AI technology in the job market is becoming increasingly high, and students' learning and mastering AI technology can improve their competitiveness in the job market. At the same time, AI technology has also led to the reduction or disappearance of traditional jobs in some industries, and students need to be aware of and prepare for this change.

Trust has a positive and significant effect on AAHE. Students' trust in AI technology is the basis for using it. Therefore, teachers need to introduce students to the basic concepts and applications of AI technology, as well as its advantages and challenges. Meanwhile, teachers must also explain the role and value of AI techniques in education to help students build trust in the sector. Student adoption of AI technology is related to its practical application in education. Hence, teachers need to integrate AI technology into their course design and prepare cases of AI technology application and practical projects suitable for students to increase students' interest and adoption of AI technology.

In the personal innovation for AAHE, students' innovation of AI technology becomes a basis for using it. Consequently, teachers must provide diverse learning resources and incentives, encourage students to learn and research AI technology independently, and provide creative and practical projects to continue innovation and improvement in practice. The use of AI technologies in higher education is based on student experience. As a result, teachers should provide various learning resources and opportunities that will enable students to experience the application and value of AI technology in different fields and scenarios and establish relevant practical cognition and experiences.

5.2 Research contribution

The process of AI learning among students is critical. Many existing research methodologies encounter challenges in depicting different learning variables from their learning, especially since the relationships between variables are nonlinear and influence each other. In this study, we proposed an integrated learning model combining SEM and BPNN and allowed students to practice projects on an AI website, proving the effectiveness of the designed approach. The primary contributions of this article are as follows. First, the neural network structure of SEM-BPNN is based on the theoretical framework of SEM causal analysis; the structural BPNN can explain the relationship and influences between network nodes, enriching the interpretability of BPNN models. Second, introducing BPNN into SEM can reveal the nonlinear relationships between the influential factors in students' learning attitudes; the powerful nonlinear goodness of fit in BPNN improves the suitability, helping teachers understand students' needs accurately and realize the causation that impacts AI products and learners. Finally, the UTAUT facet evaluation was completed by a questionnaire survey. With the popularization of IoT and AI learning products, researchers can achieve the goal of collecting information about students' use of a new product through their interactions with AI technology, enabling developers to create more accurate, objective, and precise learning models.

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About the Authors

Chien-Hung Wu received his Ed.D. degree in sports management from the United States Sports Academy, Alabama, U.S.A., in 2010. He is currently working at National Penghu University of Science and Technology, Taiwan. His research interests include sports management, health and fitness, and sailing activities.

Chih-Hsiang Hung received his Ed.D. degree in sports management from the United States Sports Academy, Alabama, U.S.A., in 2009. He is currently working at Taipei Medical University, Taiwan. His research interests include sports management, sports training, and volleyball training.

Chih-Chien Shen received his Ed.D. degree in sports management from the United States Sports Academy, Alabama, U.S.A., in 2007. He is currently working at Hanjiang Normal University, China. His research interests include business management, social sciences, energy, environmental science, physics, and astronomy.

Jo-Hung Yu received his Ed.D. degree in sports management from the United States Sports Academy, Alabama, U.S.A., in 2010. He is currently working at National Kaohsiung University of Science and Technology, Taiwan. His research interests include water sports management, leisure activity design, and sports management.