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Analysis of the Impact of Artificial Intelligence on College Students' Learning

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Abstract: *Using factor analysis method to evaluate the impact of artificial intelligence on college students' learning. By using SPSS software to test the reliability and validity of the questionnaire, key factors were selected and a factor analysis evaluation model was constructed, revealing the key factors that affect the understanding of artificial intelligence among science and engineering freshmen. This study explores students' behavior and attitudes towards the use of artificial intelligence learning tools, including time investment, proportion of using artificial intelligence tools to complete assignments, participation in online activities, use of artificial intelligence learning tools, perspectives on replacing teachers with artificial intelligence tools, and recognition of the advantages of learning software over traditional classroom teaching. By analyzing the factor load matrix and scores, the importance of each factor can be explained. These technologies provide in-depth insights into the impact of artificial intelligence. The establishment of the model reveals the key factors that affect college students and obtains ratings for each factor. Finally, a rating table was generated and compared, and the results were evaluated and analyzed. In summary, through factor analysis, we can comprehensively evaluate the impact of artificial intelligence on college students' learning and provide useful references for further research and educational practice.*

Keywords: *Artificial Intelligence, SPSS, Key Factors, Factor Analysis Evaluation Model*

1. Introduction

The paper "Research on Evaluating the Impact of Artificial Intelligence on College Students' Learning Based on Cluster Analysis and Factor Analysis Models" uses cluster analysis and factor analysis models to evaluate the impact of artificial intelligence on college students' learning [1]. The research aims to identify patterns and key factors related to the impact of artificial intelligence on students' learning, and evaluate their effectiveness. The study covers students' behavior and attitudes towards using artificial intelligence learning tools, including time expenditure, completion rate of homework using artificial intelligence learning tools, participation in online activities, use of artificial intelligence learning tools, views on replacing teachers with artificial intelligence tools, and recognition of the advantages of learning software over classroom teaching. By analyzing survey data from first-year students majoring in natural sciences, the study successfully identified the factors that affect students' learning in the context of artificial intelligence. The study constructed an evaluation model based on cluster analysis and factor analysis, simplifying the data analysis process and revealing potential structures and correlations [2]. The research findings provide valuable insights into the impact of artificial intelligence on students' learning, revealing patterns and key factors, and evaluating their effectiveness [3]. This study proposes an evaluation model based on cluster analysis and factor analysis, providing valuable reference for understanding the impact of artificial intelligence in the field of education.

2. The Basic Principles of Factor Analysis

2.1 The Structure of Factor Analysis Method

In the data provided in the survey, there will be some internal connections between each item. In order to demonstrate the degree of intrinsic connection between them, factor analysis was used to identify six main factors that affect the learning of college students influenced by artificial intelligence [4]. Before analyzing, in order to make the results obvious and reliable, it is necessary to remove some options that

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have no impact on college students' learning, and then evaluate and score them, such as some qualitative questions.

According to the literature review, the structure of factor analysis methods includes variable selection, factor extraction, factor rotation, factor interpretation and naming, and factor score calculation [5]. According to the requirements of the problem, we established a mathematical model using factor analysis to evaluate the impact of artificial intelligence on college students' learning. Select the six most important questions, which are also used to represent the specific impact indicators of the model. The following are the steps of the factor analysis model corresponding to the six evaluation indicators:

1) Collect the survey data related to the six evaluation indicators, and conduct Data cleansing and pre-processing to ensure the accuracy and consistency of the data.

2) Apply factor analysis method to extract factors from six evaluation indicators. By using statistical techniques, highly correlated indicators are grouped into the same factor to reduce the number of indicators and retain key information in the data.

3) Rotate the extracted factors to ensure better interpretability and interpretability. Common rotation methods include orthogonal rotation (such as variance maximization rotation) and oblique rotation (such as maximum likelihood estimation rotation).

4) Calculate the scores of each sample on each factor based on the rotated factor load matrix. These scores represent the relative positions of the samples on different factors and reflect the importance of the corresponding evaluation indicators.

5) Based on the factor load matrix and factor scores, explain the meaning represented by each factor, and analyze and discuss it in conjunction with actual situations. Evaluate the impact of artificial intelligence on college students' learning based on the magnitude and direction of factor scores, and provide clear and convincing conclusions.

Flow Chart for Establishing a Factor Analysis Model see Figure 1.

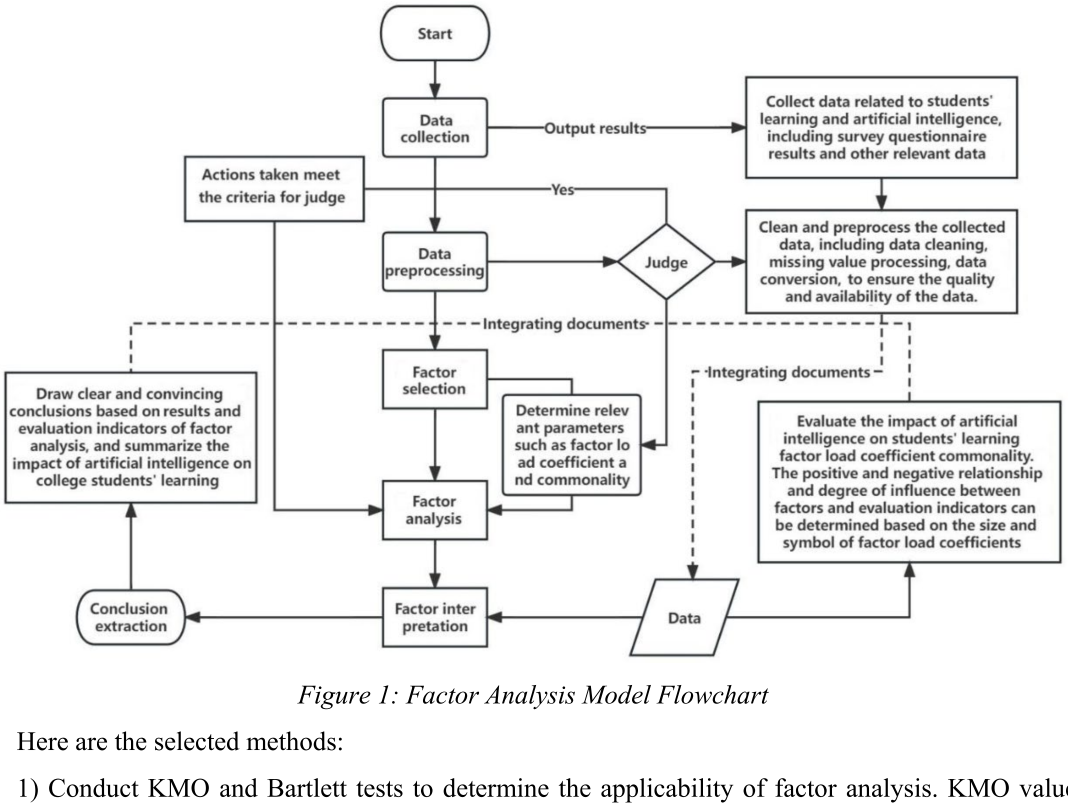

Figure 1: Factor Analysis Model Flowchart

Here are the selected methods:

1) Conduct KMO and Bartlett tests to determine the applicability of factor analysis. KMO values greater than 0.9 are very suitable for factor analysis; Suitable between 0.7 and 0.9; Acceptable between 0.6 and 0.7; Poor between 0.5 and 0.6; Less than 0.5 is not suitable. KMO testing determines the applicability of factor analysis. In Bartlett's test, if the p-value is less than 0.05, reject the null hypothesis and apply factor analysis. If the null hypothesis is not rejected, the variable may provide independent information and is not suitable for factor analysis.

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2) Analyze the variance explanation table and screen images to determine the number of factors. The variance explanation table shows the contribution of each factor to the variance of the variable. If the contribution is low (<60%), the factor data needs to be adjusted. The screen image determines the number of factors through the slope of feature values.

3) Analyze the factor load coefficient and heat map, and evaluate the importance of potential variables in each factor. The factor load matrix can be used to derive factor formulas.

4) Use factor loading plots to reduce multiple factors to two or three factors and visualize their spatial distribution. If extracting two factors, a three-dimensional scatter plot cannot be displayed. If extracting one factor, a quadrant plot cannot be displayed.

5) Derive factor component formulas and weights from factor load matrix analysis.

6) Comprehensive score based on factor analysis output.

Here are some formulas commonly used in factor analysis:

1) Factor loading:

$$\lambda = \mathrm{cov}(X, F) / \mathrm{var}(F) \tag{1}$$

2) Factor scores:

$$S = XF' \tag{2}$$

3) Communality:

$$h^2 = \sum \lambda^2 \tag{3}$$

These formulas are used to calculate factor loadings, factor scores, and communality, revealing the relationships between observed variables and factors and interpreting the results of factor analysis. The specific calculation methods may vary depending on the chosen factor analysis approach and software used [6].

Factor analysis reveals the underlying structure and relationships among observed variables, extracting fewer but more meaningful factors to simplify data analysis and provide deeper insights.

2.2 Steps for Solving Factor Analysis Model

Reliability refers to the consistency, stability, and reliability of test results, usually measured by a reliability coefficient. A higher reliability coefficient indicates a higher reliability of the questionnaire survey results. Effectiveness refers to the degree to which a measuring tool can accurately measure the object being measured. A higher validity indicates a higher degree of consistency between the measurement results and the survey content, while conversely, a lower validity [7].

We will use the method of Simple function change to analyze the data and carry out correlation analysis to get Table 1.

Table 1: Cronbach Reliability Analysis - Simplified Format Table

Cronbach Reliability Analysis - Simplified Format		
Number of items	sample size	Cronbach α coefficient
23	1123	0.755

Table 1 Cronbach Reliability Analysis - Simplified Format Table shows the reliability and accuracy of reliability analysis used to study quantitative data, especially attitude scale issues;

Firstly, it indicates high reliability; If this value is between 0.7 and 0.8, it indicates good reliability; If this value is between 0.6 and 0.7, it indicates acceptable reliability; If this value is less than 0.6, it indicates poor reliability; From this, it can be seen that the data α The coefficient is 0. 755, between 0. A range of 7-0.8 indicates good reliability.

Validity research aims to analyze whether the research items are reasonable and meaningful, using factor analysis as a data analysis method. Conduct a comprehensive analysis of the validity level of the data through indicators such as KMO value, commonality, variance interpretation rate, and factor loading

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coefficient to verify its rationality. The KMO value is used to evaluate the suitability of information extraction, the commonality value is used to exclude unreasonable research items, the variance interpretation rate value is used to explain the level of information extraction, and the factor loading coefficient is used to measure the relationship between factors (dimensions) and items (See Table 2).

Table 2: KMO and Bartlett's inspection table

KMO and Bartlett's test		
KMO value		0.831
Bartlett Sphericity inspection	Approximate chi square	1228.01
	freedom	186
	significance	.000

According to the results in the Table 2, the commonality values corresponding to all research items are higher than 0.4, indicating that the information of the research items can be effectively extracted. For the analysis of KMO values, according to its introduction, the KMO value of 0.831 exceeds the threshold of 0.8, indicating that the data is very suitable for information extraction.

Finally, six impact indicators were obtained: Weekly Internet Usage, AI Learning Tools for Homework, Online Activities, Using artificial intelligence learning tools, AI Tools Replacing Teachers, Advantages of Learning Software Compared to Classroom Teaching.

Explanation of variance in the model:

Table 3: Explanation table for variance of the model

Total variance explanation						
component	Interpretation rate of variance before rotation			Interpretation rate of variance after rotation		
	Eigenvalue	Variance Interpretation Rate (%)	Cumulative variance interpretation rate (%)	Eigenvalue	Variance Interpretation Rate (%)	Cumulative variance interpretation rate (%)
1	1.706	28.428	28.428	1.706	28.428	28.428
2	1.075	17.912	46.341			
3	1.026	17.106	63.447			
4	0.915	15.255	78.702			
5	0.873	14.544	93.246			
6	0.405	6.754	100			

In the variance explanation table 3, at principal component 1, the characteristic root of the total variance explanation is less than 2.0.

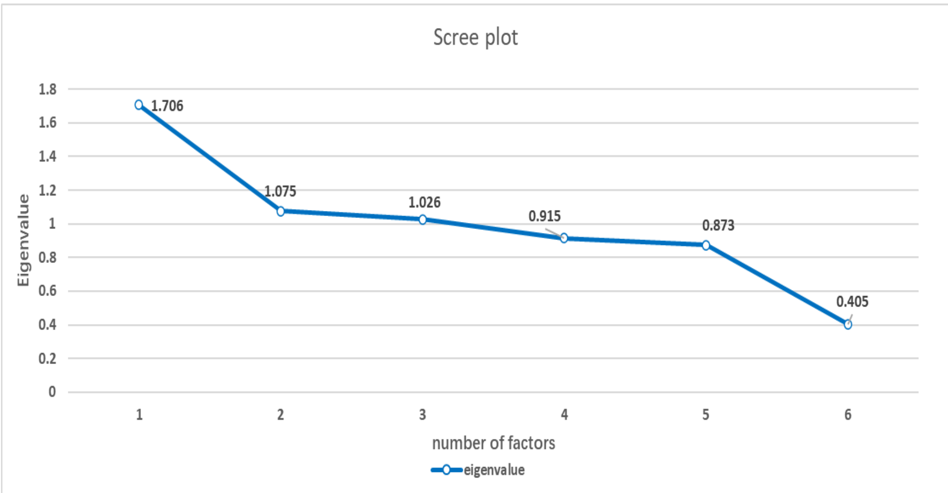

Figure 2: Gravel diagram of the model

Figure 2 is a chart drawn based on the degree to which each major component explains the changes in data. Its function is to determine the number of factor principal components to be selected based on the slope of feature value decrease, and combined with the variance interpretation table, it can be used to determine or adjust the number of factor principal component scores. Each principal component is a point, and the number of extracted principal components is determined by the position where the slope tends to be flat, as shown in Table 4.

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Table 4: Factor Load Factor Table

Table of factor load coefficients after rotation		
	Factor load factor after rotation	Commonality (common factor variance)
	Factor 1	
6,Weekly Internet Usage?	0.124	0.015
13,AI Learning Tools for Homework?	0.85	0.722
14,Online Activities?	0.84	0.705
21,Using artificial intelligence learning tools?	0.341	0.116
23,AI Tools Replacing Teachers?	-0.144	0.021
24,Advantages of Learning Software Compared to Classroom Teaching?	-0.356	0.127

The importance of hidden variables in each principal component can be analyzed. Assuming that n factors are determined in the previous text, and the factor load coefficients of a, b, c, and d in factor i are relatively large, factor i can be determined as a certain component.

Based on the obtained options, it was found that the six selected items showed significant significance in all the items. The following is the thermodynamic diagram of the significant factors obtained in Figure 3:

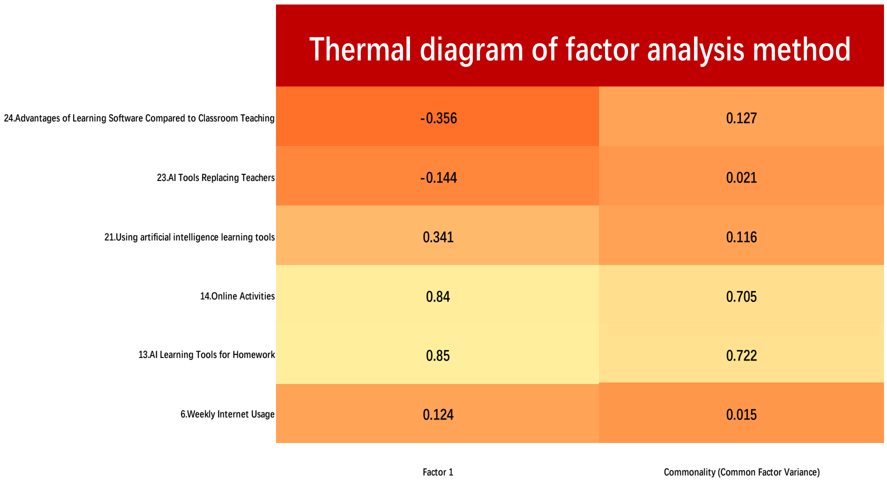

Figure 3: Thermal diagram of factor analysis method

Factor Weight Analysis:

Table 5: Factor Weight Analysis Table

title	Interpretation rate of variance after rotation (%)	Interpretation rate of cumulative variance after rotation (%)	Weight (%)
Factor 1	1.706	28.428	100

Table 5 The principal component weight analysis based on information such as load coefficients for factor analysis is calculated using the formula: variance interpretation rate/cumulative variance interpretation rate after rotation. The weight calculation results of factor analysis show that the weight of factor 1 is 100%.

From this, the comprehensive score table of the model is obtained

To evaluate the impact of artificial intelligence on college students' learning based on selected evaluation indicators and data characteristics, a mathematical model can be established using the factor analysis method. This model quantifies the extent of artificial intelligence's influence on learning by analyzing the interrelationships and correlations within the data [8].

It should be noted that factor analysis methods are based on some assumptions, such as linear relationships between variables, factor independence, etc. Before applying factor analysis, it is necessary to ensure the satisfaction of these assumptions and verify the applicability of the data [9].

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3. Results

3.1 The establishment of simulation model

Using a factor analysis model based on artificial intelligence in the SPSS software, we analyze the factors influencing college students by incorporating survey data.

3.2 Analysis of experimental results

Through the above steps, factor analysis can be used to establish mathematical models, evaluate the impact of artificial intelligence on college students' learning, and provide clear and convincing conclusions.

Table 6: Table of Test Data Prediction and Evaluation Results

Prediction Result Y	Your Major	Prediction Probability_ Grammar	Prediction Probability_ Science/ Engineering	Prediction Probability_ Business/ Management	Prediction Probability_ Arts/ Education	6, Weekly Internet Usage?	13, AI Learning Tools for Homework?	23,Online Activities?	14,Using artificial intelligence learning tools?	21,AI Tools Replacing Teachers?	24, Advantages of Learning Software Compared to Classroom Teaching?
Science and engineering	Economic management category	0.134	0.547	0.204	0.115	2	0	3	-1	0	2
Science and engineering	Science and engineering	0.059	0.680	0.174	0.086	3	0	3	-1	0	5
Science and engineering	Science and engineering	0.059	0.680	0.174	0.086	2	1	28	-1	-2	4
Science and engineering	Science and engineering	0.059	0.680	0.174	0.086	2	0	67	-1	0	4
Science and engineering	Science and engineering	0.046	0.646	0.154	0.154	1	1	19	1	1	1
Science and engineering	Science and engineering	0.045	0.701	0.224	0.030	2	0	33	-1	0	2
Science and engineering	Science and engineering	0.087	0.608	0.235	0.069	1	0	5	-1	0	2
Science and engineering	Economic management category	0.045	0.701	0.224	0.030	2	0	32	-1	0	2
Science and engineering	Science and engineering	0.134	0.547	0.204	0.115	3	1	3	-1	0	2
Science and engineering	Science and engineering	0.059	0.680	0.174	0.086	3	0	3	-1	0	5
Science and engineering	Science and engineering	0.087	0.608	0.235	0.069	2	0	15	0	0	2
Science and engineering	Science and engineering	0.084	0.579	0.271	0.065	3	0	5	1	0	2
Science and engineering	Economic management category	0.059	0.680	0.174	0.086	3	0	22	-1	0	4
Science and engineering	Science and engineering	0.087	0.608	0.235	0.069	1	0	5	0	-1	2
Science and engineering	Science and engineering	0.087	0.608	0.235	0.069	0	0	5	-1	0	2

Table 6 Table of Test Data Prediction and Evaluation Results shows the classification evaluation indicators for the training and testing sets, which measure the classification effectiveness of the training and testing data through quantitative indicators. Then, a table of test data prediction and evaluation results was further developed [10].

According to the comprehensive score table in Table 7, the impact of artificial intelligence on college students' learning can be summarized as follows:

The idea of using artificial intelligence learning tools to complete assignments and tests has a positive impact on college students' learning and is highly correlated with potential factors.

1) Artificial intelligence tools can replace the unclear relationship between teachers' ideas and college students' learning, and have a low correlation with potential factors.

2) There is a weak correlation between variables such as weekly online time, online activities, and recognition of the advantages of learning software over traditional classroom teaching and potential factors. These variables may be influenced by other factors, and their relationship with the impact of artificial intelligence on college students' learning is still uncertain.

In summary, the idea of using artificial intelligence learning tools to complete assignments and tests has a positive impact on college students' learning, while the relationship between other indicators and potential factors is weak, and the impact on college students' learning is still unclear.

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Table 7: Comprehensive Score Table

Rank	Category	Composite Score	6,Weekly Internet Usage?	13,AI Learning Tools for Homework?	14,AI Learning Tools for Quizzes?	21,AI Tools Replacing Teachers?	23,Using artificial intelligence learning tools?	24,Advantages of Learning Software Compared to Classroom Teaching?
1	Business	1.893	3	1	1	1	1	1
2	Engineering	1.893	3	1	1	1	1	1
3	Arts Education	1.893	3	1	1	1	1	1
4	Engineering	1.893	3	1	1	1	1	1
5	Business	1.893	3	1	1	1	1	1
6	Engineering	1.893	3	1	1	1	1	1
7	Business	1.893	3	1	1	1	1	1
8	Engineering	1.893	3	1	1	1	1	1
9	Engineering	1.893	3	1	1	1	1	1
10	Engineering	1.893	3	1	1	1	1	1
11	Engineering	1.893	3	1	1	1	1	1
12	Engineering	1.893	3	1	1	1	1	1
13	Humanities	1.893	3	1	1	1	1	1
14	Engineering	1.893	3	1	1	1	1	1
15	Engineering	1.893	3	1	1	1	1	1

4. Conclusions

The clustering analysis method used in this study is an unsupervised learning technique that identifies patterns and similarities within the data, grouping data points into clusters. This approach simplifies data complexity and provides comprehensive insights into the data by uncovering internal patterns and similarities.

The advantages of factor analysis in the given context include integrating multiple related variables into a smaller number of latent factors, reducing data dimensionality, revealing underlying structures and relationships within the data, and providing interpretable results. By conducting factor analysis on survey data, we can eliminate redundancy among variables, uncover hidden structures and patterns, and gain deeper insights into the phenomena and associations underlying the data.

In summary, cluster analysis and factor analysis methods can help us discover the intrinsic structure of data, reduce data complexity, and provide interpretable results. They hold great importance in model evaluation and data analysis.

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