Study on the Evaluation Method of Blended Learning Effect Based on Multiple Linear Regression Analysis

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ABSTRACT

With the development of information technology, blended learning has been widely used in the education field, and the evaluation of blended learning effect has become one of the research hotspots. Taking the automobile theory course as an example, a blended learning process with online and offline is designed, and the main learning behaviors that affect learning effect are analyzed. By extracting data on the main learning behaviors of students during the learning process, correlation and linear regression methods are used to analyze the influencing factors of blended learning effect, and a linear regression prediction model is established. The results show that students' online testing, classroom performance, unit testing, feature assessment, and experimental performance are key indicators for predicting learning performance. According to the analysis of influencing factors of blended learning, the countermeasures and suggestions for improving the effect of blended learning are proposed.

KEYWORDS

Blended Learning, Correlation Analysis, Learning Effect, Multiple Linear Regression

Blended learning, originally defined as the combination of multiple learning methods, is not a new concept in terms of its connotation (Cleveland-Innes et al., 2018; Hubackova et al., 2016). For example, combining learning methods that use audio-visual media (slide projection, audio, and video recording) with traditional learning methods such as chalk and blackboard is a relatively early hybrid learning method. With the popularization of computer networks and the introduction of e-learning (digital learning or networked learning), the rapid development of information technology in higher education has brought new meaning to blended learning, which now refers to the combination of online and offline learning and the improvement of e-learning through face-to-face teaching. In this learning mode, the advantages of traditional learning methods and e-learning complement each other.

K. He (2005) of Beijing Normal University officially advocated the implementation of blended learning in domestic universities. Blended learning can balance the advantages of traditional learning

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methods and online learning, not only playing a leading role in guiding and inspiring teachers but also fully reflecting the initiative, enthusiasm, and creativity of students as the main elements of the learning process. Better learning results can be achieved by combining these two learning methods and allowing their advantages to complement one another. Research has shown that blended learning can significantly improve teaching quality.

The learning effect results from individual psychological and behavioral changes caused by learning (Bowyer, 2017). As blended learning is a new learning mode, researchers must evaluate its effectiveness (Thurab-Nkhosi, 2019), analyze its influencing factors, understand students' individual learning situations, promote teaching reflection, and guide teaching improvement.

In order to improve the outcomes of blended learning, this study takes the blended teaching of automotive theory as a case study. It uses the multiple linear regression method to evaluate the effect of hybrid learning, analyze its influencing factors, and make suggestions for improvement.

ANALYSIS OF INFLUENCING FACTORS OF BLENDED LEARNING EFFECT

Factors Influencing the Effectiveness of Blended Learning

Learner Characteristics

Learner characteristics are important factors that affect blended learning (Kiezebrink, 2021). G. Wang et al. (2021) used the path "demographic factors → cognitive factors → emotional factors → willpower factors → behavioral factors" to analyze the impact of multiple factors on the blended learning effect by using multiple linear regression methods. Lv (2022) analyzed learners' characteristics based on the five dimensions of "basic characteristics—cognition—emotion—will—behavior," classified learners, and analyzed the impact of learners' characteristics on learning outcomes.

Learning Behavior

Jia et al. (2014) argued that online learning performance is related to indicators such as time spent online, number of times watching videos, number of times viewing web pages and browsing and downloading lectures,average test scores, forum participation, and learning start time. Zong et al. (2016), Jiang et al. (2015), He and Wu (2016), and others have also analyzed the factors influencing online learning effectiveness. Yang (2022) studied and analyzed the correlation between students' online learning behavior and their final exam scores in terms of four aspects—namely, the number of times they entered the classroom, the number of times they participated in discussions, the duration of online learning, and the number of times they read the teaching materials of the course—to measure the relationship between online learning behavior and learning effectiveness. The above research mainly analyzed the impact of online learning behavior on learning outcomes without considering classroom teaching situations.

Other Factors

Zhang et al. (2021) conducted a questionnaire survey to investigate the effects of learner characteristics, curriculum characteristics, technical characteristics, cognitive usefulness, and cognitive ease of use on blended learning outcomes. Zhang (2022) utilized group experiments and empirical analysis to evaluate the impact of online learning groups, online homework, and their different combinations on teaching effectiveness among college students. Gao and Liu (2021) constructed a multiple linear regression model to analyze the impact of online teaching videos, online assignments, online tests, and offline classroom teaching on the teaching effectiveness of university mathematics courses.

Based on the above analyses, many factors affect teaching effectiveness in the blended online and offline teaching mode, and these must be considered comprehensively.

Blended Learning Design for Automotive Theory

In the context of the application of information technology in teaching, this study takes the automobile theory course of Linyi University as a case study for practice and exploration to improve the effectiveness of blended learning.

Automobile theory is a core course for automotive majors, such as vehicle engineering and automotive service engineering, playing an essential role in the professional curriculum. The main teaching content involves performance related to vehicle dynamics, including evaluation indicators, calculation methods, and influencing factors. With the development of student abilities as the core of the teaching process, adhering to the laws of education, teaching, and student growth, making full use of a variety of online and offline resources, and implementing a blended learning model, the course aims to combine online autonomous learning with classroom learning, with teachers playing the leading role and students serving as the body of learners.

The organization and implementation of teaching activities mainly follow a inverted classroom approach. The typical teaching process comprises three stages and twelve steps. The three stages refer to the periods before, during, and after class, and each stage has four steps, totaling twelve steps, as shown in Figure 1.

The course on automobile theory mainly comprises online resources available on the Zhihuishu website, the world's largest credit course-sharing platform, with over 1,800 members among higher education institutions in China, covering over 10 million college students. The online automobile theory course includes 85 teaching videos totaling 822 minutes, eight unit tests, and one online test. At present, the course has been open for seven semesters, covering a total of 17 selected schools, over 1,400 participants, and a total of 14,400 interactions. The automotive theory online course is rich in resources and can support the application of blended learning.

Analysis of Factors Affecting Blended Learning Outcomes in Automobile Theory

According to the blended learning design of the automotive theory course, students' behaviors related to learning effectiveness can be divided into seven stages: online course registration and login, online autonomous learning, online testing, online communication, classroom learning, after-school testing, and course practice. In the blended learning process, students carry out 17 typical learning behaviors, as shown in Table 1.

### Online Course Registration and Login

The online course in automotive theory requires students to register before logging in, and then they can start learning the instructional content online. Registration time refers to the start time of online learning, and the last login time denotes the end of online learning. The number of days between the two times represents the number of online learning days but not the number of effective learning days. The number of available logins represents the number of effective learning times.

Online Autonomous Learning

Video is the most crucial learning resource in online courses. Watching videos and completing exercises is the automotive theory course's primary method of autonomous online learning. Here, online video learning is represented by four indicators: number of learning videos viewed, video learning duration, learning progress, and regular learning days.

Video learning duration is the total time students have spent watching all videos. The learning progress is the total time students have spent watching learning videos divided by the total time of all videos in the course, which reflects the completion of course resources. A student's effective online learning duration of more than 25 minutes on a single day is recorded as a regular learning session. The number of regular learning days represents the student's learning habits and can indicate a deep learning situation.

Figure 1. Design for automobile theory blended learning
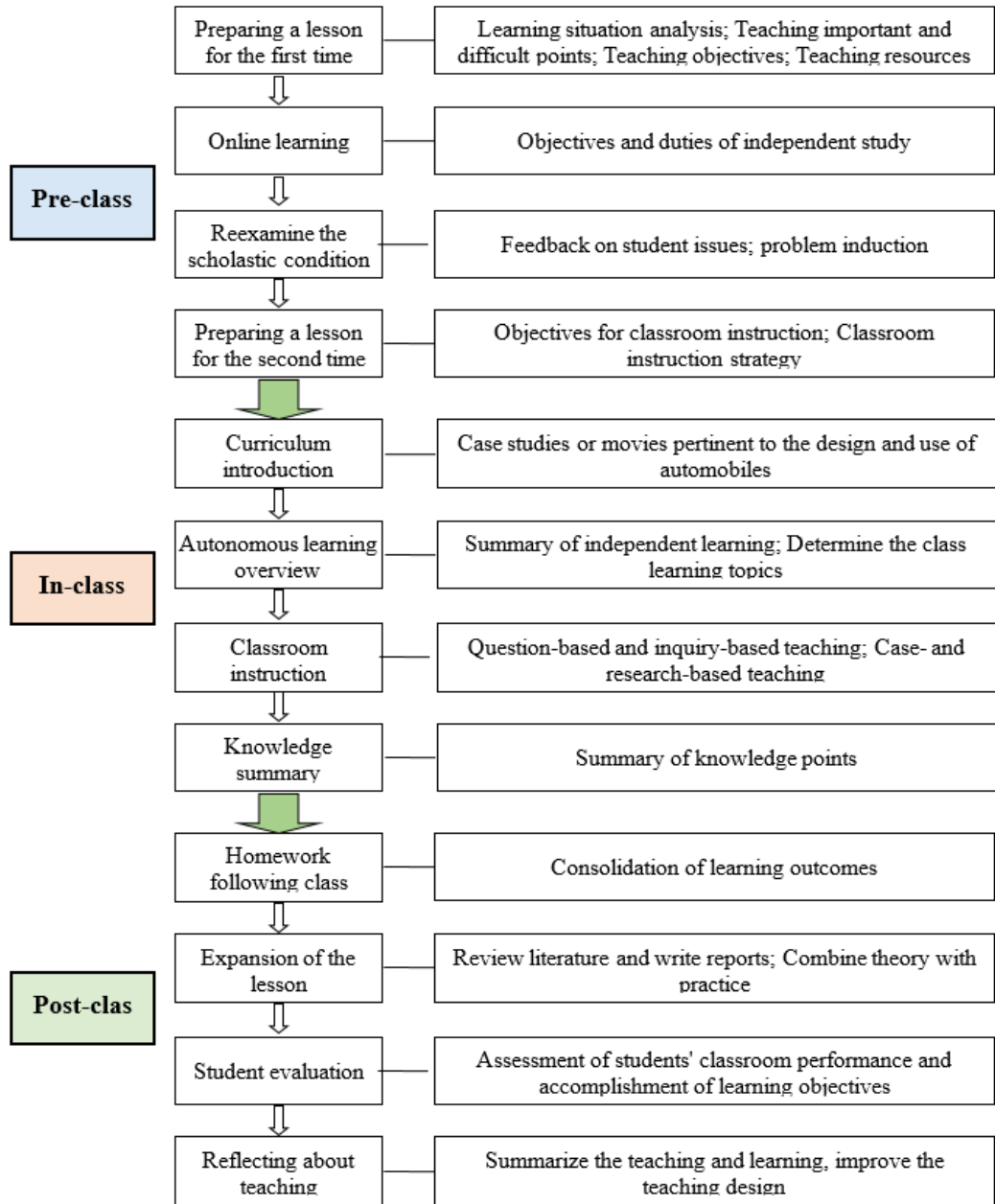
Online Homework and Testing

The learning evaluation methods for the online course in automotive theory mainly include unit tests and simulation tests, with two indicators selected: completion times and test scores. The number of test completion times represents the degree of learning task completion. Test scores comprise unit test scores and simulation test scores in proportion, indicating the quality of learning completion.

Table 1. Blended learning behaviors in the automobile theory course

Learning Process	Behavior Indicator	Indicator Code	Data Source
Online course registration and login	Online course registration time	B_ORR	Online course export
	Last login time	B_ORL	Online course export
	Online course days	B_ORD	Online course data calculation
	Number of online course logins	B_ORN	Online course data count
Online autonomous learning	Number of learning videos	B_OLN	Online course data count
	Video learning duration	B_OLT	Online course export
	Learning progress	B_OLP	Online course export
	Regular study days	B_OLD	Online course export
Online testing	Number of tests	B_OTN	Online course export
	Test performance	B_OTS	Online course export
Online communication	Number of interactions	B_OCN	Online course export
Classroom learning	Number of participation	B_CLN	Rain Classroom derivation
	Classroom performance	B_CLS	Rain Classroom derivation
Review testing	Unit test	B_ATU	Test record
	Characteristic assessment	B_ATC	Test record
Course practice	Number of participation	B_CPN	Laboratory course record
	Experimental results	B_CPS	Experimental report record

Online Communication

The online course on automotive theory includes an exchange area where students can communicate with teachers and other students in a forum. The number of interactions is the total number of questions and responses that students have effectively answered in the course, representing the students' enthusiasm for interaction.

Classroom Learning

Classroom performance is mainly based on classroom quizzes. The teacher designs the in-class quiz questions based on the classroom teaching content included during lesson preparation. They are sent to students through Rain Classroom and submitted within a limited timeframe.

After Class Test

The unit test takes the average value of multiple assignments. The featured assessment items include tools such as learning notes, software simulation, experimental schemes, and innovative designs, which students can choose to complete.

Course Practice

Both theory and practice are emphasized in the course on automobile theory. Course practice mainly refers to experiments and student assessment. The course has three experiments, which students must complete in groups during class, after which they must submit experimental reports.

Evaluation Method of Learning Effect

This study aimed to assess the blended learning effect of the automobile theory course, analyze the influence factors, and assist instructors in providing higher-quality instruction. Based on the learning behavior and associated data in the blended learning process, a multivariate linear regression model was used to assess the causal link between variables and determine the primary elements that influence the success of blended learning.

Model for Multiple Linear Regression

Linear regression is a commonly used regression analysis method that uses the linear relationship between independent and dependent variables. It can comprehend and interpret the meaning of each variable based on coefficients and has the advantages of quick modeling speed and sensitivity to outliers (Guo et al., 2022). It is frequently employed in various domains, including model interpretation, economic forecasting, and medical diagnostics (Wang, 2021; J. Wang et al., 2021). The multiple linear regression mathematical model is shown in Equation 1.

$$y = \alpha + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n + \varepsilon \tag{1}$$

Its matrix form is as follows:

$$y = \alpha + x\beta + \varepsilon$$

where $y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$, dependent variable; $\alpha = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{bmatrix}$, intercept; $\beta =$, estimated coefficient;

$x = \begin{bmatrix} x_{11} & x_{12} & x_{1n} \\ x_{21} & x_{22} & x_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ x_{n1} & x_{n2} & x_{nn} \end{bmatrix}$, independent variable; $\varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}$, error term.

It is assumed that there is no multicollinearity between independent variables, that the error terms are independent of each other, and that they all follow the same normal distribution. Changes in dependent variables can be explained in two parts: the linear part of the equation, $\alpha + x\beta$, and the random error term ε. The most commonly used estimation method for the parameter β is the ordinary least squares (OLS) estimation method (Liu et al., 2022), whose objective function is shown in Equation 2.

$$Q(\beta) = \sum_{i=1}^{n} || y_i - x_i\beta ||^2 \tag{2}$$

In order to analyze the effects of blended learning in automobile theory and its influencing factors, this study employed a multiple linear regression model. Assuming that learning achievement y is the dependent variable and the influencing factors, x_1, x_2, x_3, ……, x_n, are the independent variables, a multiple linear regression equation was established.

Analysis of Variable Correlation

This study selected data from the autumn semester of 2022 of the automobile theory course. It used the 17 indicators mentioned above as independent variables and conducted screening and analysis.

Variable Filtering

In practice, students can continue to access the online course after the exam, so it was necessary to check the final exported login time of the online course. If this occurred after the exam, the final login was uniformly set to the exam day. The number of study days correlates closely with the registration time and last login for the online course; thus, only the number of study days was chosen for these three variables.

Only one learning progress or online learning duration variable could be chosen since online learning progress = video learning duration / total video learning duration. Learning progress was used in this instance. After the analysis, the vast majority of students were found to have studied all the videos, so the parameter number of videos learned was ignored.

The online course on automobile theory includes 9 tests. According to the analysis of the original data, most students could complete those tests, with less than 8% completing in fewer than 8 tests. The independent variable of test times was therefore removed.

The participation times and performance scores in classroom learning were derived from Rain Classroom. Each student participated roughly the same number of times; hence this variable was not considered.

Every student conducted three experiments, so the parameter involving the number of practice participation times was eliminated.

Ten independent variables were selected for the specific analysis, including the number of online learning days B_ORD, online course login times B_ORN, online course learning progress B_OLP, the number of regular learning days for online courses B_OLD, the number of online test scores B_OTS, the number of instances of online communication and interaction B_OCN, classroom performance score B_CLS, unit test score B_ATU, characteristic assessment score B_ATC, and experiment score B_CPS.

Correlation Analysis

The correlation analysis was conducted on the 10 selected learning indicators and academic achievement, and the results are given in Table 2.

Multiple Collinearity Diagnosis and Principal Component Analysis

Multiple collinearity describes the correlation between explanatory variables in a model. If a model has multiple collinearity, the analysis results may be inaccurate. Therefore, it is necessary to diagnose whether there is multiple collinearity in the model so measures can be taken to correct it.

The main diagnostic indicators for multiple collinearity include tolerance (T) and variance inflation factor (VIF, F). If the tolerance is less than 0.1—that is, the variance expansion factor VIF is greater than 10—it indicates collinearity between the independent variables and vice versa. The results of collinearity statistical diagnosis among factors affecting the effectiveness of blended learning in the automobile theory course are given in Table 3.

Analysis of Multiple Linear Regression

The seven variables are adopted, namely, B_OLD, B_OTS, B_OCN, B_CLS, B_ATU, B_ATC, B_CPS. The multiple linear regression method was used to analyze the impact of those variables on blended learning performance. The analysis results are given in Table 4.

A strong correlation can be seen between the dependent variable automobile theory student achievement and the independent variable, with $R^2 = 0.777$, indicating that the linear regression model

Table 2. Correlation analysis between blended learning effect and various factors

	Item	Y_SCOR	B_ORD	B_ORN	B_OLP	B_OLD	B_OTS	B_OCN	B_CLS	B_ATU	B_ATC	B_CPS
Y_SCOR	Pearson Correlation	1	.340**	.613**	.302**	.506**	.635**	.602**	.741**	.513**	.613**	.589**
	Sig. (2-tailed)		0.000	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000
B_ORD	Pearson Correlation	.340**	1	.428**	.423**	.405**	.217*	0.171	.462**	.246*	.236*	0.185
	Sig. (2-tailed)	0.000		0.000	0.000	0.000	0.027	0.082	0.000	0.012	0.016	0.061
B_ORN	Pearson Correlation	.613**	.428**	1	.617**	.929**	.451**	.681**	.578**	.367**	.468**	.407**
	Sig. (2-tailed)	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
B_OLP	Pearson Correlation	.302**	.423**	.617**	1	.450**	.248*	.264**	.279**	0.132	.279**	.231*
	Sig. (2-tailed)	0.002	0.000	0.000		0.000	0.011	0.007	0.004	0.183	0.004	0.018
B_OLD	Pearson Correlation	.506**	.405**	.929**	.450**	1	.393**	.429**	.515**	.314**	.386**	.296**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.001	0.000	0.002
B_OTS	Pearson Correlation	.635**	.217*	.451**	.248*	.393**	1	.381**	.523**	.283**	.240*	.436**
	Sig. (2-tailed)	0.000	0.027	0.000	0.011	0.000		0.000	0.000	0.004	0.014	0.000
B_OCN	Pearson Correlation	.602**	0.171	.681**	.264**	.429**	.381**	1	.496**	.370**	.425**	.466**
	Sig. (2-tailed)	0.000	0.082	0.000	0.007	0.000	0.000		0.000	0.000	0.000	0.000
B_CLS	Pearson Correlation	.741**	.462**	.578**	.279**	.515**	.523**	.496**	1	.418**	.628**	.379**
	Sig. (2-tailed)	0.000	0.000	0.000	0.004	0.000	0.000	0.000		0.000	0.000	0.000
B_ATU	Pearson Correlation	.513**	.246*	.367**	0.132	.314**	.283**	.370**	.418**	1	.209*	.314**
	Sig. (2-tailed)	0.000	0.012	0.000	0.183	0.001	0.004	0.000	0.000		0.033	0.001
B_ATC	Pearson Correlation	.613**	.236*	.468**	.279**	.386**	.240*	.425**	.628**	.209*	1	.322**
	Sig. (2-tailed)	0.000	0.016	0.000	0.004	0.000	0.014	0.000	0.000	0.033		0.001
B_CPS	Pearson Correlation	.589**	0.185	.407**	.231*	.296**	.436**	.466**	.379**	.314**	.322**	1
	Sig. (2-tailed)	0.000	0.061	0.000	0.018	0.002	0.000	0.000	0.000	0.001	0.001	

** Correlation is significant at the 0.01 level (2-tailed). * Correlation is significant at the 0.05 level (2-tailed).

Table 3. Results of collinearity diagnosis for various factors of blended learning effect

Indicator	Collinearity Statistics	
	Tolerance	VIF
B_ORN	0.000	5489.024
B_OLP	0.004	266.011
B_OLD	0.000	2619.222
B_OTS	0.604	1.656
B_OCN	0.002	588.109
B_CLS	0.375	2.664
B_ATU	0.758	1.319
B_ATC	0.527	1.898
B_CPS	0.675	1.481

has a good fit. This means that the results of this analysis reliably reflect the impact of influencing factors on academic performance.

Two parameters were discarded after the multiple collinearity analysis, and then the collinearity statistics were performed again. The tolerance values for each factor were greater than 0.1, and the VIFs were less than 10, indicating that the collinearity was eliminated. The Durbin–Watson test value was 1.896, which is relatively close to 2, indicating that the observations of linear regression in this study have strong mutual independence.

Table 4. Results of blended learning linear regression analysis

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
Constant	20.390	5.267		3.872	0.000		
B_OLD	0.026	0.063	0.025	0.420	0.675	0.672	1.487
B_OTS	0.145	0.033	0.269	4.407	0.000	0.621	1.611
B_OCN	0.131	0.069	0.116	1.883	0.063	0.610	1.640
B_CLS	0.099	0.034	0.227	2.946	0.004	0.392	2.549
B_ATU	0.154	0.047	0.180	3.267	0.002	0.760	1.316
B_ATC	0.174	0.045	0.249	3.847	0.000	0.553	1.810
B_CPS	0.135	0.042	0.188	3.217	0.002	0.681	1.469

Dependent Variable: Y_SCOR
R^2 0.777 Adjusted R^2 0.761 Durbin-Watson 1.896
F 47.872 Sig. 0.000

The regression equation was significant (F = 47.872), where the P values of the five independent variables, namely B_OTS, B_CLS, B_ATU, B_ATC, B_CPS, were less than 0.01, which means that they significantly affect the behavioral willingness of the dependent variable. By contrast, B_OLD and B_OCN showed poor significance.

The regression equation between learning performance and learning behaviors was obtained, as shown in Equation 3.

$$Y\_XXCJ = 49.529 + 0.436*V\_DLCS + 0.202*V\_CSCJ + 0.647*V\_HDCS \tag{3}$$

The standardized residual histogram of automobile theory blended learning scores is shown in Figure 2. It can be seen that the dependent variables exhibit good normal distributional properties.

The normalized residual normal probability diagram is shown in Figure 3, which approximates a straight line and has a good normal distribution.

The scatter plot is shown in Figure 4. The fitting lines are basically parallel to the abscissa, and the residuals are homogeneous.

Discussion of Results

The findings of a correlation analysis and linear regression analysis of online course learning performance and various learning behaviors demonstrated that students' online tests, classroom performance, unit tests, feature assessments, and experimental practices are key indicators for predicting learning performance. In addition, regular learning days and online communication also play a role. Accordingly, to improve the learning effect of online courses, the following suggestions are proposed.

Improve Students' Autonomous Learning Ability

Online test results reflect the daily learning effect and autonomous learning ability of students taking online courses and play an essential role in learning performance. As a result, it is necessary to upgrade the online learning resources continuously that better match students' demands. The design of exam questions is more scientific, standardized, and targeted, which can accurately reflect students' learning.

In addition, regular learning days and online interactive communication in online courses also contribute to learning efficiency and reflect students' capacity for independent learning. Developing

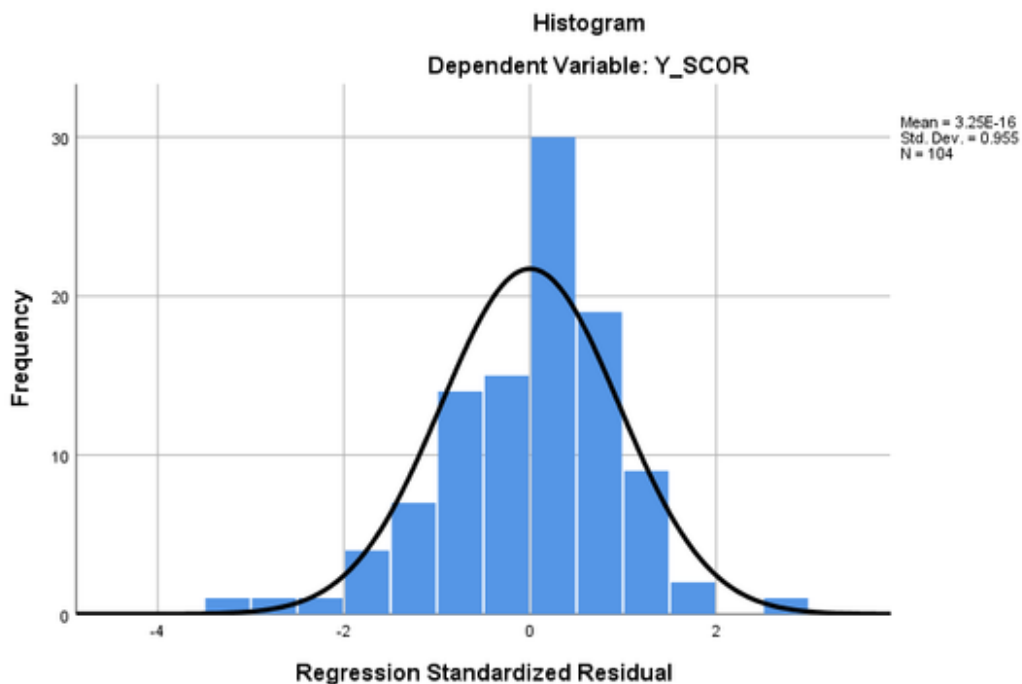**Figure 2. Standardized residual histogram of blended learning scores**

Figure 3. Normalized residual normal probability diagram
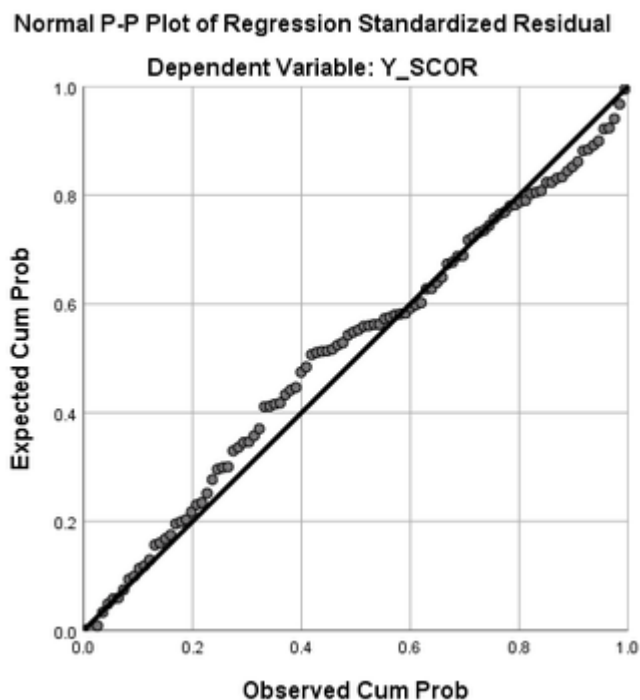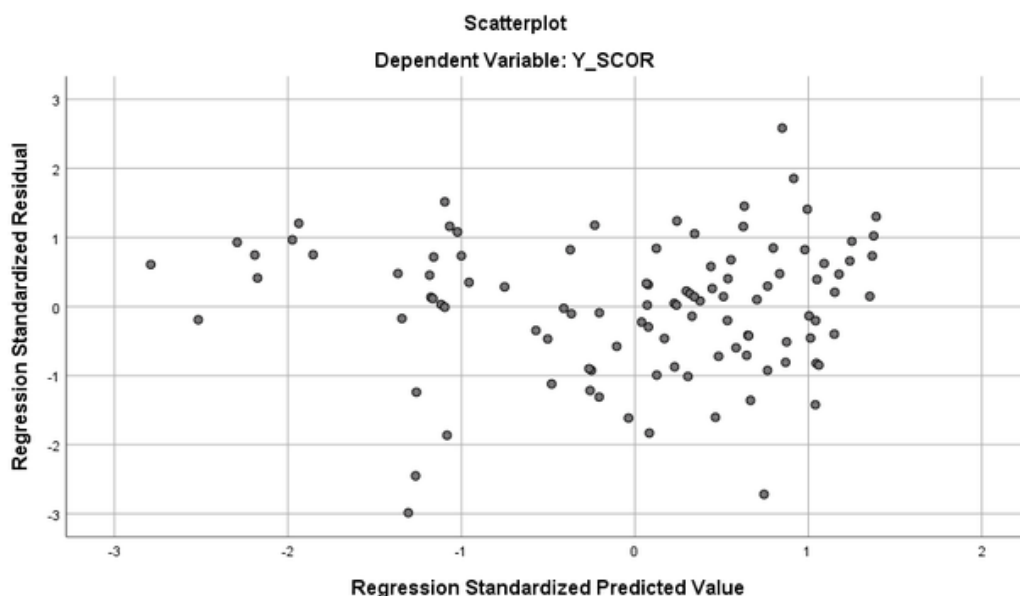
Figure 4. Standardized residual scatter diagram

time management skills is an important learning strategy that improves students' learning ability. However, surveys have revealed that ineffective time management and low learning efficiency are the main challenges of taking online courses. Therefore, it is necessary to continually enhance the design of online video instructional materials, improve teaching quality, motivate students to increase their participation in online courses, and help them develop effective learning habits.

The most extensive and productive method of communication between lecturers and students in online courses involves online engagement. This method is not appropriate for real-time discussions; however, it is not constrained by time or place, and because the information is open and shared, participants can communicate as they go. Interaction in online course forums is crucial for information transfer. In order to enhance students' enthusiasm for participation, teachers should list discussion topics based on course characteristics and learning conditions, guide student discussions, and create a good atmosphere for communication. They can establish an effective feedback system, keep abreast of students' learning and communication, make timely comments, and encourage students to participate actively.

Establish a Dominant Position for Students in the Classroom

Students' classroom performance also plays a particular role in their overall performance, so it is necessary to improve their performance, establish their dominant position, and actively participate in educational activities.

Firstly, it is essential to fully utilize information technology, enhance instructional design, employ suitable teaching techniques, and direct students' interests in accordance with the teaching content and features. Secondly, it is important to scientifically construct instructional problems, combine theory and practice, and help students develop critical thinking skills. Thirdly, students can be divided into groups, and self- and mutual evaluation exercises can foster competition and encourage pupils to participate.

Pay Close Attention to the Process Assessment of Students

According to the using performance of an automobile, the course content of automobile theory can be organized into various teaching units. Unit testing is one crucial process assessment method that evaluates learning effectiveness over time. It can be used to better understand students' learning situations, provide direction and references for further teaching, and improve teaching design.

In order to fully utilize the feedback effect of unit testing, it is possible to introduce student value-added evaluation, track changes in student learning, establish targeted guidance and plans, and encourage students to develop comprehensively.

Widen Student Self-Selected Assessment Projects

Students can complete projects such as software simulation and experimental scheme design for characteristic assessment, which primarily evaluates students' aptitude for innovation and engineering practice and their capacity to use the knowledge they have learned to analyze issues and solve complex engineering problems in the workplace.

In order to provide students with more assessment projects, after the first class, students are given an assessment project based on teaching content, cutting-edge knowledge of the subject, teacher research, and other content. According to their interests, students can select one of these projects to finish for characteristic evaluation.

Cultivate Students to Combine Theory and Practice

Student experiments have a significant impact on learning outcomes, indicating that experimental practices have a catalytic effect on course learning. Firstly, experiments can be used to promote students' better understanding of the professional knowledge they have learned; secondly, conducting experiments can help improve students' initiative and enthusiasm for learning.

Based on experiments conducted in class, additional professional practice opportunities can be offered to better train students to connect their theories with practice. First, the teaching can be combined with innovative disciplinary competitions, such as car production and debugging. Second, the students can visit and practice at a car testing station to connect with actual production practices.

CONCLUSION

With the development of information technology and the construction and improvement of online course resources, the blended learning mode has become not only possible but also essential in higher education. Indeed, it has become the new "normal" in teaching. In order to improve the effectiveness of blended learning, this study analyzed the relationship between students' learning behaviors and academic achievement in the process of blended learning. The primary influencing factors of learning effectiveness were analyzed using multiple linear regression analysis methods, and a regression model was established. This method can effectively predict the effectiveness of blended learning and verify the practical value of linear regression analysis methods in the reform of blended learning teaching.

In the process of model construction and analysis, large amounts of data from effective learning behaviors are essential. An authentic and reliable model could be constructed only by refining various learning behavior data. Therefore, future research should continue mining various online and offline teaching data, pay attention to additional data mining techniques and analysis methods, deeply interpret the analysis results, and improve the blended learning achievement prediction model. In addition, a blended learning achievement prediction model can offer real-time early warnings regarding students' learning situations, provide targeted push services, and further improve learning effectiveness.

COMPETING INTERESTS

The authors of this publication declare there are no competing interests.

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