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Analysis of Artificial Intelligence Applications and Their Impacts on Higher Education

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Abstract: *In today's era, the rapid development of artificial intelligence is reshaping higher education, and influencing our learning, life, and work. This study investigates the impact of artificial intelligence (AI) on college students' learning attitudes and effectiveness. A comprehensive evaluation model was developed from a survey of 4605 students, using principal component analysis and entropy weighting. The attitudes of 1729 students towards AI were analyzed, showing a normal distribution trend. The study utilized logistic regression to examine the influence of respondent characteristics on attitudes toward AI, establishing a 12-group correlation model. Tests confirmed the model's validity. The findings revealed that internet usage time negatively correlates with AI learning inclination, while factors like gender and personality show minimal impact. The study encapsulates 19 significant conclusions, providing practical insights aligned with real-world contexts.*

Keywords: *Questionnaire, Artificial Intelligence, College Student Learning, Logistic Regression*

1. Introduction

With the rapid advancement of AI technology, its application in various sectors, especially in higher education, is profound. AI is revolutionizing teaching methods and the student learning experience in colleges. However, there's a gap in detailed, systematic research on college students' perceptions and use of AI in learning, including its differentiated impact on male and female students and across various majors. To address this, our study employs a mathematical modeling approach.

Our research, part of the 'Artificial Intelligence for Future Education Development' project led by Gu Xiaoqing, reveals AI's role in addressing challenges in innovative talent development, supporting personalized education at scale, reshaping knowledge and teaching concepts, empowering future teacher development, and driving systematic changes in the educational ecosystem. Similarly, Du Shudong's[1] team is investigating the impact of AI on higher education. They have improved the entropy weight method for comprehensive water quality evaluation, using Baiyun Lake as a case study. Additionally, Shi Yafeng's[2] team has developed a non-parametric method to test volatility proxy variables, aiding in building models to analyze AI's influence on college students.

4605 questionnaires were distributed, followed by the creation of a comprehensive evaluation model based on principal component analysis and entropy weighting method. Analysis of 1729 samples using non-parametric tests showed that college students' attitudes towards artificial intelligence roughly follow a normal distribution. Differences in respondents' characteristics were examined using logistic regression, with 'characteristics of the respondent group' as the independent variable and 'orderliness' as the dependent variable, forming a 12-group correlation model. This model was validated through the rent test, model inter-check, and robustness testing. Regression results revealed insights such as students spending more time on the Internet having a lower propensity for AI learning. The summarized findings and their real-world implications are presented in the following table.

2. Principal Component Analysis and Dimensionality Reduction of Evaluation Indicators

2.1 Principal Component Analysis

The basic steps are (1) Perform KMO and Bartlett's test to determine whether principal component analysis can be performed. (2) Determine the number of principal components by analyzing the variance

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explained table. (3) Analyze the importance of the hidden variables in each principal component by analyzing the principal component loading coefficients and heat map[3].

Table 1: KMO and Bartlett test results

KMO value		0.849
Bartlett test	Approximate chi-square	11438.20
	df	253
	p	0.000***

The following Table 1 shows the results of the M test and the Bartlett test, the result of the M test is 0.849 and the result of the Bartlett test shows a significance P-value of 0.000***, which presents significance at the level, and it is considered that there is a correlation between the variables, and the principal component analysis is valid.

The following table 2 shows the total variance explained table, the higher the variance explained indicates that the principal component is more important and the weight share should be higher. In the table of variance explained, when the principal component = 6, the eigenroot of total variance explained is lower than 1, and the contribution rate of the variable explained reaches 56.885.

Table 2: Total Variance Explained Table

Ingredient	Characteristic root	Explanation of variance (%)	Cumulative variance explained (%)
1	4.581	19.919	19.919
2	3.156	13.721	33.639
3	1.953	8.489	42.129
4	1.275	5.542	47.671
5	1.183	5.142	52.813
6	0.937	4.073	56.885
7	0.867	3.768	60.653

The following Figure 1 shows the heat map of the loading matrix, which can be analyzed to the importance of the hidden variables in each principal component. In summary, this paper combines the technology acceptance model to construct the following three dimensions: perceived ease of use, perceived usefulness, and AI expectation trust.

Among them, perceived ease of use is perceived ease of use refers to people's perception of the degree of difficulty in using a specific technology system; perceived usefulness refers to the degree to which people believe that the application of a certain system can improve their work efficiency and the perceived usefulness of such an application system. Artificial Intelligence Expectation Trust evaluates the various expectations of individuals about AI, including the cost of AI, learning effect expectations, and safety considerations.

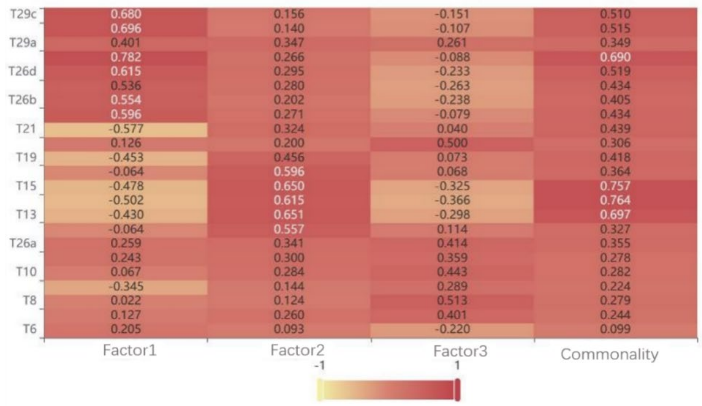

Figure 1: Thermal diagram of the load matrix

Perceived usefulness and perceived ease of use are two variables that positively affect attitudes toward use, which in turn affects willingness to use, leading to actual use, while perceived usefulness also has a direct effect on the intention to use. Attitude toward use refers to the subjective feelings of technology users toward the new technology. Intention to use refers to the intensity of the technology user's willingness to adopt the new technology. Perceived usefulness, as opposed to perceived ease of use, has been recognized as the strongest predictor of willingness to use and adopt technology and is a key variable in influencing consumer attitudes. Table 3 below is a description of the evaluation dimensions that can perceive the impact of the variables perceived usefulness and perceived ease of use on users.

Table 3: Description of evaluation dimensions

Dimension (math)	**Subject**
Perceived ease of use	26b. Are you most concerned about learning resources in the form of learning software? 26c. Are you most concerned about the ease of use of learning software? 6. How many hours per week do you spend on the Internet? 9. Will you upload your information to the Internet and share it with others?
Perceived usefulness	29a. Should the AI learning tool you have in mind have superior performance 12. If there are AI learning tools, would you choose to use them? 13. Do you have any idea of getting help with homework through AI learning tools? 14. Do you have an idea of an AI learning tool to help you complete your quizzes? 15. Do you have an idea of an AI learning tool to help you with your dissertation? 17. Do you agree with the use of AI learning tools for college students? 19. What is your attitude towards the credibility of AI learning tools in answering questions?
Artificial intelligence expects trust	21. Do you think AI tools could replace teachers in the future? 26d. Are you most concerned about the cost of learning in the form of utilizing learning software? 27a. What safety aspects of using AI tools have you considered? 29b. Should the AI learning tool you have in mind have a wide range of knowledge 29c. Should the AI learning tools you have in mind be free of charge 7. Have you used learning software tools? 8. When do you use the learning software tools? 10. Do you want to access learning resources from colleges and universities across the country? 22. How do you think students should adapt when AI tools are integrated with education to a certain extent? 26a. Are you most concerned about the effectiveness of learning in the form of utilizing learning software?

2.2 Entropy weight method

In this paper, a mathematical model will be constructed based on the above indicators to conduct a comprehensive evaluation of the impact of artificial intelligence on college students' learning. To realize the problem of comprehensive evaluation of multiple indicators, the first step is to establish a suitable mathematical model for calculating weights.

The basic idea of the entropy weighting method is to determine the objective weights based on the magnitude of indicator variability[1]. Generally speaking, if the information entropy of a certain indicator is smaller, it indicates that the indicator is worth a greater degree of variability, provides more information, and plays a greater role in the comprehensive evaluation, and its weight will be greater. On the contrary, the larger the information entropy of an indicator is, the smaller the degree of variability of the indicator is, the less information it provides, the smaller the role it plays in the comprehensive evaluation, and the smaller its weight is. The entropy value method is an objective assignment method, which determines the weights according to the degree of variability of the indicators and does not bring subjective bias. Therefore, the entropy weight method is selected as the modeling method in this paper.

(1) Data standardization: this paper uses the $\mathrm{Z-Score}$ Standardized method of de-measurement processing, this method is relatively simple, and the standardization effect is better.

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(2) Find the ratio of each indicator under each program.

$$P_{ij} = \frac{Y_{ij}}{\sum_{i=1}^{n} Y_{ij}} (i = 1,2, \dots, nj = 1,2, \dots, m) \tag{1}$$

(3) Find the information entropy of each indicator

$$E_j = -\ln(n)^{-1} \sum_{i=1}^{n} p_{ij} \ln p_{ij} \tag{2}$$

(4) Calculation of information margins

$$D_j = 1 - E_j \tag{3}$$

(5) Solve for the entropy weight magnitude of the selected 20 indicators as follows.

$$w_i = \frac{D_i}{\sum_{j=1}^{m} D_j} \tag{4}$$

The data of the selected indicators were summed up and averaged according to the dimensions, and the entropy weighting method mentioned above was used to obtain the entropy weights for each of the indicators.

The weights of the indicators are shown in the table 4 below:

Table 4: Evaluation dimension weights

Dimension (math.)	The information entropy value e	information utility value	Weighting (%)
Perceived Ease of Use	0.993	0.007	26.333
Perceived usefulness	0.991	0.009	36.766
Artificial Intelligence Expects Trust	0.991	0.009	36.901

A composite score is then calculated and the higher the score the more likely the individual is to accept the use of AI in learning[4].

3. Exploring the Impact of AI

3.1 Statistical tests

This paper assesses the impact of Artificial Intelligence (AI) on college students' learning from two perspectives: post-evaluation based on model construction and solving" and "evaluation based on differences in respondent groups". First, this paper constructed a comprehensive evaluation system using principal component analysis and entropy weighting to analyze 1,729 samples to measure overall attitudes toward AI. This involves statistical analysis and nonparametric tests to approximate the overall distribution. Second, the paper explores the impact on 'differences in respondent characteristics' through a logistic regression model. The model assesses the impact of these characteristics on respondents' attitudes towards AI.

The methodology of this paper uses three evaluation dimensions and their corresponding weights determined by principal component analysis and entropy weighting. After removing "respondent characteristics" and screening out the remaining 1,729 samples, the paper provides a comprehensive assessment of each sample and calculates a score. This score, defined as ce, reflects an individual's attitude toward AI in learning; a higher score indicates a more positive attitude.

The paper then analyzes the scores of these samples, looking at means, quartiles, variances, and other statistics. Given the unknown distribution of students' attitudes toward AI, this paper relies on statistical analysis of sample data and nonparametric tests to infer general trends. The findings include sample means, standard deviations, maximum and minimum values, medians, upper and lower quartiles, and

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deviation points. In addition, Figure 2 shows box plots and histograms of frequency distributions to illustrate these results.

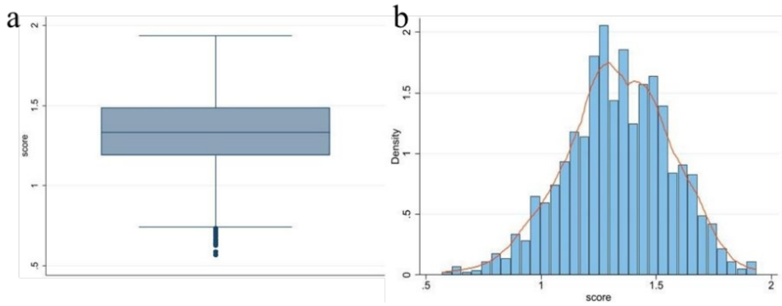

Figure 2: Score Boxplots and Histograms

Under the law of large numbers, the frequency distribution of different samples' ce scores across intervals should mirror the probability distribution of the overall population X within those intervals ($f_i \approx P(t_{i-1} < X \leq t_i)$). The figure's contour line closely matches the overall population's density function, suggesting that the ce scores generally adhere to a normal distribution.

In statistical analysis, the assumed distribution of a sample can often be ambiguous and not fully representative of the entire population [2]. To address this, we rely on nonparametric tests for more accurate conclusions. We applied the Traveler's test and the Kolmogorov-Smirnov (K-S) test using 'tata17' software to estimate the aggregate of ce and to assess the randomness of the sample sequence. Both the mean and median were used as benchmarks in this analysis, with detailed comparison results provided in Table 5.

Table 5: Travel test results

norm	upper quartile	average value	norm	upper quartile	average value
z	0.12	0.02	p	0.9	0.98

In the case of the sums, there is little difference between the two, and both exhibit randomness in the data and no autocorrelation.

In general, when analyzing large samples of data larger than 50 rows, we tend to look at the normality test results obtained by the K-S test; the K-S test, or kurtosis-skewness test, is a commonly used test for normal distribution, and the results are reported in table 6 below:

Table 6: K-S test results

variant	skewness	kurtosis	Adj chi2	p
scope	0.0015	0.7264	9.91	0.07

The above results show that ce approximately follows a normal distribution. It shows that the attitude of the student group towards "the application of AI in daily learning" is mixed, but the overall performance is inclined to be positive. In the above paper, the three dimensions of "perceived ease of use", "perceived usefulness", and "trust in AI expectations" were considered to estimate the total with the samples, which lacks the analysis and discussion of heterogeneity of different groups of respondents. To discuss the heterogeneity of different groups of respondents, this paper conducts the following research.

3.2 Modeling and conclusions based on logistic regression

First of all, based on the analysis and processing of the questionnaire set in the previous section, questions 1-7 were selected as the feature set of "respondent group", which contains seven features: gender, major, grade, personality, Internet access, Internet duration, and preference of learning software, and questions 8-10, 12-15, and 17-22 were selected as the explanatory variables. The original dataset was obtained according to the numerical treatment of question one, and this part does not show descriptive statistics. The grounded theory model was set up as follows:

$$q = \alpha + \beta X + \varepsilon \tag{5}$$

In the above equation, the explanatory variable represents the corresponding explanation of the selected question, which is an ordinal variable. For example, 2 corresponds to question 9, which is

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"Willingness to share learning materials over the Internet," and has five scales, with higher values indicating greater willingness. The explanatory variables are the factors affecting the above questions, which represent the respondents' attitudes towards the different questions in terms of their characteristics; they are the corresponding regression coefficients. The explanatory variables represent the factors affecting the above questions, indicating the respondents' attitudes toward the different questions; and the corresponding regression coefficients.

When using gt regression to deal with the regression of categorical variables, it is required that the categorical variable problem satisfies the parallelism assumption[5], which needs to be tested during the calculation process, and in this paper, we use the at method to test the parallelism assumption of the explanatory variables. Specifically, this paper constructs an ordered gt regression based on the 7 types of characteristics of the interviewed subjects, and the form of the measurement model is as follows:

$$q_i = \alpha + \beta_1 x_1 + \cdots + \beta_7 x_7 + \varepsilon \tag{6}$$

In the above equation, denotes the ordinal number of the question, i.e. = 1, ..., 12; denotes the random error of the regression of the question; and 1, ..., 7 represent the gender, major, grade, personality, Internet access, Internet duration, and learning software preference of the respondents, respectively. In this question, the coefficients of the independent variables require special attention. Considering the specificity of gt regression, the coefficients do not represent the degree of influence of the explanatory variables on the explanatory variables, and need to be further analyzed and calculated.

In this paper, the indicator "odds ratio" was chosen to characterize the effect of changes in the independent variable on attitudes toward question answering, which is also

The unique advantage of gt regression for questionnaire analysis. The odds ratio is defined as follows:

$$e^{\beta} = \frac{p*/(1-p*)}{p/(1-p)} = \frac{\exp\left(\alpha + \beta_1 x_1 + \cdots + \beta_j\left(x_j + 1\right) + \cdots + \beta_7 x_7 + \varepsilon\right)}{\exp\left(\alpha + \beta_1 x_1 + \cdots + \beta_j x_j + \cdots + \beta_7 x_7 + \varepsilon\right)} \tag{7}$$

In our study, we examine how a one-unit increase in an independent variable influences the incidence ratio, denoted by *. This measure reflects the multiplicative change in the incidence ratio between high and low-level groups for a given characteristic change in respondents, effectively capturing the variance in student attitudes towards specific questions.

Table 7: Logistic regression results (q1-q6)

Variant	(1)	(2)	(3)	(4)	(5)	(6)
	q1	q2	q3	q4	q5	q6
x1	0.928	1.150	0.877	0.970	0.898	1.117
	(-0.55)	(1.39)	(-0.61)	(-0.17)	(-0.88)	(0.95)
x2	1.007	0.898**	1.127	1.100	0.894*	0.847***
	(0.10)	(-2.23)	(1.28)	(1.18)	(-1.90)	(-2.94)
x3	0.968	1.120**	0.875	0.955	1.079	1.170***
	(-0.53)	(2.46)	(-1.41)	(-0.56)	(1.37)	(2.95)
x4	1.012	1.006	1.037	0.983	0.960	0.969
	(0.42)	(0.29)	(0.81)	(-0.45)	(-1.59)	(-1.28)
x5	1.012	1.339***	0.892	0.925	1.225***	1.218***
	(0.19)	(5.98)	(-1.25)	(-0.97)	(3.41)	(3.50)
x6	0.799***	0.791***	0.814***	1.080	1.079*	1.010
	(-4.64)	(-6.50)	(-2.77)	(1.23)	(1.80)	(0.25)
x7	8.797***	2.511***	8.325***	5.802***	1.281	0.849
	(8.13)	(3.47)	(6.89)	(5.98)	(0.84)	(-0.55)
cut1	0.488*	0.265***	0.363*	0.838	0.684	0.652
	(-1.81)	(-3.84)	(-1.90)	(-0.37)	(-0.96)	(-1.10)
cut2	1.294 (0.65)	0.902 (-0.30)				
cut3		3.420*** (3.57)				
cut4		9.420*** (6.45)				
statistical value	82.18	112.79	56.51	43.20	23.94	37.38
	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
sample size	1,729	1,729	1,729	1,729	1,729	1,729

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The data analyzed here are derived from numerical processing of responses to questions 1-10, 12-15, and 17-22 in our survey. We forego the analysis of categorical bases and descriptive statistics in this section. Initially, we conducted an F test on the explanatory variables, confirming the absence of multicollinearity among the seven variables. We then tested the parallelism assumption; the at test results allowed for the regression of 12 questions on gt, all meeting the assumption. This informed our selection of variables for Ologit regression analysis. This analysis included 12 variable sets, providing odds ratios, standard errors (using robust errors indicated in parentheses in the table), statistics, and corresponding p-values. Our sample size was 1729. The 'cut' value in the table serves as a breakpoint for predicting new samples, with 'cut+1' indicating the number of ordered variable categories. The results for these 12 sets are detailed in the table7, table8

The number of *'s represents the level of significance. * indicates a p-value of less than 0.05, ** indicates a p-value of less than 0.01, and *** indicates a p-value of less than 0.001.

From the statistics and their corresponding values, it can be seen that all 12 models are significant and the models are valid. Robustness tests are also conducted in this paper, and the results show that all 12 regressions have good robustness. Here the focus is more on the results of the models and the robustness tests are not reported in detail.

Table 8: Logistic regression results (q7-q12)

Variant	(7)	(8)	(9)	(10)	(11)	(12)
	q7	q8	q9	q10	q11	q12
x1	1.049	0.611***	1.096	0.964	1.809***	0.887
	-0.41	(-2.81)	-0.79	(-0.26)	-5.37	(-0.67)
x2	0.856***	1.076	0.974	1.062	0.830***	1.042
	(-2.76)	-0.96	(-0.48)	-0.94	(-3.66)	-0.51
x3	1.159***	1.091	1.091*	0.863**	1.099*	0.826**
	-2.78	-1.14	-1.65	(-2.34)	-1.93	(-2.41)
x4	0.977	0.935*	0.987	0.974	0.942***	1.013
	(-0.93)	(-1.92)	(-0.54)	(-0.88)	(-2.62)	-0.33
x5	1.251***	0.989	1.321***	0.858**	1.346***	0.946
	-3.99	(-0.15)	-5.12	(-2.43)	-5.87	(-0.70)
x6	1.057	1.188***	0.900***	0.872***	0.848***	1.083
	-1.38	-3.01	(-2.62)	(-2.80)	(-4.38)	-1.31
x7	1.585	4.969***	1.493	3.132***	1.264	4.983***
	-1.62	-5.46	-1.31	-4.16	-0.86	-5.46
Cut1	1.432	0.972	0.077***	0.016***	0.861	0.112***
	-0.94	(-0.06)	(-6.30)	(-9.13)	(-0.42)	(-4.49)
Cut2			3.592***	0.055***	2.783***	0.472
			-3.23	(-6.92)	-2.87	(-1.57)
Cut3				0.350**		600.832***
				(-2.57)		-11.44
Statisticians value	36.66	51.68	48.02	40.11	130.72	41.15
	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
sample size	1,729	1,729	1,729	1,729	1,729	1,729

Model (1): Significant variables are internet usage time and learning software preference. More time online correlates with less initiative in using learning software, while a preference for such software greatly increases this initiative.

Model (2): Factors including major, grade, online mode, and time duration are significant. Liberal arts students are slightly more likely to share materials online; longer internet usage time decreases this likelihood. Students with a strong preference for learning software are twice as likely to share materials.

Model (3): Only internet time and software preference are significant. Longer internet usage negatively affects, while preference for learning software positively influences, attitudes towards e-learning.

Model (4): Learning software preference is the only significant variable, showing a strong positive relationship with AI tool usage.

Model (5): Science-oriented students are less inclined to complete assignments with AI compared to liberal arts students. Advanced internet access increases this willingness.

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Models (6) and (7): Major, grade level and internet access are significant. Higher grade levels correlate with a greater inclination to use AI for quizzes and essays.

Model (8): Female students and those with longer internet usage or a strong software preference show more positive attitudes towards AI tools for learning.

Model (9): Grade level and internet access mode are significant, with higher grades and better devices increasing trust in AI. Longer internet usage shows a negative relationship.

Model (10): Lower-grade students and those with less advanced devices have a narrower desired application range for AI learning. A strong preference for learning software expands this range.

Model (11) and (12): Gender differences are notable in attitudes towards AI replacing teachers, with males showing a stronger positive attitude. Grade level and software usage preference are also significant, confirming the trends observed in the model (10).

3.3 Heterogeneity analysis

In the above regression results, "learning software usage preference" is strongly significant for almost all models, which is likely to affect their evaluation of the question[6]. In this paper, the 1729 samples were divided into two groups, Group A representing preferences (1674 samples) and Group B representing no preferences (55 samples), and analyzed for heterogeneity. The results are as follows Table 9:

Table 9: Results of heterogeneity analysis

Group A	1	2	3	4	5	6	Group B	1	2	3	4	5	6
Q1-A						-/***	Q1-B						
Q2-A	+/*	-/**	+/***		+/***	-/***	Q2-B						
Q2-B						-/**	Q2-B						
Q3-A						+/*	Q3-B	-/*					
Q4-A		-/**	+/*		+/***	+/**	Q4-B			-/**		-/*	-/***
Q5-A		-/***	+/***		+/***		Q5-B						
Q6-A		-/***	+/***		+/***		Q6-B	-/*					-/*
Q7-A	-/**					+/***	Q7-B						
Q8-A			+/*		+/***	-/**	Q8-B						
Q9-A			-/**		-/**	-/***	Q9-B				-/*		
Q10-A	+/***	-/***	+/**	-/**	+/***	-/***	Q10-B						-/***
Q11-A			-/**				Q11-B					-/*	
Q12-A						-/***	Q12-A						-/***

The table primarily presents heterogeneity results, the symbols +/- indicate the direction of influence, while * denotes significance levels. The table reveals significant discrepancies between two regression analyses for the same question, highlighting notable differences in how two groups evaluate and perceive 'AI in university students' learning'. This disparity is understandable, as less frequent use of learning software might diminish trust in AI or reflect a lack of proficiency in its use. This heterogeneity underscores the importance of targeted research for different groups to reach precise evaluation conclusions. The same approach can be applied to the other six variables.

In conclusion, this paper quantitatively analyzes the impact of AI on college students, focusing on various student characteristics like initiative in using learning software, willingness to share learning materials, expectations from learning resources, preferences for AI learning tools, attitudes towards using AI for assignments, overall stance on AI tool application, trust in AI, anticipated scope of AI application, and the balance between AI and traditional teaching methods. This provides a more scientific perspective on quantitative analysis[7].

4. Conclusions

In this paper, various graphical representations were used for comparative analysis. After refining the unstructured data (including binary assignment and Likert scale assignment), we eliminated the fuzzy responses and retained 1729 valid samples. The evaluation index system was constructed on the basis of data analysis Through principal component analysis, we reduced the numerous questionnaire items to three dimensions: perceived ease of use, perceived usefulness, and AI trust expectations. These

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dimensions were weighted using the entropy weighting method to form our evaluation framework. A nonparametric test analysis of the 1,729 samples showed that students' attitudes toward AI were normally distributed. We used logistic regression to analyze attitudinal tendencies and formed a 12-group correlation model with "respondent characteristics group" as the independent variable and "orderliness issue" as the dependent variable. Validity tests including rnt test, internal model test and robustness test confirmed the reliability of the model. The regression results (expressed as ds - t) revealed 19 noteworthy findings. For example, students who spend more time online have a lower propensity to learn about AI, and factors such as gender and personality have little effect on attitudes.

References

[1] Du Shudong, Guan Yannan, Li Xin, Zhao Yuqiang, Liu Shanjun, Yan Chongyu, Bai Junhong. Evaluation of water quality based on entropy weighting method with improved integrated pollution index - An example of Baiyun Lake [J]. Journal of Environmental Science, 2022,42(01):205-212.

[2] SHI Ya-Feng,YING Ting-Ting,SHI Yan-Long,FAN Kui-Kui. Necessary conditions for qualified proxy variables of volatility and their nonparametric tests[J]. Statistics and Information Forum,2018,33(10): 43-48.

[3] LIN Hai-Ming, DU Zi-Fang. Issues to be noted in the integrated evaluation of principal component analysis [J]. Statistical Research,2013,30(08):25-31.

[4] Gu Xiaoqing, Li Shijin. Artificial Intelligence for Future Education Development: Essential Connotation and Contingent Path[J]. Journal of East China Normal University (Education Science Edition), 2022, 40(09):1-9.

[5] Wu Ke, Yuan Shengmin, Xing Wei. Analysis of factors affecting school soccer game performance based on the Ologit model[J]. Journal of Shanghai Institute of Physical Education,2019, 43(03):100-105+112.

[6] DONG Yinguo,FENG Meili,ZHANG Linchen. Impact of heterogeneous SPS measures on agricultural export trade: an empirical analysis based on RCEP members[J]. World Economic Studies, 2023(05):46-60+136.

[7] He Yongbin,Tang Haifeng,Wang Dongxue,Gu Shuqin,Ni Guoxin,Wu Haiyang. Will ChatGPT/GPT-4 be a Lighthouse to Guide Spinal Surgeons?[J]. Annals of biomedical engineering, 2023.