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PAPER

Evaluation and Analysis of the Implementation Effects in Practical-Course Blended Learning Based on Virtual Reality Technology

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ABSTRACT

Practical-course blended learning based on virtual reality (VR) technology combines VR with traditional practical teaching, which provides students with a more diverse and personalized learning experience. The existing evaluation and analysis methods of teaching model implementation effects have shortcomings. Although VR technology plays an important role in practical-course blended learning, excessive reliance on technical means may lead to limitations in evaluation methods. Therefore, this study aimed to explore the evaluation and analysis of implementation effects of VR-based practical-course blended learning. Different types of teaching models were represented. A robust multi-target collaborative tracking method based on variational Bayesian inference was applied to track and evaluate the implementation effects of practical-course blended learning. The experimental results verified the effectiveness of the proposed method and explored the impact of different teaching models on the average scores and score stability of evaluation methods. Analysis results of score data showed that the assisted-teaching model improved the homework performance of students and the blended-learning model improved the performance of students in tests and final exams, while the complete teaching model performed more balanced in all aspects.

KEYWORDS

virtual reality, practical courses, blended learning

1 INTRODUCTION

With the rapid technological development, the application of VR technology is becoming increasingly widespread in the field of education. As an immersive and interactive technology, VR provides educators with a new teaching method, and has increasingly evident advantages especially in practical courses [1–16]. For the practical teaching problems in current preschool education, such as widespread shortage of teaching resources, numerous teaching difficulties with difficult solutions,

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dispersed resources, and difficulty in meeting students' personalized learning demand, Liao [17] developed a "virtual factory" using VR technology, integrated relevant VR practical teaching resources, constructed a practical teaching environment combining virtuality with reality, and innovated the VR technology application mode of "cultivating preschool education talents with vocational skills, combining virtual with real environments, supporting and innovating practical teaching, and conducting research," which achieved "teaching+practical training," thus transforming the traditional practical teaching model into a blended practical teaching model of "online self-learning+virtual practical training+face-to-face teaching+practical training." In addition, advantages of applying VR technology in courses and issues to be considered were studied in order to provide assistance for the application and promotion of VR technology in courses.

Blended learning combines online with offline learning, aiming to fully utilize network and digital technology to improve teaching quality and effectiveness [18–24]. Xu [25] summarized and analyzed the theoretical research and application status of blended and collaborative learning, integrated their advantages, and promoted the occurrence of deep learning. As a new teaching model, the proposed method solved the challenge for teachers when choosing a teaching model that will cultivate students' high-level thinking and improve their comprehension. The method also has value as a reference for how to construct a teaching model supported by information technology, and better utilize it to improve the quality of classroom teaching.

It is necessary to evaluate the implementation effects of VR-based practical-course blended learning in order to assess its strengths. Previous studies have shown that blended learning has significant advantages in improving students' learning motivation, scores, and satisfaction [26]. However, there are still limited studies on the evaluation and analysis of implementation effects of VR-based practical-course blended learning.

Although the evaluation and analysis methods for implementation effects of VR-based practical-course blended learning provide valuable feedback and guidance to educators, these methods have certain shortcomings [27–30]. For example, educators may have different expectations and standards according to the learning characteristics and demands of different students, leading to a decrease in the consistency of evaluation results. At the same time, VR technology plays an important role in practical-course blended learning when the proportion of practical courses is high, such as physical education, but excessive reliance on technical means may lead to limitations in evaluation methods. Therefore, this study aimed to explore the evaluation and analysis of implementation effects of VR-based practical-course blended learning.

2 REPRESENTATION OF VR-BASED PRACTICAL-COURSE BLENDED LEARNING

The VR-based practical-course blended-learning process included several steps, such as demand analysis, teaching resource development, teaching design, implementation and evaluation. Educators first needed to comprehensively analyze the teaching objectives and content of practical courses and characteristics of students to clarify the specific demand to be met. Based on the results of demand analysis, the educators needed to develop corresponding VR teaching resources, such as virtual laboratories and scenes and models. Then they needed to design specific blended learning plans, including the combined method of online VR teaching and offline practical operation teaching, teaching progress and strategies, etc. Finally, blended learning was implemented according to the teaching design plans. During this process, students rehearsed the practical operations and were trained in an online VR environment to improve their hands-on ability. After the blended learning was implemented, educators needed to evaluate students' learning effects, including theoretical knowledge mastery, practical operation ability, problem-solving ability, and other aspects.

Before studying the evaluation and analysis of implementation effects of VR-based practical-course blended learning, this study represented different types of teaching models based on the understanding of the teaching process in Figure 1, which clarified the specific teaching objectives and contents of practical-course blended learning, thus helping educators better understand the core requirements of the courses and design teaching plans that were more in line with practical demand. Representation of teaching models helped summarize the specific teaching methods and strategies adopted in VR-based practical-course blended learning, which helped educators understand the application of different teaching methods and strategies in the actual teaching process and provided important references for subsequent study of evaluation and analysis.

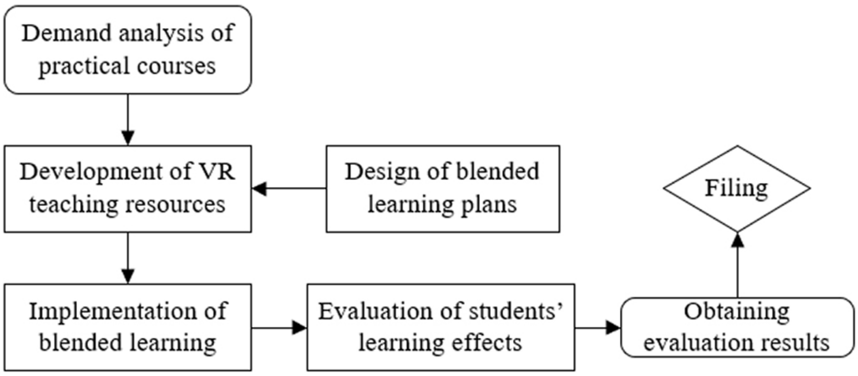

Fig. 1. VR-based practical-course blended-learning process

This study defined the VR-based practical-course blended-learning behavior as a quadruple (student number, VR teaching activity number, timestamp, behavior type). The behavior sequence was composed of multiple quadruples, with each quadruple corresponding to the blended-learning behavior on each timestamp. Let event $r_m \in$ {normal, active and passive participation} be the m-th blended-learning behavior which occurred on timestamp y_m, and B_r be the total number of events, then the practical-course blended-learning behavior sequence was represented by the following equation:

$$A^{Br} = \left\{(r_m, y_m)\right\}_{m=1}^{Br} \tag{1}$$

Let $|\Omega|$ be the number of practical-course blended-learning behaviors in the quantity space, and b be the behavior vector dimensions in Ω. Then the representation of the behavior sequence was considered as the mapping of $|\Omega| \times b$ real number dimensional vector space of each event in the behavior sequence. Figure 2 provides a schematic diagram of the learning-behavior sequence. Let r_u be the u-th behavior in A, and l be the number of behaviors in the behavior sequence. The following equation provided the expression for the practical-course blended-learning behavior sequence A:

$$A = ((r_1, y_1), (r_2, y_2), ..., (r_u, y_u), ..., (r_l, y_l)) \tag{2}$$

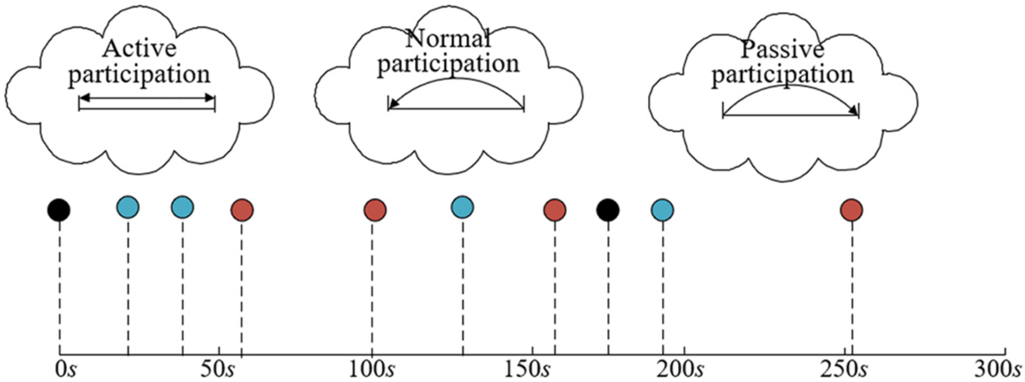

Fig. 2. Schematic diagram of learning-behavior sequence

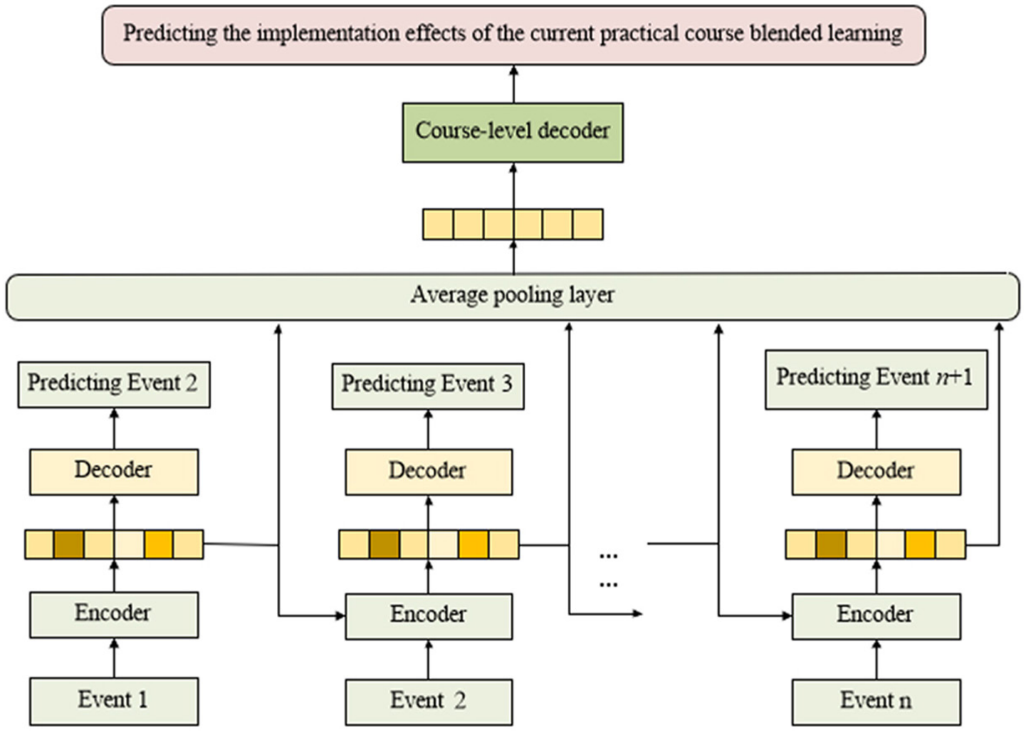

Fig. 3. New Hawkes-process framework

A mapping function $d:A \rightarrow C$ was introduced, which took the behavior sequence A as the input and a series of relations changing with time as the output. The following equation gave the vectorized expression of the function output:

$$C = [c_u]_{u=1}^{B} \tag{3}$$

This achieved the dynamic mode quantification of online practical-course blended-learning behavior of students.

A new Hawkes process was further proposed in this study and applied to represent the practical-course blended-learning behavior. The framework is shown in Figure 3. Learning behaviors of students in blended learning had sequential characteristics. The new Hawkes process captured the sequential characteristics of online and offline learning behaviors, and the mutual influence between these behaviors, thus providing a deep understanding of the learning process. At the same time, students' learning behaviors were often incentivized by the behaviors of other students and teachers in the practical-course blended learning. The new Hawkes process established causal relationships between learning behaviors and revealed the interaction mechanism between various behaviors, thus providing a basis for formulating a teaching strategy.

Let $\bar{\eta}_j(y)$ be the intensity of the current event j, $\omega_j \geq 0$ be the basic intensity of the event occurrence process, $r^{-\sigma(y-yu)}$ be the time-decay coefficient, y be the time when the current event occurred, y_u be the time when the historical event u occurred, $\beta_{uj} \geq 0$ be the degree of the current event j incentivized by the historical event u, and σ be the decay degree of the impact of historical events over time. The resulting equation of the classic Hawkes process was as follows:

$$\bar{\eta}_j(y) = \omega_j + \sum_{u:y_u<y} \beta_{uj} r^{-\sigma(y-y_u)} \tag{4}$$

Expressiveness of the Hawkes process was expanded while retaining its original structure, which addressed the limitations that the original process may exhibit when representing complex event sequences. The expressiveness expansion helped enhance the flexibility of the model, enabled it to better capture various complex phenomena in practical application scenarios, and analyzed the interaction between students and between students and teachers, and the interrelationships between teaching resources in a practical course using blended-learning scenarios.

The value range of β_{uj} and ω_j was redefined to make them less than 0. The nonlinear function d_j was introduced in this study to force the intensity function to be always greater than 0, with the following result:

$$\eta_j(y) = d_j(\tilde{\eta}_j(y)) \tag{5}$$

As y continued to change, $\eta_j(y)$ correspondingly increased or decreased to represent the incentivizing and inhibiting effects between events. The impact of historical events decreased towards 0 at a decay rate σ, and the intensity approached $d(\omega_j + 0)$. When selecting d_j, this study selected a softplus function with a proportionality coefficient as the nonlinear function, and the specific expression was as follows:

$$d(z) = a\log(1+\exp(z/a)) \tag{6}$$

Letting A_j be the proportionality coefficient of event j, then combine the Eq. (5) and Eq. (6):

$$\eta_j(y) = a_j \log(1+\exp(\bar{\eta}_k(y)/a_j)) \tag{7}$$

In the practical course using a blended-learning scenario, students' learning behaviors may be influenced by long-term historical events. After combining LSTM, which has the ability to capture long-term dependencies, with the optimized Hawkes process, the model better captured the complex dependency relationships between the intensity of behavior events and the quantity, sequence, and time of previous events. As a deep-learning model, LSTM showed high prediction accuracy in many time-series prediction tasks. Combining LSTM with the optimized Hawkes process further improved the prediction performance of practical-course blended-learning behaviors and helped identify students' learning difficulties in a timely manner and develop effective intervention measures.

With the occurrence of different types of practical-course blended-learning-behavior events, the event intensity $\eta_j(y)$ discontinuously jumped and gradually approached the basic intensity. In LSTM, the size of $g(y)$ depended on the cell state $v(y)$; then there were:

$$g(y) = p_u * (2\delta(2v(y)) - 1) \tag{8}$$

$v(y)$ decayed continuously over time:

$$v(y)^{def} = \bar{v}_{u+1} + (v_{u+1} - \bar{v}_{u+1})\exp(-\sigma_{u+1}(y - y_u)) \tag{9}$$

When the optimized Hawkes process was combined with LSTM in the practical-course blended-learning scenario, it solved the potential problem of students' learning behaviors in blended learning from being influenced by multiple factors and long-term historical events, thus improving the prediction performance of the learning behaviors and helping identify students' learning difficulties in a timely manner and develop effective intervention measures. In addition, the improvement of prediction performance promoted the optimization of teaching resources and strategies.

3 TRACKING AND EVALUATION OF IMPLEMENTATION EFFECTS OF PRACTICAL-COURSE BLENDED LEARNING

During practical-course blended learning, there may be many uncertainties in students' learning behaviors and the utilization of teaching resources. A robust multi-target collaborative tracking method based on variational Bayesian inference was used in this study to track and evaluate the implementation effects of practical-course blended learning, mainly because the inference effectively handled these uncertainties in the tracking-and-evaluation process and provided educators with more accurate evaluation results. At the same time, evaluation indicators (e.g., learning progress and interaction of students) were updated in real time using the collaborative tracking method, which helped educators adjust teaching strategies in a timely manner to improve teaching effects. Figure 4 shows a schematic diagram of the probability graph model of the algorithm.

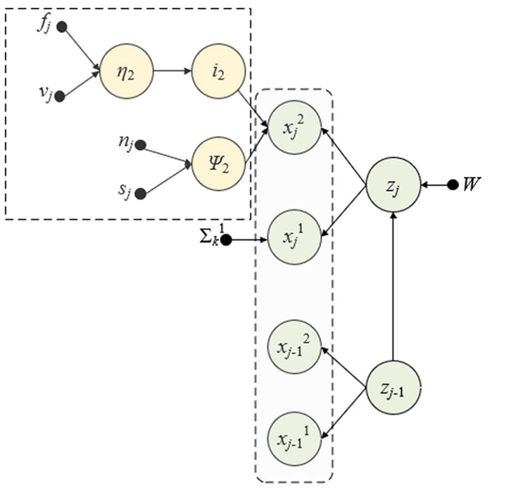

Fig. 4. Schematic diagram of the probability graph model of the algorithm

This study set specific target measurement values and targets for this method. The former included the interaction frequency, learning time, and learning effects of students in blended learning. The latter included evaluating the effectiveness of practical-course blended learning, identifying the directions for optimizing teaching strategies, promoting personalized teaching effects, and improving the efficiency of utilizing teaching resources.

Let π be the artificially set distance threshold. If the distance between target b and each measured value at time j was greater than π, it was determined that the target was not achieved. To achieve the incidence relation between target measurement values and B targets, this study constructed the incidence cost matrix VL_j^G in the following equation:

$$VL_j^G = \begin{bmatrix} f(1,1) & f(1,2) & \cdots & f(1,B) \\ f(2,1) & f(2,2) & \cdots & f(2,B) \\ \vdots & \vdots & \ddots & \vdots \\ f(l_j^G,1) & f(l_j^G,2) & \cdots & f(l_j^G,B) \\ \pi & \pi & \pi & \pi \end{bmatrix}_{(l_j^G+1)\times B} \tag{10}$$

The optimal incidence matrix was obtained using HA, which further obtained the corresponding relationship between B targets and all measured values. Let UL_j be the Hungarian incidence matrix; then the matching relationships between each measured value and the target at time j were UL_j^G and UL_j^V. The following equation calculated values of the matrix elements:

$$IM_k(n,i) = \begin{cases} 1, & n \text{ is associated with } i \\ 0, & \text{else} \end{cases} \tag{11}$$

$$UL_j^G = \begin{bmatrix} 0 & 1 & \cdots & 0 \\ 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \end{bmatrix}_{l_j^G\times B}, \quad UL_j^V = \begin{bmatrix} 0 & 1 & \cdots & 0 \\ 0 & 0 & \cdots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & \cdots & 0 \end{bmatrix}_{l_j^C\times B} \tag{12}$$

Based on the existing incidence matrix, the measurement functions $g^{G(j)}(z_j)$ and $g^{V(k)}(z_j)$ in the following equations were constructed:

$$g^{G(u)}(z_j) = \begin{bmatrix} 0 & G' & \cdots & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ G' & 0 & \cdots & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}_{(l_j^G+l_j^V)\times(4B+6)} \bullet z_j \tag{13}$$

$$g^{V(k)}(z_j) = \begin{bmatrix} 0 & G' & \cdots & 0 & -G'' & 0 & 0 \\ 0 & 0 & \cdots & G' & -G'' & 0 & 0 \\ 0 & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots \\ G' & 0 & \cdots & 0 & -G'' & 0 & 0 \end{bmatrix}_{(l_j^G+l_j^V)\times(4B+6)} \bullet z_j \tag{14}$$

Student t-distribution had a fat tail, meaning that it had greater probability quality on both sides of the probability density function and better tolerated outlier data. In the multi-target tracking process, observation data was often affected by several factors, such as noise, occlusion, and mutual interference between targets, which may result in abnormal observed values. Compared with Gaussian models or finite-mixture Gaussian models, Student t-distribution had stronger robustness in processing these outlier data, thus reducing the impact of abnormal observed values on target-tracking results.

Let $\Pi(\cdot)$ be the gamma function, $\omega_j \in E^{l2}$ be the mean, $\psi_j \in E^{l2\times l2}$ be the accuracy, and η_j be the degree of freedom. The following equation gave the expression of probability density function of l_2-dimensional Student t-distribution:

$$\sigma\pi(c_j^2;\omega_j,\eta_j)=\frac{\Pi\left(\frac{f+\eta}{2}\right)}{\Pi\left(\frac{\eta_j}{2}\right)(\eta_j\tau)^{\frac{l_2}{2}}}\left|\Psi_j\right|^{\frac{1}{2}}\left[1+\frac{1}{\eta_j}(c_j^2-\omega_j)^Y\psi_j(c_j^2-\omega_j)\right]^{-\frac{l_2+\eta_j}{2}} \tag{15}$$

With the decrease of η, the tail decay gradually slowed down. When η was less than 2, the variance was infinite. When η approached ∞, the above equation converged to a Gaussian distribution. The likelihood probability density function $o(x_j^2|z_j)$ of x_j^2 was obtained by the following equation:

$$o(x_j^2\mid z_j)=\sigma\pi(x_j^2;Gz_j,\Psi_j,\eta_j) \tag{16}$$

After introducing the bootstrap variable ω_j, the above equation was decomposed as follows:

$$\begin{cases} o(x_j^2\mid z_j)=B\left(x_j^2;Gz_j,\sum_j^2\right),\sum_j^2=(i_j\Psi_j)^{-1} \\ o(i_j|\eta_j)=\xi\left(i_j;\frac{\eta_j}{2},\frac{\eta_j}{2}\right) \end{cases} \tag{17}$$

Based on four hyper-parameters, namely, $\hat{s}_{m,0}$, $\hat{n}_{m,0}$, $\hat{v}_0$, and $\hat{f}_0$, the gamma prior was set for the accuracy Ψ_0 and the degrees of freedom η_0, which were used as the initial input values for the algorithm:

$$\begin{cases} o(\Psi_0)=\prod_{m=1}^{l2}\xi(\Psi_{m,0};\hat{s}_{m,0},\hat{n}_{m,0}) \\ o(\eta_0)=\xi(\eta_0;\hat{v}_0,\hat{f}_0) \end{cases} \tag{18}$$

4 EXPERIMENTAL RESULTS AND ANALYSIS

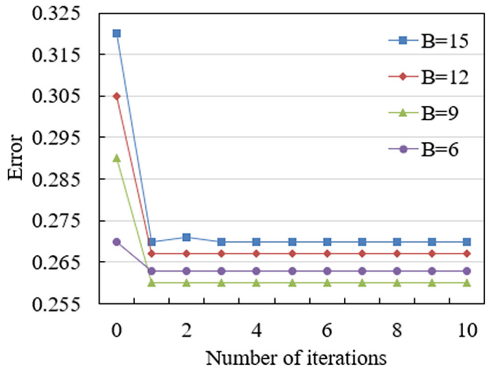

Fig. 5. Tracking error iteration curves with different numbers of targets

Based on Figure 5, it was possible to analyze the variation of tracking error along with the number of iterations under different numbers of targets. As shown in the figure, as the number of iterations increases, the tracking error decreases in all cases. When the number of iterations reaches 2, the tracking error tends to stabilize, indicating that the convergence speed of the algorithm is fast. When the number of targets is large (e.g., B=15), the initial tracking error is relatively large. However, as the number of iterations increases, the tracking error decreases and tends to stabilize with a faster convergence speed. When the number of targets is small (e.g., B=6), the initial tracking error is small. As the number of iterations increases, the tracking error decreases and tends to stabilize, and the convergence speed is relatively slow. With the same number of iterations, the tracking error is relatively small when the number of targets is small (e.g., B=6), indicating that the tracking performance of the algorithm is better when the number of targets is small. When the number of targets is large (e.g., B=15), the tracking error is relatively large, indicating poor tracking performance of the algorithm. Therefore, in the practical application of the proposed method, an appropriate number of iterations was selected based on the number of targets to achieve good tracking performance. In the case of a large number of targets, the number of iterations was appropriately increased to improve tracking accuracy. At the same time, when designing the algorithm, attention should be paid to improving the tracking performance of the algorithm with different numbers of targets, especially when the number of targets is high.

Table 1. Understanding and mastery of knowledge by students in practical-course blended learning

Categories	Participation in Virtual Practice Only			Participation in Both Virtual and Real Practice		
Evaluation Contents	Number of Students at Each Level			Number of Students at Each Level		
	A	B	C	A	B	C
Knowledge point 1	13	2	1	26	6	3
Knowledge point 2	19	4	4	28	1	8
Knowledge point 3	24	7	2	21	4	2
Knowledge point 4	20	1	1	22	2	4
Knowledge point 5	25	5	3	24	5	1

Based on the data in Table 1, it was possible to analyze students' understanding and mastery of knowledge in practical-course blended learning. A, B, and C represent the students' mastery levels (good, average, and poor, respectively) of each knowledge point. The table is divided into two categories: students participating in virtual practical courses only, and students participating in both virtual and real practical courses. It can be seen from the table that students participating in both virtual and real practice have better knowledge mastery for most knowledge points, maybe because real practical courses provide students with richer practical operation experience, which helps deepen their understanding and application ability of knowledge. However, for certain knowledge points, such as Knowledge point 2, the number of students participating in both forms of practice is higher at the C level, mainly because the combination of virtual and real practice at that knowledge point is not sufficient, or it is difficult to understand some parts in the actual operation process, resulting in poor knowledge mastery of some students. In response to this situation, teachers could explain Knowledge point 2 more deeply and design practical activities closer to practical applications, thus helping students improve their mastery of the knowledge point.

Table 2. Proportions and pass rates of different practical-course teaching models

Modes	Assisted	Complete	Blended
Sample size	105	348	1528
Sample proportion	7.5%	21.5%	63.5%
Homework pass rate	96.3%	91.4%	97.2%
Test pass rate	91.4%	95.8%	93.5%
Final exam pass rate	95.8%	97.4%	91.7%

Based on the data in Table 2, it was possible to analyze the proportions and pass rates of different practical-course teaching models. The table is divided into three models: assisted, complete, and blended. It can be seen from the table that the blended model has the highest sample proportion (63.5%), indicating that the blended learning model is widely adopted in practical courses. The blended model has the highest homework pass rate (97.2%), which is followed by the assisted model (96.3%) and the complete model (91.4%), indicating that the blended learning model has good teaching effects in terms of homework. The complete model has the highest test pass rate (95.8%), which is followed by the blended model (93.5%) and the assisted model (91.4%), indicating that the complete teaching model has good teaching effects in terms of tests. The complete teaching model has the highest final exam pass rate (97.4%), which is followed by the assisted model (95.8%) and the blended model (91.7%), indicating that the complete teaching model has good teaching effects in final exams. Overall, the blended learning model has the highest proportion in practical courses and a higher homework pass rate but has slightly lower pass rates than the complete teaching model in terms of tests and final exams, because the blended learning model has advantages in combining practical operation with theoretical knowledge, which improves the homework performance of students.

Based on the data in Table 3, it was possible to analyze the impact of different practical-course teaching models on learning effects. The table is divided into three models, namely, assisted, complete, and blended. As shown in the table, the assisted model has the highest homework average scores (91.8), which is followed by the complete model (85.4) and the blended model (81.9), which is consistent with previous analysis that the assisted model performs better in terms of homework. The assisted model has the highest test average scores (87.4), which is followed by the complete model (81.9) and the blended model (80.5), which is slightly different from the previous pass-rate analysis but still shows that the assisted and complete models perform better in tests. The complete model has the highest final exam average scores (86.5), which is followed by the assisted model (84.7) and the blended model (81.9), which is consistent with previous analysis that the complete model performs well in final exams. The complete model has the highest score variances in homework, tests, and final exams, indicating a dispersed distribution of scores. The blended model has the lowest test score variance, while the assisted model has the lowest homework score variance, indicating that the two models have relatively stable teaching effects in terms of tests and homework. Overall, the assisted teaching model performs well in homework and tests, while the complete teaching model performs well in final exams. The performance of the blended learning model is relatively average in all aspects.

Table 3. Impact of different practical course teaching models on learning effects

Comparison Items	Homework Average Scores	Test Average Scores	Final Exam Average Scores	Homework Score Variance	Test Score Variance	Final Exam Score Variance
Assisted model	91.8	87.4	84.7	125.4	241.9	251.8
Complete model	85.4	81.9	86.5	184.6	264.7	295.3
Blended model	81.9	80.5	81.9	138.4	162.5	257.7

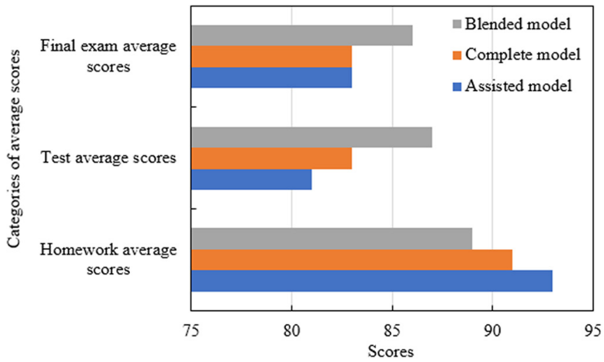

Fig. 6. Impact of different practical course teaching models on the average scores of evaluation methods

According to Figure 6, it was possible to analyze the impact of different practical-course teaching models on the average scores of evaluation methods. It can be seen from the figure that students have the best homework performance in the assisted teaching model, with an average score of 93. However, the performance of students in tests and final exams is relatively low, with average scores of 81 and 83, respectively, possibly indicating that students better grasp knowledge during the autonomous learning process after class in the assisted teaching model but may feel certain pressure when dealing with exams or have weak test-taking ability. In the complete teaching model, students have a relatively balanced performance in homework, tests, and final exams, with average scores of 91, 83, and 83, respectively, indicating that this model may help improve students' comprehensive ability in various aspects. In the blended learning model, the homework performance of students is slightly lower than other two models, with an average score of 89. But students have a relatively good performance in tests and final exams, with average scores of 87 and 86, respectively, possibly indicating that the blended learning model helps improve the test-taking ability and overall quality of students' performance.

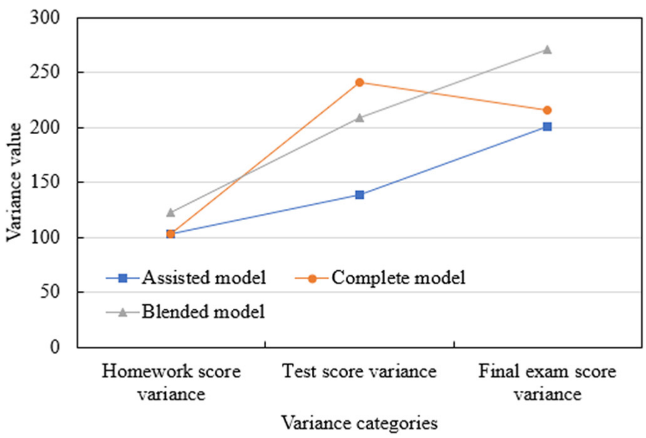

Fig. 7. Impact of different practical-course teaching models on the score stability of evaluation methods

According to Figure 7, it was possible to analyze the impact of different practical-course teaching models on the score stability of evaluation methods. It can be seen from the figure that the homework score variance is the smallest in the assisted model, indicating that students' performance in homework is relatively stable. However, the score variances in both tests and final exams are relatively large, especially the final exam score variance of 201, indicating students have greatly fluctuating performance in these two aspects. In the complete model, the homework score variance is relatively small, which is the same as the assisted model. However, the score variances of tests and final exams are relatively high, which are 241 and 215, respectively, indicating that students have greatly fluctuating performance in these two aspects. In the blended model, the score variances of homework, tests, and final exams are all relatively large, especially the final exam score variance of 271, indicating that students have greatly fluctuating performance in various aspects. In summary, different practical-course teaching models have a certain impact on the score stability of evaluation methods. Students have a relatively stable performance in homework and a greatly fluctuating performance in tests and final exams in assisted and complete teaching models. In the blended learning model, students have a greatly fluctuating performance in various aspects.

In order to improve the stability of scores, teachers could try to adopt different strategies based on the demand of students and course objectives when designing teaching models and evaluation methods. For example, it was possible to strengthen tutoring for students in tests and final exams to improve their stable performance in these two aspects. At the same time, teachers could pay attention to the performance differences of students in various aspects and make targeted teaching adjustments to improve teaching quality.

5 CONCLUSION

This study explored the evaluation and analysis methods of implementation effects of VR-based practical-course blended learning. Different types of teaching models were represented. A robust multi-target collaborative tracking method based on variational Bayesian inference was applied to track and evaluate the implementation effects of practical course blended learning. The experimental results verified the effectiveness of the proposed method and explored the impact of different practical-course teaching models on the average scores and score stability of evaluation methods.

The following conclusions were drawn based on the comprehensive study results:

1. Different practical-course teaching models have a certain impact on the average scores of evaluation methods. The assisted teaching model may be more conducive to the homework performance of students, while the blended learning model may be more conducive to improving students' performance in tests and final exams. The performance of the complete teaching model is relatively balanced in all aspects.
2. Different practical-course teaching models have a certain impact on the score stability of evaluation methods. Students have a relatively stable performance in homework and a greatly fluctuating performance in tests and final exams in assisted and complete teaching models. They have a greatly fluctuating performance in various aspects in the blended learning model.

In order to improve teaching quality and the stability of scores, teachers could comprehensively consider the demand of students and course objectives when selecting teaching models and evaluation methods. Teachers could make targeted teaching adjustments based on the performance differences of students in different aspects. At the same time, teachers could pay attention to the performance fluctuations of students in tests and final exams, and strengthen tutoring for students in these two aspects to improve their performance stability.

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