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Empirical Analysis of Influencing Factors of Desktop Virtual Experiment Teaching Platforms Based on Deep Learning

Jiahua Zhu[1, *], Fangna Chen[2], Wanbing Ma[3], Xiaolei Wang[2, 4], Nini Cheng[1]

[1]School of Life Sciences, Linyi University, Linyi Shandong 276000, China

[2]College of Education, Linyi University, Linyi Shandong 276000, China

[3]Zhengzhou Fengyang Foreign Language School, Zhengzhou Henan 450000, China

[4]Center for International Education, Philippine Christian University, Manila 1004, Philippine

*Corresponding author: zhujiahua@lyu.edu.cn

Abstract

The virtual experiment teaching platform meets the needs of information-based learning which is personalized, fragmented, and all-day-long. At the same time, it emphasizes situativity, interactivity, immersion, and behavioral reality and thereby can effectively promote the occurrence and maintenance of deep learning among students. The research analyzed the influencing factors of deep learning based on desktop virtual experiment teaching platforms. Based on the literature research and questionnaire survey, the theoretical model of the influence factors was constructed. The data were processed through the component analysis, correlation analysis, multiple regression analysis, and other quantitative methods. The results show that the influencing factors of deep learning by virtual experiment teaching platforms are situational verisimilitude, modes of knowledge presentation, overall interface settings, software feedback, operational credibility, operational guidance settings, self-inquiry space, and so on.

Keywords

Virtual experiment; Deep learning; Influence factors; Correlation analysis; Component analysis.

1. Introduction

Activities of teaching and learning depend on some tools, so tools of information technology teaching are developed successively to promote the revolution of teaching and learning. Virtual experiments combine multiple media techniques, virtual reality techniques, and emulation techniques, and they play an increasingly important role in teaching. [1]*Outline of the 10-year Development Plan for Education Informatization of China(2010-2020)* states, "We need to build virtual laboratories"; In 2017, *Notice of the General Office of the Ministry of Education of China on the Construction of Virtual Simulation Experimental Teaching Projects from 2017 to 2020 was* released, and it became an powerful measure that promotes Chinese top institutions of higher learning to explore new experimental teaching models that combine online and offline teaching. In 2018, the Ministry of Education of China issued the *Notice on the Construction of National Virtual Simulation Experiment Teaching Project* which has been selecting virtual simulation experiment teaching projects for five consecutive years and shares virtual experiment resources on the national virtual simulation experiment teaching project sharing platform. By 2023, the platform has launched 2,255 desktop virtual simulation experiment courses.

Deep learning means that students learn new ideas and facts critically on the basis of understanding, integrate them into existing cognitive structures, and then make decisions and solve problems by transferring learned knowledge to new situations.[2] Keeping deep learning

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is the ideal state of teaching and learning for teachers and students. How to facilitate learning in the information environment? Some scholars propose that promoting deep learning should depend on the increase in students' cognitive investment, take the revolution of learning styles as a prerequisite[3], combine information technology and learning, and direct students to construct knowledge actively. Virtual experiments are a way that combines information technology and learning, which overcomes the shortcomings of traditional experiments which are complex, highly difficult, dangerous, and difficult to replicate to some degree. Additionally, virtual experiments adapt to the learning characteristics of personalized, fragmented and all-day-long learning. Virtual experiments emphasize situationality, interactivity, immersion and realistic behaviors, and enable students to solve realistic problems in similar situations in real life[4], which is consistent with the connotation of deep learning. Therefore, virtual experiment teaching platforms can be effectively used in teaching to promote deep learning.

The desktop virtual experiment teaching platform refers to a sort of virtual experiment that uses PC to simulate experimental materials, instruments and equipment, etc., from which students can input commands by clicking, dragging or using the keyboard on the interface, simulate the operation process of virtual experiments, and observe the experimental results on the screen[5]. Flash images, situation interactions, dynamic simulations, scene synthesis, virtual reality and other technologies have been fully applied in this kind of virtual experiment platform. The desktop virtual experiment teaching platform is the most widely used virtual experiment platform in teaching at present. Based on the above discussion, this study takes desktop virtual experiment teaching platform as the research object with the empirical research paradigm, and discusses "the influencing factors of virtual experiment teaching platform promoting deep learning", in order to provide a practical basis for better development of virtual experiment teaching platforms and promoting the integration of virtual experiment technology and deep learning.

2. Construction of Theoretical Model of Influencing Factors

2.1. Construction of First-Level Index

The virtual experiment teaching platform is essentially a kind of learning tool based on information technology. Jonathan and some other scholars believe that there are six functional attributes of information technology as a learning tool: an effectiveness tool, an information tool, a communication tool, an evaluation tool, a cognitive tool, and a situational tool[6]. Of these, the latter two attributes help to facilitate deep learning.

When the virtual experiment is used as a cognitive tool, it has the characteristics of a sense of realism, immersion, and so on. Content construction, learning navigation and other functions are completed by means of technology. In this process, students' mental structures go through the cognitive periods of equilibrium and disequilibrium [7]. Besides, the virtual experiment can minimize the cognitive load and cognitive friction caused by information technologies. It will also guide students to experience real learning in an immersive environment, to link up the meaning world and the external world, and to achieve deep learning.

When the virtual experiment is used as a situational tool, it helps students to construct the situation of real experience on the premise of reducing energy consumption as much as possible, which is a significant feature that distinguishes virtual experiments from other information technology means. Students can simulate real operations in a virtual situation to achieve deep learning.

Based on the above discussion, this study should start from the design elements of cognitive and situational tools, and determine the key factors that affect the deep learning of the virtual experimental teaching platform. When the virtual experimental teaching platform functions as a cognitive and situational tool, it is actually constructing an information channel to interact

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with students. The interfaces, interactive sections, and operation characteristics of virtual experimental software constitute the basic form of information interactions with students. Therefore, interface design, interaction design and operation design become the first level index to analyze the influencing factors of virtual experiment teaching platforms in the research.

2.2. Theoretical Modeling of Influencing Factors from First-level Index to Third-Level Index

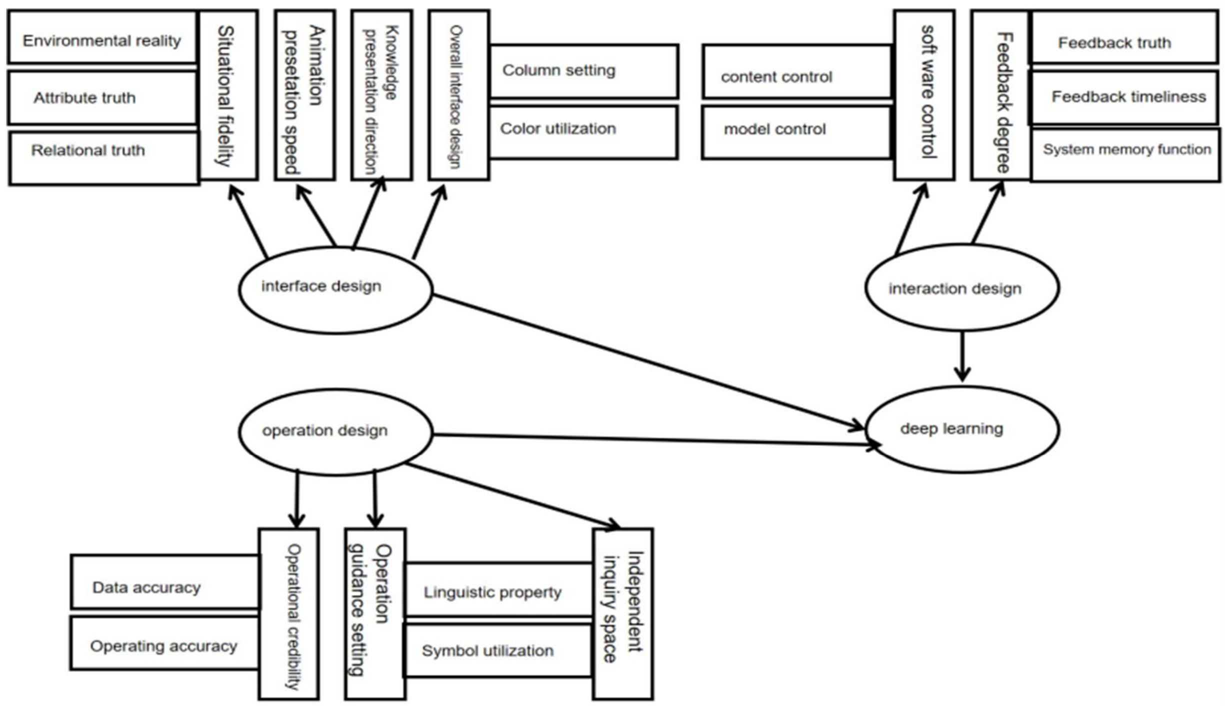

Figure 1. Theoretical model of influencing factors of virtual experimental teaching platform to promote deep learning

In the existing relevant studies, researchers have conducted extensive research on situation construction, operation control, user experience, operation credibility, feedback degree, and other aspects. For example, Jos J. Beishuizen proposed that the role of computer assisted learning environment in facilitating deep learning is mainly reflected in the construction of learning environment [8]. The study of Guido Makransky and Gustav Petersen showed that features of desktop virtual reality simulations, such as user control and representational fidelity, could boost learners' self-efficacy and intrinsic motivation and thereby enhance their learning outcomes[9]. Verstege et al. established fourteen principles of creating a virtual experiment environment, which encompass incorporating motivational elements, segmenting learning materials, using multimedia, providing formative feedback, and other conducive rules[10]. Zhang Mengxin et al. introduced the inquiry community theory into virtual simulation teaching for the first time in their research and proposed that the focus of research on the sense of presence in the desktop virtual reality environment should shifted from immersion to learning activities and cognitive construction of learners in the process to promote more effective learning with desktop virtual reality[11].

Yang Xue studied the perceptual design of virtual experiments , and proposed that reasonable design of interactive functions and feedback settings of virtual experiments would bring physiological satisfaction and psychological pleasure to students[12]; Wei Shuli conducted an

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in-depth study on cognitive friction in virtual experiment platforms and proposed that the improvement in virtual experiment recording functions and operation guidance functions could be an effective solution[13]. Based on the immersion theory, Tao Minghua et al. proposed that in the design of a virtual learning environment, the more feedback students could get from software, the better learning experience they would get[14]. The study of Filius et al. confirmed the significance of peer feedback for students' deep learning, as feedback could stimulate students' feelings of commitment in an online environment [15]. Petersen et al. investigated the roles of immersion and interactivity in virtual learning and their study revealed that immersion and interactivity could enhance learners' sense of physical presence, reduce their cognitive load, and increase their situational interest[16]. Huang Lu et al. studied the design of gamified virtual experiments in integrated situations, which provided implications on how to design immersive virtual experiments [17]. Kun Huang et al. concluded that the degree of interactive feedback and the design space of relevant questions in the experiment may have a positive impact on students' deep learning[18]. Huang Yuxing summarized the intrinsic characteristics of virtual simulation experiments as sensory immersion, perceptual interaction, and consciousness construction, and proposed research hypotheses based on existing studies to build a theoretical model of the influence of virtual simulation experiment on the metacognitive ability of college students[19]. Robyn Cant and Colleen Ryan reviewed the significant roles of desktop virtual simulation software in the distance learning of students majoring in nursing during the recent pandemic, and claimed that educators should make full use of virtual simulation experiments to implement teaching activities[20].

Based on relevant studies, this study constructed a preliminary theoretical model with the first-level index of interface design, interaction design and operation design, and through the processes of feature extraction, operation transformation, element recombination and clustering integration, as shown in Figure 1.

2.3. Perception of Deep Learning

Zhang Hao et al. constructed a multidimensional theoretical system for deep learning evaluation and evaluated students' deep learning from four aspects: cognition, thinking, skills and emotion[21]. Since the evaluation of thinking focus on the process of students' problem-solving so as to determine their "thinking level," questionnaires are not appropriate for the assessment. Therefore, the research measures the self-evaluation of cognition, skills and emotions of the survey subjects when they learn through the virtual experiment platform to measure their deep learning performance and describe the quality of deep learning. Compared with superficial learning, deep learning possesses the following characteristics: at the cognitive level, students can apply, analyze, evaluate and create knowledge; at the skill level, students can master complex behavioral skills and even adapt to or innovate new skill models; at the emotional level, students can correctly evaluate the value of a certain kind of phenomenon, and even construct a personalized value system.

3. Development and Improvement of Measurement Tools

3.1. Conceptualization of Theoretical Models of Influencing Factors

In the research, based on the theoretical model of influencing factors in Figure 1, the observation variables are formed from the secondary and tertiary index of "interface design", "interaction design" and "operation design", and the measurement terms are further formed. The questionnaire survey was used to develop measurement tools. In order to ensure that the respondents can understand questionnaire questions consistently and clearly to control errors, the research conceptualized the variables according to the observation variables, as table 1 shows.

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202412_7(12).0062

Table 1. Conceptualization of the Variables

first-level index	**Second-level index**	**observation variable**	**Conceptual expression**
Interface design	Situational fidelity	Environmental reality	The shape of the experimental objects and the environment, such as the the space collocation、the color collocation、the sound image of the design of virtual environment of the experimental scene , etc
		Attribute truth	The physical attributes of the tested object, including the size, color, motion shape, sound effect, structure, speed, temperature and other attributes of the tested object
		Relational truth	The relative spatial position relation and the size proportion relation of the experimental objects、the degree of agreement between the virtual environment and the real space
	Animation display speed		The playback speed or interface residence time of the content dynamically displayed in the virtual experiment interface
con	Knowledge presentation		The form of knowledge presentation in the interface of virtual experiment software, such as explanation, pictures, subtitles, etc
	Overall interface Settings	Column setting	The size of the column icon, font setting, font size setting, functional elements (software operation subject and visual subject) and non-functional elements (background content subject), etc
		Color utilization	Color matching, color application, color orientation, etc
Interaction design	Software control	Information transfer control	Students can control the suspension and playback of dynamic images in the interface and mark of important content in the interface
		Content control	The degree of convenience of parameter input and output and experimental condition setting in the interface of virtual experiment software
		Mode control	The fluency of rotating, scaling, translating and changing color operations on the experimental objects
	Feedback degree	Feedback truth	When students make a certain action, the system can give close to the true response, including the truth of the action and the truth of the time, and give close to the truth of the response at the appropriate time
		Feedback timeliness	
		System memory function	Whether the virtual experiment system can remember some initial settings and learning progress of the operators
Operation design	Operational credibility	Process reducibility	the operation of the experimental instrument and the implementation of the experimental steps, and approaching degree of real operation process
		Data accuracy	The accuracy of virtual experimental data and the timeliness of data recording
		Motion accuracy	The degree of accuracy with which the controlled subjects perform the action according to the input command
	Operation guidance setting	Linguistic property	The categories of auxiliary language, including identification language, situational language, operant prompt language and informative explanation
		Symbol utilization	The application of physical symbols in the operation interface or navigation interface, such as arrows, boxes, etc.
	Independent inquiry space		Provide space for students to conduct experimental interaction or design independently

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202412_7(12).0062

3.2. Operationalization of the Theoretical Model of Influencing Factors

After the conceptualization was completed, the concepts were operationalized according to the cognitive ability of the survey subjects, and the concepts in Table 1 were converted into specific and measurable questionnaire questions in the form of positive first-person statements. The design consisted of 20 questions in three dimensions: "interface design", "interaction design" and "operation design". At the same time, in order to perceive and measure the deep learning performance of the survey subjects, 14 questions were designed from the above three dimensions and the overall evaluation of the virtual experiment platform, which aimed to evaluate learners' cognition, skill and emotion. In summary, the research designed 34 questions for the questionnaire.

A five-level Likert scale was used in the questionnaire: "strongly inconsistent" with 1 point, "not quite inconsistent" with 2 points, "somewhat consistent" with 3 points, "relatively consistent" with 4 points, "very consistent" with 5 points. The higher the score, the more strongly the respondents are influenced by the measure item (in the perception of deep learning, the higher the score, the higher the respondent's level of deep learning).

After the first draft of the questionnaire was designed, the Delphi method was used where two or three backbone teachers who were specialized in curriculum and instructional theory, educational technology and virtual experiment teaching were selected for expert consultation. The actual questionnaire was finalized after modification based on experts' feedback.

4. Sampling Implementation and Reliability Test

4.1. Sampling, Questionnaire Distribution and Recovery

Participants were in-service biology teachers with a major in biological science. In total, 140 participants were recruited through cluster sampling. The sample was selected for two reasons: first, the participants had desktop virtual experiment learning experience on the national virtual simulation experiment platform when they were in university; second, as normal university graduates, they have a clear perception of deep learning and virtual experiment teaching, and they can complete the test better.

In the study, 140 paper questionnaires were sent out through field research, and 129 valid questionnaires were obtained by using questionnaire questions and other strategies. The valid survey response rate was 92.1%.

4.2. Reliability Test

After the questionnaires were collected, the software SPSS22.0 was used for data recording, screening and processing. Firstly, the reliability test of the questionnaire was carried out with Cronbach's alpha. The scale used in the research contained four constructs: "interface design", "interaction design", "operation design" and "deep learning performance". Reliability analysis revealed that Cronbach alpha coefficients of three constructs were all higher than 0.7, which suggested that the scale was reliable and thereby suitable for research analysis.

5. Results and Analysis

5.1. Sample Descriptive Statistics

Descriptive statistics were used on the samples. According to the statistical description of the average, among the 34 measurement items, respondents were inclined to be "more consistent" to "very consistent" in 16 items (47.06%); "somewhat consistent" to "relatively consistent" in 17 items (50.00%); and "less consistent" to "somewhat consistent" in 1 item (2.94%). The data above shows that respondents have a consistent attitude toward the impact of virtual experiments on deep learning.

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202412_7(12).0062

5.2. Principal Component Analysis

The main idea of principal component analysis is to reduce the dimensionality of variables through linear transformation of much more observed variables and filter a small number of main variables. In this study, the principal component analysis method was used to screen out the major measurement items from the 34 measurement items, verify the validity of the questionnaire, and provide an analysis basis for the "theoretical model of influencing factors of the desktop virtual experimental teaching platform that promotes deep learning".

Two assumptions need to be met for principal component analysis. Assumption #1: The observed variables are continuous or ordered categorical variables; Assumption #2: There is a linear relationship between variables.

The research used a 5-point Likert scale, and the observed variables were all continuous variables, and thereby assumption #1 was satisfied. For assumption #2, KMO and Bartlett's sphericity tests were used to verify the results, as shown in Table 2.

Table 2. KMO and Bartlett's test

Kaiser-Meyer-Olkin sample appropriateness measure		.823
Bartlett's spherical test	Approximate chi-square distribution	1758.201
	freedom	561
	significance	.000

As can be seen from the above table, the KMO value is 0.823. When the KMO value is closer to 1, it indicates that the variables share more common factors and are more suitable for factor analysis. In this study, the KMO value is 0.823, indicating that there are common factors among variables, and the variables are suitable for factor analysis.

The chi-square value of Bartlett's sphericity test is 1758.201, with a degree of freedom of 561, and it reaches the significant level of 0.05. The null hypothesis can be rejected, that is, the hypothesis that the net correlation matrix is a unit matrix is accepted, which reveals the existence of common factors among the correlation matrices of the sample and the correlation matrix is suitable for factor analysis.

Therefore, based on KMO and Bartlett's sphericity tests, assumption #2 of the principal component analysis can be satisfied.

The principal component analysis is carried out on the samples. First, the commonality of each measurement item extracted by the principal component analysis is counted. The results showed that the value range of variable commonality of the 34 items was between 0.420-0.786 (no less than 0.2), indicating that the variables generally shared high commonality and could be used for principal component analysis. In the study, the principal component analysis method was further used to analyze the total explanatory variance of the sample, as picture 2 shows.

The results showed that, first, 9 principal components with eigenvalues greater than 1 were extracted through the principal component analysis, and the cumulative explanatory variance was 63.624%, which was only slightly different from the theoretical hypothesis of 10 secondary indicators in the measurement tool (the difference was 1). Second, among the 9 principal components whose eigenvalues are greater than 1, the first principal component and the second principal component have higher eigenvalues. The characteristics of the remaining principal component are not prominent. The reason for the results may be that the

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measurement items under each secondary index in the theoretical framework of the measurement tool have great heterogeneity and insufficient correlation.

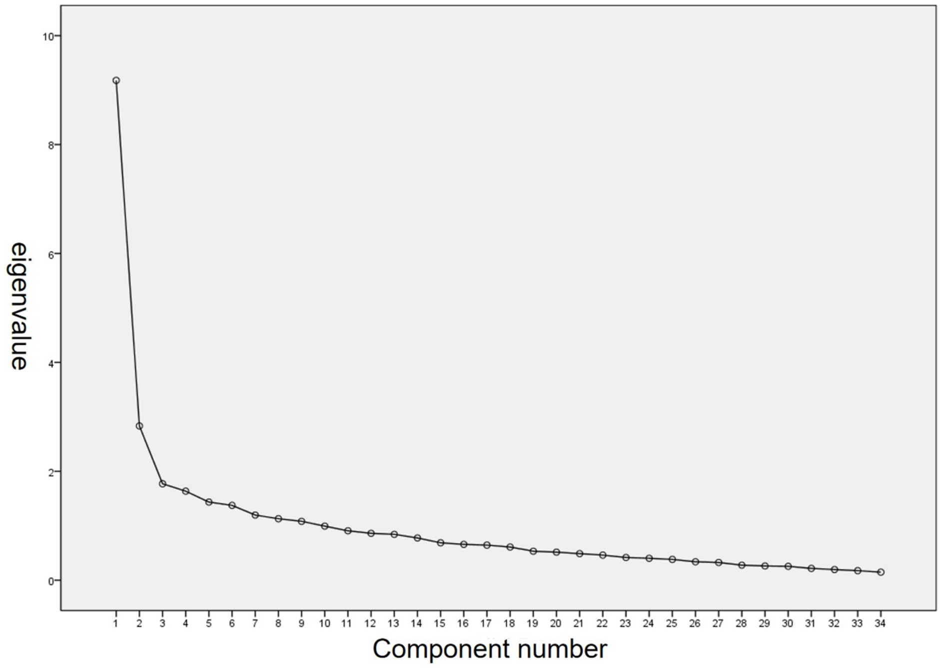

Figure 2. Steep slope map

Factor rotation was performed using varimax, and the components related to “deep learning performance” were eliminated to obtain the rotated component matrix , as table 3 shows.

Table 3. Rotate component matrix

component	Component 1	Component 2	Component 3	Component 4	Component 5	Component 6	Component 7	Component 8	Component 9
Environmental reality	.273	.085	.729	.171	.067	.074	.193	-.054	-.018
Attribute truth	.120	.222	.739	.120	.099	.055	.092	-.087	-.157
Relational truth	-.003	.073	.787	.123	.075	-.080	.005	.304	.003
Visualization processing	.026	-.039	.555	.472	-.119	.014	.361	-.011	.074
Animation speed 1	-.119	.031	.198	.044	.152	-.067	-.036	-.084	-.833
Animation Speed 2	-.008	.191	.071	.747	.067	.025	.059	-.028	-.038
Knowledge presentation	.075	.086	.005	.021	.139	.777	.022	.253	.056
Column setup 1	-.007	.214	.280	.040	.501	.235	.033	-.030	.404
Column setup 2	.043	.088	.151	-.021	.677	.201	.039	.314	-.163
Color application	.125	.207	.384	-.067	.657	.099	.116	.178	.037
Content control	-.288	-.045	.581	-.128	.062	-.332	-.239	-.201	-.243
Model control	.204	.468	.506	-.016	.022	.001	.116	-.017	.054
Feedback truth	.066	-.161	.247	.432	.103	-.025	.576	.100	.011
Timely feedback	.142	.078	.038	-.050	.179	.158	.788	-.002	.074
System memory	.136	.214	.123	.264	.434	-.028	.571	.079	.060
Data accuracy	.279	.092	.023	.098	.104	-.003	.482	-.611	.016
Action accuracy	.237	.075	.441	-.225	.097	.081	.156	-.551	.023
Linguistic property	.049	.647	.121	.033	.149	.135	.240	-.064	-.073
Symbol utilization	.306	.644	-.101	.123	-.067	-.171	-.015	.272	.158
Independent inquiry	.079	.496	.360	.055	-.133	.108	-.080	.332	.155

Rotation method: Maximum variation method with Kaiser normalization.

a. Converges the loop in 22 iterations.

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In the construction of the "theoretical model of influencing factors of virtual experimental teaching platform for promoting deep learning", a secondary index system of 9 dimensions is constructed, which included situational verisimilitude, animation display speed, knowledge presentation mode, overall interface setting, software control, feedback degree, operation credibility, operation guidance setting, and independent inquiry space.

In Table 2, the higher the eigenvalue, the stronger the explanatory ability of the principal component to the corresponding measure item (generally greater than 0.5). Based on the above analysis, it is found that the results of principal component extraction are consistent with the 9-dimension second-level index system in the theoretical model. Among the dimensions in the secondary index system with more lower measurement items, such as situational verisimilitude, overall interface setting, software control, feedback degree, operation credibility, operation guidance setting, deep learning performance, etc., the principal component extraction results are consistent with the secondary index system, except for the lack of explanatory power for the measurement item "animation presentation speed" in "animation display speed". The reason may be that the two measurement items of "animation display speed" have strong homogeneity. The results show that "the theoretical model of influencing factors of virtual experimental teaching platform for promoting deep learning" is relatively reliable.

5.3. Correlation Analysis

The correlation analysis between "interface design", "interaction design", "operation design" and "deep learning performance" of the first indexes was used respectively. The results are shown in Table 4.

Table 4. Correlation test of the effects of first-level indicators on deep learning (N=129)

dimension dimensionality Interface design Interaction design Operation design	**Minimum**	**maximum**	**mean standard**	**deviation**	**correlation test** Pearson co-relation	Significance (bilateral)
Interface design	2.90	4.90	3.9566	.41511	.268***	.000
Interaction design	2.60	5.00	3.8465	.48122	.255***	.000
Operation design	2.80	5.00	4.0992	.47836	.420***	.000

Note: *** indicates a significant association at the 0.001 level (bilateral).

The results show that "interface design", "interaction design", "operation design" and other first indexes are significantly correlated with deep learning performance at the 0.001 level.

In terms of the nine secondary indexes belonging to the three first-level indicators, such as "situational verisimilitude", "software control" and "operation credibility" and so on of the measurement tools, the tools also designed measurement items for the "deep learning performance" from cognition, skill and emotion. The average the secondary indexes and the measurement items of the secondary index on deep learning is calculated and the correlation analysis is conducted. The results are shown in Table 5.

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202412_7(12).0062

Table 5. Correlation test of the effects of second-level indexes on deep learning (N=129)

First index	Secondary index	mean standard	deviation	correlation test	
				Pearson correlation	Significance (bilateral)
Interface design	Situational fidelity	4.1434	.56835	.464***	.000
	Animation display speed	3.7713	.67026	.056	.530
	Knowledge presentation mode	3.4341	1.12392	.268***	.002
	Overall interface Settings	4.0051	.53975	.272***	.000
Interaction design	Software control	3.6512	.75675	-.024	.790
	Feedback degree	3.9715	.62354	.467***	.000
Operation design	Operational credibility	4.1434	.55267	.588***	.000
	Operation guidance setting	4.0543	.62575	.459***	.000
	Independent inquiry space	4.1008	.65960	.434***	.000

Note: *** indicates a significant association at the 0.001 level (bilateral).

The results show that in the first index of "interface design", "situational verisimilitude", "knowledge presentation mode" and "overall interface setting" have significant influence on deep learning at the 0.001 level, while "animation display speed" has no significant correlation with deep learning, which is consistent with the conclusion of "principal component analysis". Considering that there is strong homogeneity between the two measurement items of "animation display speed", the index of "animation display speed" was deleted in the following analysis to eliminate the interference of irrelevant variables. In the first index of "interaction design", "feedback degree" has a significant impact on deep learning at the 0.001 level, and "software control" has no significant correlation with deep learning. With regard to the index of "operation design", "operation credibility", "operation guidance setting" and "independent inquiry space" have significant effects on deep learning at the 0.001 level.

5.4. Multiple Regression Analysis

According to the above principal component analysis and correlation analysis, measurement items such as "animation display speed" and "software control" on deep learning are eliminated. Based on the above conclusions, the questionnaire data were sorted out again. Based on the first-level indexes of "interface design", "interaction design" and "operation design", according to the three independent variables of the first-level indicators, and taking "deep learning performance" as the dependent variable, the mathematical representation model was constructed, that is: The amount of explanation for deep learning performance =α× interface design factor +β× interaction design factor +γ× operation design factor (α, β, γ are the influence coefficients).

A multiple regression analysis of independent and dependent variables was performed with the SPSS software. First of all, based on the above discussion and the re-combination and integration of the questionnaire data, a correlation analysis is conducted on the three independent variables of "interface design", "operation design" and "interaction design" in the above estimation model, and the results are shown in Table 6.

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202412_7(12).0062

Table 6. Summary of independent variable correlation analysis

Dimension	Interface design	Interaction design	Operation design
Interface design	1		
Interaction design	.455**	1	
Operation design	.412**	.375**	1

**p<0.01

As can be seen from the above table, the correlation coefficients among the three variables that affect “deep learning performance” range from 0.375-0.455, indicating that there are significantly positive correlations between the variables and deep learning performance at the level of 0.01. Based on this, the SPSS software was used to conduct the stepwise multiple regression analysis, and the results were presented in Table 7.

Table 7. Summary of stepwise multiple regression analysis of influencing factors in deep learning

Predictors sequential (cumulative)	multivariate correlation coefficient R	Determination coefficient R2	R2 changes	F test	Change of F test	Original regression coefficient（B）	Standardized regression coefficient（β）	T test	Collinearity diagnosis	
									allowance	VIF
Interface design	.624	.389	.389	24.188***	24.188***	.601	.624	4.918***	1.000	1.000
Interface design and Interaction design	.696	.484	.456	17.337***	6.796**	.458	.359	2.607*	.737	1.356
Interface design、Interaction design and operation design	.746	.556	.519	15.032***	5.864*	.291	.323	2.422*	.691	1.447

*p<0.05, **p<0.01, ***p<0.001

The effects of interaction design, operation design, interface design and other factors on deep learning performance were tested by the stepwise multiple regression. The analysis results gradually accumulated and produced three factor models, in which model 3 included 3 preset independent variables. The analysis results are as follows:

First, there is no collinearity for the factor model and it is suitable for regression analysis. In multiple regression analysis, if the correlation of independent variables is too high, it will lead to collinearity. Therefore, regression analysis is suitable only when collinearity is excluded by testing. The collinearity test is generally carried out by “allowable value” and “variance inflation factor (VIF)”. An allowable value less than 0.2 and a VIF greater than 10 indicate collinearity of the model. In the stepwise regression, the allowable values of the model were between 0.691 and 1.000, and none were less than 0.2. The VIFs were between 1.000 and 1.447, all of which were less than 10. Both allowable values and VIFs meet the standard, so there is no collinearity for the model and the model is suitable for regression analysis.

Second, the independent variables “interaction design”, “operation design” and “interface design” have a significant impact on the dependent variable “deep learning performance”, and can explain 55.6% of the change of the dependent variable. As shown in the table above, a significance test (T test) was conducted for the independent variables, and the results showed that the independent variables had a significant impact on the dependent variables (p<0.05). The results of the variance analysis for independent variables show that if the F value of the overall test for model 3 is 15.032 (P<0.001), and thereby the null hypothesis is rejected, that is, the model composed of the three independent variables has a significant impact on the

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202412_7(12).0062

dependent variable. According to the goodness of fit test, the closer the value of multivariate correlation coefficient R was to 1, the better the model fit was. The results showed that the multiple correlation coefficient ® in the relationship between the three independent variables and deep learning performance was 0.746, and the coefficient of determination (R^2) was 0.556. It indicates that the independent variables "interaction design", "operation design" and "interface design" can explain 55.6% of the variation of the dependent variable "deep learning performance".

Third, from the explanatory power of individual variables, the variable with the most explanatory power for deep learning performance is "interaction design", whose individual explanatory volume is 38.9%, followed by "interaction design" (9.5%) and "interface design (7.2%)". As shown in the table above, the change of R^2 represents the explanatory volume corresponding to the predicted cumulative variable, and the individual explanatory volumes of the independent variables "interaction design", "operation design" and "interface design" are 38.9%, 9.5% and 7.2%.

Fourth, from the perspective of standardized regression coefficients, the standardized regression coefficients of the three independent variables in the model are0.624 for interaction design ($t=4.918$, $p<0.001$), 0.359 for operation design ($t=2.607$, $p<0.005$), and 0.323 for interface design ($t=2.422$, $p<0.005$). The standardized regression coefficients are all positive, indicating that the three independent variables have a positive effect on deep learning performance.

To sum up, according to the standardized regression coefficient, the standardized equation of the dependent variable and its influencing factors is as follows: Deep learning performance Z-score =0.323×interface design Z-score +0.624×interaction design Z-score +0.359×operation design Z-score.

6. Conclusion

In summary, the scientificity of "theoretical model of influencing factors of the virtual experimental teaching platform that promotes deep learning" is verified, and "animation display speed" is not an influencing factor that promotes deep learning. "Knowledge presentation mode" and "overall interface setting" have little impact on deep learning; "Operational credibility" has a great impact on deep learning.

Based on the three first-level index of "Interface design", "Interaction design" and "Operation design", the research provides three implications for the development of virtual experimental teaching platforms:

First, the "interface design" should improve situational verisimilitude and enhance immersion. The results show that "situational verisimilitude" has a great influence on students' deep learning. In other words, whether the situations constructed in the interface are close to the real environment, whether the situational attributes such as the size, color, sound effect and action shape of the experiment object are consistent with students' cognition, and whether the scenes of the virtual laboratory, the size, proportion, and spatial relationship of the experimental equipment are authentic and truthful can all have an impact on students' deep learning. Developers should fully design the platform interface with a strong sense of realism through technology to increase students' "immersion". At the same time, they should construct scenes with appropriate and trustful proportions, and pay attention to color schemes and the aesthetic appeal of the virtual experiment software interface to provide a better sensory experience for users.

Second, the interaction design should attach more importance to technical optimization to create a sense of realism. The results show that "interaction design" is the most powerful explanatory factor variable for deep learning performance. "Interaction" refers to the interaction between the platform and students. It mainly means the degree of software feedback, that is, the authenticity of feedback, the timeliness of feedback, and the memory function of the system. In the process of software design, the feedback function should be optimized by technical means. For example, developers should adopt more scientific visual instruction inputs to optimize students' feedback experience, ensure the fluency of operation, and improve the efficiency of knowledge absorption, etc.

Third, the operational design should conform to scientific facts to ensure credibility. The results show that "operational design" has a significant impact on deep learning at the 0.001 level. Among the measurement items, "operational credibility" has the greatest impact on deep learning. Whether the design of the relevant experimental parameters in the software conforms to the experimental facts, whether the data changes are in a reasonable range, and whether the data changes are consistent with the corresponding chart changes are all important components of the operation credibility. Software designers should fully communicate with academic professionals during the design process to ensure the coincidence of variations in data from the software and those in the real experimental. In addition, the accurate movement of the experimental objects and the accurate presentation of the experimental phenomenon are also important aspects to improve the credibility of the operation.

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