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DATA-DRIVEN PERSONALIZED TEACHING IN PRIVATE UNIVERSITIES: A PRACTICAL EXPLORATION BASED ON THE K-MEANS CLUSTERING ALGORITHM

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Abstract: Addressing the practical problem that students in private universities exhibit significant individual differences and that the traditional unified teaching model can hardly accommodate personalized needs, this paper proposes a data-driven personalized teaching reform path based on the K-means clustering algorithm. Taking 43 students from the 2024 cohort of the Artificial Intelligence program at a private university as the practical subjects, this study selects three categories of multi-dimensional feature indicators—daily performance, teacher feedback, and final examination scores—and employs the K-means clustering algorithm to divide students into four learning types with internal homogeneity, based on which differentiated teaching objectives, content organization, teaching methods, and evaluation strategies are formulated. Through a comparative practice in two subsequent specialized courses taught by the same teacher to the same class, the class pass rate increased from 95.35% to 100%, while the average score and excellence rate also showed a continuous upward trend. The study demonstrates that cluster analysis based on routine teaching data can effectively identify the internal differences among student groups, provide an objective basis for differentiated instruction, and features low implementation cost and strong operability, thereby offering a practical and feasible path for AI-empowered teaching reform in private universities.
Keywords: Private universities; Personalized teaching; K-means clustering; Teaching according to aptitude; Learning analytics

1 INTRODUCTION

The rapid development of artificial intelligence technology and its deep penetration into the field of education are systematically reshaping traditional teaching paradigms and learning forms. Technical means such as learning analytics, intelligent tutoring, and automated assessment provide new technological paths and methodological support for the implementation of personalized teaching [1-3]. Against this backdrop, how to accurately characterize individual differences among students and dynamically optimize teaching strategies through data mining methods has become one of the core issues in current university teaching reform. For private universities, this issue is particularly prominent and urgent due to the particularity of their student source structure, educational positioning, and resource allocation.

There are systematic differences between private universities and public regular universities in terms of educational positioning, student source structure, and faculty allocation. In terms of educational positioning, private universities mostly take the cultivation of applied and skilled talents as their core objective, emphasize deep alignment with industrial needs, and focus on the development of students' practical abilities. In terms of student source structure, students in private universities generally have lower entrance scores and uneven learning foundations; some students have problems such as weak knowledge reserves, poor learning habits, and insufficient self-directed learning ability, and the individual heterogeneity among students is significantly higher than that in ordinary public universities. In terms of faculty and teaching resources, the teaching staff in private universities is generally young and bears heavy teaching workloads; one teacher often needs to teach the same class across semesters and courses, class sizes are large, and the construction of informatized teaching resources lags relatively behind. Although this faculty allocation model gives teachers the advantage of long-term tracking of students in the same class, which is conducive to grasping students' development trajectories from a longitudinal dimension, it also intensifies teachers' workload, making it difficult for them to provide continuous and refined guidance to each student. The above multiple differences make the traditional teaching model—taking the class as the unit, teacher lecturing as the dominant approach, and final examinations as the main evaluation means—reveal more obvious limitations in private universities: unified teaching progress and evaluation standards cannot effectively accommodate the development needs of students with different starting points and learning styles, and the overall improvement of teaching quality faces structural bottlenecks.

The key to breaking the above dilemma lies in scientifically identifying the types of student differences and then implementing precise teaching according to aptitude. However, in traditional teaching practice, teachers' assessment of student differences mostly relies on subjective experience and scattered classroom observations, making it difficult to form systematic, objective, and operable bases for student classification. In recent years, with the continuous advancement of educational informatization, massive amounts of student learning data have been accumulated in educational administration management systems, online learning platforms, and teachers' daily teaching records, covering multiple dimensions such as attendance, classroom participation, homework completion quality, periodic test scores, and teachers' qualitative evaluations [4-5]. These multi-source heterogeneous data provide rich information materials for objectively characterizing students' learning states, but how to extract effective features from them and achieve scientific classification of student groups remains a key issue that urgently needs to be broken through in the teaching reform of private universities. Based on this, this paper proposes a practical path for personalized teaching in private universities based on the K-means clustering algorithm, on the basis of a systematic analysis of the current teaching situation and core problems in private universities.

2 CURRENT SITUATION AND PROBLEMS

2.1 Significant Differences Among Private University Students, Unified Teaching Can Hardly Accommodate All

The student sources of private universities are relatively diverse, including both students admitted through the regular college entrance examination and students enrolled through classified enrollment, separate examinations, and other channels, with significant differences in their learning foundations and learning abilities. Within the same class, there are both students with solid foundations and strong learning initiative, and a large number of students with weak knowledge reserves, deficient learning methods, and insufficient learning motivation. This high degree of individual heterogeneity poses severe challenges to the traditional class-based teaching system. Teachers organize teaching according to unified syllabi, teaching progress, and assessment standards, often only targeting students at an intermediate level, resulting in students with better foundations lacking challenges and room for improvement, while students with weak foundations struggle to keep up with the teaching pace, continuously accumulating learning frustration and declining classroom participation, ultimately constraining the overall improvement of teaching quality. It is worth noting that teachers in private universities often undertake teaching tasks for the same class for multiple consecutive semesters, which provides favorable conditions for longitudinally tracking students' development trajectories; however, limited by heavy teaching tasks and large class sizes, teachers find it difficult to fully utilize this advantage through manual means, and their understanding of students mostly remains at the level of scattered impressions, which is difficult to effectively transform into systematic teaching decisions.

2.2 Single Evaluation Method, Difficult to Comprehensively Reflect Student Development

Currently, student evaluation in private universities is still dominated by summative assessment, with final examination scores accounting for a large proportion of the overall grade; although regular grades occupy a certain proportion, they often only cover attendance and homework completion, lacking systematic recording and scientific quantification of students' process performance such as classroom participation, cooperation ability, practical operation, and innovative thinking. On the one hand, this evaluation model is difficult to objectively reflect students' true learning investment and ability development level; on the other hand, it cannot provide teachers with effective feedback for teaching improvement. Existing studies have pointed out that classroom teaching evaluation supported by artificial intelligence should focus on the collection and fusion analysis of multimodal data to comprehensively characterize the learning process [4-6]. However, in the actual teaching of private universities, multi-dimensional and process-based evaluation data are still in a scattered and fragmented state, failing to achieve effective integration and in-depth utilization.

2.3 Rich Data Accumulation but Insufficient Analysis and Utilization

With the in-depth advancement of educational informatization, relatively rich student learning data have been accumulated in the educational administration management systems, online teaching platforms, and teachers' daily teaching records of private universities, covering multiple dimensions such as attendance, homework, quizzes, classroom interaction, and online learning behavior. However, most of these data exist in isolated forms, lacking unified data standards and effective analysis methods. Faced with massive amounts of raw data, teachers find it difficult to extract accurate judgments about students' learning states, and even more difficult to formulate targeted teaching strategies based on them. Existing studies have used machine learning methods to model and analyze learning behavior data, achieving positive progress in academic performance prediction, learning risk early warning, and other aspects [7], but the transformation and application of these research results in the teaching practice of private universities remain relatively limited.

2.4 Existing Studies Lack Targeted Focus on Private Universities

From the perspective of research status, scholars at home and abroad have conducted extensive research in the fields of AI educational applications and learner group classification. Foreign studies earlier focused on the application of machine learning in educational data analysis, such as using supervised learning methods for academic prediction and learning behavior analysis [8], and using natural language processing technology to achieve automated assessment and feedback [9]. Domestic studies have also achieved positive results in AI-supported classroom teaching, learning evaluation, and personalized learning. However, most existing studies take students from ordinary universities or learners of online open courses as research subjects, with data sources mostly concentrated on online learning platform logs or single examination scores, and rarely integrate multi-source data such as daily performance in offline classrooms and teacher feedback. Studies that comprehensively use multi-source data for cluster analysis and systematically transform the results into teaching-according-to-aptitude strategies, targeting the characteristics of student groups in private universities, are relatively scarce. The complexity of the student group composition and the particularity of teaching conditions in private universities determine that research conclusions oriented toward ordinary universities cannot be simply applied, and there is an urgent need to carry out targeted practical exploration.

3 REFORM APPROACH AND THEORETICAL BASIS

3.1 Reform Approach

Addressing the above problems, this paper proposes a reform approach for student classification and teaching according to aptitude in private universities based on the K-means clustering algorithm. Its core logic lies in: based on multi-dimensional data such as students' daily performance, teacher feedback, and examination scores, using cluster analysis technology to scientifically classify student groups, identify the learning characteristics and development needs of different types of students, and then formulate differentiated teaching strategies to achieve a paradigm shift from unified instruction to classified instruction. The specific reform path includes the following four links.

First, construct a multi-dimensional feature dataset of students. Select multiple indicators that can comprehensively reflect students' learning states, covering dimensions such as daily performance (attendance rate, classroom participation, homework completion, etc.), teacher feedback (classroom observation evaluation, process comments, etc.), and examination scores. Clean, quantify, and standardize the raw data to form a normalized dataset suitable for cluster analysis.

Second, use the K-means algorithm for cluster classification. Through unsupervised cluster analysis, divide students into several groups with internal homogeneity and external heterogeneity, revealing the internal structural characteristics of the student group.

Third, analyze the characteristic differences among various types of students. Starting from the indicators of each dimension, systematically compare the distribution characteristics of different categories of students in daily performance, teacher feedback, and examination scores, and summarize the typical learning states and core problems of each category of students.

Fourth, formulate teaching-according-to-aptitude strategies. Based on the clustering results, design differentiated teaching objectives, content organization, teaching methods, and evaluation approaches for different categories of students. For example, for students with weak foundations and low participation, focus on strengthening basic knowledge remediation and learning habit cultivation; for students with good foundations but unstable process performance, focus on improving learning challenge and autonomy; for students with balanced performance in all aspects, further expand their application ability and innovative thinking. Meanwhile, given the characteristic that teachers in private universities often teach the same class for multiple consecutive semesters, teachers can track changes in students' cluster membership over a longer time span, dynamically adjust teaching strategies, and form a closed-loop mechanism of identification–intervention–feedback–optimization. Subsequently, this paper selects a teaching class as the practical subject and uses the above methods to carry out teaching intervention; preliminary results show that students' overall academic performance has improved, verifying the feasibility of this reform approach.

3.2 Theoretical Basis

This reform approach takes the theory of teaching according to aptitude as its fundamental guidance. Teaching according to aptitude is one of the core principles of traditional Chinese educational thought, emphasizing the adoption of differentiated educational methods based on students' individual differences. Modern educational psychology research also shows that when teaching content matches students' existing knowledge level, learning style, and interest characteristics, learning outcomes are optimal. Cluster analysis, as a data-based method for identifying student differences, can provide objective and systematic decision-making basis for the implementation of teaching according to aptitude.

Mastery learning theory provides important theoretical support for this study. This theory holds that differences among students are mainly reflected in learning speed and learning style, rather than essential differences in learning ability. Identifying student groups with different learning speeds and learning styles through clustering, and providing targeted teaching support and time arrangements, helps promote more students to reach mastery standards, which is highly consistent with the goal of improving overall teaching quality in private universities.

Learning analytics theory provides a methodological basis for data-driven teaching decisions. Learning analytics emphasizes understanding and optimizing the learning process by measuring, collecting, analyzing, and reporting data about learners and their learning environments [4]. Clustering algorithms are commonly used technical means in learning analytics, capable of discovering the internal structure of student groups without preset categories. Existing studies have shown that machine learning methods have broad application prospects in educational data analysis and learner group classification, and can effectively support learning behavior modeling and teaching strategy optimization [7-8].

In addition, multiple intelligences theory also provides a theoretical basis for the selection of multi-dimensional indicators and the construction of evaluation systems. Gardner believes that human intelligence structure is pluralistic, and different students have different emphases in different intelligence dimensions. Therefore, the evaluation of students' learning states should not be limited to examination scores, but should integrate multiple dimensions such as daily performance, classroom participation, and practical operation. This paper selects three categories of indicators—daily performance, teacher feedback, and examination scores—which precisely reflects attention to students' diversified development and also provides a richer and more comprehensive data basis for cluster analysis.

In summary, the reform approach of teaching according to aptitude based on clustering algorithms is guided by classic educational theories such as teaching according to aptitude and mastery learning, and supported by modern technical theories such as learning analytics and educational data mining, possessing theoretical rationality and practical feasibility. Integrating cluster analysis into the teaching reform of private universities can improve the precision and effectiveness of teaching strategies without significantly increasing teachers' workload, providing a practical and feasible path for AI-empowered educational and teaching reform in private universities.

4 PRACTICAL EXPLORATION

This paper takes 43 students from a class of the 2024 cohort of the Artificial Intelligence program at a private university as the research subjects, and carries out a practical exploration of personalized teaching in private universities based on the K-means clustering algorithm. The study first conducts K-means cluster analysis based on students' relevant data in Specialized Course A during the second semester of the 2024–2025 academic year, and then verifies the effectiveness of the proposed personalized teaching scheme by comparing the academic performance in Specialized Course B and Specialized Course C (in first semester and second semester of the 2025–2026 academic year), both taught by the same teacher to the same class.

The student dataset used for cluster analysis covers multi-dimensional information of 43 students in Specialized Course A, including daily performance (attendance rate and regular homework completion), teacher feedback, and final examination scores. Among them, daily performance is based on regular homework scores, with appropriate deductions if the attendance rate does not meet requirements; teacher feedback is quantified into four grades—excellent, good, average, and poor—corresponding to 90, 80, 70, and 60 points respectively, with an additional 5 points if students actively ask questions during regular classes; examination scores directly adopt the final examination scores. Figure 1 and Table 1 present the clustering results of dividing 43 students into 4 categories using the K-means algorithm.

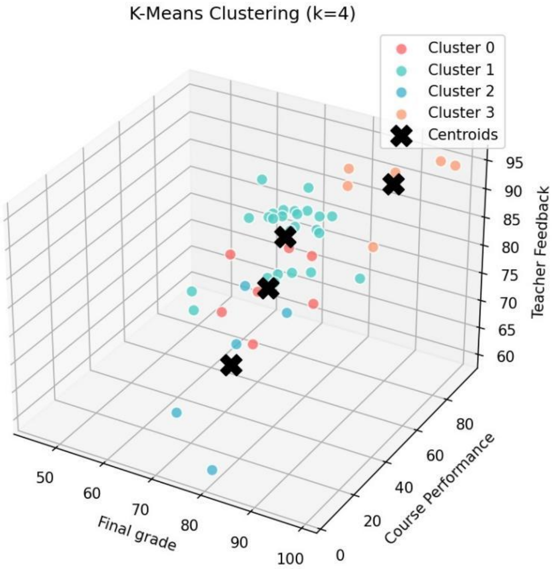

Figure 1 Student Clustering Results Based on the K-means Algorithm (N = 43, K = 4)

Table 1 Clustering Results and Feature Descriptions

Cluster	n	Cluster Center*	Core Feature	Teaching Strategy
0	7	(69.71, 67.13, 72.86)	Weak foundation, low participation	Remediate basics; cultivate learning habits; process-focused evaluation with positive feedback
1	25	(66.64, 86.89, 76.40)	Positive learning attitude, but exam performance needs improvement	Strengthen learning methods and exam-oriented training; error analysis, variant practice, and knowledge structuring
2	5	(74.80, 30.24, 70.00)	Irregular learning behavior, low process participation	Standardize learning behavior; strict attendance and homework management; project-based tasks to stimulate intrinsic motivation
3	6	(88.50, 87.55, 90.83)	Balanced and excellent overall performance	Project-based learning, subject competitions, research tasks; reduce mechanical drills; strengthen innovation and collaboration

*Cluster center coordinates: (Exam Score, Daily Performance, Teacher Feedback). Values are approximate, read from the 3-D scatter plot.

Addressing the different characteristics of the above four categories of students, this study has formulated differentiated personalized teaching schemes respectively: Category 0 students focus on consolidating foundations and cultivating learning habits, by reducing task difficulty, strengthening after-school tutoring and group mutual assistance to fill knowledge gaps, with evaluation focusing on process progress and positive feedback; Category 1 students, on the basis of affirming their learning attitudes, focus on strengthening learning method guidance and exam-oriented training, promoting the effective transformation of learning investment into academic performance through error cause analysis, variant practice, and structured knowledge organization; Category 2 students take standardizing learning behavior and improving process participation as the core, strictly managing attendance and homework, and stimulating their intrinsic learning motivation through project-based tasks; Category 3 students are provided with high-challenge activities such as project-based learning, subject competitions, and research tasks, reducing the proportion of mechanical practice and strengthening the cultivation of innovative practice and collaboration abilities.

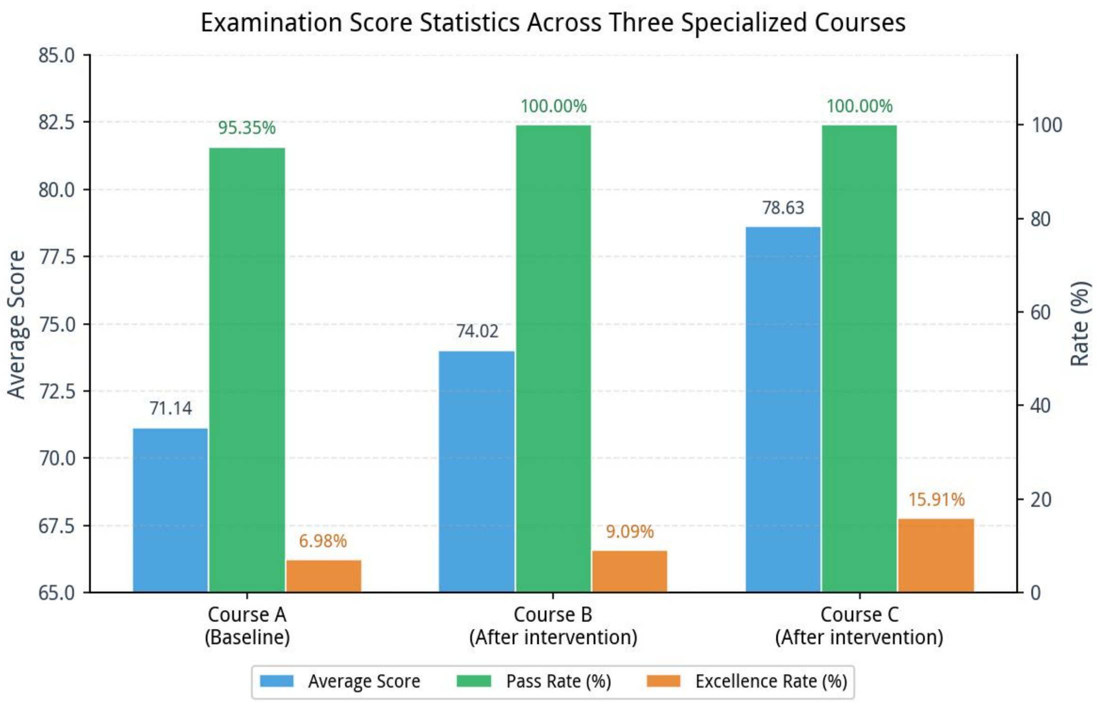

Figure 2 Statistics of Examination Scores in Three Specialized Courses

Based on the above personalized teaching scheme, after one academic year of continuous teaching practice, the academic performance of students in this class in Specialized Course B and Specialized Course C showed positive changes. Figure 2 shows the statistical results of the average score, pass rate, and excellence rate of students in this class across the three courses. The average score of Specialized Course A was 71.14, with a pass rate of 95.35% and an excellence rate of 6.98%; after the implementation of personalized teaching, the pass rates of both Specialized Course B and Specialized Course C increased to 100%, and the average scores and excellence rates also showed a continuous upward trend. The above results indicate that the personalized teaching scheme based on the K-means clustering algorithm has improved the overall learning effect of the class to a certain extent, preliminarily verifying the effectiveness of this method in the teaching scenarios of private universities.

5 CONCLUSION

Addressing the practical problems of significant individual differences among students, tight faculty allocation, and the difficulty of the traditional teaching model in accommodating personalized needs in private universities, this paper proposes a personalized teaching reform path based on the K-means clustering algorithm. Taking students' daily performance, teacher feedback, and examination scores as feature indicators, the study divides students into four learning types through cluster analysis, and formulates differentiated teaching objectives, content organization, teaching methods, and evaluation strategies for different types. Practical cases show that this method can effectively identify the internal differences among student groups and provide an objective basis for teachers to implement classified instruction; after one academic year of teaching practice, the class's pass rate, average score, and excellence rate have all improved, preliminarily verifying its feasibility and effectiveness in the teaching of private universities. This study integrates data mining technology into the daily teaching scenarios of private universities, without relying on complex intelligent teaching systems, and can achieve student classification and personalized intervention using only routine teaching data, possessing strong operability and promotion value. Meanwhile, combining the characteristic of long-cycle class teaching by teachers in private universities, the study focuses on dynamic tracking of clustering results and iterative adjustment of teaching strategies, providing a feasible practical path for AI-empowered teaching reform in private universities. Future research can further expand the sample size, introduce more dimensions of learning behavior data, and explore the optimization and dynamic update mechanisms of clustering algorithms to improve the precision and adaptability of personalized teaching.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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