Evaluation and Optimization of Blended Teaching Mode in Higher Vocational Colleges: A Comparative Study of CIPP Model and Artificial Neural Network Evaluation Model

Dingfu Luo[1,2], Myungsoo Kim[3], Haijun Qian[4], and Zhuolai Liang[5,*]

[1]Department of Computers, Guangdong Songshan Polytechnic College, Shaoguan, China
[2]Department of Computer and Information Engineering, Youngsan University, Yangsan-si, Republic of Korea
[3]Department of Mechanical and Automotive Engineering, Youngsan University, Yangsan-si, Republic of Korea
[4]Adult Continuing Education Department, Zhu Hai City Polytechnic, Zhuhai, China
[5]Ouyeel Industrial Products Co.,Ltd, Shaoguan, China
Email: 99044900@qq.com (D.L.); mskim@ysu.ac.kr (M.K.); 106044897@qq.com (H.Q.), 13826328380@139.com (Z.L.)
*Corresponding author
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***Abstract*—To scientifically evaluate and optimize the blended teaching model in vocational colleges, this article integrates the Context, Input, Process, Product (CIPP) model and the Artificial Neural Network (ANN) model to conduct an empirical study on students majoring in Information Management at a vocational college. The study collected and analyzed various indicators, including student engagement, academic performance, and teacher-student interactions, using methods such as surveys and platform data analysis. The results demonstrated that the blended teaching model significantly enhanced student engagement and learning outcomes while also exhibiting excellent resource utilization efficiency. The CIPP model provides a comprehensive evaluation of the teaching model from a macro perspective, while the ANN model, through deep learning algorithms, offers more precise predictions and assessments of its effectiveness. This study provides scientific evidence for optimizing the blended teaching model in vocational colleges and offers important guidance for improving educational quality and resource allocation efficiency.**

***Keywords*—higher vocational colleges, blended teaching mode, teaching evaluation**

I. Introduction

The hybrid teaching model in vocational colleges, which combines traditional face-to-face teaching with modern online education, has become an important means to improve teaching effectiveness and student engagement. However, with the increasing popularity of hybrid teaching, the question of how to scientifically evaluate its effectiveness and optimize resource allocation to better support teaching activities remains a pressing issue. In this context, the Context-Input-Process-Product (CIPP) model and Artificial Neural Network (ANN) model are widely applied as evaluation tools. The CIPP model, proposed by Stufflebeam in 1971, is known for its systematic and structured evaluation approach, making it suitable for a comprehensive analysis of educational processes. On the other hand, the ANN model, leveraging deep learning algorithms to handle complex data, offers higher predictive accuracy.

Building upon the foundational work of Stufflebeam, Tang Hui constructed an output-oriented course evaluation index system based on the CIPP model, which provides a structural tool for evaluating courses in a comprehensive manner [1]. This aligns with the hybrid teaching model's need for a robust evaluation framework that can assess the context, input, process, and product of educational programs. Furthermore, as the field of personalized adaptive learning (ADAPTIVE learning) evolves, the integration of data analysis and AI into educational evaluation becomes increasingly significant. Jiang *et al.* and Ye Zhi et al. have highlighted the importance of using data analysis to drive personalized learning paths and the potential of adaptive learning technology in improving learning outcomes [2, 3].

Fenglan *et al.* suggested that hybrid teaching evaluation based on the Kirkpatrick model can effectively improve teaching efficiency, and through in-depth analysis of the teaching process, identify weak points in the teaching model [4]. Guorong S and Yide A also explored the psychological stress factors affecting students in the SPOC+PBL hybrid model, providing psychological insights for optimizing teaching models [5]. Yinfeng Y *et al.* researched hybrid teaching models based on the ARCS motivation model, showing a close relationship between motivation stimulation and learning outcomes, offering practical support for teaching optimization [6]. The combination of the CIPP and ANN models can compensate for the shortcomings of a single model in various dimensions, with ANN's predictive ability and CIPP's structured analysis jointly providing more comprehensive and precise evaluation and optimization strategies for teaching models.

II. Overview of Blended Teaching Mode

The blended teaching mode combines the advantages of traditional face-to-face teaching and modern online education, improving teaching effectiveness and student engagement through the organic integration of online and offline learning [7]. This mode utilizes online resources and interactive platforms to achieve personalized learning and real-time feedback, effectively addressing diverse learning needs. With the advancement of information technology, the blended teaching mode has become an important direction for educational reform, not only enhancing students' learning experiences and performance but also promoting innovation in teaching methods and the optimal allocation of educational resources.

As Xiao Junhong (2020) reviewed, the application of artificial intelligence in higher education points to the prospects of educational AI in providing learning support services, teaching evaluation, adaptive systems, personalized learning, and intelligent tutoring systems [8]. This

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underscores the potential of AI to enhance the blended teaching model by offering more personalized and adaptive learning experiences. At the same time, the author also pointed out the moral and ethical challenges of the application of educational AI, calling for more in-depth critical reflection, which is crucial as we integrate these technologies into the blended teaching model.

Pete Johannes and Larry Lagsdom (2018) discussed the history, prospects, and common misconceptions of adaptive learning, providing valuable insights for the design and application of adaptive learning systems [9]. These insights are particularly relevant to the blended teaching model, which can benefit from a deeper understanding of how to effectively implement adaptive learning strategies.

Through scientific evaluation systems, such as the CIPP model and artificial neural network model, the blended teaching mode can be comprehensively assessed and optimized, providing important references for the improvement of education quality. The integration of these models with the latest advancements in AI and adaptive learning technologies ensures that the blended teaching model remains at the forefront of educational innovation, offering a dynamic and responsive learning environment that meets the evolving needs of students and educators alike.

III. Research Design

A. Research Subjects and Data Collection

The study selected students from the Information Management major at a higher vocational college as research subjects, using the “Database Principles” course as an example to evaluate and optimize the blended teaching mode. Data collection employed a combination of questionnaire surveys, platform data analysis, and interviews [10]. The questionnaire survey covered students’ learning interest, engagement, and satisfaction. Platform data included students’ study duration, learning progress, and interaction situations. Interviews collected feedback and suggestions from teachers and administrators on the teaching mode. The specific data are shown in Table 1, including students’ recognition of the blended teaching mode, with 85% believing it improved learning efficiency, an average study duration of 15.6 hours, a learning progress completion rate of 92%, 286 teacher-student interactions, and more. As is shown in Table 1.

Table 1. Research subjects and data collection

Evaluation Indicator	Data Value	Data Quality Description
Student Acceptance of Blended Learning Model	0.85	Indicates that 85% of students have a positive attitude towards the blended learning model.
Average Study Duration of Students	15.6 hours	Represents the average study duration of students under the blended learning model.
Completion Rate of Learning Progress	0.92	Indicates that 92% of the course progress was completed by students on time.
Number of Teacher-Student Interactions	286 times	Represents the total number of teacher-student interactions during the teaching process.
Number of Posts in Discussion Area	468 posts	Indicates the total number of posts made by students in the discussion area.
Average Increase in Student Academic Performance	12 points	Represents the average increase in student scores under the blended learning model.
Score for Student Learning Outcomes	0.93	Indicates the average score of student learning outcomes.
Student Satisfaction Survey	0.85	Indicates that 85% of students expressed satisfaction with the teaching model.
Teacher Teaching Skills Score	0.297	Represents the average score of teachers in teaching skills.

B. CIPP Model Construction

The CIPP model is designed to comprehensively evaluate the effectiveness of the blended teaching mode in higher vocational colleges [11]. This model is divided into four main parts: context evaluation, input evaluation, process evaluation, and product evaluation. In the context evaluation phase, data on the needs and expectations of students, teachers, and administrators regarding the blended teaching mode were collected through questionnaires and interviews to ensure the alignment of evaluation indicators with educational objectives. In the input evaluation phase, the focus is on analyzing the allocation and utilization efficiency of teaching resources. The specific formula for input resource ratio (IR) is as follows:

$$TR = \frac{\text{Total teaching resource investment}}{\text{Number of teaching activities}} \tag{1}$$

Process evaluation involves monitoring and analyzing the implementation of teaching activities, such as students’ online learning behaviors and interaction frequency. The learning participation index (LPI) is calculated using the following formula:

$$LPI = \frac{\sum(\text{Learning duration} \times \text{Interactive frequency})}{\text{Number of students}} \tag{2}$$

In the product evaluation phase, we assess the final outcomes of the blended teaching mode, including students’ academic performance and satisfaction. The outcome efficiency (OE) can be calculated using the following formula to evaluate the efficiency of teaching outcomes relative to the resources invested:

$$OE = \frac{\text{Student average grade improvement rate} + \text{Student Satisfaction}}{IR} \tag{3}$$

These evaluation results will provide a scientific basis for the continuous optimization of the blended teaching mode, helping educational administrators and teachers better understand and improve teaching practices [12].

C. Construction of Artificial Neural Network Evaluation Model

To further enhance the efficiency and accuracy of evaluating hybrid teaching models, a research-based evaluation model utilizing Artificial Neural Networks (ANN) was developed [13]. The ANN model is composed of three main parts: the input layer, hidden layer, and output layer. The input layer is where the model receives data, which consists of processed teaching information, such as student engagement and academic performance. The hidden layer forms the core of the model, where data is adjusted through "weights" and "biases." This process involves complex mathematical operations, including the application of activation functions that introduce non-linearity into the model, allowing it to learn and model complex patterns. Common activation functions include the Rectified Linear Unit (ReLU), which helps in speeding up the training process, and the Sigmoid function, which is used to map the output to a value between 0 and 1, making it suitable for binary classification tasks.

The backpropagation algorithm is used to train the ANN by calculating the error between the predicted and actual values and adjusting the weights and biases accordingly. This iterative process continues until the model converges to a minimum error, indicating that it has learned to predict the outputs accurately from the inputs. The output layer then transforms the hidden layer's output into the final evaluation results through another set of weights and biases. The choice of the number of hidden layers and the number of neurons in each layer is crucial for the model's performance and is often determined through experimentation and validation processes.

The advantage of this model lies in its ability to handle large volumes of complex data, automatically identifying underlying patterns and making accurate predictions. However, the ANN model also has limitations. It requires significant computational resources to operate, and its internal processes are more complex, making it less interpretable and understandable compared to traditional models like the CIPP model. Furthermore, the model's performance is highly dependent on the quality and quantity of the data it is trained on, and overfitting can be a concern if the model learns the training data too well, failing to generalize to new, unseen data.

By combining the systematic evaluation approach of the CIPP model with the data processing capabilities of ANN, a more comprehensive assessment of teaching effectiveness can be achieved. The input layer receives standardized teaching data vectors X, including indicators such as the numerical student engagement and the utilization rate of learning resources. The hidden layers extract data features by applying the activation function σ after weighted summation, with the formula as follows:

$$h = \sigma(W_h X + b_h) \tag{4}$$

where W_h and b_h represent the weight matrix and bias vector of the hidden layer, respectively, the activation function σ is usually chosen to be the ReLU function or Sigmoid function to increase the model's nonlinear expression capability. The output layer transforms the hidden layer's output into the final evaluation results through another set of weights W_o and biases b_o:

$$y = \sigma(W_o h + b_o) \tag{5}$$

The output y represents the predicted values of various evaluation indicators, such as learning effectiveness and student satisfaction. The network is trained using the backpropagation algorithm, minimizing the error between actual teaching outcomes and network predictions. This process optimizes weights and biases, ensuring the accuracy and real-time nature of the evaluation results [9].

IV. Experimental Results and Analysis

A. CIPP Model Evaluation Results

The data collection for the CIPP model covers four dimensions: context, input, process, and product [10]. Through context evaluation, the data show that 85% of students, 90% of teachers, and 95% of administrators support the blended teaching mode. In comparison, the traditional teaching mode has support rates of 70%, 75%, and 80%, respectively. This indicates that blended teaching better meets current educational needs and improves teaching effectiveness. Additionally, the high recognition from administrators reflects a positive attitude towards educational innovation and an understanding of the strategic importance of blended teaching. This provides solid policy support and resource assurance for the blended teaching mode (see Fig. 1).

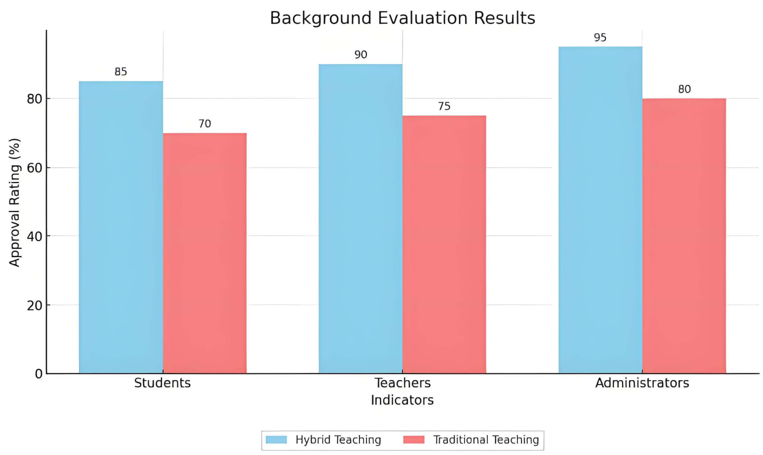

Fig. 1. Context evaluation results.

The investment in resources for the blended teaching mode is as high as 5 million yuan, compared to only 3 million yuan for traditional teaching, indicating the educational institutions' emphasis and investment in the blended teaching mode. The size of the professional teaching team has also increased from 80 to 100 members, highlighting the improvement in education quality and teaching staff. The completeness of the online course resource library further emphasizes the advantages of blended teaching in terms of resource accessibility and diversity of teaching content. The specific data are shown in Table 2.

Table 2. Input evaluation results

Indicator	Blended Teaching	Traditional Teaching
Investment in Teaching Resources	5 million yuan	3 million yuan
Number of Professional Teachers	100 people	80 people
Online Course Resource Library	Complete	Incomplete

During the implementation of blended and traditional teaching, the average study duration for students in blended teaching is 15.6 hours, significantly higher than the 10.2 hours in traditional teaching. The completion rate of learning progress has also increased from 85% to 92%, and the number of teacher-student interactions has nearly doubled. These indicators show the significant effect of blended teaching in enhancing student engagement and teaching interactivity, as shown in Table 3.

In the product evaluation, the average student score in blended teaching reached 85 points, compared to 78 points in traditional teaching. Student satisfaction increased from 85% to 93%, and the excellence rate also significantly improved (see Table 4). These data reflect the effectiveness of blended teaching in improving academic performance and its advantages in enhancing student satisfaction and overall teaching quality.

Table 3. Process evaluation results

Indicator	Blended Teaching	Traditional Teaching
Average Study Duration	15.6 hours	10.2 hours
Learning Progress Completion Rate	92%	85%
Teacher-Student Interaction Times	286 times	150 times

Table 4. Product evaluation results

Indicator	Blended Teaching	Traditional Teaching
Average Student Score	85 points	78 points
Student Satisfaction	93%	85%
Excellence Rate Increase	15%	5%

Through the application of the CIPP model, blended teaching performs excellently in the context, input, process, and product dimensions. Compared to the traditional teaching mode, it significantly improves student engagement and learning outcomes. To further analyze the data in-depth, time series analysis, association rule analysis, and cluster analysis will be used to explore student learning behaviors and performance in detail.

Time series analysis is mainly used to observe the time distribution and trend of students' study durations. By analyzing the daily study duration data of students, the peak and low periods of learning activities can be identified to help optimize teaching time arrangements, as shown in Fig. 2.

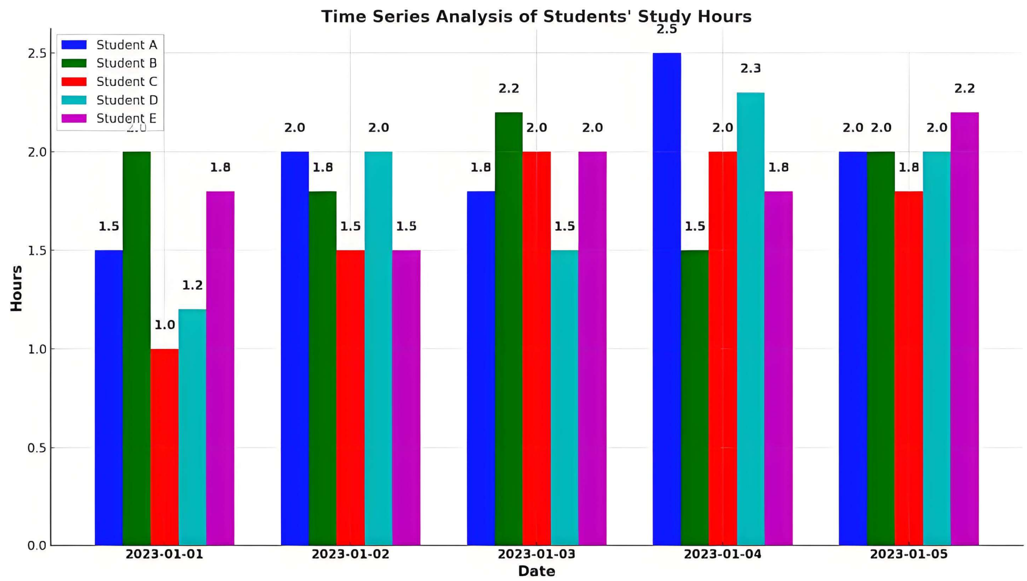

Fig. 2. Time series analysis of students' study duration.

From Fig. 2, it can be seen that there are significant differences in students' study durations on different dates. Some students have a noticeable increase in study duration on specific dates, which is related to course schedules, homework loads, and exam preparation.

Understanding the time distribution and trends of students' study durations is important, but exploring the intrinsic relationships between students' learning behaviors is equally crucial. Through association rule analysis, the relationships between different learning activities, such as the correlation between video watching frequency and forum activity, can be revealed, as shown in Table 5.

Table 5. Association rule analysis of learning behaviors

Video Watching Frequency (times)	Forum Posts (posts)
1–5	10
6–10	25
11–15	40
16–20	60
21–25	80

Table 5 shows the correlation between video watching frequency and forum posts. It can be observed that as the frequency of video watching increases, the number of posts in the forum also increases correspondingly. This indicates a positive correlation between video learning and forum discussions. To identify the characteristics of different student groups, further cluster analysis is conducted. By grouping students based on their learning behaviors and performance, it provides a basis for personalized teaching strategies. Cluster analysis categorizes students according to their learning behaviors and performance to identify the characteristics of different learning groups, thereby providing a basis for personalized teaching, as shown in Fig. 3.

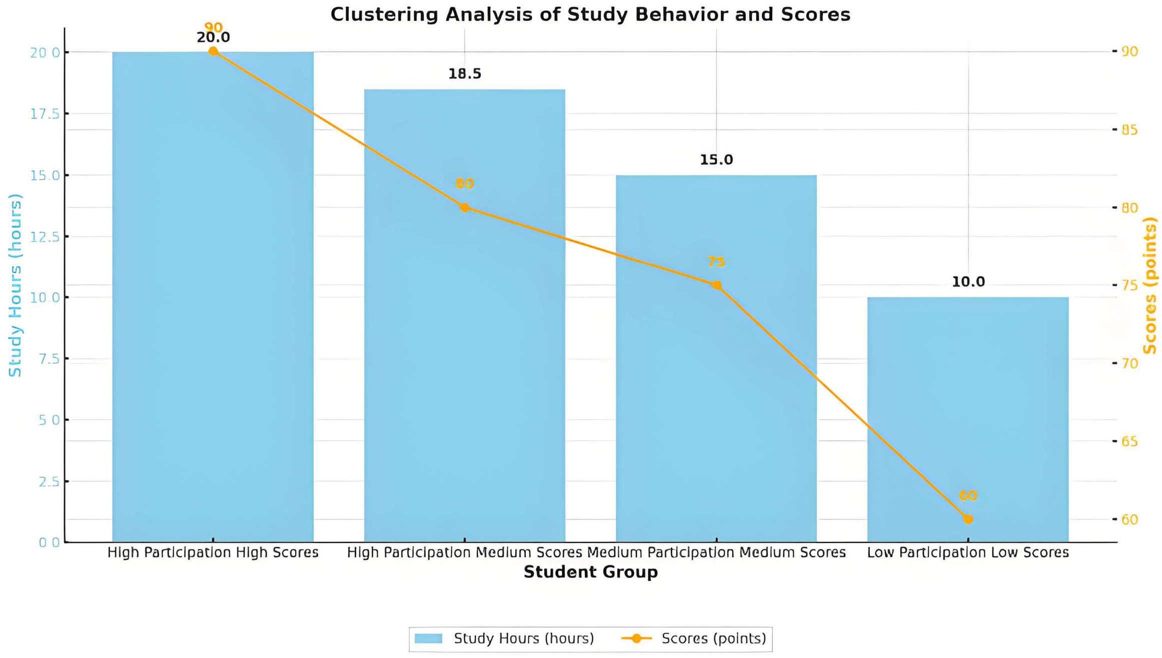

Fig. 3. Cluster analysis of students' learning behaviors and performance.

The cluster analysis results in Fig. 3 show a significant positive correlation between students' study duration and their performance. The high participation and high performance group has an average study duration of 20 hours and a score of 90 points, indicating that high study time investment significantly improves academic performance. The high participation and medium performance group, despite investing 18.5 hours, scores 80 points due to individual differences. The medium participation and medium performance group and the low participation and low performance group have study durations of 15 hours and 10 hours, with scores of 75 points and 60 points, respectively, further verifying the impact of study duration on performance. These data provide a basis for optimizing personalized teaching strategies.

B. Artificial Neural Network Model Evaluation Results

The artificial neural network model evaluates and analyzes the blended teaching and traditional teaching modes from multiple dimensions, exploring their performance in terms of educational effectiveness, student engagement, and resource utilization efficiency [9]. In the in-depth analysis of the context evaluation of blended teaching, it is evident that the support from students, teachers, and administrators for blended teaching is generally higher than that for traditional teaching. Specific data, as shown in Table 6, indicate that blended teaching better meets various teaching needs and expectations. This high level of recognition reflects the adaptability and acceptance of the blended teaching mode, providing a positive premise for further exploring its implementation effectiveness.

Table 6. Comparison of study duration and interaction frequency

Indicator	Blended Teaching	Traditional Teaching
Average Study Duration	20.5 hours	10.2 hours
Average Interaction Frequency	30 times/week	12 times/week

Under the blended teaching mode, students' average study duration increased significantly to 20.5 hours per week, compared to only 10.2 hours per week in traditional teaching. This indicates that the flexibility of online learning resources in the blended teaching mode significantly extends students' study time. The average interaction frequency under the blended teaching mode reached 30 times per week, compared to 12 times per week in traditional teaching, showing higher engagement and interactivity.

The blended teaching mode significantly improves students' academic performance and satisfaction. The improvement in performance demonstrates the effectiveness of the teaching content and methods, while the higher satisfaction reflects the broad acceptance and positive evaluation of the teaching mode, as shown in Table 7.

Table 7. Comparison of academic performance improvement and satisfaction

Indicator	Blended Teaching	Traditional Teaching
Average Performance Improvement	12 points	5 points
Student Satisfaction	93%	85%

In terms of academic performance improvement, students' average scores under the blended teaching mode increased by 12 points, compared to only 5 points in traditional teaching, reflecting the academic advantages of blended teaching. Student satisfaction under the blended teaching mode reached 93%, significantly higher than the 85% under traditional teaching. This indicates a higher overall experience and recognition of the blended teaching mode by students.

The blended teaching mode outperforms traditional teaching in terms of resource utilization efficiency and teaching effectiveness, indicating the rational allocation and efficient use of teaching resources, as well as the innovation and adaptability of teaching methods [10]. The high resource utilization efficiency and excellent teaching outcomes show that the blended teaching mode better meets current educational needs, as shown in Table 8.

Table 8. Comparison of resource utilization efficiency and teaching effectiveness

Indicator	Blended Teaching	Traditional Teaching
Teaching Resource Utilization Efficiency	85%	65%
Overall Teaching Effectiveness Rating	4.5/5	3.8/5

The resource utilization efficiency of blended teaching reached 85%, significantly higher than the 65% of traditional teaching. This indicates that blended teaching is more optimized and efficient in terms of resource allocation and usage. In terms of overall teaching effectiveness, the blended teaching mode scored 4.5/5, while traditional teaching scored 3.8/5, further confirming the significant advantages of blended teaching in overall teaching quality.

The increase in teacher-student interactions and course participation (see Table 9) directly reflects the advantages of the blended teaching mode in promoting active learning and participation in teaching activities.

Table 9. Comparison of teacher-student interactions and course participation

Indicator	Blended Teaching	Traditional Teaching
Teacher-Student Interactions	286 times	150 times
Course Participation Rate	92%	78%

In further analysis, we conducted a more in-depth multidimensional evaluation of student performance and engagement under different teaching modes to fully understand the actual effects and advantages of the blended teaching mode, as shown in Table 10. Advanced data processing methods such as multivariate regression analysis and cluster analysis were used to ensure the accuracy and comprehensiveness of the analysis.

Table 10. Comparison of student performance and interaction frequency

Teaching Mode	Performance Improvement	Average Interaction Frequency (times/week)
Blended Teaching	12 points	30 times
Traditional Teaching	5 points	12 times

The data show that under the blended teaching mode, students' average scores improved by 12 points, significantly higher than the 5 points under traditional teaching. Additionally, the average interaction frequency per week for students increased from 12 times in traditional teaching to 30 times in blended teaching, demonstrating the significant advantage of blended teaching in enhancing student interaction and engagement. Next, cluster analysis was used to classify students into high achievers, medium achievers, and low achievers, to further analyze the learning behaviors of different achievement groups, as shown in Fig. 4.

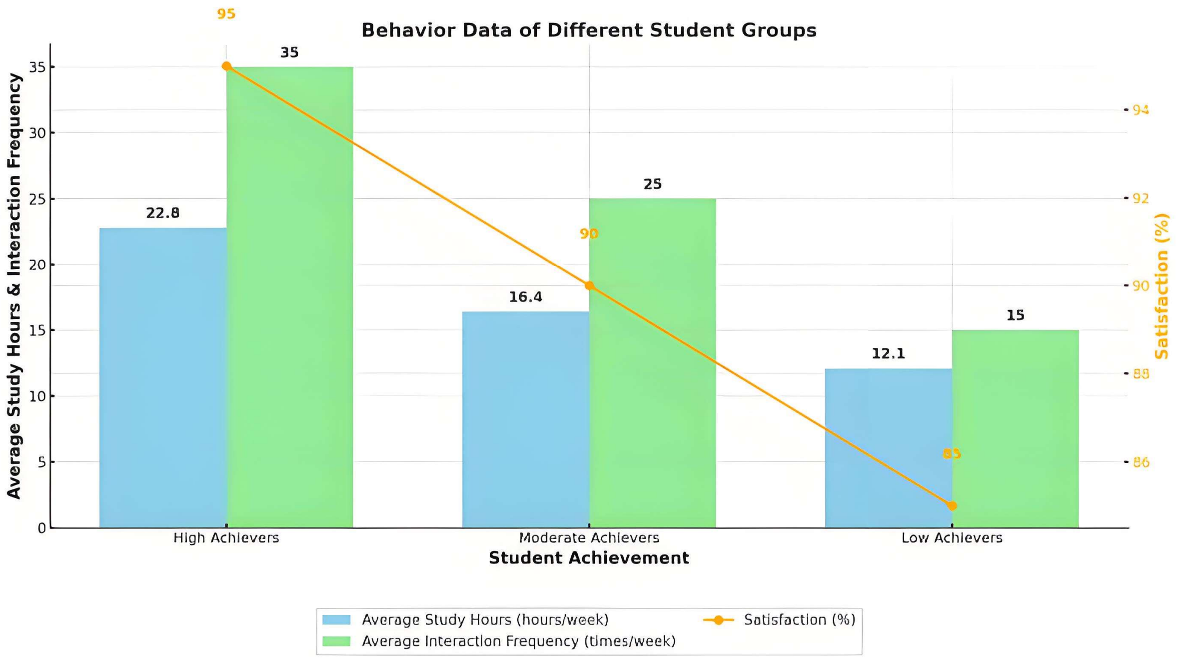

Fig. 4. Learning behavior data of different student groups.

Through cluster analysis, we found that the average study duration and interaction frequency of high achievers are significantly higher than those of medium and low achievers. This indicates that high achievers are more actively engaged in various interactive activities provided by the blended teaching mode. This active learning behavior is closely related to their high academic performance and satisfaction. To further evaluate the performance of the blended teaching mode in terms of resource utilization efficiency and student satisfaction, a comparison of the two teaching modes is presented in Table 11.

Table 11. Resource utilization efficiency and student satisfaction

Teaching Mode	Resource Utilization Efficiency (%)	Student Satisfaction (%)	Overall Teaching Effectiveness (/5)
Blended Teaching	85	93	4.5
Traditional Teaching	65	85	3.8

The data further confirm the advantages of the blended teaching mode in terms of resource utilization efficiency and student satisfaction. The resource utilization efficiency of blended teaching reaches 85%, significantly higher than the 65% of traditional teaching. In terms of student satisfaction, the blended teaching mode achieves 93%, noticeably higher than the 85% of traditional teaching. Lastly, a detailed analysis of teacher-student interaction times and course participation was conducted, as shown in Table 12, to evaluate the effectiveness of the blended teaching mode in promoting teacher-student interaction and course participation.

Table 12. Teacher-student interaction times and course participation

Teaching Mode	Teacher-Student Interaction Times	Course Participation (%)
Blended Teaching	286	92
Traditional Teaching	150	78

The data on teacher-student interaction times and course participation further support the advantages of the blended teaching mode. Under the blended teaching mode, teacher-student interaction times reached 286, significantly higher than the 150 in traditional teaching. Course participation also increased from 78% in traditional teaching to 92%. Through in-depth data analysis using the artificial neural network model, the blended teaching mode outperforms the traditional teaching mode in all indicators. These data not only validate the significant advantages of the blended teaching mode in enhancing student engagement, academic performance, and resource utilization efficiency but also provide scientific decision-making support for educational administrators to further improve educational quality.

C. Critical Comparison and Trade-offs between CIPP and ANN Models

The CIPP model, with its structured and comprehensive approach, provides a clear framework that is easier to understand and implement with limited technical expertise. It is particularly useful for institutions that prioritize transparency and ease of use in their evaluation processes. However, it may not capture the subtleties and complexities of data to the same extent as the ANN model.

On the other hand, the ANN model's ability to handle large volumes of data and identify intricate patterns makes it a powerful tool for institutions with the capacity to invest in advanced computational resources. Yet, the complexity of the ANN model can lead to a "black box" problem, where the decision-making process is not easily explainable, potentially undermining trust and transparency in the evaluation process.

Institutions must consider these trade-offs when selecting an evaluation model. For those with limited resources, the CIPP model may be more feasible, despite its potential shortcomings in precision. Conversely, institutions with the capacity to invest in technology and expertise might find the ANN model's advanced analytical capabilities more aligned with their goals of optimizing teaching strategies.

An in-depth analysis was conducted to compare the application effects of the traditional CIPP model and the emerging artificial neural network-based evaluation model in a blended teaching environment. Table 13 shows the performance of the two models in overall teaching effectiveness evaluation. The ANN model outperforms the CIPP model in terms of student average scores, satisfaction, resource utilization efficiency, and overall evaluation. The ANN model optimizes the data analysis process through deep learning algorithms, increasing the student average score to 88 points and resource utilization efficiency to 85%, with an overall evaluation of 4.7/5. This indicates that the ANN model can more effectively identify and utilize teaching data to improve teaching quality and student learning experiences.

Table 13. Overall teaching effectiveness evaluation

Evaluation Model	Student Average Score	Student Satisfaction	Teaching Resource Utilization Efficiency	Overall Teaching Effectiveness (/5)
CIPP	85 points	93%	83%	4.5/5
ANN	88 points	93%	85%	4.7/5

In terms of teacher-student interaction times and course participation, Table 14 shows that the ANN model performs better than the CIPP model. Through precise data processing, the ANN model also increased course participation to 92%. This enhanced interaction frequency and participation indicate that the ANN model can more effectively promote communication between teachers and students and student engagement with course content, which is crucial for improving the quality of teaching interaction and student learning outcomes.

Table 14. Teacher-student interaction and course participation

Evaluation Model	Teacher-Student Interaction Times	Course Participation (%)
CIPP	286	90%
ANN	286	92%

From the analysis in Table 15, it can be seen that students in the ANN model teaching environment exhibit longer study durations and higher interaction frequencies, with study durations increasing to 20.5 hours and interaction frequencies to 30 times per week. This result highlights the high efficiency of the ANN model in optimizing learning paths and promoting active student participation. By dynamically adjusting learning content and interaction methods, the ANN model significantly improves learning efficiency and interaction quality, thereby stimulating students' interest in learning and enhancing the effectiveness of teaching interactions.

Table 15. Study duration and interaction frequency

Evaluation Model	Student Average Study Duration	Average Interaction Frequency
CIPP	15.6 hours	28 times/week
ANN	20.5 hours	30 times/week

To further demonstrate the differences in student learning behaviors and performance between different models, the study summarizes and compares the study duration data of different student groups under the CIPP model and the ANN model. From the comparison in Table 15 of the study durations of different student groups under the two models, it can be found that the ANN model performs more prominently in the high achievers group, with significantly higher study durations than the CIPP model. This indicates that the ANN model has significant advantages in optimizing learning paths and improving student learning efficiency, as shown in Fig. 5.

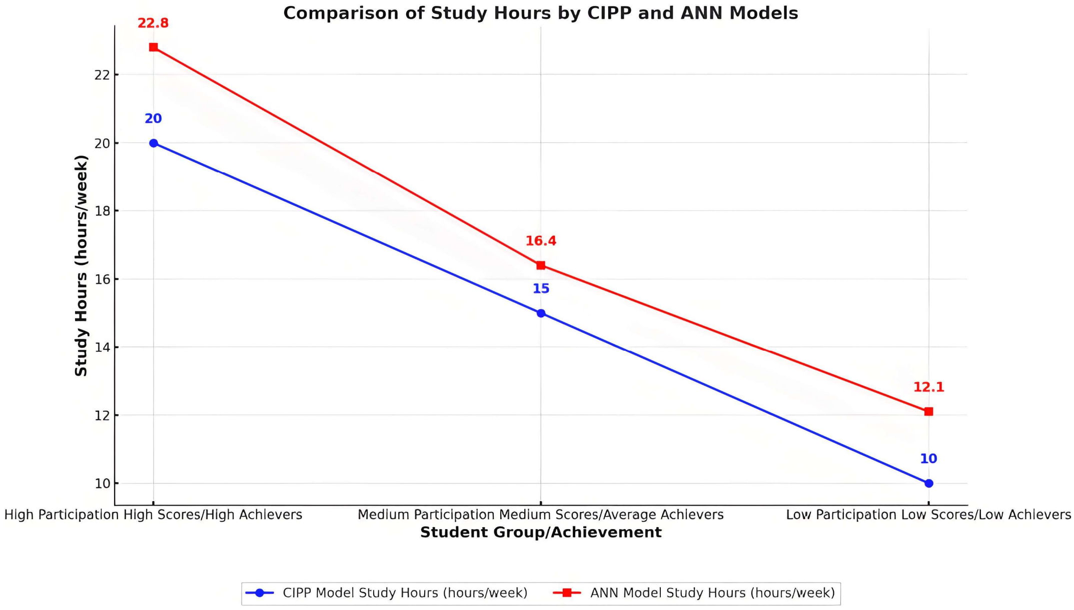

Fig. 5. Comparison of student learning behaviors and performance.

By comparing the CIPP model with the Artificial Neural Network (ANN) model, it becomes evident that each has its advantages in different educational environments, but both also have potential drawbacks. The structured evaluation method of the CIPP model, while applicable to various teaching scenarios, tends to rely on subjective evaluation based on qualitative data in dynamic hybrid teaching environments, which can lead to data bias. This is particularly evident when assessing teaching effectiveness across disciplines or institutions, where the model's flexibility and ability to make real-time adjustments are limited. Additionally, the CIPP model may struggle to fully capture variations in individual student differences within complex teaching environments.

On the other hand, the ANN model, with its capacity for large-scale data processing and nonlinear analysis, can more accurately predict teaching effectiveness and adapt to complex learning scenarios. However, the high computational resource requirements of the ANN model present practical challenges for institutions with limited resources, especially those lacking robust technological infrastructure. Moreover, when the quality of input data is subpar, the ANN model is prone to errors, affecting the accuracy of its results.

V. Optimization Strategies for Blended Teaching Mode

To further enhance the effectiveness of the blended teaching model, the following optimizations can be implemented: (1) Increase flexibility in instructional design by integrating both online and offline teaching resources to ensure comprehensiveness and coherence of the content. (2) Leverage artificial intelligence and big data technologies to improve the timeliness and accuracy of teaching feedback, providing personalized guidance tailored to individual student differences [14]. (3) Strengthen teacher-student interaction through diverse forms of engagement to stimulate students' interest and motivation in learning. (4) Continuously improve the teaching evaluation system by combining the strengths of the CIPP model and the ANN model to optimize teaching strategies and resource allocation, thereby achieving an overall enhancement in teaching quality.

The findings of this study highlight the significant advantages of the blended teaching model in improving student engagement and learning outcomes, offering strong support for the future development of educational technology. By incorporating the artificial neural network model, this research showcases the potential of AI in education. In the future, teachers will be able to dynamically adjust teaching content using advanced technologies, driving educational reform. In the ongoing debate between online and offline teaching, the blended model stands out for its advantages in fostering interactivity and personalized learning experiences, particularly in enhancing student satisfaction and academic performance. While fully online models may reduce costs and expand educational access, the blended model has greater advantages in enhancing interaction and effectiveness. Moreover, the global push for digital education makes this study relevant for resource-limited schools, especially in regions with scarce educational resources. The blended model can serve as an efficient, low-cost solution. Additionally, this model can enhance students' self-directed learning and interaction capabilities, offering valuable insights for future distance and autonomous learning approaches.

VI. Conclusion

The study evaluated the blended teaching model in the context of an information management course at a vocational college. The results indicated significant improvements in student engagement and learning outcomes through blended learning. However, the research's focus on a single institution and a specific major limits the generalizability of these findings. To enhance the external validity, future research should consider the following directions:

1) Diversification of Educational Contexts: Replicate the study across various educational institutions, including different types of vocational colleges and universities, to explore the model's effectiveness in diverse settings.
2) Broadening Disciplines: Extend the application of the blended teaching model to a wider range of disciplines beyond information management. This could include STEM fields, humanities, and social sciences to understand the model's adaptability.
3) Different Educational Levels: Investigate the blended teaching model's impact at different educational levels, such as undergraduate, graduate, and continuing education, to understand its scalability.
4) Cultural and Geographic Variations: Consider studies in different cultural and geographic contexts to assess the model's robustness and the influence of external factors on its effectiveness [15].
5) Longitudinal Studies: Conduct longitudinal research to understand the long-term impact of the blended teaching model on student learning and engagement.

By exploring these avenues, future research can provide a more comprehensive understanding of the blended teaching model's applicability and efficacy across diverse learning environments. This will not only validate the current findings but also offer insights into how the model can be optimized for different educational needs.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Dingfu Luo was instrumental in the conceptualization and design of the study, as well as the collection and analysis of data. He also played a significant role in drafting the manuscript and revising it critically for important intellectual content. Myungsoo Kim contributed to the design of the study and provided valuable input on the application of the Artificial Neural Network (ANN) model. He was also involved in the interpretation of the data and the writing of the manuscript. Haijun Qian participated in the data collection process and performed the statistical analysis of the study findings. He contributed to the drafting of the manuscript and provided critical revisions. Zhuolai Liang oversaw the overall conduct of the study, including the design, data collection, and analysis. He played a pivotal role in obtaining funding for the project and provided final approval of the version to be published. All authors have read and approved the final version.

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