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Integrating Structural Equation Modelling and Artificial Neural Networks to Enhance Predictive Accuracy in Understanding Behavioural Intentions towards Blended Learning Systems

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Abstract: Blended learning (BL) integrates technology with traditional teaching to enhance student engagement and learning outcomes. While BL offers numerous advantages, most research relies on linear models which limit the understanding of complex adoption factors. Conventional methods such as linear regression and Structural Equation Modelling (SEM) can reveal relationships between variables but often miss the more complex and nonlinear interactions that influence learning behaviours. Aiming to bridge this gap, the present study integrates Artificial Neural Networks (ANN) with SEM to enhance predictive accuracy and provide deeper analytical insights. The results indicate that effort expectancy (EE), performance expectancy (PE) and perceived playfulness (PP) contribute to blended learning adoption, with EE and PE driving adoption and PP enhancing user engagement. ANN improves prediction accuracy by capturing nonlinear relationships, reducing error margins and increasing explanatory power. The combined SEM–ANN approach offers a more comprehensive and precise analysis and helping educational institutions design more effective and engaging BL systems.

Keywords: Artificial Neural Network, Behavioural Intentions, Blended Learning System, Structural Equation Modelling

1. Introduction

In the dynamic educational landscape of today, blended learning (BL) stands out as a transformative approach to modern education, offering a flexible, engaging, and personalised way to meet the diverse needs of students. By integrating technology with traditional teaching methods, BL enhances learning outcomes, cultivates digital skills and fosters a culture of continuous learning. As education evolves, this hybrid model is expected to play an even greater role in delivering high-quality, accessible and sustainable education for learners across various contexts. The effectiveness of BL lies in its simplicity and flexibility, leveraging the strengths of both traditional and digital pedagogies to accommodate different learning styles and preferences. For instance, visual learners learn better with videos, while hands-on learners enjoy virtual labs. This integration enriches the educational experience, supports personalised learning pathways and boosts student engagement and academic performance. The growing adoption of BL reflects a significant shift in educational paradigms, underscoring the dynamic synergy between technology and pedagogy in fostering innovative and effective learning environments (Sarkam et al., 2024).

Previous studies have demonstrated the positive impact of BL on student engagement and satisfaction, particularly when digital tools facilitate collaboration and active participation (Almarzuqi et al., 2024). Moreover, the strategic implementation of BL enables educational institutions to align their curricula with 21st century competencies, enhancing critical thinking, digital literacy and problem-solving skills. However, successful implementation requires continuous faculty development, alignment with institutional goals and equitable access to digital resources (Basri, 2024).

Despite the proven benefits of BL, a critical gap persists at understanding the factors influencing its adoption. Existing research predominantly relies on linear methodologies such as Structural Equation Modelling (SEM) and regression analysis. These methods are effective in identifying relationships between variables, but often fail to capture complex, nonlinear interactions that shape learning behaviours. This limitation hampers the ability to generate nuanced insights into the adoption process.

To address this challenge, the present study introduces Artificial Neural Networks (ANN) as a complementary analytical tool. Unlike traditional linear models, ANNs are capable of recognising complex, nonlinear patterns by mimicking the human brain's mechanisms for processing information. By combining SEM with ANN, this study offers a comprehensive approach that captures both linear and nonlinear relationships, thereby improving the predictive accuracy of factors influencing BL adoption.

This study pursues two primary objectives: (1) to identify the key factors of Performance expectancy (PE), Effort expectancy (EE), Perceived playfulness (PP), Facilitating conditions (FC) and Social influence (SI) in shaping the behavioural intentions of learners towards BL and (2) to evaluate the performance of the SEM and ANN models in predicting these factors with greater accuracy. By moving beyond conventional methods, this study aims to deepen the understanding of BL adoption, contributing valuable insights for educators, policymakers and researchers. Incorporating ANN alongside SEM enhances the precision of predictive models and provides a more holistic view of the factors driving BL adoption. This innovative methodological integration marks a significant advancement in educational research, offering practical guidance for designing more effective BL environments. Ultimately, this study aspires to support the ongoing transformation of education through the adoption of sophisticated analytical approaches that better reflect the complexities of modern learning dynamics.

2. Literature Review

2.1 Blended Learning Systems

Blended learning is a transformative instructional approach that merges traditional face-to-face teaching with interactive online activities, creating a dynamic and flexible educational model. By blending the best of physical and digital learning environments, this hybrid approach enhances student engagement, academic performance and overall learning experiences (Mohammad et.al.,2023;Sahiman & Arokiasamy, 2024). The significance of this approach in modern education stems from its capacity to address diverse learning needs through personalised pathways that promote deeper understanding and sustained knowledge retention.

Blended learning has proven particularly effective in developing productive skills like speaking and writing with interactive digital platforms and virtual practice opportunities. These tools provide immediate feedback and personalised engagement, which are essential elements for skill mastery (Roinah et al., 2024). The self-paced nature of online components empowers students to revisit materials as needed, reinforcing key concepts and boosting confidence. Additionally, the integration of technology makes learning more interactive and appealing, which increases student motivation and engagement (Guan et al., 2023; Bruggeman, 2022). The adaptability of blended learning was especially evident during the COVID-19 pandemic when it became a critical solution for maintaining educational continuity while ensuring safety.

Despite the many benefits of BL, this approach also presents challenges that must be addressed to maximise effectiveness. Issues such as technological dependence, digital inequality and the need for robust assessment methods can impact its implementation. To overcome these obstacles, institutions must invest in reliable infrastructure, provide ongoing support for educators and learners and integrate innovative technologies to enhance the learning experience. By addressing these challenges, blended learning can continue to serve as a versatile and effective approach in an ever-evolving educational landscape (Bandara & Jayaweera, 2024).

2.2 Technology Acceptance Model (TAM)

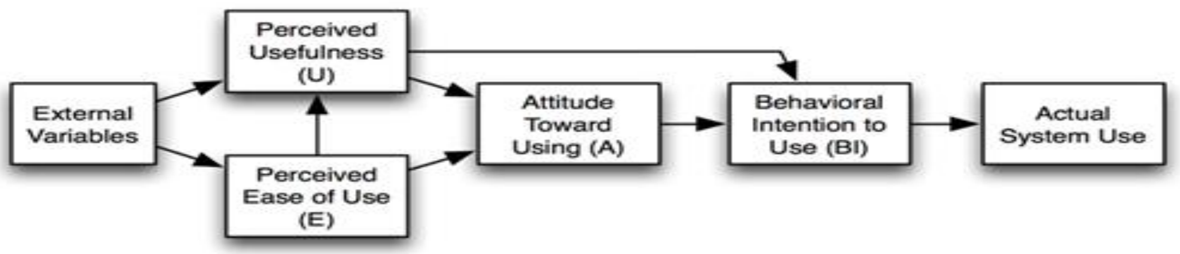
The Technology Acceptance Model (TAM), introduced by Fred Davis in 1989, serves as a widely recognised framework for understanding and researching technology adoption (Zhou et al., 2022; Abdullah et al., 2023). TAM identifies two key determinants that influence users' acceptance of technology: perceived usefulness (PU) and perceived ease of use (PEU) (Zhou et al., 2022; Fearnley & Amora, 2020; Sukendro et al., 2020). Perceived usefulness refers to the belief that utilising the technology enhances performance and simplifies tasks, while perceived ease of use reflects the belief that the technology is simple and straightforward to use. Recent findings further demonstrate that Technology Readiness factors, particularly optimism and innovativeness, strengthen the relationship between perceived ease of use, perceived usefulness, and users' behavioural intention to adopt online distance learning (ODL) technologies (Humaidi et al.,2022).

Previous studies have consistently reinforced the importance of these factors. Ibrahim and Shiring (2022) emphasised the critical roles of perceived usefulness (PU) and perceived ease of use (PEU) in technology adoption (Alsyouf et al., 2023). For instance, Luan and Teo (2009) demonstrated the relevance of the model in examining technology acceptance among Malaysian student teachers. Similarly, Granić & Marangunić (2019) highlighted perceived usefulness (PU) and perceived ease of use (PEU) as key antecedents of learning technology adoption across educational contexts. Meanwhile, Ibrahim and Shiring (2022) extended TAM by incorporating self-efficacy (SE), social influence (SI) and system accessibility (SA) to better understand the behavioural intentions of university academics toward educational technologies. Fearnley and Amora (2020) added system quality and facilitating conditions to further explain how these factors shape user perceptions and influence willingness to adopt technology. Their findings underscore the significance of system quality and self-efficacy in shaping PUs, attitudes towards technology and subsequent behavioural intentions. In addition, Sukendro et al. (2020) found that external factors like facilitating conditions significantly impacted e-learning adoption during the COVID-19 pandemic among sport science students in Indonesian higher education institutions.

Figure 1 illustrates the evolution of TAM, highlighting its core components and recent adaptations (Venkatesh & Davis, 2000). For instance, in exploring technology acceptance among primary school teachers in Malaysia, researchers have incorporated factors such as digital literacy and teacher attitudes.

Figure 1

TAM Model growth (Venkatesh & Davis, 2000)



2.3 The Conceptual Framework and Proposed Hypotheses

The present study proposes a conceptual model to predict behavioural intentions towards blended learning adoption among academics, focusing on performance expectancy (PE), effort expectancy (EE), perceived playfulness (PP), facilitating conditions (FC) and social influence (SI) due to their established relevance in influencing technology acceptance in educational contexts. The hypotheses are informed by previous research (Alsyouf et al., 2023; Cabero-Almenara et al., 2019), which consistently identifies TAM as a reliable model for examining educational technology adoption (Davis, 1989). Trivunović and Kosanović (2024) emphasised TAM's relevance by explaining the factors influencing technology use in educational settings.

This study adopts a modified and streamlined version of the augmented reality acceptance model, adapted from TAM (Cabero-Almenara et al., 2016). The proposed model suggests that performance expectancy (PE), effort expectancy (EE), perceived playfulness (PP), facilitating conditions (FC) and social influence (SI) serve as predictors of behavioural intention (BI). The conceptual framework and proposed hypotheses are depicted in Figure 2.

2.3.1 The Structural Equation Model (SEM) and Artificial Neutral Network (ANN) (Integrated Approaches)

The integrated techniques in SEM–ANN involve a dual-stage approach: (1) to model the underlying theoretical structure of data validation by using Structural Equation Modelling (SEM) and (2) to improve the accuracy of prediction by using the output from the SEM model as input to the Artificial Neural Networks (ANN) model. The SEM–ANN hybrid approach combines the strengths of both methods to enhance predictive accuracy. SEM models theoretical relationships among variables, while ANN captures nonlinear interactions, improving the robustness of predictions (Albahri et al., 2022; Qasem et al., 2020).

This integrated approach has been widely used in education and computer science. Researchers use it to refine model fits and improve accuracy when predicting behavioural intentions. For instance, ANN helps uncover complex patterns in user behaviour that traditional SEM may overlook (Elareshi et al., 2022; Mohd Rahim et al., 2022). Prior studies confirm its effectiveness in areas such as cloud computing adoption, e-learning engagement and chatbot interactions (Hauf et al., 2024; Aghaei et al., 2023). Elareshi et al. (2022) employed SEM–ANN approaches to explore how YouTube video content influences the behavioural intentions of students toward e-learning acceptance in Jordan. The hybrid SEM–ANN model predicts undergraduate e-learning continuance intentions by examining how perceived educational and emotional support affect the intention to continue using e-learning platforms, key components of BL system. The hybrid model provided a nuanced understanding of the predictors of continuance intention (Xu et al., 2024). Elareshi et al.'s (2022) This study examined how YouTube content affected the behavioural intentions of students toward accepting e-learning with the results offering insights into BL system adoption methods by identifying performance expectancy as a critical driver.

Meanwhile, several studies (Albahri et al., 2022; Elareshi et al., 2022) entail estimating a set of structural equations that represent the hypothesised relationships between variables, as well as estimating the parameters that describe those relationships. According to Mohd Rahim et al. (2022), the variables that were involved in their studies are interactivity, design and ethics to influence perceived trust, performance expectancy and habit towards using chatbot applications to affect behavioural intention. The study also aligns with Aghaei et al. (2023), who applied the SEM–ANN approaches to study perceptions related to student satisfaction by identifying several components, including educational services, sociocultural and economic-entrepreneurial aspects. A comparison chart illustrating the use of SEM and ANN to understand behavioural intentions towards blended learning systems is shown in Table 1.

Table 1

Comparison illustrating the SEM, ANN, and Hybrid SEM–ANN approaches

Criteria	Structural Equation Modelling (SEM)	Artificial Neural Network (ANN)	Hybrid SEM–ANN Approach
Analytical Foundation	Statistical (covariance-based)	Machine Learning (non-linear computational modelling)	Combines statistical validation with computational modelling
Nature of Relationships	Linear	Non-linear and complex	Linear and non-linear
Data Requirements	Large samples preferred, parametric assumptions	Flexible, handles noisy and incomplete data effectively	Large sample ideal, benefits from clean, structured datasets
Interpretability	High (clearly interpretable path relationships)	Low (acts as a 'black box')	Balanced interpretability and clearer with SEM support
Model Validation	Confirmatory (tests existing theoretical frameworks)	Predictive (identifies patterns or predictions)	Both confirmatory and predictive
Usage in BL	Validates hypotheses on learner behaviour determinants	Predicts learner behaviours, performances and intentions	Validates theory and predicts complex user behaviours
Key Strengths	Transparent modelling, strong theoretical grounding	Able to model complexity, adaptive and highly accurate	Robust, enhanced accuracy, theoretical and practical insight
Key Limitations	Limited ability for complex non-linear relationships	Difficult interpretability and lacks theoretical insight alone	Requires significant analytical expertise

Despite its advantages, the hybrid SEM–ANN approach faces challenges related to research design, data variability and model complexity. However, its ability to combine linear and nonlinear insights makes it a valuable tool for investigating technology adoption in education. This study applies the SEM–ANN model to examine how key factors influence blended learning adoption, offering a more precise and holistic analysis. The integration of SEM and ANN in studying behavioural intentions toward blended learning systems offers a comprehensive analytical framework. SEM facilitates the validation of theoretical constructs and their interrelationships, while ANN captures complex, non-linear patterns in user behaviour. Recent studies employing these methodologies have provided valuable insights into the factors influencing the adoption and continued use of BLS, informing the development of more effective and user-centric educational environments.

3. Methodology

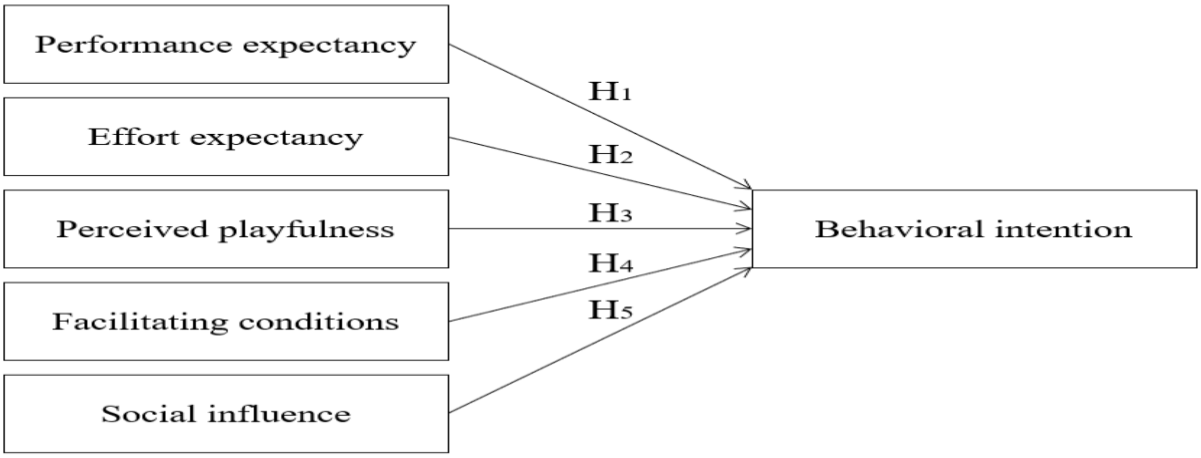
This study used a quantitative research approach with Structural Equation Modelling (SEM) and Artificial Neural Network (ANN) techniques. SEM is a statistical method that analyses relationships between variables while accounting for measurement errors and ensuring model accuracy. It was selected over traditional methods like regression because it can handle multiple hidden variables simultaneously. Meanwhile, ANN consists of artificial neurons organised into three main layers of input, hidden and output. It uses mathematical equations to identify and predict patterns in the data. Additionally, neural networks rely on training data to improve their accuracy over time.

3.1 Research Framework

Figure 2 presents the conceptual framework, showing behavioural intention (BI) as the dependent variable and the five independent variables of performance expectancy (PE), effort expectancy (EE), perceived playfulness (PP), facilitating conditions (FC) and social influence (SI).

Figure 2

Conceptual framework



The following hypotheses are proposed for this study:

H_1: Performance expectancy (PE) has a significant effect on BI.
H_2: Effort expectancy (EE) has a significant effect on BI.
H_3: Perceived playfulness (PP) has a significant effect on BI.
H_4: Facilitating conditions (FC) has a significant effect on BI.
H_5: Social influence (SI) has a significant effect on BI.

3.2 Data Collection

The dataset consists of 200 academics from higher education institutions in Malaysia and is organised into three sections: (1) demographic information, (2) key factors of Performance expectancy (PE), Effort expectancy (EE), Perceived playfulness (PP), Facilitating conditions (FC) and Social influence (SI) and (3) Blended learning (SI). A five-point Likert scale was used in the questionnaire. The data analysis tools used in this study include SEM for hypothesis testing, utilising software such as AMOS and ANN for predictive analysis. A detailed overview of the constructs is presented in Table 2.

Table 2

Description of the dataset

Role	Construct	No of Item(s)	Sources
Independent variables	Performance Expectancy (PE)	8	Lescevica et al., 2013 Onaolapo & Oyewole (2018)
	Effort Expectancy (EE)	7	
	Perceived Playfulness (PP)	7	
	Facilitating Conditions (FC)	7	
	Social Influence (SI)	5	
Dependent variable	Behavioural Intention (BI)	5	
Overall		**39**	

3.3 Integrated SEM–ANN Process

3.3.1 Structural Equation Modelling

The general equation for Structural Equation Modelling (SEM) consists of two main components. The first component is the measurement model, which defines the relationships between latent variables and their observable indicators. The second component is the structural model, which describes the relationships between latent variables. Latent refers to something hidden or not directly measurable but can be inferred from observed data. In SEM, latent variables, such as motivation, satisfaction or attitudes are estimated using multiple observable indicators. For instance, these latent variables are measured through survey responses.

The measurement model explains how observable indicators relate to latent variables, as in Equation (1) for independent latent variables and Equation (2) for dependent latent variables.

$$X = \Lambda_x \xi + \epsilon_x \tag{1}$$

$$Y = \Lambda_y \eta + \epsilon_y \tag{2}$$

where X and Y are observed indicator variables for independent and dependent latent variables, respectively. Λ_x and Λ_y are factor loading matrices that show how strong each observed variable is related to its latent variables. ξ and η are independent and dependent latent variables, respectively, while ϵ_x and ϵ_y are measurement errors. The structural model defines relationships between latent variables as in Equation (3).

$$\eta = B\eta + \Gamma\xi + \zeta \tag{3}$$

where B represents the relationships among independent latent variables. Γ represents the influence of dependent latent variables on independent latent variables, while ζ is the structural error term.

3.3.2 Artificial Neural Network (ANN)

ANN is used to validate Structural Equation Modelling (SEM) analysis and assess how independent variables influence a dependent variable. ANN is preferred for its ability to model complex relationships between inputs and outputs with high prediction accuracy, without requiring hypothesis testing (Varzura, 2022; Mehedintu & Soava, 2022). The study specifically used a multilayer perceptron (MLP) model due to its flexibility in handling indicators and compatibility with regression analysis.

The MLP model consists of three main layers of input, hidden and output. Activation functions play a key role in determining network performance, enhancing capacity in the hidden layer, and validating the regression model in the output layer. Synaptic weights define the strength and direction of connections between nodes. It influences how much an input contributes to the activation of the next neuron. A higher weight means a stronger impact, while a lower weight reduces the influence. Positive weights indicate a direct relationship, where an increase in input leads to an increase in output. On the other hand, negative weights signify an inverse relationship, where an increase in input decreases the output. These weights play a crucial role in how the neural network learns and adapts to data, affecting its accuracy and performance. An additional bias parameter helps improve the fit of the network to the data. (Mehedintu & Soava, 2022; Mundt et al., 2021).

Figure 3

Stages of the research methodology

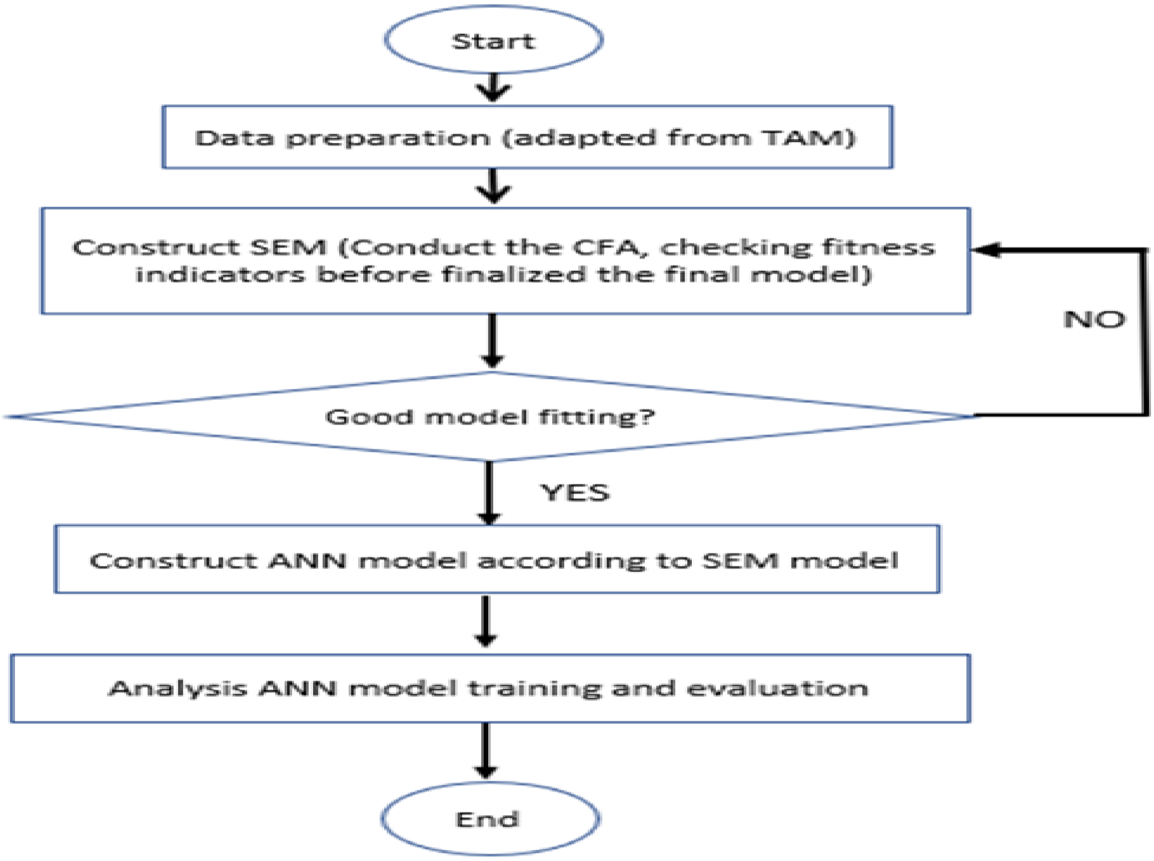


Figure 3 outlines a hybrid modelling approach that integrates SEM and ANN to enhance predictive accuracy. The process begins with data preparation, adapted from TAM. SEM is first constructed by conducting Confirmatory Factor Analysis (CFA) and evaluating model fit using fitness indicators. If the model fit is unsatisfactory, modifications are made before finalising SEM. Once an acceptable SEM model is obtained, it serves as the foundation for constructing the ANN model. The ANN model is then trained and evaluated, leveraging validated SEM relationships to capture complex nonlinear patterns and improve prediction accuracy in behavioural intention studies.

3.4 Model Evaluation

In Structural Equation Modelling (SEM), the goodness-of-fit is often assessed using Root Mean Square Error of Approximation (RMSEA), with lower values indicating better model fit. In Artificial Neural Networks (ANNs), model evaluation relies on Root Mean Square Error (RMSE), which measures prediction error and coefficient of determination (R^2) which indicates the proportion of variance explained by the model. These parameters can be referred to in Section 4.4.

4. Results and Discussion

The sample consists of academics at all higher education institutions in Malaysia, who used the BL system in teaching. Females constitute the majority (67%) of respondents. The largest group of respondents falls in the 25–35 years age range, suggesting a relatively younger demographic in terms of career stages. In terms of teaching experience, a significant majority of the respondents (82%) have over 5 years of teaching experience which shows that the sample consists mainly of experienced educators. Table 3 summarises the demographic sample.

Table 3

The *demographic features (n = 200)*

Variable	**Indicator**	**Frequency (%)**
Gender	Male	66 (33)
	Female	134 (67)
Age	Less than 25	4 (2)
	25–35	117 (58.5)
	36–45	45 (22.5)
	46–55	20 (10)
	Above 55	14 (7)
Teaching experience	Less than 1 year	24 (12)
	2–5 years	12 (6.0)
	More than 5 years	164 (82)

4.1 Measurement Model Analysis

Table 4 presents Cronbach's alpha coefficients for six constructs with 200 participants (n=200). Cronbach's alpha (α) evaluates the reliability or internal consistency of questionnaire items. The overall reliability of the 39 items is 0.962, indicating excellent internal consistency. Performance expectancy (α=0.912) and perceived playfulness (α = 0.914) show high reliability, while effort expectancy (α=0.843) and facilitating conditions (α=0.868) demonstrate good reliability. Social influence (α=0.771) has the lowest reliability but remains acceptable. Meanwhile, behavioural intention (α=0.897) has high reliability.

Table 4

Cronbach's alpha coefficient

Item	**Number of Items**	**Cronbach alpha, α n = 200**
Overall	**39**	**0.962**
Performance expectancy (PE)	8	0.912
Effort expectancy (EE)	7	0.843
Perceived playfulness (PP)	7	0.914
Facilitating conditions (FC)	7	0.868
Social influence (SI)	5	0.771
Behavioural intention (BI)	5	0.897

SEM-AMOS was employed to develop the initial BL system measurement model using the final indicators from exploratory factor analysis (EFA). This analysis aims to validate the latent constructs and ensure that the data for each category is adequate. Once the EFA criteria are met, this process transitions into confirmatory factor analysis (CFA).

Table 5 shows the final CFA results, which indicate that social influence should be excluded from the study. According to Zainudin (2015), factors with a loading value below 0.60 should be removed. Furthermore, social influence could not be retained as a latent variable due to an insufficient number of items. To be valid, a latent variable must have at least two items. Moreover, as the indicators for performance expectancy (PE6) and perceived playfulness (PP6 and PP7) did not meet this criterion and thus were also eliminated.

Table 5

Factor loading coefficient for each indicator

Construct	Indicator	Factor Loading	Cronbach Alpha, α
Performance expectancy (PE)	PE1	0.797	0.908
	PE2	0.747	
	PE3	0.844	
	PE4	0.844	
	PE5	0.813	
	PE7	0.636	
Effort expectancy (EE)	EE1	0.853	0.869
	EE2	0.806	
	EE3	0.693	
	EE4	0.693	
	EE5	0.662	
Perceived playfulness (PP)	PP1	0.900	0.925
	PP2	0.873	
	PP3	0.875	
	PP4	0.892	
	PP5	0.719	
Facilitating conditions (FC)	FC1	0.850	0.867
	FC2	0.946	
	FC3	0.610	
	FC4	0.701	
Behavioural intention (BI)	BI1	0.849	0.921
	BI2	0.874	
	BI3	0.950	

Table 6 presents construct reliability (CR), average variance extracted (AVE) and correlation values to assess discriminant validity for the study variables of performance expectancy (PE), effort expectancy (EE), perceived playfulness (PP), facilitating conditions (FC) and behavioural intention (BI). Social influence was not included as it had already been excluded from the BL system measurement model due to low factor loadings and an insufficient number of retained items, as shown in Table 5. All constructs have CR values above 0.60, indicating excellent internal consistency. Similarly, the AVE for each construct exceeds 0.50 confirming convergent validity by ensuring that the items within each construct are well-related. For discriminant validity, the diagonal values (bolded) represent the square root of AVE and should be higher than the correlation values in the same row or column (Hair et al., 2017). As this condition is satisfied for all constructs, it verifies discriminant validity. Overall, the measurement model demonstrates strong reliability, convergent validity and discriminant validity and thus ensuring that the constructs are robust and suitable for further analysis.

Table 6

The assessment of measurement model

Construct	CR >0.60	AVE >0.50	Correlation (Discriminant validity)				
			PE	EE	PP	FC	BI
PE	0.904	0.614	**0.784**				
EE	0.861	0.555	0.692	**0.745**			
PP	0.931	0.730	0.774	0.771	**0.854**		

FC	0.864	0.620	0.344	0.423	0.398	**0.787**	
BI	0.921	0.796	0.638	0.630	0.759	0.327	**0.892**

Note: CA = Cronbach alpha; CR = Composite reliability; AVE = Average variance extracted

Table 7 presents the fitness indexes used to evaluate how well the measurement model fits the data. The key fit indices include Chi-square (X^2), Chi-square/df ratio (X^2/df), root mean square error of approximation (RMSEA), comparative fit index (CFI) and Tucker-Lewis index (TLI). The Chi-square/df ratio of 3.963 is below the acceptable threshold of 5, indicating a reasonable model fit. The RMSEA value of 0.093 is below 1.0, suggesting an acceptable error of approximation. The CFI and TLI values both equal to 0.862, exceeding the recommended minimum threshold of 0.85. The measurement model meets the necessary fitness criteria, demonstrating an acceptable model fit for further analysis.

Table 7

The fitness indexes for the measurement model

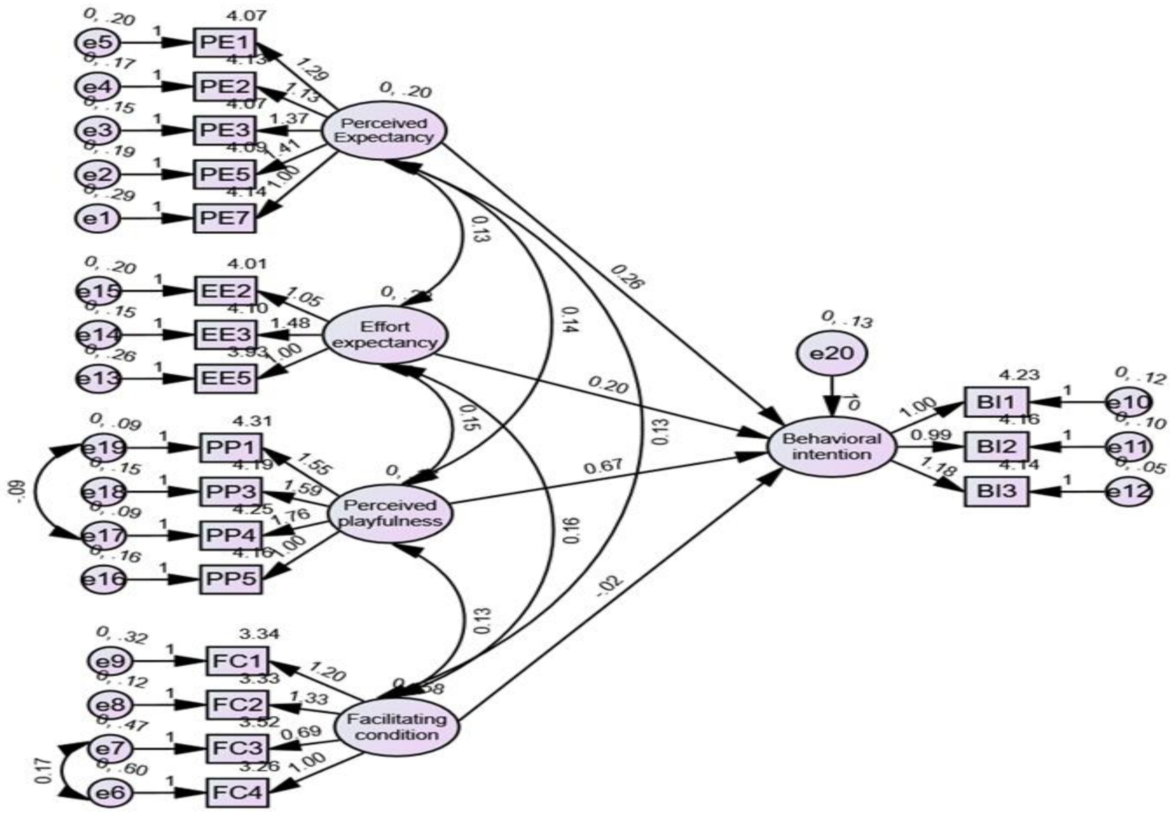
Fit Index	X^2	df	X^2/df	RMSEA	CFI	TLI
Index value	554.775	140	3.963	0.093	0.862	0.862

4.2 Structural Model Analysis

Figure 4 shows the SEM path diagram, which explains how different latent independent variables influence behavioural intention (BI). Perceived expectancy (PE) shows a moderate effect (0.26) on BI, meaning users are more likely to adopt the system if they see it as beneficial. Effort expectancy (EE) has a weaker impact (0.20), showing that an easier system slightly increases adoption. Perceived playfulness (PP) has the strongest effect (0.67), indicating that users are significantly more inclined to adopt the system if it is perceived as engaging. Facilitating conditions (FC) exhibit a minimal effect (–0.02) on BI, indicating that although support may be advantageous it does not significantly influence BL system adoption.

Figure 4

The regression path coefficient among construct in the structural model



4.3 ANN Results

This section highlights the development and training of an Artificial Neural Network (ANN) model to predict behavioural intention (BI). The model incorporates key factors identified through Structural Equation Modelling (SEM), such as effort expectancy (EE), performance expectancy (PE), perceived playfulness (PP) and facilitating conditions (FC).

Figure 5

Artificial neural network diagrams among constructs

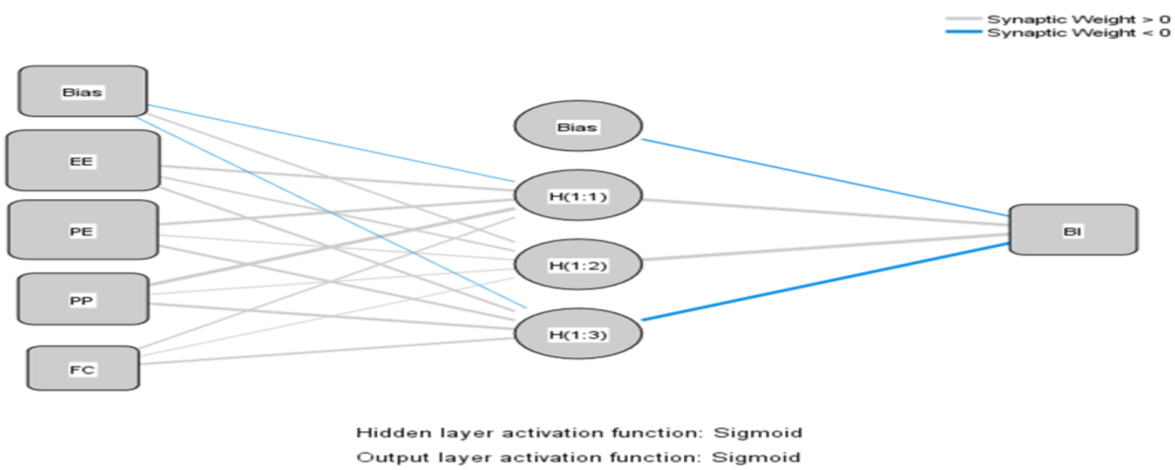


Figure 5 represents an Artificial Neural Network model with a single hidden layer used to predict behavioural intention (BI). The input layer consists of four independent variables of Effort Expectancy (EE), Perceived Expectancy (PE), Perceived Playfulness (PP) and Facilitating Conditions (FC) along with a bias node. These inputs are connected to three hidden layer neurons (H1:1, H1:2, H1:3) which process the information before passing it to the output layer (BI).

The ANN model visualises the relationships between the independent variables (EE, PE, PP and FC) in relation to BI. In most neural network diagrams, line thickness reflects the strength of the connection with thicker lines representing stronger weights and thinner lines representing weaker weights. Effort Expectancy (EE), Performance Expectancy (PE) and Perceived Playfulness (PP) shown as grey lines generally have positive influences with the line thickness indicating their relative strength. Facilitating Conditions (FC) also in grey are represented by thinner lines suggesting a weaker influence on the BL system.

Negative synaptic weights (blue lines) indicate inverse relationships. Some hidden neurons may negatively impact BI, possibly due to indirect effects or interdependencies between variables. As a conclusion, the ANN model confirms that Perceived Playfulness (PP), Performance Expectancy (PE) and Effort Expectancy (EE) are key drivers of Behavioural Intention (BI). Meanwhile, Facilitating Conditions (FC) exert only a minor direct influence on user decisions to adopt the BL system.

Figure 6

Construct importance in predicting BL

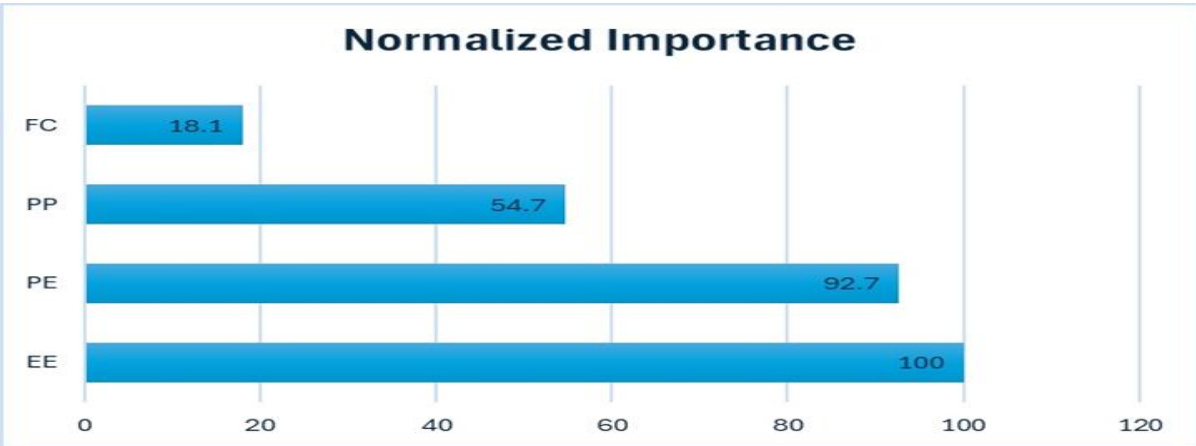


Figure 6 illustrates the normalised importance of four constructs of effort expectancy (EE), performance expectancy (PE), perceived playfulness (PP) and facilitating conditions (FC) in a predictive model. Effort expectancy has the highest importance, indicating it is the most influential factor in determining the outcome, followed closely by performance expectancy. Perceived playfulness holds moderate importance contributing significantly. In contrast, FC has the lowest importance, suggesting it has minimal impact on the model compared to the other variables. Overall, the results highlight the dominance of effort expectancy and performance expectancy in driving BL adoption.

4.4 Comparative Analysis

Table 8 presents a comparison of performance metrics between the SEM and the hybrid SEM–ANN models that highlighted a marked improvement with the integration of ANN. Specifically, the root mean square error (RMSE) reduce significantly from 2.074 in SEM to 0.093 in SEM–ANN, while the coefficient of determination (R^2) increase from 60.5% to 97.7% which reflecting a substantial increase in predictive accuracy with the integration of SEM and ANN.

Table 8

Model Evaluation

	RMSE	R^2
SEM	2.074	60.5%
SEM–ANN	0.093	97.7%

The integration of ANN with SEM leads to a significant enhancement in performance metrics, demonstrated by a notable reduction in Root Mean Square Error (RMSE) and an increase in the coefficient of determination (R^2). Artificial Neural Networks (ANN) are capable of capturing complex, nonlinear relationships that traditional SEM is unable to adequately capture. By integrating ANN with SEM, the hybrid model combines the structural interpretability of SEM with the enhanced predictive capacity of ANN. Consequently, the SEM–ANN approach achieves markedly higher predictive accuracy, indicating its superiority over SEM alone in modelling complex data patterns.

5. Conclusion

This study examines blended learning adoption by integrating Structural Equation Modelling (SEM) and Artificial Neural Networks (ANN), leading to improved predictive accuracy. The integration reduces RMSE from 2.074 to 0.093 and increases R^2 from 60.5% to 97.7% which highlighting the ability of the model to capture both linear and nonlinear relationships. This hybrid SEM–ANN approach addresses the limitations of traditional linear methods offering a more accurate and comprehensive understanding of blended learning adoption. The findings of this study underscore the significant influence of effort expectancy (EE) and performance expectancy (PE) on the adoption of blended learning systems, as these factors exhibited the strongest impact. This study indicates that students place high importance on the ease of use of the system and its perceived benefits for academic performance. Moreover, perceived playfulness (PP) suggests that interactive and engaging features can enhance user acceptance. In contrast, facilitating conditions (FC) had the least influence and while infrastructure and resources are necessary, student expectations and experiences play a more decisive role in BL adoption.

From a practical perspective, the findings suggest that educational institutions should prioritise designing user-friendly systems that clearly demonstrate academic benefits to promote adoption. Adding interactive and enjoyable features can further enhance engagement, while infrastructure improvements should be considered only when essential. These insights can help policymakers, educators and system developers create more effective strategies for blended learning, leading to higher adoption rates and better learning experiences for students.

However, this study has certain limitations. The focus on a single demographic group may limit the generalisability of the findings to larger populations. Additionally, the absence of longitudinal data limits the ability of this study to assess long-term behavioural changes in blended learning adoption. Future research should apply the SEM–ANN model across diverse educational contexts and consider additional factors such as cultural influences, social norms and sustained user engagement over time. Addressing these aspects will enhance the understanding of blended learning adoption and contribute to its more effective implementation in various settings.

6. Co-Author Contributions

The authors confirm that there are no conflicts of interest in this article. Author 1 and Author 2 conducted the fieldwork, prepared the literature review and methodology, and supervised the overall writing of the article. Author 3 and Author 4 were responsible for instrument and data validation, reviewed the interpretation of the results and contributed to refining the article. Author 5 thoroughly proofreads the article and provided suggestions for improvement.

7. Declaration of AI-Generated Content

The authors declare that generative artificial intelligence (AI), specifically ChatGPT developed by OpenAI, was used in improving sentence structure, grammar, and overall clarity of the text. All intellectual content, research design, data analysis, and conclusions presented in this study are the sole responsibility of the authors. The authors have carefully reviewed and edited all AI-assisted outputs to ensure accuracy, originality, and compliance with academic standards.

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