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An Iterative Optimization Algorithm Study of Virtual Reality Technology in Self-Efficacy Enhancement for College Students

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ABSTRACT

This paper discusses the application of virtual reality technology in enhancing college students' self-efficacy and proposes an iterative optimization algorithm based on learning experience. By analyzing self-efficacy, the application of virtual reality technology machines in education, and combining relevant theories and empirical studies, the structural equation model of virtual reality technology influencing college students' self-efficacy is constructed. The original structural equation model is optimized by using algorithms such as stochastic gradient descent method and stochastic average gradient, and the effectiveness of the algorithms is verified through experiments. This paper concludes that virtual reality technology can significantly improve college students' self-efficacy, and the proposed iterative optimization algorithm can effectively improve the prediction accuracy and fit of the original structural equation model.

Keywords: iterative optimization algorithm, stochastic gradient descent, stochastic mean gradient, self-efficacy

1. Introduction

In the course of university, students' self-consciousness develops rapidly, and they are concerned about the acquisition of knowledge and skills, as well as changes in social status and future survival, especially about others' evaluation of themselves and their status in the group [1-2]. However, due to various subjective and objective reasons, these needs are often difficult to meet, affecting the healthy development of students, especially the development of self-efficacy. It is necessary for colleges and universities to carry out the cultivation of students' self-efficacy in teaching methods and teaching modes, and strive to achieve the purpose of cultivating and molding students through the enhancement of their psychological literacy and ideology [3-5].

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Self-efficacy comes from personal perception and involves a variety of knowledge in psychology and sociology, and is the degree of confidence an individual has in his or her ability to perform a certain behavior in a specific situation [6-7]. Because of the different abilities and skills involved in different behaviors, an individual's self-efficacy is not static, and can vary in high and low levels due to differences in behaviors. Self-efficacy is an individual's speculation and judgment about his or her ability to perform a behavior. It refers to the individual's subjective feelings about his or her ability rather than the ability itself. It also refers to the individual's prediction and subjective feelings about his or her ability to perform a behavioral action before performing it. Individuals with low self-efficacy doubt their own ability and do not result in the behavior even if they have the ability to perform the task [8-10]. Individuals with higher self-efficacy, on the other hand, choose to act, have greater persistence when encountering difficulties, and are more able to break through and complete the task [11-12].

There are many factors that affect individual self-efficacy, and it is because of the existence of these factors that individual self-efficacy is in a long-term change. Therefore, if these influencing factors can be effectively grasped, the self-efficacy of individuals can be influenced by the pull of external forces, thus achieving the purpose of cultivating college students' self-efficacy [13-14]. Specifically, the factors affecting individual self-efficacy mainly include the following aspects, the acquisition of a sense of achievement, the acquisition of experience, the acquisition of opinions, and the acquisition of bad emotions [15-16].

After students enter the university, although they live in the same environment and learn the same knowledge, they will gradually become different in their ideological understanding and personal psychology, mainly because there are differences in students' self-perception, and different students have different interests and hobbies, so there will be a big difference in their exposure to culture, ideas, values and so on [17-18]. Moreover, college campuses focus on tolerance and inclusion, and within the school, Chinese and Western thinking coexist, and old and new cultures collide, which also creates conditions for students to grow differently. Although the internal environment of colleges and universities can give students a more free and diversified development, it also aggravates students' confusion about life to a certain extent, especially some students who have just entered the campus will gradually question their original ideology in the collision of ideas and cultures, which leads to problems in self-improvement and self-development of students [19-21]. In view of this, schools should pay attention to the cultivation of students' self-efficacy, with the help of self-efficacy, so that students can better adapt to the environment, so that they can adjust their behaviors in colleges and universities, and can be brave enough to face the conflicts and drawbacks that exist in their lives, and from them they can find their own focus, plan their own lives, and find the right direction for development [22-23].

This paper proposes a research hypothesis by theoretically analyzing self-efficacy and virtual reality technology and virtual reality technology in the field of education. Data and information are collected using research tools such as self-efficacy scales, eye-tracking equipment and brain-wave meter equipment, and structural equation modeling is constructed to analyze the data. An iterative optimization algorithm based on learning experience is proposed, and the original structural equation model is optimized by stochastic gradient descent algorithm and stochastic mean gradient algorithm. The overall characteristics of college students' self-efficacy before the experiment are analyzed, and the differences in college students' self-efficacy in terms of gender, grade, and subject categories are explored. Structural equation modeling was used to regress the relationship between virtual reality technology, mindfulness experience and college students' self-efficacy, and the bias-corrected nonparametric percentile Bootstrap method was used to test the mediating role of mindfulness experience in the process of enhancing college students' self-efficacy by virtual reality technology, in order to fully validate the correctness of the hypotheses of this paper. The results of the self-efficacy scale scores of the experimental and control groups before and after the experiment were compared and analyzed to highlight the role of virtual reality technology in enhancing college students' self-efficacy. Taking the mean square error and goodness of fit as evaluation indexes, the changes in prediction accuracy and goodness of fit before and after the optimization of the structural equation model are analyzed to verify the effectiveness of the iterative optimization algorithm in this paper.

2. Basis and assumptions of the study

2.1. Basis of research

2.1.1. Self-efficacy. Self-efficacy theory, literally, in which "self" refers to the individual himself or herself, and "efficacy" denotes performance or usefulness in a given situation [24]. The theory suggests that individuals can make judgments about their own behavior in accomplishing a particular task. The expectations that result from this judgment can determine the individual's choices and motivation. The concept of self-efficacy captures a form of thinking in which the individual takes himself or herself as the object, and is the belief, judgment, or subjective self-feeling that the individual has about the level at which he or she is able to complete the behavioral activity prior to performing a certain behavioral operation, and self-efficacy is the judgment and the self-confidence, i.e., non-trait-based self-confidence, that an individual is in a specific domain, and the individual possesses the ability to complete the tasks and behaviors in that context. Self-efficacy is an individual's judgment and confidence in his or her ability to perform tasks and behaviors in a specific domain.

The most commonly used method for evaluating self-efficacy is the Self-Efficacy Scale (SES), which is the most widely used generalized scale for self-efficacy research with the largest number of experimental items, and scholars in various countries have gradually improved their theories based on this scale. Tests need to be carried out according to specific environments, different behavioral abilities and the needs of specific groups. Self-efficacy is not a quantitative data that can be assessed by a single figure, and the results of the test vary greatly under different circumstances and situations. A suitable self-efficacy scale needs to be constructed according to the specific situation and characteristics of the target. In order to obtain effective results in self-efficacy measurement, it is necessary to set up specific scenarios, application scenarios, and types of tasks for specific groups of people and targets, so as to enhance the accuracy of self-efficacy measurement.

2.1.2. Virtual reality technology. Virtual reality technology is a simulation of the way, generated by the computer and through the visual, auditory, tactile and other effects on the experiencer to create and experience the virtual world, so that the experiencer in the real space through the sensor collection equipment, computer hardware and the VR engine under the joint action of the three produces visual, auditory, tactile and other perceptual behaviors to produce an immersive feeling and can interact with the virtual environment, thus causing virtual environment The technology of interactive behavior that changes in real time [25]. Interactivity, experience, imagination, feedback are the main characteristics of virtual reality technology. Virtual reality technology can break through the original two-dimensional presentation, so that the space can be presented through the three-dimensional form, and through human-computer interaction to bring a sense of experience of the real environment, thus generating a sense of immersion and immersion, completely changing the traditional interaction between people and people, people and computers.

Virtual reality technology provides users with an immersive experience by simulating real-world environments and situations. In education, VR technology is used to create simulation labs, historical scene reenactments, language learning, and many other teaching activities that stimulate students' interest in learning and increase their engagement and learning outcomes.

2.2. Research hypotheses

2.2.1. Direct Impact of Virtual Reality Technology. Traditional teaching lacks contextualization and interactivity of textbook knowledge due to the limitations of the teaching environment, hardware conditions and other factors. Therefore, when students have cognitive difficulties, they are often irritated or even disgusted, which in turn affects their self-efficacy. Virtual reality technology provides curriculum resources to meet students' cognitive needs, transferring abstract "flat knowledge" to a more "three-dimensional" and "real" virtual environment, helping them to visualize scientific concepts and engage in multi-sensory immersion experiences. When students perceive that their knowledge is understood and mastered, and that they are destined to learn, a higher sense of self-efficacy emerges. Similar studies have shown that virtual reality technology can increase college students' self-efficacy. Interviews revealed that students perceived that the VR program increased their confidence to succeed in science. Based on this, the following research hypotheses are proposed:

H1: Virtual reality technology can significantly increase college students' self-efficacy.

2.2.2. The mediating role of the mindstream experience. A mindstream experience is an overall feeling that occurs when an individual is completely immersed in something or a situation. When individuals are in the state of mindstream, they are completely attracted to what they are engaged in, and they are so serious and focused on the activities they are engaged in that they forget about time, ignore other things, and are in a very happy mood and feel that time passes quickly. The application of virtual reality technology makes it easier for college students to have a mind-flow experience and feel a higher sense of self-efficacy in learning, which will make individuals more willing to engage in it. Relevant empirical studies also support the view that in learning activities, the mind-flow experience runs through the whole process of learning activities, which will have a positive and direct impact on students' self-efficacy in learning. Based on the above analysis, this paper proposes another research hypothesis:

H2: Virtual reality technology can enhance college students' self-efficacy by influencing students' mindstream experience.

3. Research methodology

3.1. Study design

3.1.1. Research Objects and Experimental Procedures. In this study, 381 study subjects were recruited through online open recruitment, all from University of T. The study subjects had normal vision in the naked eye or normal vision after correction, and had no eye diseases such as color blindness or color weakness. There was no history of brain injury or mental illness, and they were eligible for the experiment. The research subjects were informed before participating in the experiment that the relevant data collected would be used only for academic research and would not be publicized. Out of 381 questionnaires, the valid questionnaires after excluding those with too high a priori knowledge level were 352, with a validity rate of 92.39%. Among the valid participants, 44.89% (158) were male and 55.11% (194) were female. A randomized controlled experimental design was used to randomly divide the subjects into an experimental group (176) and a control group (176). The experimental group was taught using virtual reality technology and the control group was taught using traditional methods.

3.1.2. Research tools:

1) Self-efficacy scale. The scale in this study consists of four items. The background condition of "virtual reality technology" was added to the study, and a five-point Likert scale was used, with scores ranging from 1 to 5 corresponding to "not at all consistent" to "completely consistent", and the higher

the score, the higher the self-efficacy of the subject. The higher the score, the higher the self-efficacy of the subject. In this study, the Cronbach's coefficient of the scale was 0.873, indicating that the questionnaire has good reliability.

2) Eye-tracking equipment. The eye-tracking device used in this study was a Tobii Studio 3.2 software model Tobii X120 with a sampling rate of 100 Hz, which was used to record eye movement data. The eye-tracker captured learners' eye-tracking behaviors during the learning process in real time, and measured learners' engagement in the process of completing the learning task. Eye movement indicators include gaze indicators, eye jump indicators and pupil diameter indicators, among which the total gaze time, which belongs to the gaze indicators, can effectively reflect the learners' cognitive input to the learning materials. Therefore, this study chooses to use the total gaze time to indicate the degree of engagement, and the longer the total gaze time, the higher the degree of engagement of learners in the learning process.

3) Brain Wave Instrument. The brainwave instrument used in this study is the portable brainwave instrument CUBand, which collects the user's EEG signals with high precision by means of non-invasive dry electrodes, inputs real-time EEG data into the EEG training feedback system, records the brainwaves formed by the EEG signals, and collects the subjects' concentration and relaxation as well as the dynamic changes in the brainwaves in the process of learning. Concentration reflects the degree of concentration when the learner enters the concentration state, and the higher the concentration, the more concentrated the learner is. Relaxation describes the learner's emotional state of calmness or relaxation, reflecting his/her pleasure in the learning process; the higher the relaxation, the higher the learner's pleasure. The students' experience of mind flow was measured by engagement, concentration and pleasure.

3.2. Data Acquisition and Analysis

Multimodal data were collected using eye-tracking, brainwave meter and other devices, including college students' self-efficacy, engagement, concentration and pleasure of the mindstream experience. Structural equation modeling was used to analyze the data and verify the research hypotheses of this paper.

4. Iterative optimization algorithms

4.1. Algorithm design

In order to optimize the effectiveness of the application of virtual reality technology in enhancing college students' self-efficacy, this study proposes an iterative optimization algorithm based on learning experience. The algorithm includes the following steps:

1) Initialization parameters. Set parameters such as learning rate and iteration number.

2) Data preprocessing. Preprocess the collected multimodal data, including data cleaning, feature extraction and so on.

3) Model construction. Based on the hypothetical model of virtual reality technology affecting self-efficacy, construct the structural equation model.

4) Algorithm optimization. Algorithms such as SGD and SAG are used to optimize the model [26-27] to improve the fit and prediction accuracy of the model.

Among them, the algorithm formula of SGD is:

$$w_{k+1} = w_k - \alpha * \frac{\partial L}{\partial w_k} \tag{1}$$

where w_k denotes the parameter value of the k nd iteration, α denotes the learning rate, and $\frac{\partial L}{\partial w_k}$ denotes the gradient of the loss function L with respect to the parameter w_k.

The formula for the SAG algorithm is:

$$w_{k+1} = w_k - \frac{\alpha}{k} * \sum(g_i(w^j)) \tag{2}$$

where $g_i(w^j)$ denotes the gradient value of the i rd sample at the j nd iteration.

4.2. *Algorithm implementation*

The above algorithm is implemented using a programming language such as Python and the model is optimized. The optimal combination of model parameters is found by continuously adjusting the parameters such as learning rate and number of get bands.

5. Experimental results and analysis

5.1. *Analysis of college students' self-efficacy*

In order to understand the overall profile of college students' self-efficacy level, descriptive statistics were analyzed before the experiment on the self-efficacy level of college students in the experimental group and the control group, and the results are shown in Fig. 1, in which E and C denote the experimental group and the control group, respectively, and SE denotes self-efficacy. The full score value of each item of self-efficacy is 4 points, and the median value is 2.5 points. The mean value of self-efficacy of college students in the two groups is 2.38 points and 2.28 points respectively, which is lower than the theoretical median value of 2.5 points, indicating that the self-efficacy of college students is in the middle-to-lower level in general.

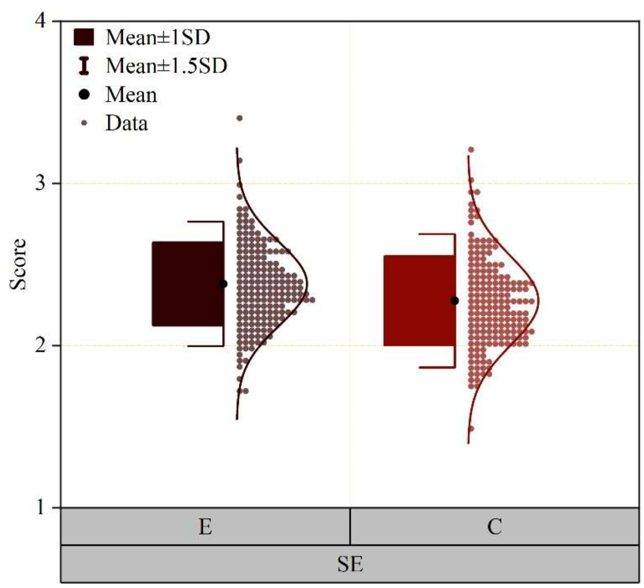


Fig. 1. Descriptive statistics of self-efficacy

5.1.1. Gender differences in self-efficacy among college students. In order to investigate whether there is a difference in college students' self-efficacy in terms of gender, the study used gender as a grouping variable and conducted independent samples t-test and statistical analysis, and the results are shown in Figure 2. In the overall self-efficacy, there is a very significant difference between males and females (P<0.01), the mean value of self-efficacy for males is 2.33, the mean value of self-efficacy for females is 1.78, and the difference in the mean value of self-efficacy between males and females is 0.55, and the mean value of self-efficacy for males is higher than that for females.

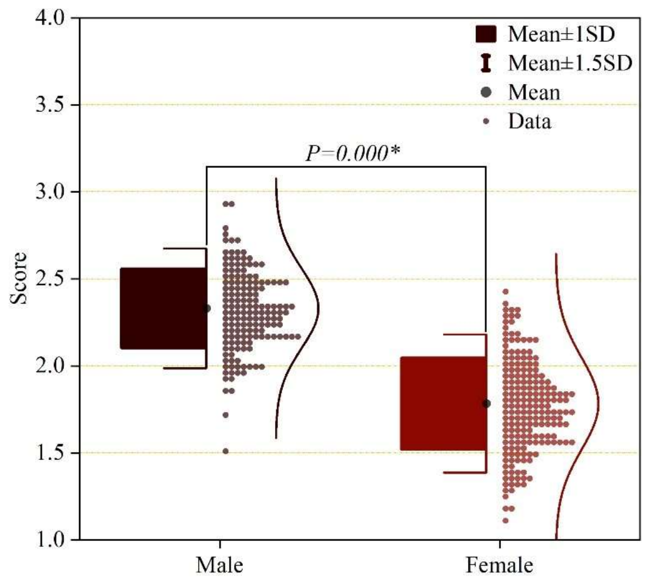


Fig. 2. Gender differences in self-efficacy

5.1.2. Grade Level Differences in College Students' Self-Efficacy. In order to investigate whether there are differences in self-efficacy among college students by grade level, the study conducted a one-way ANOVA test, and the results are shown in Table 1. There was an extremely significant difference in the overall self-efficacy of college students in different grades (p<0.001). By further multiple comparisons to analyze the specific differences in self-efficacy among university students in different grades, the results are shown in Table 2, there are significant differences between the first year of university and the second year of university, the third year of university, and the fourth year of university (P=0.026<0.05), of which the first year of university and the third year of university and the fourth year of university are significantly different from each other (P=0.000<0.001). There is a significant difference between the second year of university and the third year of university and the fourth year of university (P=0.000<0.001), and there is no significant difference between the third year of university and the fourth year of university (P=0.167>0.05). In the relationship between high and low overall levels of self-efficacy, university fourth year > university third year > university second year > university first year.

Table 1. Grade difference in self-efficacy

		Sum of squares	Freedom	Mean square	F	P
SE	Intergroup	17.483	5	5.364	112.751	0.026
	Within group	60.842	1083	0.073		
	Total	78.325	1088			

Table 2. Multiple comparisons of grade differences

Grade(i)	Grade(j)	Mean difference	Standard error	P	Confidence interval	
					Lower	Upper
Freshman	Sophomore	-0.362*	0.169	0.031	-0.638	-0.029

	Junior	-2.741*	0.173	0.000	-2.759	-2.083
	Senior	-2.728*	0.192	0.000	-3.114	-2.317
Sophomore	Freshman	0.376*	0.164	0.031	0.028	0.697
	Junior	-2.076*	0.201	0.000	-2.467	-1.682
	Senior	-2.371*	0.217	0.000	-2.796	-1.945
Junior	Freshman	2.426*	0.178	0.000	2.083	2.772
	Sophomore	2.073*	0.203	0.000	1.682	2.463
	Senior	-0.304	0.224	0.167	-0.734	0.145
Senior	Freshman	2.736*	0.198	0.000	2.315	3.118
	Sophomore	2.379*	0.219	0.000	1.928	2.794
	Junior	0.312	0.231	0.167	-0.137	0.737

5.1.3. Disciplinary categories of self-efficacy among college students. In order to investigate whether there is any difference in self-efficacy among college students in terms of disciplinary categories, the study conducted a one-way ANOVA test and statistical analysis, and the results are shown in Figure 3. There is no significant difference in the overall self-efficacy of college students in different disciplinary categories, and the means of each disciplinary category are 2.45, 2.39, 2.34, 2.31, 2.35, 2.45, 2.32, 2.38, 2.35, 2.38, 2.35, 2.32, 2.36, and 2.29, respectively.

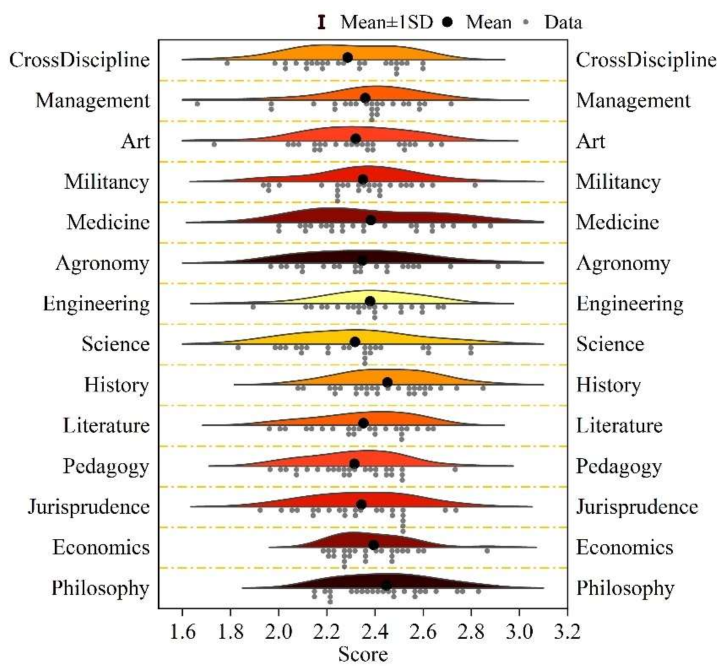


Fig. 3. Disciplinary differences in self-efficacy

5.2. Regression analysis

In order to investigate the relationship between virtual reality technology, mindstream experience and college students' self-efficacy, the study is based on the theoretical assumptions, and firstly, the relationship between virtual reality technology, mindstream experience and self-efficacy is explored. Secondly, structural equation modeling was constructed with virtual reality technology as the independent variable, mindstream experience as the mediator variable, and self-efficacy as the dependent variable. Finally, structural equation analysis was conducted using Amos 24.0 software to further explore the relationship between the variables. Before testing the hypothesized path coefficients of each study, the overall fitness of the structural equation model needs to be examined through the goodness-of-fit index. The study optimized the model fit through an iterative optimization algorithm, using absolute fit metrics: GFI (>0.9 indicates better fit), RMR (<0.1 indicates better fit), and with incremental fit metrics: AGFI (>0.9 indicates better fit), and CFI (>0.9 indicates better fit), to test the overall fitness of structural equation models.

5.2.1. Regression Analysis of Virtual Reality Technology and Heart Flow Experience. The study takes virtual reality technology as exogenous latent variable and mind flow experience as endogenous latent variable, and its observed variables are engagement (Z1), concentration (Z2) and pleasure (Z3) to construct the regression model of virtual reality technology and mind flow experience, and the results are shown in Table 3. The data in the table are realistic, and the absolute fit index of the model: GFI=0.983, RMR=0.017 conforms to the index range of GFI>0.9, RMR<0.1. The incremental fit metrics: AGFI=0.976, CFI=0.981 are consistent with the range of metrics for AGFI>0.9 and CFI>0.9. Therefore the regression model of virtual reality technology and heart flow experience has a good fit.

Table 3. Regression model fitting

Fitting index			Recommended range
Absolute fitting index	GFI	0.983	>0.9
	RMR	0.017	<0.1
Incremental fitting index	AGFI	0.976	>0.9
	CFI	0.981	>0.9

Run the regression model of virtual reality technology and heart flow experience, get the regression path relationship table and regression path graph of virtual reality technology and heart flow experience, the results are shown in Table 4 and Figure 4, in which NRC denotes the non-standardized regression coefficient and SRC denotes the standardized regression coefficient. The standardized path coefficient between virtual reality technology and heart flow experience is 0.413, and P is significant at the 0.001 level, indicating that virtual reality technology has a significant positive effect on heart flow experience.

Table 4. Regression path relation

Regression path	NRC	SRC	S.E.	C.R.	P
Cardiac fluid test←VR	0.027	0.413	0.005	12.378	0.000
Z1←Cardiac fluid test	0.984	0.626	0.048	17.836	0.000
Z2←Cardiac fluid test	0.992	0.573	0.051	18.525	0.000
Z3←Cardiac fluid test	0.783	0.648	0.042	14.376	0.000

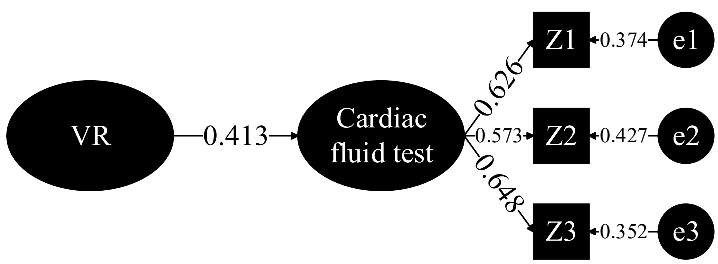


Fig. 4. Regression path

5.2.2. Regression analysis of virtual reality technology and college students' self-efficacy. The study constructs a regression model of virtual reality technology and college students' self-efficacy by taking virtual reality technology as an exogenous latent variable, college students' self-efficacy as an endogenous latent variable, and the three core components of self-efficacy, individual (Y1), psychological (Y2), and environmental (Y3), as observed variables. Table 5 shows the calculation results of the fit index of the regression model. From the table, the absolute fit index of the model: GFI=0.992, RMR=0.013 conforms to the index range of GFI>0.9, RMR<0.1. The incremental fit index: AGFI=0.986, CFI=0.975 conforms to the index range of AGFI>0.9, CFI>0.9. Therefore the regression model of virtual reality technology and college students' self-efficacy has a good overall fit.

Table 5. Regression model fitting

Fitting index			Recommended range
Absolute fitting index	GFI	0.992	>0.9
	RMR	0.013	<0.1
Incremental fitting index	AGFI	0.986	>0.9
	CFI	0.975	>0.9

Run the regression model of virtual reality technology and college students' self-efficacy, get the regression path relationship table and regression path diagram of virtual reality technology and college students' self-efficacy, and the results are shown in Table 6 and Fig. 5, in which NRC denotes non-standardized regression coefficients, SRC denotes standardized regression coefficients, and SE denotes college students' self-efficacy. The standardized path coefficient between virtual reality technology and college students' self-efficacy is 0.694, and P is significant at the 0.01 level, indicating that virtual reality technology has a significant positive effect on college students' self-efficacy, and hypothesis H1 of this paper is verified.

Table 6. Regression path relation

Regression path	NRC	RC	S.E.	C.R.	P
SE←VR	0.336	0.694	0.019	20.726	0.000
Y1←SE	1.032	0.874	0.033	22.784	0.000
Y2←SE	1.471	0.832	0.059	25.983	0.000
Y3←SE	2.598	0.749	0.112	24.837	0.000

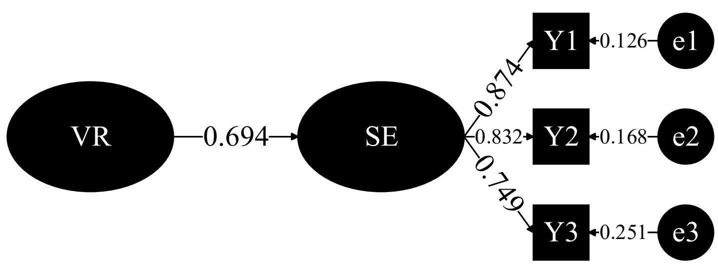


Fig. 5. Regression path

5.2.3. Regression Analysis of Heart Stream Experience and College Students' Self-Efficacy. The study constructed a regression model of heart flow experience and college students' self-efficacy by taking heart flow experience as an exogenous latent variable, with its observational variables of engagement (Z1), concentration (Z2), and pleasantness (Z3), and taking college students' self-efficacy as an endogenous latent variable, with the three core constituents of self-efficacy, namely, individual (Y1), psychological (Y2), and environmental (Y3), as the observational variables. Table 7 shows the results of calculating the fit index of the regression model of heart flow experience and self-efficacy. From the table, the absolute fit index of the model: GFI=0.976, RMR=0.008 conforms to the index range of GFI>0.9, RMR<0.1. The incremental fit metrics: AGFI=0.982, CFI=0.984 conformed to the range of metrics for AGFI>0.9 and CFI>0.9. Therefore, the regression model of heart flow experience and self-efficacy has a good overall fit.

Table 7. Regression model fitting

Fitting index			Recommended range
Absolute fitting index	GFI	0.976	>0.9
	RMR	0.008	<0.1
Incremental fitting index	AGFI	0.982	>0.9
	CFI	0.984	>0.9

Running the regression model of heart flow experience and self-efficacy, we get the regression path relationship table and regression path diagram of heart flow experience and college students' self-efficacy, and the results are shown in Table 8 and Figure 6, where NRC denotes non-standardized regression coefficients, SRC denotes standardized regression coefficients, and SE denotes college students' self-efficacy. The standardized path coefficient between heart flow experience and college students' self-efficacy is 0.763, and P is significant at the 0.001 level, indicating that heart flow experience has a significant positive effect on college students' self-efficacy.

Table 8. Regression path relation

	NRC	RC	S.E.	C.R.	P
SE←Cardiac fluid test	5.084	0.763	0.296	16.837	0.000
Z1←Cardiac fluid test	1.004	0.698	0.045	20.823	0.000
Z2←Cardiac fluid test	0.796	0.572	0.043	18.837	0.000
Z3←Cardiac fluid test	0.938	0.671	0.046	20.541	0.000
Y1←SE	1.006	0.658	0.074	23.527	0.000
Y2←SE	2.013	0.682	0.089	24.868	0.000
Y3←SE	2.556	0.647	0.124	20.347	0.000

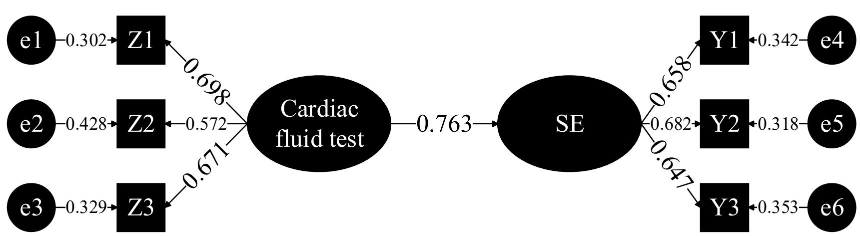


Fig. 6. Regression path

5.3. Tests of the mediating effect of heart flow experience

5.3.1. Analysis of intermediation effects. The mediating role of the mindstream experience in the relationship between college students' self-efficacy and virtual reality technology was tested through structural equations. Great likelihood estimation was applied as the model estimation method. The virtual reality technology, mindstream experience, and college students' self-efficacy were the latent variables, and the three dimensions of mindstream experience and the three dimensions of self-efficacy were the indicator variables for measurement.

The standardized path coefficients of the model are shown in Fig. 7, where virtual reality technology positively predicts mind-flow experience ($\beta = 0.696, P < 0.001$), mind-flow experience positively predicts college students' self-efficacy ($\beta = 0.736, P < 0.001$), and virtual reality technology positively predicts college students' self-efficacy ($\beta = 0.778, P < 0.001$). This indicates that the mindstream experience mediates the relationship between virtual reality technology and college students' self-efficacy, and hypothesis H2 of this paper is verified.

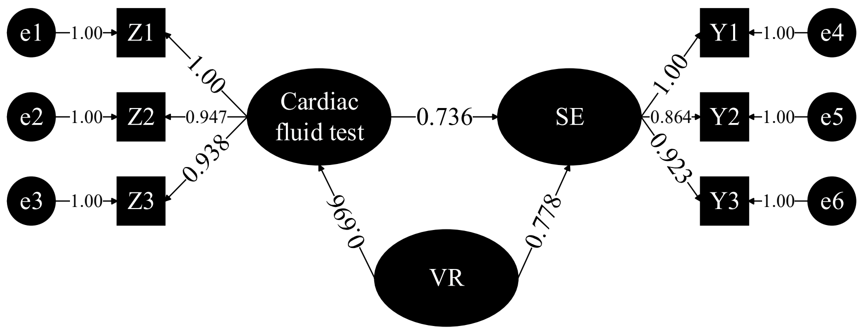


Fig. 7. Model test results of the structural equation

5.3.2. Mediated effects test:

1) Overall test of structural equation modeling. After researching and confirming the correlation between virtual reality technology, mindstream experience and college students' self-efficacy, this study establishes a structural equation model through AMOS software as a way to further explore the path of interaction between the three. In this study, virtual reality technology was used as the independent variable and college students' self-efficacy as the dependent variable, and the overall modeling results were obtained as shown in Table 9. The fit test data of each item of this structural equation model are: $\chi^2 / df = 4.038, RMSEA = 0.042, CFI = 0.994, TLI = 0.963, RFI = 0.971,$ $NFI = 0.982$. Referring to related studies, this model $RMSEA$ is not greater than 0.05, and all other items are greater than 0.9, which is in line with the psychological measurement standard, indicating that this measurement model is applicable to the actual situation.

Table 9. Model suitability test

Index	Reference standard	Measured result
χ^2 / df	Excellence:1-3, Good:3-5	4.038
$RMSEA$	Excellence:<0.05, Good:<0.08	0.042
CFI	Excellence:>0.9, Good:>0.8	0.994
TLI	Excellence: >0.9 Good: >0.8	0.963
RFI	Excellence: >0.9 Good: >0.8	0.971
NFI	Excellence: >0.9 Good: >0.8	0.982

2) Boostrap mediation effect test. In order to ensure the validity of the mediation effect analysis, this study used the bias-corrected nonparametric percentile Bootstrap method to test the mediation effect of “mindstream experience” in the path “virtual reality technology→mindstream experience→college students' self-efficacy”. The mediating effect of “mental flow experience” in the path “virtual reality technology → mental flow experience → college students' self-efficacy” was tested by Bootstrap method. Sampling was repeated 3,000 times with playback, and the mediation effect was tested to be significant according to whether the 95% confidence interval contained 0. If the confidence interval did not contain 0, then the mediation effect was significant, and if it contained 0, then the mediation effect was not significant. The results were calculated as shown in Table 10, and the following conclusions were analyzed: the value of the indirect effect was 0.582, the value of the total effect was 0.864, and the indirect effect accounted for 67.36% of the total effect. The 95% confidence intervals of [0.282, 0.541] and [0.594, 0.897] were obtained by the bias correction method and the percentile method, respectively, which did not include 0, indicating that the mediating effect of “heart flow experience” was significant.

Table 10. Intermediate effect test

Parameter	Estimate	Lower	Upper	P	Effect ratio
Indirect effect	0.582	0.282	0.594	0.000	67.36
Total effect	0.864	0.541	0.897	0.000	

5.4. Analysis of Self-efficacy Enhancement among College Students

Through the previous analysis, it can be concluded that virtual reality technology can significantly and directly enhance college students' self-efficacy, and at the same time, virtual reality technology can further enhance college students' self-efficacy through the mediation of the mind-flow experience. Figure 8 shows the comparison of self-efficacy test scores between the experimental group and the control group before and after the experiment, E is the experimental group, and C indicates the control group. The experimental group adopts the learning mode of virtual reality technology, and the control group adopts the traditional learning mode. From the figure, it can be seen that the self-efficacy of the experimental group after the experiment is significantly improved compared with the preexperiment, the mean value of the improvement is 62.61%, P value is 0.000<0.001, which is statistically significant. While the mean value of self-efficacy score of the control group students was 2.28 before the experiment and 2.31 after the experiment, with a P value of 0.065>0.05, indicating that the traditional learning method cannot effectively enhance the self-efficacy of college students.

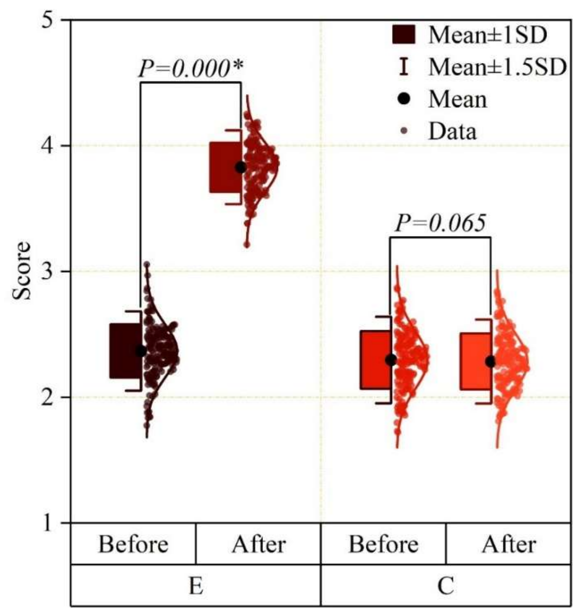
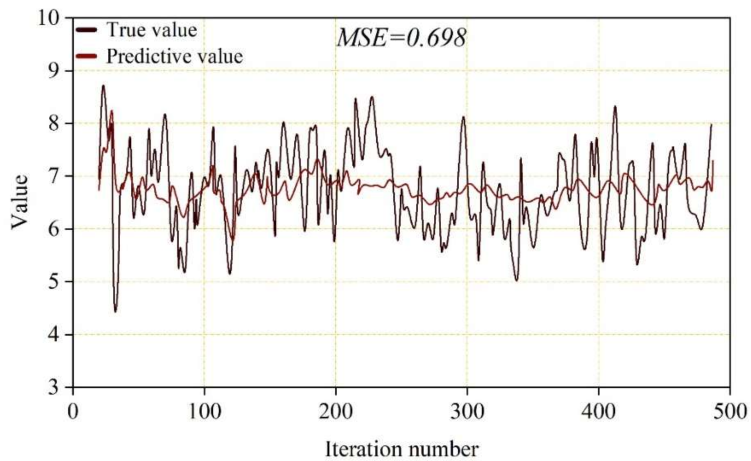


Fig. 8. Experimental results comparison

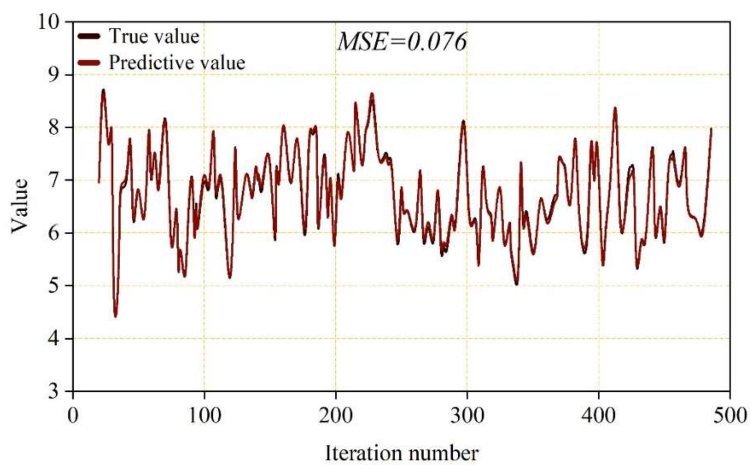
5.5. Algorithm optimization effect analysis

In this paper, the fit of structural equation model is iteratively optimized by algorithms such as SGD and SAG to improve the fit and prediction accuracy of structural equation model. In this section, experiments will be conducted to demonstrate the effectiveness of the practical application of the iterative optimization algorithms in this paper in improving the model fit and other aspects. The experiments use the mean square error and goodness of fit as the evaluation indexes of the algorithm to test the effectiveness of the algorithm in practical applications.

5.5.1. Comparative analysis of model predictions. The divided training sample data are fed into the iterative optimization algorithm for training regression to obtain a trained parameter optimization model, and the model is validated using the validation set. In order to test the performance improvement effect of this paper's iterative optimization algorithm to the original structural equation model, this paper carries out the same training and validation of the original model, and compares the predicted values obtained with the real values of the samples, and the results are shown in Fig. 9, in which (a) denotes the original model results, and (b) denotes the results of the model optimized by this paper's iterative algorithm. From Fig. 9(a), it can be seen that the fitting accuracy of the prediction results of the original structural equation model is not high, and the error between the predicted value and the true value is large. While the model optimized using the iterative algorithm, by choosing appropriate parameters such as the learning rate and the number of iterations, the model prediction accuracy will be significantly improved, and the prediction results are fitted to the real values to a higher degree, indicating that the iteratively optimized model performs better, the error is smaller, and the prediction accuracy is higher.



(a) Original model



(b) Optimized model

Fig. 9. Comparison of prediction with actual value before and after optimized

5.5.2. Comparative analysis of goodness of fit. In this paper, the model fit was visualized and analyzed, and the results are shown in Figure 10. As can be seen from Figure 10, the predictive fit of the optimized structural equation model basically converges after 4 iterations of regression, and the fit between the predicted value and the real value is maintained at 0.943. It shows that the iterative optimization algorithm used in this paper can effectively improve the predictive fit of the structural equation model, and provide a technical support for the study of the relationship between the virtual reality technology and the experience of the heart flow as well as the sense of self-efficacy of college students using the structural equation model. Technical Support.

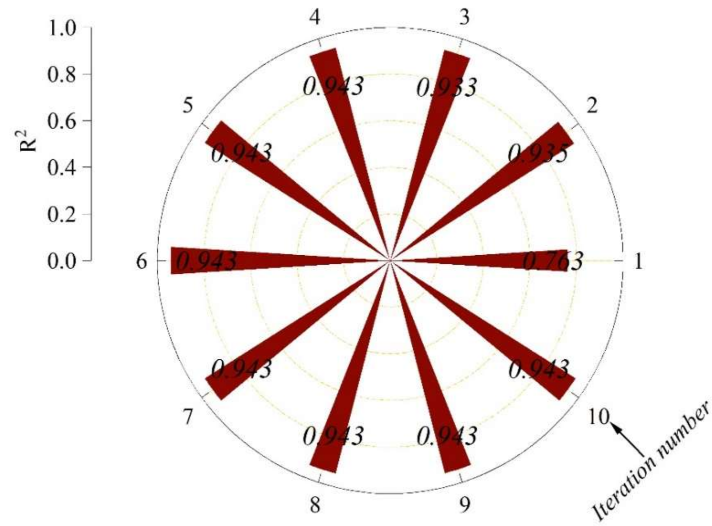


Fig. 10. The fitting after model optimization

6. Conclusion

This paper focuses on the enhancement effect of virtual reality technology on college students' self-efficacy and proposes an iterative optimization algorithm based on learning experience to improve the prediction accuracy and fit of the original structural equation model.

The standardized regression path coefficients between virtual reality technology and mind-flow experience, virtual reality technology and college students' self-efficacy, and mind-flow experience and college students' self-efficacy are 0.413, 0.694, and 0.746, respectively, which indicate that there are significant positive influences of virtual reality technology on mind-flow experience and college students' self-efficacy, and mind-flow experience on college students' self-efficacy. In the mediation effect test, the indirect effect of the mindstream experience was 0.582, which accounted for 67.36% of the total effect value. The results by bias correction method and percentile method indicate that the mindstream experience plays a significant mediating role in the enhancement of college students' self-efficacy by virtual reality technology. Meanwhile, the mean value of self-efficacy scale score of students in the experimental group after the experiment was 3.87, which was 62.61% higher compared with that before the experiment. The mean score of self-efficacy scale of students in the control group was 3.87 after the experiment, which was 62.61% higher than that before the experiment. This indicates that the use of virtual reality technology can effectively improve the self-efficacy of college students.

After optimizing the structural equation model using the iterative optimization algorithm proposed in this paper, the fit of the model reaches the ideal effect, and the fit between the predicted value and the real value is maintained at 0.943, which indicates that the iterative optimization algorithm in this paper can effectively improve the prediction accuracy and the goodness-of-fit of the structural equation model through the learning rate and the parameter settings, which can fully support the research of enhancing college students' self-efficacy by the virtual reality technology in this paper. Research.

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