Evaluation of the Effect of Virtual Simulation Teaching on Learning Behavior of College Students

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Abstract—As a new learning model that breaks the barriers of time and space, virtual simulation covers a variety of learning behaviors. To evaluate the effect of virtual simulation teaching on college students' learning behavior, with the help of a course integration model which reduces the omissions in the process of data collection, the data collection process of college students on the online platform was constructed. The collected data before storage were preprocessed which reduces the repetition rate of the original data of learning behavior, and the correlation between the collected data and the actual learning behavior was analyzed. Results show that learners' specific process of online learning can be summarized into four stages: login trajectory, core learning, social interaction, and learning evaluation. Then, the actual final examination scores of the college students who participated in the test are all above 90 points, and their academic achievements are significantly improved. The use of the virtual simulation teaching method also enhances the overall satisfaction of college students with experimental courses, and the accuracy of the analysis results of course results is 99%, with better results. Conclusions are helpful to build college students' active learning consciousness of virtual simulation teaching courses.

Keywords—virtual simulation teaching, learning behavior of college students, course integration model, evaluation indicators

1 Introduction

The integration of big data technology, cloud computing, the Internet of Things, and other technologies has produced massive data, which gradually affects people's work and lifestyle. As a carrier for cultivating talents and promoting innovation, colleges undertake the important tasks of serving society, developing science, and cultivating talents [1, 2]. In the face of the social market background of the urgent need for talent in the industry, colleges are optimizing the positioning of disciplines and improving their competitiveness in the industrial market [3, 4]. At present, some problems may persist in the teaching quality and teaching methods of virtual simulation teaching courses in China's colleges and universities. Therefore, teaching reforms in virtual simulation teaching courses oriented by the professional application should be proposed.

After several course reforms, the course teaching gradually tends to be comprehensive, balanced, and selective; however, previous course reforms were mainly aimed at the basic teaching of primary and secondary schools, which is not quite applicable to professional teaching in colleges and universities [5]. At present, virtual simulation teaching courses in colleges and universities emphasize too much the integrity and theory of the course system and lack the interconnection among big data, professional courses, and practical application, thus failing to train the ability of college students to apply big data knowledge [6, 7]. In addition, outdated teaching content and single course form cause issues in the virtual simulation teaching system [8]. To solve such current problems, the new system makes teaching reforms oriented to professional application, increases the importance of professional and practical aspects based on the big data theory course, and adopts the evaluation method to evaluate and analyze the teaching system of the virtual simulation teaching course after reform. These solutions help to ensure that the proposed course reform method can play a good teaching effect. Thus, such research is of great significance to the study of the influence of virtual simulation teaching on the learning behavior of college students.

In the current era of big data, various industries in society are producing massive data, thereby gradually forming the Internet+ model with the development of modern information technology. In the education industry, the new learning mode of Internet + Education, which relies on online learning platforms, promotes the transformation of college students' learning mode from traditional classroom teaching to the combination of traditional and online platforms [9, 10]. However, with the increase in the number of online learning platform users and the development of mature technology, this model also faces challenges, among which the problem regarding the low completion rate of online learning courses is more prominent. Moreover, the behavioral data of learners are the premise and basis of studying the online learning behavior of college students. However, given the characteristics of massive and dispersed platform data, the collected data lack comprehensiveness, efficiency, and accuracy of data classification, thus affecting the reliability of the research results on online learning behavior. Hence, this research explores the online learning behavior of college students and identifies the problems and shortcomings of traditional research methods. Then, it proposes the influence of virtual simulation teaching on the learning behavior of college students and verifies the feasibility of this method through experiments to obtain more accurate learning behavior research results.

2 Literature review

Dolmark et al. [11] pointed out the influence of individual technological beliefs and use on the absorptive capacity of learning behavior in a learning environment. Furthermore, absorptive capacity is a common obstacle to knowledge transfer at the individual level. However, technology absorptive capacity can enhance individual learning behavior. Their study investigated the effects of technical readiness, knowledge source tools, social influence, and social networks on the absorptive capacity to adapt to individual learning behaviors. The quantitative methods were used to evaluate the presence of causality in the above structure, and data were collected from college students in Australia to test the hypotheses. The results indicated that individual technological beliefs about optimism and innovation and their social influence had significantly weaker impacts on individual absorptive capacity and, in turn, had significantly weaker impacts on their learning behavior. In another study, Si et al. [12] put forward the daily dynamics of travelers' learning behavior and the incentive solutions for one-way car-sharing service operators. Car-sharing travelers make route selection decisions according to their perceived travel costs, which may be affected by experience and car-sharing operator incentive solutions. More specifically, the self-adaptive scheme does not require specific information about the behavioral characteristics of travelers, which is adopted by operators to motivate travelers to rent cars from oversupplied stations and/or return them to undersupplied stations, thereby reducing the expected cost of using dedicated personnel to relocate cars. Moreover, travelers tend to underestimate the value of the reward, thus making them less effective at relocation. Then, it studied the equilibrium state and stability of the evolutionary model. Finally, the application of this method is illustrated by numerical experiments. Kar et al. [13] determined a learning behavior modeling for professionals in the industrial Internet of Things and emerging digital technologies. This study extended the individual ambidextrous learning theory and the unified theory of technology acceptance and application. Furthermore, it developed a quantitative behavioral model for learning emerging digital skills. The LED model described the antecedents of the learning behavior of professionals about rapidly changing emerging digital technologies involving IoT. A nationwide structured survey was conducted among 685 professionals in 95 companies across India on IoT products and solutions development in industries, such as automotive, aerospace, health care, and energy. A qualitative study was conducted to verify the result of structural equation modeling, which demonstrated that social influence and individual innovation, anxiety, long-term consequences, and work relevance affect learning behavior intentions. The performance level and technical preference of professionals moderated the relationship between antecedents and willingness to learn. For excellent performers, individual innovation is a key driver of willingness to learn. For general performers, social influence and anxiety are other important factors affecting such willingness. The technology itself regulates learning behaviors, thus indicating that professionals prefer to learn technologies based on their maturity and potential for use. Hence, this study can help practitioners to design promotion strategies to meet market needs.

Furthermore, Hang et al. [14] proposed a learning performance prediction model provided by learning behavior and big data analysis. Their study used log data collected from 823 college students under two environments: their online learning environment and their daily living environment (using campus ID cards for consumption and borrowing books from the university libraries) to create indicators for online learning behavior, early rising behavior, book borrowing behavior, and learning performance prediction. Five machine learning models were used to analyze learning performance predictions, and boosting and bagging were used to improve the accuracy of the prediction models. The predictability of the proposed model was compared with that of the artificial neural network model and the deep neural network model. The results showed that the multi-scenario behavioral performance indicators had the strong predictive ability, while the prediction accuracy of the deep neural network model was 82% at most. The rule-set-based model has a high degree of accuracy, readability, and operability, which may help to perform accurate teaching interventions and provide proper resource suggestions. Meanwhile, Zhang et al. [15] observed the influence of college students' autonomous learning behavior based on network learning platforms; for college students, network learning habits will have a lasting impact on subsequent learning production as support of a set of external conditions and with a strong sense of autonomy. Moreover, they can even become the second important approach to knowledge acquisition in addition to the classroom. Based on TAM and UTAUT, this study complemented perception theory and autonomous learning theory by extracting the influencing factors of the real-time platform. Based on data analysis of SmartPLS and SPSS, this study constructs a structural equation model of the autonomous learning behavior of college students on the online learning platform, explores the external and internal influencing mechanisms of autonomous learning behavior, and provides guidance for the autonomous learning behavior of practitioners and college students on the online learning platform. Feng et al. [16] demonstrated the learning behavior analysis based on edX open data. Since 2012, the continuous development of MOOCs has triggered new thinking and research in many aspects, and the massive data generated by MOOCs has provided a foundation for learning behavior analysis and education data research. Dulaney et al. [17] proposed the influence of machine learning on the behavior of active matter systems. By creating phase concepts at the particle level, deep learning techniques can be used to predict motion-induced phase separation in the suspension of active Brownian particles. Using fully connected networks and graphical neural networks, we can predict the phase to which the particles belong through the characteristics of a single particle. Therefore, the fraction of diluted particles can be calculated to determine whether the system is in a uniformly diluted, dense, or coexisting region. Our predictions were compared with simulated MIPS binomials. The strong agreement between the two suggests that machine learning can provide an effective way to determine learning behavior and can be used to determine more complex outcomes.

3 Methodology

3.1 Sample collection process

As a new type of learning model breaks the limits of time and space, virtual simulation teaching also covers a variety of learning behavior of learners. Some examples include previewing the task assigned by teachers, watching classroom video resources, finishing homework after class, and engaging in mutual communication between learners. These online operations will leave traces and produce huge amounts of data [18, 19]. After classifying the online learning behaviors of college students, how to collect online learning data of college students comprehensively and effectively will become the basis of studying online learning behaviors, which is also the premise of mining and evaluating online learning behavior data in the future [20, 21]. Since the diverse, massive, and complex types of learning behaviors of college students, to cover and collect the data comprehensively, it can use the course integration model reduces omissions in the process of data collection. The flows are roughly shown in Figure 1.

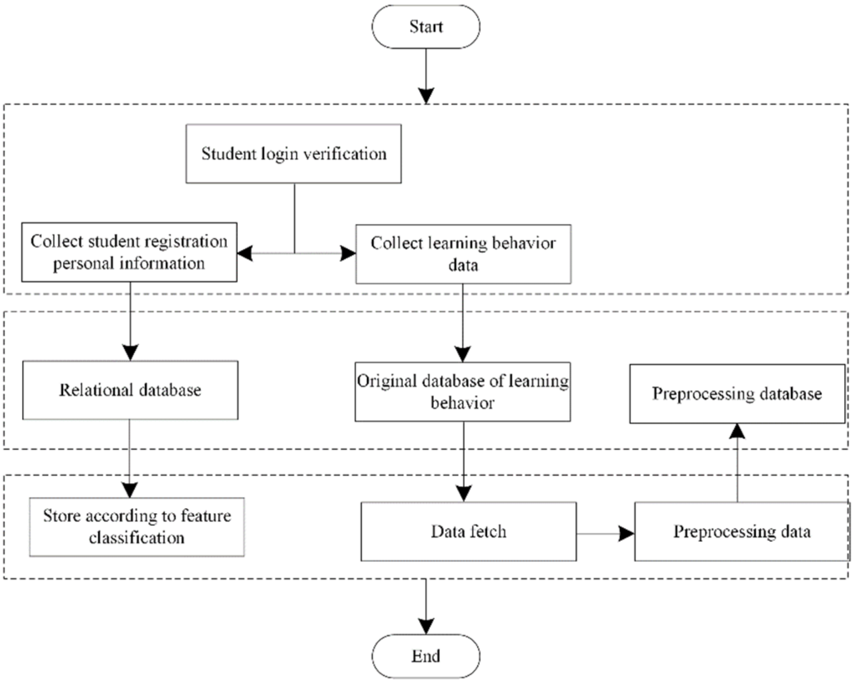

Fig. 1. Flow chart of data collection of college students on the online platform

According to the flows illustrated in Figure 1, the learning behaviors of college students in virtual simulation teaching can be divided into two types. One is individual information, and the other is learning behavior information. The process of collecting the personal information of college students is relatively simple, as it is conducted when college students register their online learning platform account for the first time, input them into the relational database, and store them in classifications according to their characteristics [22]. More importantly, the data collection on the learning behavior of college students helps form an original and untreated database of learning behaviors according to the operation records of college students during online learning. Then, the model can be used to read and identify huge amounts of data, which can be roughly divided into the following categories. The data on college students are mainly tracked through browsing traces in the process of online learning [23, 24]. The core learning behavior of online learning includes the kind of video resources or courseware the learner watches, their social interaction behavior, that is, how often college students communicate in the process of learning, and their learning evaluation behavior, which refers to the evaluation obtained by college students using online learning platform after a certain stage of learning [25]. Finally, the online learning behavior is evaluated according to the evaluation index set for different types of learning behavior.

Using the course integration model to collect data can extract learning behavior data separately, improve the coverage rate as far as possible, and avoid omission. Meanwhile, it can preprocess the collected data before storage and reduce the repetition rate of the original learning behavior data to provide data processing guarantee for the study of college students' online behavior.

3.2 Set evaluation index of online learning behavior

After the data collection for college students' online study behavior through the course integration model in the previous section, the correlation between data collection and actual learning behavior must be further analyzed accurately. Thus, the model needs to set a corresponding specific evaluation index for different online learning behaviors of learners to clarify the specific process of online learning. The flows are shown in Figure 2.

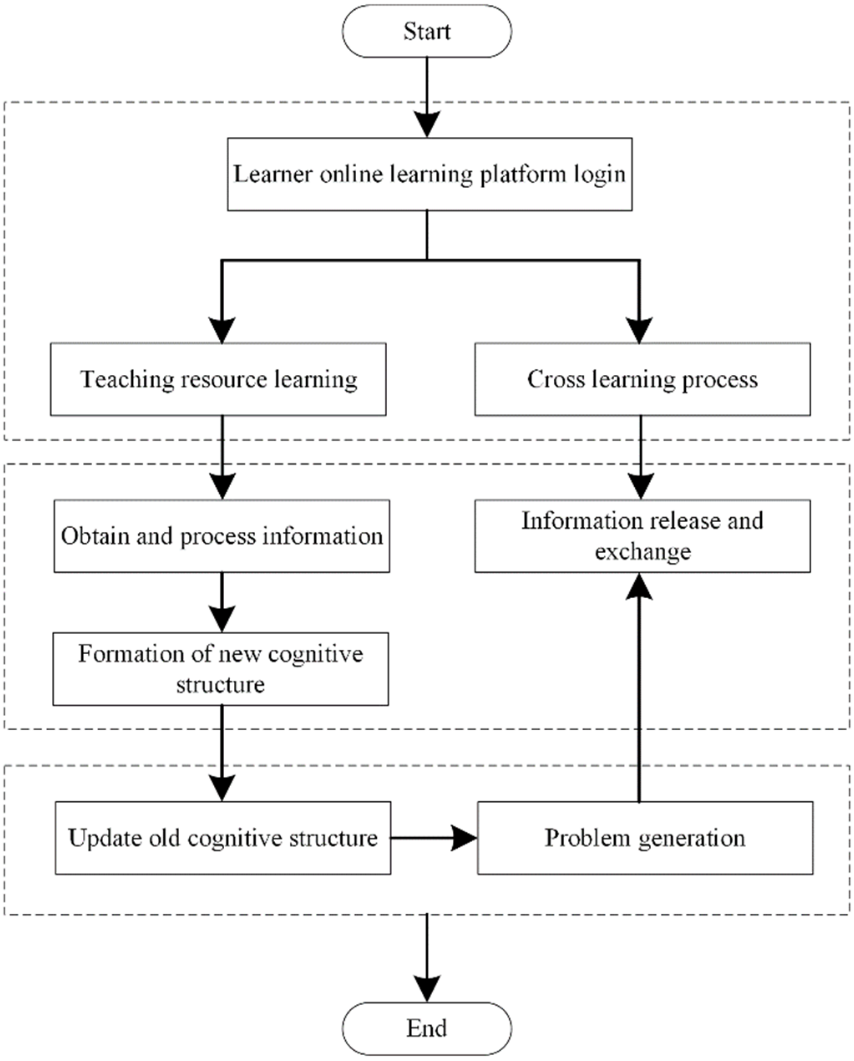

Fig. 2. Flow chart of online learning behaviors of college student

According to the different categories identified in the process of the data collection of online learning behavior, the online learning behavior process described in Figure 2 can be summarized into four stages: login trajectory, core learning, social interaction, and learning evaluation. Based on this process, we can set the evaluation indicators for four stages, respectively, which are shown in Table 1.

Table 1. Stage indicators of online learning behavior

Stage	Content	Standard	Specific Properties
Stage I	Login trajectory	Attendance rate	Number and frequency of logins on the online learning platform
Stage II	Core Learning	Teaching materials	Watching times and duration
		Online learning situation	Watching the density and completion of teaching resources
Stage III	Social interaction	Participate in social interaction	Online discussion frequency
Stage IV	Learning evaluation	Completion of learning tasks	Number of submitted homework assignments Number of exams

Table 1 demonstrates that after collecting and exploring massive online learning behavior data of college students, it can specify the evaluation criteria of the four stages of college students' online learning behaviors by setting indicators to analyze the process of online learning behaviors. Then, it can reflect the influence of many learning behavior factors on the online learning effect of college students with a specific number, time, and frequency values. Based on the specific indicators of online behavior data, it can use the evaluation model to analyze the correlation between data indicators and actual learning behavior. Then, it can select learning behavior attributes with the most profound effect on the online learning performance of college students. Moreover, it can pay more attention to optimizing the attribute in the future, give full play to the important role of research on the online learning behavior of college students, and enhance the realistic significance of the research.

3.3 Online learning behavior evaluation model

After collecting the online learning behavior data of college students and setting a specific index, an evaluation model of online learning behavior can be built to present the online learning results of college students directly. The establishment of such model can clarify the evaluation objectives, methods, results presentation, and other elements. Moreover, the model can pay attention to following the changes and development of learners in the process of online learning behavior, integrate dynamic variables into the evaluation model, and reflect the evaluation results of the online learning behaviors of college students in real-time. The internal measurement criteria should be included as much as possible in the construction of the evaluation model, such as whether college students can conduct online learning independently. It can also include students' learning attitudes and motivations during online learning, as well as whether the expectations of college students for their future learning behavior are improved after completing online learning. The specific proportion weight can be calculated by Formula (1):

$$Q_{AS} = \frac{T_{max} - n}{1 + n} \tag{1}$$

In Formula (1), Q_{AS} is the set of proportion weight values of the evaluation indicators, T_{max} is the maximum eigenvalue, and n is the sum of standard values of evaluation indicators. It can examine and analyze the learning behavior based on the proportion weight value, which is as shown in Formula (2):

$$D_e = \sum \frac{B - B_{min}}{B - B_{max}} \times Q_{AS} \tag{2}$$

In Formula (2), D_e is the learning result of learning behaviors, B is the specific data of research indicators, and B_{max} and B_{min} are the maximum value and minimum values, respectively, which will obtain the final result of the research and analysis of college students' online learning behaviors. Therefore, it can conclude the operation mechanism of the evaluation model for online learning behavior. The operation includes evaluating the linear indicators of external standards and internal factors at the same time, calculating the proportion weight and forming subjective intention of learners and data reflecting of learning effect. Then, it entails providing feedback to teachers through evaluation results so that the model can become a circular research method.

4 Results analysis

4.1 Experimental parameters and objects

The experimental parameters are shown in Table 2.

Table 2. Experimental parameters

Parameters	Data
Power	≥200W
Hard disk	160GB
Response time	≤5ms
Observation angle	≥120°
Cache mode	Level 3
Storage capacity	8GB

According to the parameters described in Table 2, the process includes a comparison experiment on the examination results of the learning behavior of college students, the evaluation result of course teaching, and the accuracy of the analysis result.

According to three experimental results, it analyzes the effect of the research on the influence of virtual simulation teaching on the learning behavior of college students.

The implementation time of the evaluation survey for virtual simulation teaching was from January 2021 to December 2021. The survey scope involved students majoring in various comprehensive colleges and universities. The survey content aimed to evaluate the effect of the course learning behavior of 3000 students majoring in French.

4.2 Examination results of college students' learning behavior

To test the reliability of the research on the influence of virtual simulation teaching on the learning behavior of college students, the concept of index membership is introduced here, which is the distance between the data of college students' learning behavior and the average value of the index. When evaluating the online learning results of college students, the index membership divides the learning behavior results into different levels, and the specific values are used as the visual presentation of the online learning results of college students. Using the research method proposed in the current study, college students majoring in French were selected randomly. Then, their learning behaviors were evaluated to verify the feasibility of the designed method.

In the experimental stage, a college student was taken as the test object. This research method was used to record the index membership of the learning behavior of college students. The specific data are shown in Table 3.

Table 3. Index membership of online learning behavior of college students

Specific Index	Proportion Weight	Index Membership	Evaluation Result
Attendance	0.76	0.3	Good
Completion of watching	0.50	0.2	Good
Task performance	0.81	0.1	OK
Discuss engagement	0.35	0.5	OK
Record of bad behavior	0.09	0	Very good

According to the data in observation Table 3, this college student performed well in attendance, watching resources and videos, and avoiding bad records. Meanwhile, the effect of homework completion and engagement discussion was not ideal. Based on the data in Table 1, the results of the final examination were predicted and calculated. The method of this research was used as the experimental group, and methods in reference [7] and reference [8] were selected as the control group to compare with the actual results of college students. To ensure the reliability of the experimental results, five courses of college students were selected for the test, namely, Basic Corresponding Language, An Introduction to Linguistics, The Theory and Practice of Translation, French Writing, and French through Watching, Listening, and Speaking. Table 4 shows the test results of this research.

Table 4. Comparison of the expected score and actual final exam score

	Actual Score	Method of this Study (Score)	Reference [7] (Score)	Reference [8] (Score)
Basic Corresponding Language	92	91	83	86
An Introduction to Linguistics	90	90	87	85
The Theory and Practice of Translation	96	95	89	84
French Writing	94	95	85	87
French Through Watching, Listening & Speaking	92	93	89	88

Table 4 demonstrates that the actual final exam scores of the method of this research are all above 90 points, while the academic scores of college students are not more than 90 points after adopting the methods of reference [7] and reference [8]. Meanwhile, the error of the method of this research is controlled within 1 point, while the error of the methods of reference [7] and reference [8] is quite different, with a maximum difference of 12 points. Compared with the method in the reference, the error of the method of this research is reduced by 11 points, thus indicating that the method of this study has a good effect and can improve the academic performance of college students.

4.3 The evaluation result of course teaching

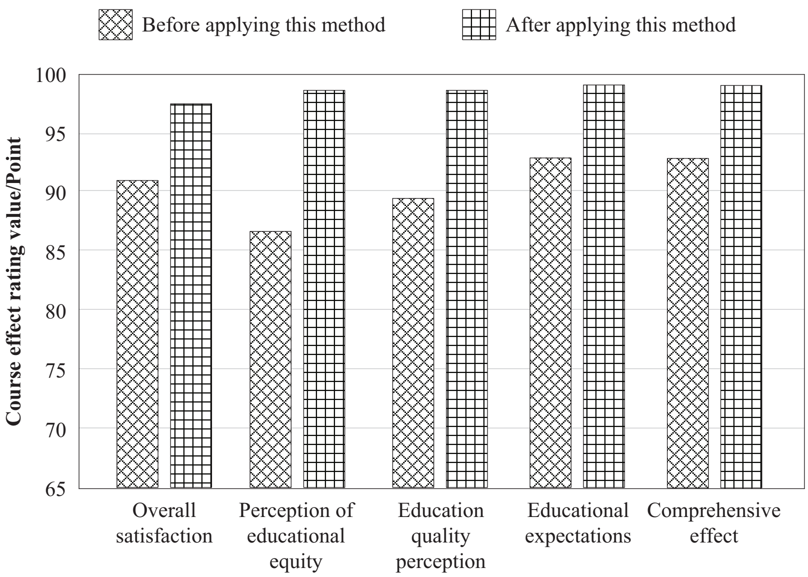

Fig. 3. The evaluation statistics of practice course teaching reform

The experiment part of the virtual simulation teaching course will check and evaluate the network configuration of the virtual simulation teaching course, the execution of the virtual simulation teaching task, and other contents according to tasks and requirements stipulated in the teaching syllabus. Combined with the statistical results of the index membership of college students' online learning behavior, it can obtain the teaching evaluation and conclusion of French courses after adopting the method of this study, which is shown in Figure 3.

In Figure 3, the comparison of college students' satisfaction before and after the reform of the French course teaching reveals that the application of this method can improve the overall satisfaction of experimental courses. In addition, the satisfaction degree of college students' perception of education fairness, comprehensive effect, quality perception, and education expectations can be improved to different degrees, which helps build active awareness of college students to learn French courses.

4.4 Comparison experiment of the accuracy of analysis results

The comparison experiment of the accuracy of the analysis results is shown in Figure 4.

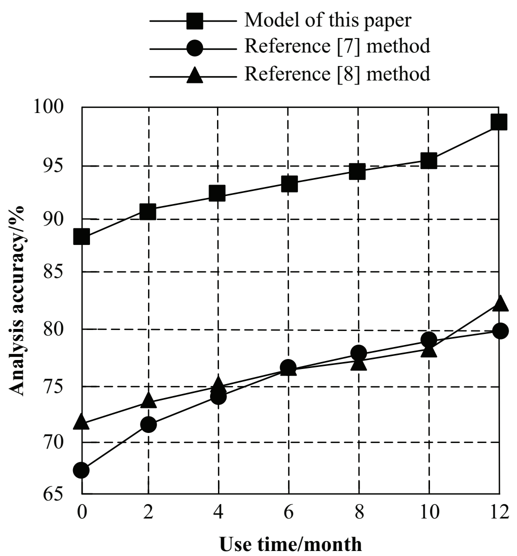

Fig. 4. Comparison experiment of accuracy of analysis results

Based on Figure 4, when the application time is two months, the accuracy of the analysis results of the methods from reference [7] and reference [8] is 72% and 74%, respectively, while the accuracy of the analysis results of the method of the current study is 91%. When the application time is six months, the accuracy of the analysis results of the methods from reference [7] and reference [8] is 77%, while the accuracy of analysis results of the method of the current study is 94%. When the application time is 12 months, the accuracy of the analysis results of the methods from reference [7] and reference [8] is 80% and 82%, respectively, while the accuracy of analysis results of the method of the current study is 99%, which indicates that the method of this study has better effect.

5 Managerial implications

5.1 Clarify the course objective of the major and adjust the planning of the virtual simulation teaching course

The course system of the applied discipline should be based on market demands and professional application. Concerning the talent position requirements, it should pay more importance to the big data application and operational personal training and rely on the cooperation between colleges and enterprises. Moreover, it should lead students to participate in the deployment of the big data platform, strengthen the development and management of the network, and help college students to use big data software. Virtual simulation teaching has been gradually applied to different industries and fields and has formed an evident development trend. Based on the above analysis, the reform plan of professional courses should be implemented from multiple directions to highlight the course reform objectives and form the characteristics of the virtual simulation teaching course.

5.2 Re-select course content of virtual simulation teaching

The virtual simulation teaching course includes Introduction to Big Data, Programming Language Design and Network Foundation, and so on. In recent years, the teaching hours of colleges and universities have been gradually reduced, and the teaching content must urgently be simplified to fit within a small number of teaching hours. According to the knowledge course system of big data, it should re-select the teaching content that is conducive to college students' further study and job needs after graduation. Under the framework of data knowledge, according to the degree of difficulty of relevant knowledge, the system should formulate reasonable major-oriented teaching content from the four aspects of class hours, theory, experiment, and practice.

5.3 Flexible use of teaching means to optimize the teaching conditions of virtual simulation teaching course

In the field of education, computer and multimedia are not only a subject but are also gradually becoming effective teaching media and teaching management means. Multimedia teaching means entails comprehensively using text, image, animation, video, audio, and other media, which has the advantages of high storage, transfer, and replication speed. The computer-related technical means can enhance the interaction of classroom teaching, increase the memory of college students in the classroom, and improve the logic of teaching to realize the integrity and unity of the virtual simulation teaching course. In addition to multimedia technology and computer technology, scenario evolution, and simulation classrooms can also be used as teaching means to apply to the actual big data classroom.

5.4 Strengthen course experiments for practice teaching and assessment method of innovation course

Virtual simulation teaching should strengthen the important position of professional application and practice in the course, introduce the actual production and development projects of enterprises, integrate social resources, and create a professional practical teaching team. According to the arrangement of the teaching hours in the course reform for virtual simulation teaching, the course of professional application accounts for 64 hours in total. This arrangement combines the practical training required for graduation and pre-job training of college students so that they can not only complete their experimental and practical tasks in school but also have a preliminary understanding of the operation process of the enterprise. The teaching of experimental practice of the virtual simulation teaching course can not only improve the application ability of college students in professional technology but also help college students to adapt to society.

6 Conclusion

As a new learning mode that breaks the barriers of time and space, virtual simulation teaching covers a variety of learning behaviors of learners. Through studying the impact of virtual simulation teaching on the learning behaviors of college students, the following research conclusions are obtained:

(1) The actual final examination scores using the method of this study are all above 90 points, which indicates that the method can improve the academic performance of college students.
(2) Study on the influence of virtual simulation teaching on the learning behavior of college students has been applied to the actual work of colleges and universities. Moreover, it has been improved in terms of course status, theory, practice, and practical training course. This improvement helps build active learning awareness of French major courses.
(3) The proposed teaching program has a good effect, which helps build active learning awareness of French major courses. The accuracy of the analysis results is 99%, which has a better effect.

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