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Exploration and Research on Improving Logical Reasoning Skills in Teaching Artificial Intelligence Driver Designs

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ABSTRACT

Studying the influencing factors of logical reasoning ability can not only help teachers to find out the effective way to cultivate students' logical reasoning ability, but also provide methodological and theoretical references for the relevant research in the area of artificial intelligence-driven program design education, which is of certain research value. The article firstly introduces the theory of structural equation modeling and the principle of algorithm used in model analysis. Then, taking the students of School S and School T as an example, we designed and distributed relevant collection questionnaires, and analyzed the data using SPSS to understand the overall status of students' logical reasoning ability and the level of each dimension. Then we make reasonable assumptions about the factors affecting students' logical reasoning ability, establish a structural equation model of the factors affecting logical reasoning ability, and analyze the effects and paths between the factors and on the logical reasoning ability. Finally, according to the experimental results, we propose targeted teaching reform methods. The results of the study show that: teacher's activities, learning interest, learning attitude, classroom environment have a positive effect on students' logical reasoning ability, in which the effect of classroom environment on logical reasoning ability is 0.48. Enhancing the teacher's power and promoting the diversified development of students is an effective way to improve logical reasoning ability.

Keywords: logical reasoning ability, structural equation modeling, artificial intelligence, programming teaching

1. Introduction

The "four new" education and teaching reforms of "new engineering, new medicine, new agriculture, and new liberal arts" of higher education issued by the Ministry of Education in 2018 and comprehensively promoted by the Ministry of Education is a new thinking and strategic plan for the overall situation of higher education in the context of information explosion, accelerated expansion of

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the volume of knowledge, and easier access to knowledge. It is a new thinking and strategic plan for the overall situation of higher education in the context of information explosion, accelerated expansion of knowledge and easier access to knowledge. At present, AI-enabled education is a major trend, which will bring great challenges to the traditional "knowledge transfer" teaching mode [1-3]. Traditional programming courses are usually teacher-centered, and students are mainly passive recipients of knowledge transfer. The application of AI technology can build virtual laboratories and programming environments, allowing students to learn through practice and exploration [4-5]. The popular "generative artificial intelligence" model ChatGPT, as the first practical general-purpose artificial intelligence model, once applied, surprised the world with its high intelligence, high accuracy and high efficiency of information integration, and thus triggered people's thoughts and concerns about the current education model of colleges and universities. However, this kind of general-purpose AI can still be regarded as an advancement in information acquisition and information integration, and has not yet left the category of "tools" [6-9].

Undoubtedly, the development of artificial intelligence will be more rapid, and the impact and change on life and teaching will be more comprehensive and thorough. However, the quality, purpose and tendency of the output of AI products depend on people's "feeding", and over-reliance on AI systems may bring certain social risks [10-13]. Therefore, in the teaching and learning process in higher education, AI systems should be regarded as tools in the transfer of knowledge, and the focus of the classroom should be gradually shifted to the ability to interact, think and reason logically with a focus on human survival and development [14-15]. The need for interaction between people and the acquisition of capabilities is more dependent on humans themselves, and the acquisition of deep thinking capabilities requires interactive experiences with the real world and is closely related to the intersection of knowledge and innovative thinking. This is the part of the education system that is closely connected to the real world and difficult to be replaced by AI, and it is also an important focus point for people to micro-reform classroom teaching [16-18]. Artificial intelligence-driven program design teaching is a topic with important research value, which focuses on how to use artificial intelligence technology to customize the learning plan and teaching content for each student, so that each student can learn at his or her own pace of learning and ability to improve the teaching quality and learning effect of program design courses [19-21].

The article gives a brief introduction to the concept of structural equation modeling, construction steps, mathematical expression and related algorithms applied in model analysis. Then it combines the questionnaire survey and teacher interviews to study the current situation of students' logical reasoning ability. Subsequently, based on the current situation of students' logical reasoning ability and the results of teachers' interviews to determine the influencing factors, four relevant variables, namely, teachers' activities, learning interests, learning attitudes, and classroom environments, were proposed, and a structural equation model of the influencing factors of students' logical reasoning ability was constructed. Further, the structural equation model was used to analyze the influence paths, derive the effect of each factor on logical reasoning ability, and finally propose a teaching reform method based on the improvement of logical reasoning ability.

2. Introduction to and construction of structural equation modeling theory

2.1. Introduction to structural equation modeling

Structural equation modeling is a hypothetical model based on theory or experience. A causal relationship is first established, and then the collected data are used to test whether the causal relationship is valid or not. Structural equation modeling mainly relies on the covariance matrix for fitting, and the corresponding system of linear equations is utilized to represent the causal relationship, and the strength of the relationship can be expressed by the relationship coefficient [22]. Variables in structural equation modeling are divided into latent variables and explicit variables, latent variables cannot be directly observed, while explicit variables can be obtained through direct observation, and two different types of paths are formed between latent variables and between latent variables and explicit variables.

Latent variables include endogenous and exogenous, endogenous latent variables are affected by other variables, while exogenous latent variables only affect other variables, in the model, it can be judged by the pointing of the arrows, only pointing to the arrow that goes is exogenous latent variables, denoted by the symbol ξ. Those with arrows pointing are endogenous latent variables and are denoted by the symbol η.

2.2. Model representation

2.2.1. Measurement models. A measurement model is a linear function of a set of explicit variables, and in SEM is a validating factor analysis used to assess the extent to which the measured variables can constitute latent variables, and to test whether the causal models of the explicit and latent variables fit the data.

It is expressed in a mathematical formula as:

$$X = \Lambda_x \xi + \varepsilon \tag{1}$$

$$Y = \Lambda_r \eta + \delta \tag{2}$$

where ξ is the exogenous latent variable and η is the endogenous latent variable. X is the explicit variable matrix of ξ. Y is the explicit variable matrix of η. Λ_X and Λ_Y are the loading coefficient matrices. ε and δ are residual matrices.

2.2.2. Structural models. The structural model is a function between the two latent variables of internal and external causes, and is able to express the causal relationship between the two, the structural model is also known as the causal model or latent variable model, which is expressed by the mathematical formula:

$$\eta = \mathrm{B}\eta + \Gamma\xi + \zeta \tag{3}$$

where, B is the coefficient matrix of η that represents the relationship between endogenous latent variables. Γ is the coefficient matrix of ξ, which can represent the effect of exogenous latent variables on endogenous latent variables. ζ is the residual term.

2.3. Introduction to Algorithms

2.3.1. Introduction to the PLS algorithm. The PLS algorithm, or Partial Least Squares algorithm, is an iterative computation that combines Principal Component Analysis and Multiple Regression for causal modeling.The PLS algorithm allows for a combination of multiple statistical analyses, simultaneous regression modeling, Principal Component Analysis, and Typical Correlation Analysis, and is applicable to small sample data.

The steps of the PLS algorithm are as follows:

Step 1: Estimate weights and hidden variable scores. Using an iterative approach, start with an external approximation and repeat the process until convergence.

1) Internal weights

$$\begin{cases} v_{ij} = sign\operatorname{cov}\left(\eta_j, \eta_i\right) & If\ \eta_j\ and\ \eta_i\ are\ directly\ related \\ 0 & If\ \eta_j\ and\ \eta_i\ are\ not\ directly\ related \end{cases} \tag{4}$$

2) Internal approximation

$$\tilde{\eta}_j = \sum_j v_{ji} Y_j \tag{5}$$

3) Solve for external weights

$$\tilde{\eta}_{jn} = \sum_k \tilde{\omega}_k y_{kn} + d_{jn} \tag{6}$$

4) External approximation

$$\eta_{jn} = f_i \sum_k \tilde{\omega}_k y_{kn},\ \textit{Where } f_i \textit{ ensures that } \operatorname{var}(\eta_i) = 1 \tag{7}$$

Step 2: Estimate path coefficients and load coefficients.
Step 3: Estimate the location parameters.

2.3.2. Introduction to the Bootstrapping Algorithm. Bootstrapping algorithm, also known as self-help method, selects a small number of samples by sampling several times, which can reflect the distribution of the parent sample, and is more effective when the dataset is very small and it is difficult to efficiently divide the training or test set [23]. Bootstrapping algorithm can be used with multiple random samples as the training set, and the initial data as the test set.

The steps of Bootstrapping algorithm are as follows:

1) Create an initial seed set.

2) According to the seed set and the extracted context patterns, build a good set of candidate patterns.

3) Patterns are respectively matched with the original patterns to form a set of candidate entity names, and samples are recognized to form a candidate set.

4) Calculate the information entropy gain of and samples, and after sorting, select the patterns and samples that meet the requirements to be added to the final pattern set and seed set respectively.

5) Repeat steps 2)-4) until a certain number of iterations (generally greater than 1000) is satisfied.

2.4. Structural equation modeling steps

The complete model construction is divided into the following steps:

1) Constructing the preliminary model. According to the actual situation of the problem to be studied, set the latent variables and explicit variables, and assume the path between the latent variables to construct the preliminary model.

2) Model fitting. After the preliminary structural equation model is constructed, the model fitting can be completed by using the great likelihood method, partial least squares method, diagonal weighted average method, general least square method, etc. The specific choice of which method needs to be combined with the actual determination of the research problem, such as: how much the sample size, the maturity of the theory, etc., and in this paper, we will choose the partial least squares method.

3) Model correction. Bring in the organized data, if the test is not qualified, according to the corresponding indicators, such as path coefficients, path coefficients of the significance of the test, etc., to remove some inappropriate paths or factors.

4) Model Analysis. According to the results of software analysis, get the relationship between the influence of each variable and the degree of model fitting, combined with the reality of the research problem, to give the conclusion of the research.

3. Survey of the current status of students' logical reasoning skills

3.1. *Subjects of study*

The research object of this paper is mainly students, according to the cognitive development theory can be learned, at this time students in the concrete operation and formal operation stage between, logical thinking in a more active state. Students as the object of study will be related to all the content of the literature for statistical analysis, concluded that students are in the critical period of logical reasoning ability development. Therefore, it is meaningful to study the factors affecting students' logical reasoning ability.

The test paper was distributed at the end of December 2023, near the end of the semester. A more representative sample of four eighth grade classes in secondary school S, three classes in school T, and the math teachers of each class were selected for the survey, with a sample of 155 students in school S, 108 students in school T, and five teacher interviews. The logical reasoning skills test paper is shown in Table 1.

Table 1. Logical reasoning ability test volume

School	Student population	Number of teachers interviewed
S school	155	3
T school	108	2
Total	263	5

3.2. *Research tools*

3.2.1. Logical reasoning test paper. The Logical Reasoning Test Paper draws on the test paper A Study of Logical Reasoning Tests for Students. The test paper focuses on testing the logical reasoning thinking skills of students. Logical reasoning skills are categorized into deductive reasoning and synoptic reasoning, and deductive reasoning is subdivided into four parts: simple reasoning, hypothetical reasoning, selective reasoning, and propositional algorithms.

The assessment framework differs from the general level-tier assessment by using categories that focus on testing students' understanding of general logical rules, and the categories are categorized according to the sub-dimensions of logical reasoning ability. Each question carries 2 marks and 1, 2, 5, 8, 9 and 10 are multiple choice with one mark for each blank. The dimensions and the division of questions in the Logical Reasoning Ability Test paper are shown in Table 2.

Table 2. Logical reasoning ability test volume dimensions and item division

Dimension	Subdimension	Item
Deductive Inference	Simple Reasoning	1, 2, 3, 4
	False Reasoning	6, 7, 15
	Optional Reasoning	5, 8, 9, 10
	Propositional Calculus	11, 12, 13, 14
Reasoning	Induction And Analogy	16, 17, 18, 19, 20, 21

1) Pre-test. The quality of the test paper is an important influence on the conclusions and analysis of this study, in order to ensure the reliability of the test paper, firstly, 60 students in class 3 of grade 8 of S school were selected to take the pre-test, the test questions were 21 multiple-choice questions, the test time was 30 minutes, and 60 valid test papers were recovered. The test scores were entered into SPSS26.0 for reliability test, and the alpha coefficient was measured to be 0.782, which indicates that

the test paper reliability is good, and the reliability statistics of the Logical Reasoning Ability Test Paper (Predictive Version) are shown in Table 3.

Table 3. Logical reasoning ability test volume (predictive) reliability statistics

Reliability statistic	
Cronbach's Alpha	Term number
0.782	21

2) Formal test. Selected S school and T school students to test, this time, the number of questionnaires distributed 263, the valid test paper is 263, the recovery rate is 100%. The test paper was corrected according to the scoring criteria, and finally the data was imported into SPSS26.0 for reliability analysis, and the value was elevated compared with the pretest, and the reliability coefficient (alpha coefficient) of the total table was 0.793>0.7, which indicates that this test paper is reliable. The reliability statistics of the Logical Reasoning Aptitude Test Paper (official version) are shown in Table 4.

Table 4. Logical reasoning ability test volume (formal version) reliability statistics

Reliability statistic	
Cronbach's Alpha	Term number
0.793	21

The results of KMO and Bartlett's test on the test papers are shown in Table 5. The KMO and Bartlett's test was first performed on the test results, and the table shows that the KMO value is 0.875, which indicates that it is suitable for factor analysis. The overall result of the test paper is good.

Table 5. Test results of the test rolls KMO and Bartlett

KMO test and Bartlett 's test		
The kaiser-Myer-Okin metric with sufficient degrees		0.875
Bartlett's spherical test	Approximate card	1853.6
	df	215
	Sig.	0.000

3.2.2. Design of the teacher interview outline. As the builder and leader of classroom teaching, teachers are not only excellent in the mastery of professional knowledge, but also need to have a place in the study of educational theories, combine their professional knowledge with them, and devote themselves to practical teaching. Teachers' own ability has a great impact on students' learning and ability development. In the article, we adopt the interview method to ask questions to find out what level of logical reasoning ability the students in the teacher's class are at, whether they will take the initiative to cultivate students' logical reasoning ability in actual teaching, and what kind of difficulties they have encountered in the process of teaching. And according to their own experience and mastery of the students' situation, they think that what are the factors affecting the students' logical reasoning ability and so on, and according to the influencing factors, they put forward some suggestions that can be used as reference by the teachers. The specific questions are as follows:

1) How is the logical reasoning ability of the students in your class?
2) The relationship between learning interest and logical reasoning ability.
3) What do you think are the influencing factors of logical reasoning ability?
4) What are the difficulties encountered in developing students' logical reasoning ability?
5) What are the suggestions for developing students' logical reasoning ability.

3.3. Design of the Logical Reasoning Questionnaire

Understanding that there are many factors affecting students' logical reasoning ability, combined with the results of teacher interviews, four main factors were finally selected namely learning attitude, learning interest, teacher activities, and classroom environment. The learning attitude factor mainly refers to the Preparation of Students' Attitude Scale, which consists of five questions. The learning interest factor draws on the Development of the Student Learning Interest Questionnaire, which consists of five questions. In the teacher's activities factor, the Questionnaire on Factors Influencing Teachers' Development of Students' Logical Reasoning, with 5 questions. For the classroom environment factor, My Classroom, with 4 questions, was used. Screening, adapting, and totaling were performed to obtain the Questionnaire of Factors Influencing Students' Logical Reasoning. The questionnaire consisted of 19 questions, and the dimensions and the division of the questions of the Questionnaire on Factors Influencing Logical Reasoning Ability are shown in Table 6. There are 19 questions in the questionnaire, and each question from 1 to 19 is scored according to the Likert scale, and the grades are divided into very compliant, compliant, basically compliant, non-compliant, and very non-compliant, which correspond to the scores of 5, 4, 3, 2, and 1, respectively.The students' attitudes toward learning, interest in learning, the teacher's teaching activities, and classroom environment were investigated respectively.

Table 6. The factors of the logical reasoning ability are divided into each dimension and item

Dimension	Item	Number Of Subjects
Study Interest	1, 2, 3, 4, 5	5
Learning Attitude	10, 11, 12, 13, 14	5
Teacher Activity	15, 16, 17, 18, 19	5
Class Environment	6, 7, 8, 9	4

3.4. Model assumptions

The article proposes the following hypotheses:

H1: Teaching and learning activities have a positive effect on learning interest.
H2: Teaching activities have a positive effect on learning attitudes.
H3: Learning interest has a positive effect on learning attitude.
H4: Instructional activities have a positive effect on classroom environment.
H5: Teaching and learning activities have a positive effect on logical reasoning ability.
H6: Learning interest positively affects logical reasoning ability.
H7: Class environment positively influences logical reasoning ability.
H8: Learning attitude has a positive effect on logical reasoning ability.

4. Empirical studies of impact factors

4.1. Statistical tests of sample data

4.1.1. Descriptive statistical analysis. First of all, the demographic characteristics of the selected sample data were analyzed descriptively and statistically, mainly in terms of gender and political affiliation, two aspects of the demographic characteristics of the sample are shown in Table 7. As can be seen from the table, using gender as an analogous variable, the sample size of male students is 155, with a higher proportion of 59%. The sample size of female students is 108 with a percentage of 41%. Using political affiliation as an analogous variable, the sample size of party members is low at 7%. The sample size of non-party members is 245, accounting for 93%. It can be seen that the sample structure of the survey is relatively reasonable, and it is well represented both in terms of gender and political appearance, indicating that this study has some general significance.

Table 7. Sample demographics

Demographic Characteristics	Cassification	Sample Size	Prcentage
Gender	Man	155	59%
	Female	108	41%
Political Appearance	Party Member	18	7%
	Nonparty Member	245	93%

The sample data were then used to analyze the descriptive statistics of the 21 observed variables. Here the minimum, maximum, mean, and standard deviation of each observed variable were selected and the descriptive statistics of the variables are shown in Table 8. As can be seen from the table, from the aspect of learning interest, except for learning interest 3, which has a mean value of 1.93, the mean values of all other variables are between 2-2.7, indicating that the overall evaluation of students' interest in learning is at an average level, while there is not a great difference in the group's evaluation of learning interest. From the aspect of class environment, the mean value of students' evaluation of class environment 4 reached 2.88, which is generally good. From the aspect of learning attitudes, students are average in learning attitudes, which need to be further strengthened. In terms of teaching and learning activities, students' evaluation of the teaching and learning activities carried out by teachers is average, and schools and teachers need to make further improvements and refinements.

Table 8. Descriptive statistics of variables

Vriable	Sample size	Minimum value	Maximum value	Mean	Standard deviation
E1	334	0	5	2.07	1.029
E2	334	0	5	2.4	0.883
E3	334	0	5	1.93	0.555
E4	334	0	5	2.61	0.747
E5	334	0	5	2.24	0.834
E6	334	0	5	2.5	0.745
E7	334	0	5	0.67	0.882
E8	334	0	5	0.37	0.483
E9	334	0	5	2.88	0.97
E10	334	0	1	2.96	0.94
E11	334	0	1	2.66	0.843
E12	334	0	1	2.42	1.038
E13	334	0	1	0.29	0.399
E14	334	0	1	0.47	0.47
E15	334	0	1	0.11	0.38
E16	334	0	1	0.28	0.493
E17	334	0	1	0.29	0.437
E18	334	0	1	0.21	0.435
E19	334	0	1	0.3	0.434

4.1.2. Correlation analysis. Correlation analysis measures the closeness between elements of a variable and generally allows for the analysis of two or more variable elements that possess a correlation. In this paper, Pearson correlation analysis is used to analyze the relationship between any two variables. The correlation analysis of each variable is shown in Table 9. As can be seen from the table, there is a significant correlation between the five variables.

Table 9. Correlation analysis of variables

		Study interest	Learning attitude	Teacher activity	Class environment	Logical reasoning ability
Study interest	Pearson Correlation	1	0.563**	0.224**	0.364**	0.372**
	Sig.(2-tailed)		0.000	0.000	0.000	0.000
Learning attitude	Pearson Correlation	0.563**	1	-0.085	0.412**	0.391**
	Sig.(2-tailed)	0.000		0.065	0.000	0.000
Teacher activity	Pearson Correlation	0.224**	-0.085	1	-0.058	-0.068
	Sig.(2-tailed)	0.000	0.065		0.312	0.209
Class environment	Pearson Correlation	0.364**	0.412**	-0.058	1	0.032
	Sig.(2-tailed)	0.000	0.000	0.312		0.562
Logical reasoning ability	Pearson Correlation	0.372**	0.391**	-0.068	0.032	1
	Sig.(2-tailed)	0.000	0.000	0.209	0.562	

1) Correlation between students' learning interest and influencing factors. The correlation coefficient between students' learning interest and class environment $r=0.563$, significance $p<0.01$, indicating that there is a significant positive correlation between students' learning interest and class environment, which is consistent with hypothesis H1. The correlation coefficient of students' interest in learning and attitude towards learning $r=0.224$, significance $p<0.01$, indicating that there is a significant positive correlation between students' interest in learning and attitude towards learning, consistent with hypothesis H2. The correlation coefficient of students' interest in learning and teaching activities $r=0.364$, significance $p<0.01$, indicating that there is a significant positive correlation between students' interest in learning and teaching activities, consistent with hypothesis H3. The correlation coefficient of students' interest in learning and logical reasoning $r=0.372$, significance $p<0.01$, indicates that there is a significant positive correlation between students' interest in learning and logical reasoning, which is consistent with hypothesis H6. Therefore the correlation hypothesis is verified.

2) Correlation between the factors influencing students' learning interest. The correlation coefficient of teaching activities and class environment $r=0.412$ with significance $p<0.01$ indicates that there is a significant positive correlation between teaching activities and class environment, which is consistent with hypothesis H4. The correlation coefficient of logical reasoning ability and class environment $r=0.388$, significance $p<0.01$, indicates that there is a significant positive correlation between logical reasoning ability and class environment, consistent with hypothesis H7. Therefore, the correlation hypothesis was verified. In addition, the correlation between teaching activities and logical reasoning ability and the correlation between logical reasoning ability and learning attitudes are not significant, so further hypothesis testing is needed.

It is generally required that the correlation between indicators should not be too high, so that the attributes characterizing the various sides of the evaluation object can be more objectively reflected. High correlation is likely to lead to the reuse of information. Although the results of the correlation analysis cannot be used as a sufficient basis for hypothesis testing, it provides the necessary empirical basis for subsequent research and analysis.

4.1.3. Data distribution tests. The normal distribution test is a test to determine whether the overall population obeys a normal distribution through the observed data, which can explain many stochastic phenomena and is also the first step of statistical analysis. As mentioned earlier, the PLS estimation method of structural equation modeling (SEM) does not have strict requirements on whether the sample satisfies normal distribution. Therefore, a normality test of the sample data is required before the specific model estimation and testing.

The experiment uses the K-S test (Kolmogorov-Smolov test) of normal hypothesis testing to test the normality of the distribution of the sample data. Using SPSS23.0 software, the P-value of the companion rate of the K-S test for each variable was calculated using the one-sample K-S test, and the Kolmogorov-Smirnov test for the normal distribution of each variable is shown in Table 10. If the P-value of the companion rate of the K-S test for the sample data is below 5%, then the assumption of normality of the sample data will be rejected and the sample will not satisfy the normal distribution. As can be seen from the table, none of the 19 observed variables obey the normal distribution at the 5% significant level. Therefore, in this paper, PLS-SEM model was chosen to analyze the factors affecting students' logical reasoning ability.

Table 10. Kolmogorov-smirnov test of variable normal distribution of each variable

Variable	Kolmogorov-Smirnov Z	P
E1	0.181	0.000
E2	0.216	0.000
E3	0.404	0.000
E4	0.278	0.000
E5	0.269	0.000
E6	0.277	0.000
E7	0.247	0.000
E8	0.424	0.000
E9	0.231	0.000
E10	0.242	0.000
E11	0.244	0.000
E12	0.26	0.000
E13	0.483	0.000
E14	0.421	0.000
E15	0.477	0.000
E16	0.429	0.000
E17	0.449	0.000
E18	0.51	0.000
E19	0.473	0.000

4.2. Reliability and validity analyses

4.2.1. Credibility analysis. Reliability analysis refers to the analysis of the reliability of measurements of the same research object in terms of consistency or stability. Cronbach's alpha coefficient is the standard of reliability coefficient commonly used in academia to test the consistency between variables under the same construct and the overall consistency.The larger the value of Cronbach's alpha coefficient, the higher the degree of reliability, the greater the degree of correlation between the variables, and the more credible it is.The alpha coefficient ranges from 0-1, and when the alpha coefficient is greater than 0.7, it indicates a high degree of reliability. When the alpha coefficient is between 0.35 and 0.7, it indicates an acceptable level of confidence. When the alpha coefficient is less than 0.35 it indicates low reliability. The paper uses Cronbach's α coefficient for reliability analysis, and the reliability analysis of the variables is shown in Table 11. It can be seen that the Cronbach's alpha coefficients for each variable and the overall Cronbach's alpha coefficient are above 0.7, which indicates that the questionnaire has good reliability.

Table 11. Variable reliability analysis

Variable	Cronbach α value	Overall Cronbach α
Study interest	0.866	0.863
Learning attitude	0.798	
Teacher activity	0.821	
Class environment	0.869	
Logical reasoning ability	0.794	

4.2.2. Validity analysis. Validity analysis refers to the analysis of the correctness of the measurement of the variable, that is, the correctness of the measurement results, the higher the validity, the more the results of the measurement reflect the characteristics of the object of interpretation.

The thesis uses factor analysis to conduct the correlation validity test. Before conducting factor analysis, KMO test and Bartlett's sphericity test were first used to determine whether the data were suitable for factor analysis. Using SPSS23.0 software, the KMO and Bartlett's test for the observed variables are shown in Table 12.The value of KMO is between 0 and 1, and the closer the value is to 1 the more suitable it is for factor analysis. The specific metrics are: KMO greater than 0.9, very suitable. 0.8-0.9, very suitable. 0.7-0.8, fair, 0.6-0.7, not very suitable. 0.5-0.6, acceptable. Less than 0.5 indicates that it is not suitable for factor analysis.The criterion for Bartlett's test of sphericity is the factor analysis is suitable when the χ^2 value is large and the concomitant probability value P is less than 0.05. From the table, it can be seen that the KMO value is equal to 0.878 and the χ^2 statistical value of Bartlett's sphericity test is 3752.952 and its concomitant probability value P=0.000 which is significantly less than 0.05, which indicates that the data is suitable for factor analysis.

Table 12. KMO and Bartlett tests of observed variables

The Cayser-Meyer-Olkin metric of the sampling is sufficient		0.878
Bartlettspherical test	Approximate card	3752.952
	df	215
	Sig.	0.000

Using SPSS 23.0 software, the validation factor analysis was conducted using principal component analysis to obtain the factor loading coefficients of the variables, and the results of the factor analysis of each observed variable are shown in Table 13. The table shows that the factor loading values of each factor are greater than the criterion of 0.5, which indicates that the validity of the questionnaire is good.

Table 13. Analysis of factors of observation variables

Variable	Factor load	KMO	Bartlett X^2	P
E1	0.809	0.905	967.6	0.000
E2	0.774			
E3	0.638			
E4	0.778			
E5	0.71			
E6	0.767	0.697	431.699	0.000
E7	0.749			
E8	0.84			
E9	0.675			
E10	0.714	0.71	387.317	0.000
E11	0.696			
E12	0.7			
E13	0.734			
E14	0.872			

E15	0.737	0.877	987.361	0.000
E16	0.724			
E17	0.765			
E18	0.711			
E19	0.804			

4.3. Hypothesis testing based on structural equation modeling

4.3.1. Modeling of structural equations. This study intends to use the dimensions of learning interest, class environment, learning attitude, and teaching activities as independent variables and the dimensions of logical reasoning ability as dependent variables. The structural equation modeling is shown in Figure 1. Where H1 corresponds to hypothesis 1, H2 corresponds to hypothesis 2, H3 corresponds to hypothesis 3, H4 corresponds to hypothesis 4, H5 corresponds to hypothesis 5, H6 corresponds to hypothesis 6, H7 corresponds to hypothesis 7, and H8 corresponds to hypothesis 8.

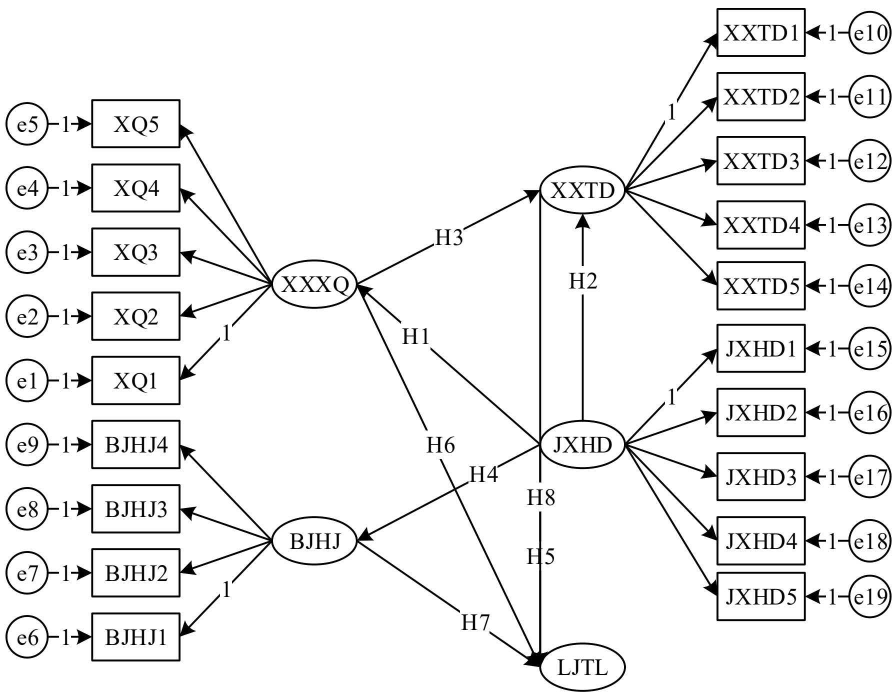

Fig. 1. Structural equation model

4.3.2. Analysis of fitness metrics associated with structural equation modeling. The model fitness index is used to evaluate whether the hypothesized path analysis model and the collected data fit each other. The fitness index cannot indicate the usefulness or otherwise of the model, but it can point out the degree of conformity between the researcher's hypothesized theoretical model diagram and the actual data, i.e., the degree of consistency between the hypothesized model and the actual data. In traditional inferential statistics, a suitable statistical method will be selected based on the properties of the variables and their interrelationships, and a significance level will be set (α=0.05 or the more stringent α=0.01 will generally be used in the social sciences) and a decision will be made to adopt a one-tailed test or a two-tailed test. After experience, the statistic and its probability of significance value, p, will be obtained, and using the probability of significance value, p, against the significance level, α (α=0.05), the null hypothesis can be rejected if $p < \alpha$, thus accepting the opposing hypothesis (the research hypothesis), and obtaining that there is a significant relationship between the variables, or that there is a significant effect of the effect of the independent variable on the dependent variable.

In traditional inferential statistics, researchers often want to reject the null hypothesis and affirm the research hypothesis. However, in structural equation modeling, the researcher wants to accept the null hypothesis. This is because an insignificant test result indicates the correctness of the null hypothesis, i.e., there is no significant difference between the variables of the study. This relates to the work of structural equation modeling, i.e., a non-significant test result indicates the proximity of the sample's covariance matrix to the overall matrix implied by the theoretical assumptions in the study, indicating the extent to which the theoretical model fits the empirical data. From the comparison of the correlation values of the model with the fitness criteria values in the table, it can be seen that all the test values of this model are within the range required by the fitness criteria, and the fitness between the model and the actual situation is good. The fitness indicators are shown in Table 14.

Table 14. Fitness indicator

Statistical inspection quantity	Fitness criteria	Correlation value of the model	Fitting evaluation
CMIN/DF	<4	2.113	Ideal
GFI	>0.85	0.904	Ideal
AGFI	>0.85	0.976	Ideal
NFI	>0.85	0.913	Ideal
RFI	>0.85	0.983	Ideal
IFI	>0.85	0.994	Ideal
CFL	>0.85	0.943	Ideal
RMSEA	<0.06	0.048	Ideal

4.3.3. Hypothesis testing. Structural equation modeling was applied to perform path analysis on the formal research data, and the standardized structural equation modeling diagram is shown in Figure 2.

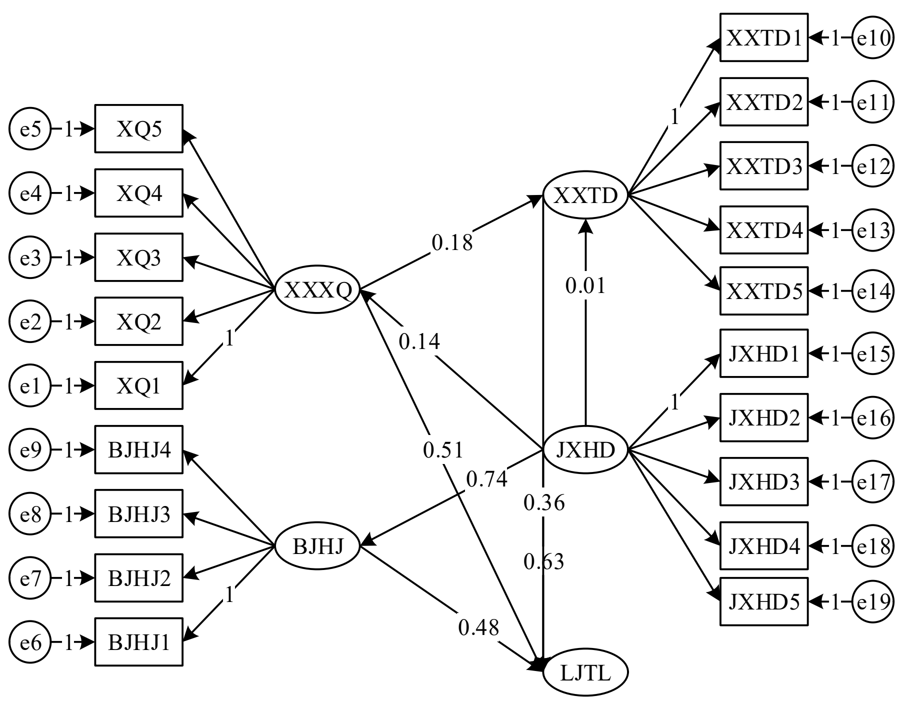

Fig. 2. Standardized structure equation model diagram

The fitting indicators of the structural equations indicate that the research model is acceptable. The results of the path analysis are summarized in Table 15. From the results of the path analysis, hypotheses H1, H2, H3, H4, H5, H6, H7, and H8 are accepted. However, the path coefficient of H2 is 0.01, which assumes a weak role.

Table 15. The path analysis results are summarized

Hypothesize	Path direction	Path coefficient	P value	conclusion
Hypothesize 1	Teaching activities have a positive effect on learning interest.	0.14	***	Acceptance
Hypothesize 2	Teaching activities have a positive effect on learning attitude.	0.01	***	Acceptance
Hypothesize 3	Learning interest has a positive effect on learning attitude.	0.18	***	Acceptance
Hypothesize 4	Teaching activities have a positive effect on the class environment.	0.74	***	Acceptance
Hypothesize 5	The teaching activity has a positive effect on logical reasoning ability.	0.63	***	Acceptance
Hypothesize 6	Learning interest has a positive effect on logical reasoning.	0.51	***	Acceptance
Hypothesize 7	The classroom environment has a positive effect on logical reasoning ability.	0.48	***	Acceptance
Hypothesize 8	Learning attitude has a positive effect on logical reasoning ability.	0.36	***	Acceptance

4.3.4. Empirical findings. Hypothesis 1, which states that instructional activities have a positive effect on learning interest, is accepted, and as shown by the path coefficient, for every 1 unit increase in instructional activities, learning interest will increase by 0.14 units.

Although hypothesis 2 is accepted in the validation, the path coefficient of the dimension of teaching activities on learning attitude is small, only 0.01, which shows a weak influence effect, so the model needs to be further revised.

Hypothesis 3, which states that interest in learning positively affects attitude to learning and that for every 1 unit increase in interest in learning, attitude to learning increases by 0.18 units, is accepted.

Hypothesis 4 is accepted, i.e., teaching and learning activities have a positive effect on classroom environment and for every 1 unit increase in teaching and learning activities, classroom environment increases by 0.74 units.

Accept Hypothesis 5, that instructional activities have a positive effect on logical reasoning ability and that for every 1 unit increase in instructional activities, logical reasoning ability increases by 0.63 units.

Accept hypothesis 6 that interest in learning positively influences logical reasoning ability and that for every 1 unit increase in interest in learning, logical reasoning ability increases by 0.51 units.

Accept hypothesis 7 that class environment positively influences logical reasoning ability and that for every 1 unit increase in class environment, logical reasoning ability increases by 0.48 units.

Hypothesis 8 is accepted that attitude towards learning has a positive effect on logical reasoning ability and that for every 1 unit increase in attitude towards learning, logical reasoning ability increases by 0.36 units.

5. Reform of teaching methods

5.1. Project-driven teaching with students as the main body and teachers as the main body

This teaching model is dominated by the project-driven teaching method, with logical reasoning ability as the entry point, using the project to link the teaching and learning activities of teachers and students, and the process of completing the implementation of the project is the whole teaching process. The model mainly consists of two main subjects: teachers and students, and five teaching processes: project design, project analysis, project implementation, and summary and evaluation, which are organized through the project series. The teaching model is shown in Figure 3.

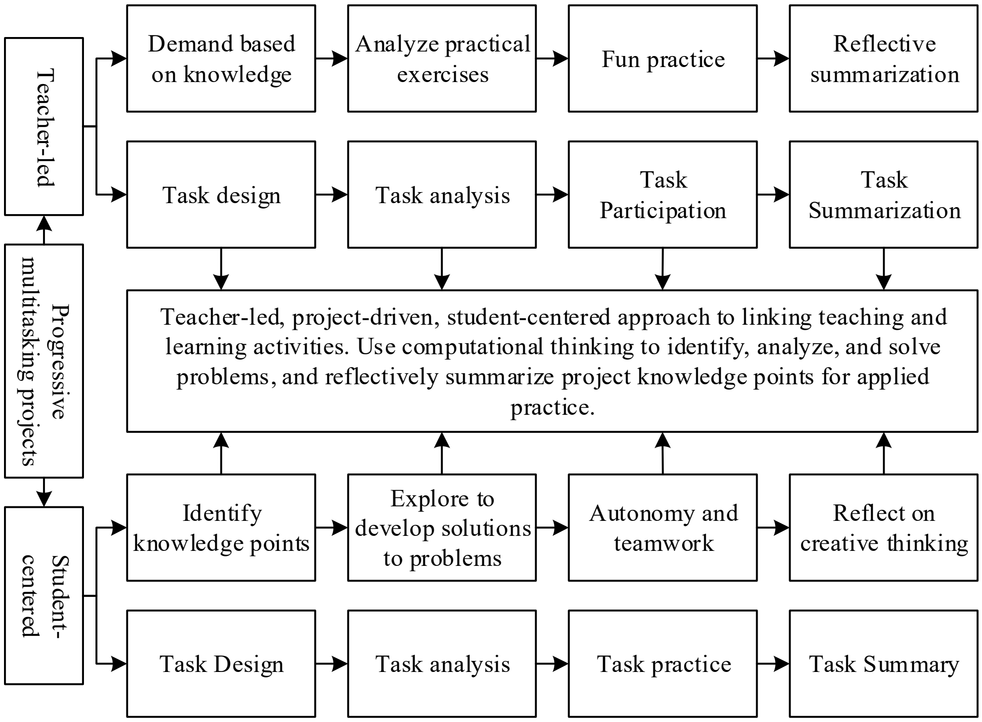

Fig. 3. Teaching model

5.2. Derived Progressive Instructional Content Design for Tailored Multi-Level Task Planning

Teaching content step by step in the process of completing the design of segmented, progressive teaching content. The project-driven teaching mode is to carry the knowledge points through the whole project operation process, mastering Python basic, including basic data types, combined data types, control structures and file operations. Master Python advanced, able to apply third-party libraries to solve more complex problems. During the completion of the project, students can also raise new questions for scientific inquiry and knowledge expansion, truly cultivate the ability to analyze and solve problems, and then achieve the cultivation of thinking ability and experience the fun of innovative practice [24]. Through the 13 segments of progressive project teaching difficult to easy, scientific and systematic development of students' ability to logical reasoning ability. Advanced modules are recommended for students who have the ability to learn, including NumPy, Pandas and Matplotlib, etc. The teaching content design based on the improvement of logical reasoning ability is shown in Table 16.

Table 16. Teaching content design

Course task	Corresponding knowledge points
Print student scores	Input output
Calculated average	Operator use
ranking	Sort operation
Statistical section	array
Achievement query	function

The average score of each student	List, dictionary
Record download	File operation
Achievement entry system	Combined operation
Face draw	Algorithm, graphics processing
Data management	database
Grade management system	Classes, object-oriented, functions
A beautiful rose	Use of class libraries
Airplane game	Class library, image processing
Advanced module	NumPy, Pandas, Matplotlib (project classification is recommended for students who are more likely to learn more.)

5.3. Online and offline hybrid teaching model

MOOC generally refers to large-scale open online courses, which greatly enriches students' theoretical learning and practical practice in and out of class [25]. Educoder (head song) platform is an integrated experimental environment for learning, practicing, evaluating, and testing, which can tightly integrate the traditional knowledge transfer and the integration of engineering practice. Using these two platforms with each other applied to the project-driven teaching of the 3 links before, during and after the class. Teachers set up students' pre-study tasks through MOOC before class, and adjust the content of project-driven teaching according to the data of students' pre-study situation. Based on the syllabus, two MOOC resources are recommended for students, so that students can study before class and review after class. Teachers in the class through the project-driven so that students do secondary school, the project completion process, the real development of analysis, problem-solving ability, and then achieve the cultivation of thinking ability and experience the fun of innovation and practice. Through the head song platform to set up after-school practical training homework. Touge platform has modules of practical courses, practical projects, subject teaching, case teaching, etc., with rich and high-quality teaching content and practical projects.

5.4. Adoption of multiple evaluation process assessment system for course assessment

Traditional exam-oriented education determines students' performance solely on the basis of the content of the one-time final grade, ignoring the learning process, which is not conducive to the improvement of comprehensive quality. Process assessment comprehensively assesses students' learning ability, application ability and innovation ability through students' learning situation and stage-by-stage learning effect. The course assessment adopts a multiple evaluation system, and the final grade is composed of pre-course (10%) + in-course (45%) + post-course (45%). The course assessment adopts multiple evaluation process assessment system as shown in Table 17. Among them, the large homework project stage assessment is defended in the form of a group, synthesizing the self-assessment of group members and the performance of questions to group members. According to the standard of 45 students in a class, teams are divided according to the students' specialties. Students are divided into 6~7 teams, each with 7~8 members, and then a captain is recommended. Objective and comprehensive grades are given to students based on their contribution to the group defense stage of the large homework system design and their mastery of the Python language. This not only assesses students' theoretical knowledge but also examines and cultivates their thinking ability, and the assessment is carried out throughout the semester, which promotes students' independent learning and improves their ability of logical reasoning ability. The post-course stage PTA test can detect students' mastery of the Python programming language. The way of evaluating students' learning outcomes can no longer be determined by the final grade across the board, but should clarify the types of learning outcomes and emphasize the multiple process assessment, through which the assessment scheme can help to further improve students' motivation to learn, stimulate the enthusiasm for innovation, and comprehensively improve the quality of teaching and learning.

Table 17. The evaluation process of the evaluation process is adopted

Preclass(10%)	In class			After class	
Resource preview (10%)	Attendance(5%)	Classroom performance(10%)	A team of work teams(30%)	Platform(15%)	Stage test 3 times(30%)

6. Conclusion

The use of artificial intelligence drivers to design teaching greatly improves students' logical reasoning ability and helps them form rational thinking. The study uses structural equation modeling to analyze the effects and paths of influence between and on the logical reasoning ability of each of the factors of teacher activity, learning interest, learning attitude and classroom environment.

After theoretical analysis and hypothesis testing, the study concludes that teacher activity, learning interest, learning attitude and classroom environment all have a significant effect on the improvement of students' logical reasoning ability in the teaching of artificial intelligence drivers. Among them, teaching activity has the greatest effect of 0.74 on class environment.

The study proposes a teaching model based on the improvement of logical reasoning ability, adopting student-oriented, teacher-led, project-driven teaching with logical reasoning ability as the entry point, derivative progression teaching with multi-level task planning according to the students' abilities, and mixed online and offline teaching modes with a multi-evaluation process assessment system. It not only stimulates students' interest in learning, but also improves students' ability to find problems, solve problems and innovate, and provides an effective solution for students to improve their logical reasoning ability in the teaching of artificial intelligence drivers.

References

[1] Xiaoyong, H. U., Shuo, S. U. N., Wenjie, Y. A. N. G., & Geying, D. I. N. G. (2023). Artificial Intelligence Empowering the High-Quality Development of Education: Demands, Visions, and Paths. Frontiers of Education in China, 18(1).

[2] Ma, B., & Hou, Y. (2021). Artificial intelligence empowers the integrated development of legal education: Challenges and responses. Future Human Image, 16, 43-54.

[3] Malliga, T. (2024). EMPOWERING EDUCATION: THE VITAL ROLE OF ARTIFICIAL INTELLIGENCE. Changing Landscape of Education.

[4] Lytras, M. D., Serban, A. C., Alkhaldi, A., Aldosemani, T., & Malik, S. (2024). Transformative Learning for Future Higher Education: The Artificial Intelligence-enabled Learning Revolution 2035. In Digital Transformation in Higher Education, Part B (pp. 231-241). Emerald Publishing Limited.

[5] Peng, Q. (2024). Lifelong Learning System in the age of Artificial Intelligence: Change, Opportunity and Reconstruction. Journal of Electrical Systems, 20(2), 1085-1091.

[6] Yu, H., & Guo, Y. (2023, June). Generative artificial intelligence empowers educational reform: current status, issues, and prospects. In Frontiers in Education (Vol. 8, p. 1183162). Frontiers Media SA.

[7] Han, Y. (2024, July). Commentary: Generative artificial intelligence empowers educational reform: current status, issues, and prospects. In Frontiers in Education (Vol. 9, p. 1445169). Frontiers Media SA.

[8] Ouyang, F., & Jiao, P. (2021). Artificial intelligence in education: The three paradigms. Computers and Education: Artificial Intelligence, 2, 100020.

[9] Tarisayi, K. (2024). Preparing For AI's Transformational Potential: Rethinking Teacher Education In South Africa. International Education Trend Issues, 2(1), 31-40.

[10] Yue, M., Jong, M. S. Y., & Dai, Y. (2022). Pedagogical design of K-12 artificial intelligence education: A systematic review. Sustainability, 14(23), 15620.

[11] Edwards, B. I., & Cheok, A. D. (2018). Why not robot teachers: artificial intelligence for addressing teacher shortage. Applied Artificial Intelligence, 32(4), 345-360.

[12] Akgun, S., & Greenhow, C. (2022). Artificial intelligence in education: Addressing ethical challenges in K-12 settings. AI and Ethics, 2(3), 431-440.

[13] Rosak-Szyrocka, J., Żywiołek, J., Nayyar, A., & Naved, M. (Eds.). (2023). The Role of Sustainability and Artificial Intelligence in Education Improvement. CRC Press.

[14] Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). Conceptualizing AI literacy: An exploratory review. Computers and Education: Artificial Intelligence, 2, 100041.

[15] Robert, A., Potter, K., & Frank, L. (2024). The impact of artificial intelligence on students' learning experience. Logical Techniques in computer science, 2(2), 71-76.

[16] Yang, S. J., Ogata, H., Matsui, T., & Chen, N. S. (2021). Human-centered artificial intelligence in education: Seeing the invisible through the visible. Computers and Education: Artificial Intelligence, 2, 100008.

[17] Xiao, P., Chen, Y., & Lu, C. (2022, December). Research on Case Teaching Reform Enabled by CNN Model. In 2nd International Conference on Internet, Education and Information Technology (IEIT 2022) (pp. 729-737). Atlantis Press.

[18] Popenici, S. A., & Kerr, S. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. Research and practice in technology enhanced learning, 12(1), 22.

[19] Lytvynova, S. H., Rashevska, N. V., & Proskura, S. L. (2024). The use of artificial intelligence in teaching students programming languages. In Proceedings of the IX International Workshop on Professional Retraining and Life-Long Learning using ICT: Person-oriented Approach (3L-Person 2024) co-located with 19th International Conference on ICT in Education, Research, and Industrial Applications (No. 3781, pp. 10-29). CEUR Workshop Proceedings.

[20] Huang, C. H. (2024). Programming Teaching in the Era of Artificial Intelligence. Eximia, 13, 583-589.

[21] Wang, X., Huang, R. T., Sommer, M., Pei, B., Shidfar, P., Rehman, M. S., ... & Martin, F. (2024). The Efficacy of Artificial Intelligence-Enabled Adaptive Learning Systems From 2010 to 2022 on Learner Outcomes: A Meta-Analysis. Journal of Educational Computing Research, 07356331241240459.

[22] Theano Papagiannopoulou & Julie Vaiopoulou. (2024). Teachers' Attitudes Towards STEM Education: Exploring the Role of Their Readiness via a Structural Equation Model. European Journal of Investigation in Health, Psychology and Education(11),2850-2864.

[23] Chen Qinxian,Zhong Xuanxuan & Liu Xinyi. (2024). A Survey Study on TPACK Framework for Normal Students of English Major in Ethnic Colleges and Universities: Empirical Analysis Based on Structural Equation Modeling. Journal of Contemporary Educational Research(9),112-119.

[24] Cai Wenming. (2024). Research on Educational and Teaching Reform of Environmental Design Major in Yili Normal University. Education Reform and Development(11),94-99.

[25] Li Wang. (2024). Exploration of Teaching Reform Path for the Course "Computer Organization Principles" Based on O2O Personalized Teaching Mode. Computer Informatization and Mechanical System(6),26-30.