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An Evaluation of the Impact of Artificial Intelligence on university Students' Learning

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Abstract: With the rapid development and increasing popularity of AI in various industries, its impact on higher education, especially on the learning experience of college students, has become more profound. Various AI-powered educational tools and smart learning software are emerging, providing students with rich and convenient learning resources. The selected impact indicators were analyzed using the K-medoids clustering algorithm, which classified them into five different clusters: attitudes and expectations towards the use of AI learning tools, future prospects and adaptability of AI learning tools, patterns and purposes of AI use, safety and related concerns of AI tools, and meaningful and desirable features of AI learning tools. Subsequent ANOVA tests yielded a p-value of less than 0.05, thus confirming the appropriateness of the selected evaluation metrics. This academic review highlights the sound selection of evaluation criteria in the context of AI educational applications.

Keywords: Artificial Intelligence; Higher Education; University Students; Learning Resources; K-medoids Algorithm.

1. Introduction

In recent years, with the continuous progress of computer technology and algorithms, artificial intelligence has achieved impressive results in the fields of image recognition, natural language processing, intelligent interaction, etc., and can even surpass the level of human intelligence. The rapid development of AI has had a far-reaching impact on all walks of life. In order to seize the important strategic opportunities for the development of AI, China's State Council and the Ministry of Education have issued relevant plans and action plans, emphasising the development of AI and the rapid construction of an innovative country and a world power in science and technology [1]. For college students, the development of AI has also had an impact on their learning. In order to understand the impact of different aspects, the researcher designed and implemented a questionnaire and collected the corresponding feedback results. The evaluation and impact of AI tools in the field of university students' learning is a multidimensional problem. Through clustering by K-Means algorithm and ANOVA by ANOVA, we identified several key indicators. The significant p-values of these indicators indicate that they are differentiated among different groups and are suitable for constructing an evaluation system.

Students' attitudes and expectations towards AI learning tools, as a first-level indicator, are key to measuring acceptance. The level of trust students has in these tools and the results they expect to produce determine their likelihood of adopting them. The future outlook and adaptability in the second-level indicators discusses the possible replacement of traditional teaching roles by AI and the ways in which students are adapting to the combined use of education and AI tools. The tertiary indicators focus on the manner and purpose of use, reflecting the actual use of AI tools by students to assist in learning tasks [2]. Level 4 indicators of safety and issues reveal students' concerns about potential problems with AI learning tools, which may affect their willingness to use them. Level 5 indicators relate to the importance and desirable features of the tool, reflecting students' expectations and needs for AI learning tools.

In summary, the evaluation of the impact of AI learning tools on university students' learning involves a number of dimensions such as attitudes, expectations, adaptability, usage, safety and desirable functions [3]. The effectiveness of these tools depends not only on their development and design, but also on their acceptance and use by students. Systematic evaluation can help us understand the actual effectiveness of the tools and guide future optimization to better meet students' learning needs.

2. Related Work

In today's higher education sector, the introduction of AI learning tools is gradually changing the way university students learn. The evaluation and impact of these tools is a complex topic that involves not only the accuracy and functionality of the technology, but is also strongly influenced by the attitudes, expectations and usage habits of individual students. By analysing the problem using the K-Means clustering algorithm and validating the reasonableness of the evaluation metrics with ANOVA, we were able to select evaluation metrics that were prioritised, scientifically valid and actionable [4]. In this process, evaluation indicators with a significance p-value lower than 0.05 indicate that they are significantly different among different groups and can be used as an important basis for constructing the evaluation system. The data captures students' attitudes and expectations towards AI learning tools, which is an important first-level indicator for assessing their acceptance. Students' trust in AI tools and desired learning outcomes play a decisive role in their likelihood of adopting these aids. At the same time, secondary indicators reveal students' perceptions of the role of AI in the future of teaching and learning and their adaptation issues [5]. The need for students to find new ways of adapting to AI tools as they are further integrated into education reflects perceptions and expectations of future changes in educational models. Tertiary indicators focus on how students actually utilise AI tools to assist with learning tasks, such as assignments, quizzes and essays, in terms of how they are used and for what purpose. It shows the actual need and reliance of students on these tools [6]. The Level 4 indicators of safety and problems, on the other hand, reflect students' concerns about the potential problems and risks they may encounter when using AI tools, which directly affects their willingness and frequency of using these tools. The Level 5 indicators for Importance and Desired Functionality of the tools demonstrate students' expectations and needs for AI learning tools. By understanding students' expectations of the desirable features of the tools, valuable user feedback can be provided for future tool development and optimization [7].

Overall, the impact of AI learning tools on university students' learning is multifaceted. Whether these tools can be utilised effectively depends not only on their design and functionality, but also on students' attitudes, expectations and adaptability. A comprehensive evaluation of these tools will help us gain a deeper understanding of the effectiveness of their application in actual teaching and provide guidance for future improvements, so as to better meet the learning needs of university students and promote innovation in education.

3. Model Building and Solving

According to the results of the analysis, the reasonableness of the selection of evaluation indexes is discussed in terms of priority, scientificity and operability, and the K-Means algorithm is used to analyse the clustering of each problem and carry out the analysis of variance, and if the p-value is less than 0.05, it can be argued that the reasonableness of the selection of evaluation indexes is demonstrated.

K-Means algorithm as a typical divisional clustering method, also belongs to the unsupervised learning algorithm, the result is designed to reduce the similarity between clusters, and improve the similarity within the clusters [8]. K-Means clustering algorithm as an indicator to assess the degree of similarity between data objects, the degree of similarity and the distance between the data objects is inversely proportional to the relationship between the similarity of the data objects, when the degree of similarity is higher, the distance is shorter. K-Means clustering algorithm steps are as follows. The steps of K-Means clustering algorithm are as follows:

Pre-set the number of initial clusters and each initial cluster prime, randomly selected k centres of mass, each centre of mass is grouped into a class, i.e., common class [9]. Assume that the sample space $C = \{x_1, x_2, L, x_i, Lx_n$, and the cluster space $C = \{c_1, c_2, \cdots, c_j, \cdots, c_k\}$.

Calculate the Euclidean distance from the remaining sample points to each centre of mass (denotes the jth attribute of the ith target; denotes the distance between the ith target and the jth attribute), and divide the sample set into a number of clusters according to the size of the distance between the samples:

$$d_{ij} = \left[\sum_{k=1}^{P} \left(x_{ik} - x_{jk}\right)^2\right]^{\frac{1}{2}} \tag{1}$$

Group them into clusters where the centre of mass with the smallest distance from each other is located and recalculate the centre of mass of the clusters. Iteratively calculate the distances of all sample points to the corresponding centre of mass of each cluster and reclassify them until the position of the centre of mass no longer changes [10]. Assume that the function D denotes the sum of the sample points in the sample space C and their corresponding cluster mean distances:

$$D = \sum_{j=1}^{K} \sum_{i \in c_j} d_{ij} \tag{2}$$

Combined with the Euclidean distance, the sum of the squares of the errors of the data set can be deduced:

$$SSE = \sum_{j=1}^{K} \left[\sum_{k=1}^{P} \left(x_{ik} - x_{jk}\right)^2\right]^{\frac{1}{2}} \tag{3}$$

Based on the similarity between the data objects and the clustering centres, the clustering centre positions are constantly updated and the sum of squares of the intra-cluster errors is reduced. When the SSE no longer changes or the objective function converges, i.e., $\frac{\partial D}{\partial c_j} = 0$, the clustering process is ended to produce the final result.

The K-Means algorithm is extremely sensitive to outliers and noise points, which means that a small number of outliers and noise points may have a great impact on the algorithm to find the average value, thus affecting the clustering results. Therefore, the K-medoids algorithm, which does not take the average value of the clusters as the datum, is chosen, and the datum object is located in the centre of the clusters. The process of the K-medoids algorithm is as follows:

First, a representative object is arbitrarily selected for each cluster, and then the remaining objects are assigned to the nearest cluster according to their distances from the selected representative object; then the clustering quality is improved by replacing the representative object with a non-representative object's distance. Finally, the quality of the clustering results is then evaluated by improving the function SSE, which measures the average degree of difference between an object and its reference object, with O_i representing the centre of cluster i and p representing the points in cluster C_i:

$$E = \sum_{j=1}^{k} \sum_{p \in C_j} (\parallel p - O_i \parallel^2) \tag{4}$$

In ANOVA, the F-test is a statistical method used to determine whether there is a significant difference between the means of the evaluation indicators in each group. The F-test is achieved by comparing two types of variance: the variance within the same group of evaluation indicators and the variance between the evaluation indicators of different groups [11]. The F value represents the ratio of the between-group variance to the within-group variance, and if there is a significant difference in the mean values of the groups, the F value will be relatively large. In ANOVA analysis, the F-test is closely related to the p-value.

After calculating the F-number, the corresponding p-value can be obtained from the F-distribution table to assess the possibility of significant differences in the group means. Typically, the p-value indicates the probability of observing the same or more extreme results than the sample statistic if the original hypothesis is true. In an ANOVA analysis, the p-value represents the probability of observing the same or more extreme results as the sample statistic when the group means are equal.

If the p-value is lower than a predetermined level of significance (0.05 in this case), the original hypothesis is rejected and it is assumed that there is a significant difference in the mean values between the groups, which should be selected as the evaluation indicator system; conversely, if the p-value is higher than the level of significance, the original hypothesis is accepted and it is assumed that there is no significant difference in the mean values between the groups, which is unsuitable for evaluating the indicators. In other words, the smaller the p-value, the higher the priority of the corresponding indicator in the evaluation system. The specific p-values are as follows.

Table 1. The p-values corresponding to specific questions

Question	P-value	Question	P-value
Question 13	0.00E+00	Question 27_C	1.81E-91
Question 14	0.00E+00	Question 27_D	1.67E-49
Question 15	0.00E+00	Question 27_E	7.32E-35
Question 16	0.00E+00	Question 27_F	6.01E-49
Question 17	9.40E-92	Question 28_A	2.05E-01
Question 17	9.40E-92	Question 28_B	4.00E-39
Question 18	3.33E-108	Question 28_C	4.34E-62
Question 19	1.66E-195	Question 29_A	2.27E-05
Question 20	1.13E-01	Question 29_B	6.48E-68
Question 21	0.00E+00	Question 29_C	1.19E-62
Question 22	2.42E-09	Question 29_D	1.90E-78
Question 27_A	1.16E-01	Question 29_E	1.34E-93
Question 27_B	7.21E-26		

Observing the data in Table 1 above, we find that the p-values of many indicators are quite low, which means that most of these indicators are significantly different among different groups, so they can basically be used as options for evaluating the indicator system. The first-level indicators include attitudes and expectations of using AI learning tools, including whether or not they are in favor of using AI learning tools for university students, what attitudes they have towards the credibility of AI learning tools in answering questions, and what effects they would most like to get if they use AI learning tools. Secondary indicators include the future outlook and adaptability of AI learning tools, including whether AI tools can replace teachers in the future, and how students should adapt when AI tools are combined with education to a certain extent. Tertiary indicators include how and for what purpose the AI will be used, where for Do you have any idea to help with homework through AI learning tools? Do you have ideas for completing quizzes with the help of AI learning tools? Do you have an idea for an AI learning tool to help you complete an essay? If you have an AI learning tool, what influences you to use the AI learning software. Level 4 indicators include safety and issues with the AI tool, which are Which of the following things would you least expect if you were to use an AI learning tool? Considered safety issues with using AI tools. Level 5 indicators include the importance and desirable features of the AI learning tool, with aspects that are important to the AI learning tool, and the features that the desired AI learning tool should have.

4. Conclusion

By analysing the p-values of the questions in Table 1, we can find that several indicators are significantly different between groups. This suggests that they have the potential to serve as powerful indicators for assessing the impact of AI on college students' learning. College students' attitudes and expectations towards AI learning tools are first-level indicators that reflect their acceptance and expectations of this emerging tool. This includes trust in AI learning tools and desired learning outcomes. Secondary indicators focus on future outlook and adaptability, concerning whether AI tools can replace traditional teaching and learning, and students' adaptation strategies to the combination of education and AI. Tertiary indicators explore usage and purpose, including whether students consider using AI tools to complete learning tasks such as assignments, quizzes, or essays, as well as motivations for using AI learning software. Level 4 indicators address the safety and issues of AI tools, which are the matters that students are most concerned about during use, especially in terms of privacy breaches and data security. Level 5 indicators, on the other hand, are about the importance and desirable functions of AI learning tools, including the features and functions that students think an ideal AI learning tool should have. These indicators reflect the specific needs and expectations of university students for AI learning tools, such as ease of use, reliability, interactivity and personalised learning support.

In conclusion, AI learning tools have a profound impact on university students' learning. Students' attitudes, expectations and needs towards these tools are diverse and the future development and improvement of AI learning tools must take these factors into account. By synthesising these indicators, it is possible to better understand the acceptance and use of AI learning tools by the student population, so that AI technology can be used more effectively in future educational practice to improve teaching quality and learning outcomes.

5. Discussion

Based on the above analyses and data, the evaluation of the impact of artificial intelligence on college students' learning can be discussed. Firstly, the evaluation indicators were analysed by clustering using the K-Means algorithm, and then the reasonableness of the indicators was verified by the analysis of variance (ANOVA) and p-value of ANOVA. The results show that the p-value of most indicators is very low, indicating that these indicators have significant differences among different groups and are suitable as an evaluation system. When evaluating the impact of AI learning tools on college students' learning, different levels should be considered. Firstly, there is the first level of indicators, i.e. students' attitudes and expectations towards AI learning tools. Whether students agree with the use of these tools and their perceptions of their credibility and desired effects have a direct impact on the acceptance and frequency of use of AI tools. Next are the secondary indicators, future outlook and adaptability. This relates to whether AI tools are likely to replace the role of teachers and how students should adapt to the combined use of education and AI tools. Tertiary indicators look at the manner and purpose of use, such as whether students plan to complete assignments, quizzes, or essays through AI tools, which reflects the actual use of AI tools in the learning process. The fourth level indicator is safety and problems, which deals with issues that students may be concerned about when using AI learning tools, including the safety of the tool and possible problems that may arise. Finally, the fifth level indicator, importance and ideal features, which includes the features and important aspects that students have in mind that an ideal AI learning tool should have. Overall, AI learning tools have a significant impact on college students' learning, and their evaluation system should be based on multiple dimensions, such as students' attitudes, expectations, adaptability, usage, safety, and ideal functions. Such a comprehensive evaluation will allow for a better understanding of the effectiveness and potential of AI tools in education and how they can be optimised to meet students' learning needs.

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