Design and Analysis of Dynamic Stratified Teaching of Advanced Mathematics Driven by Artificial Intelligence Archives

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Abstract: This study explores the necessity and practical value of differentiated teaching reform in advanced mathematics based on the school-running features and talent cultivation objectives of application-oriented universities. It develops a data-driven intelligent student learning profile platform and applies quantitative analysis to evaluate students' learning status, habits and academic progress, enabling dynamic and accurate implementation of tiered teaching. From the perspective of technical pathway design, this paper proposes multi-dimensional dynamic teaching optimization strategies covering student ability classification, hierarchical teaching objectives, modularized teaching content, diverse teaching methods and comprehensive evaluation systems based on intelligent data monitoring. Adopting statistical analysis to objectively assess students' learning behaviors and academic performance, this research addresses major bottlenecks in traditional advanced mathematics teaching. Under the background of intelligent education, this study aims to improve the overall teaching quality of advanced mathematics, cultivate students' innovative and practical abilities, and promote the high-quality achievement of talent cultivation goals in tertiary institutions.

Keywords: Intelligent Archives; Advanced Mathematics; Stratified Teaching; Statistical Analysis

1. Introduction

As a core public basic course for majors including science, engineering, economics and management in higher education, Advanced Mathematics provides essential mathematical tools for students' subsequent study of core specialized courses such as Mechanical Design, Principles of Economics, Computer Algorithms and Civil Engineering Mechanics. For application-oriented undergraduate universities that attach greater importance to cultivating students' practical application capabilities, Advanced Mathematics plays a vital role in developing students' logical reasoning, abstract thinking, data analysis and problem-solving abilities, and its teaching quality exerts a direct impact on the realization of application-oriented talent training objectives.

This paper constructs an artificial intelligence-based student learning data archive, namely an intelligent data system composed of students' basic personal information, academic records and behavioral data. Intelligent data analysis is leveraged to assist the implementation of dynamic stratified teaching in Advanced Mathematics, and the practical effects on curriculum teaching quality and students' ability cultivation are explored.

2. Current Teaching Status of Advanced Mathematics and Optimization Schemes

2.1 Current Teaching Status of Advanced Mathematics

First, in teaching design, most universities adopt a unified Advanced Mathematics teaching mode, lacking differentiated teaching tailored to the talent training goals and professional competency requirements of different majors [1]. Engineering majors require mathematical application in engineering modeling and mechanical computation; economics and management majors focus on limits and derivatives for economic analysis and risk decision-making; humanities majors only need basic mathematical thinking and quantitative analysis ability. Meanwhile, the compact teaching schedule restricts students' knowledge digestion and in-depth learning.

Second, current teaching objectives are largely exam-oriented, focusing on students' mastery of formulas, theorems and problem-solving skills. Students mainly receive mechanical exercises rather than in-depth exploration of mathematical essence, which fails to cultivate their independent problem-solving ability. Systematic training in mathematical thinking, innovation and practical competence is also insufficient [2,3].

Third, teaching content follows traditional textbook frameworks and emphasizes theoretical derivation. When teaching derivatives, integrals and other core knowledge, teachers mostly explain formulas and classic examples [4], rarely introducing practical cases in artificial intelligence, big data, financial risk control and biostatistics. The abstract nature of mathematics makes students fail to recognize its practical value, thus reducing their learning enthusiasm and initiative.

Fourth, teaching methods are monotonous. The traditional lecture-based teaching still dominates mathematics classrooms with low student participation. Although multimedia, flipped classrooms and case teaching are occasionally applied, such attempts are superficial and lack systematic integration. Relevant studies have proven that heuristic, inquiry-based and cooperative teaching can effectively improve students' learning engagement and understanding [5,6].

2.2 Teaching Optimization Schemes

Appication-oriented undergraduate universities feature a large number of science and engineering majors and prioritize cultivating students' practical application capabilities. The incoming students have multi-level academic foundations with obvious gaps in mathematics scores upon enrollment. Most students have weak mathematical foundations and lack capabilities for comprehensive knowledge application and practical transformation, while a small number of students possess solid foundations and strong inquiry willingness for postgraduate entrance examinations. Therefore, in the intelligent era, guiding the implementation of stratified teaching with data archives and conducting comprehensive consideration of students' actual majors, personal willingness and application capabilities bears great practical significance.

Adhering to the student-centered educational philosophy, universities shall improve stratified teaching standards in response to diversified student sources and differentiated majors, establish a comprehensive "quantitative + qualitative" stratification standard to ensure accurate stratification matching actual conditions, and strengthen supervision and management of the dynamic stratification implementation process [7].

AI technologies and mathematical models are adopted to conduct quantitative research on multi-dimensional archive data. Teachers' responsibilities are clarified [8]; real-time analytical feedback is used to dynamically adjust learning contents, difficulty levels and teaching rhythms, so as to fully implement student stratification and teaching stratification. Students' learning enthusiasm is fully stimulated to promote their personalized development.

The practical application effects of optimized stratified mathematics teaching are analyzed in depth, and its application in other general education courses and specialized courses is further explored, so as to improve students' comprehensive capabilities and meet the training objectives of application-oriented talents.

3. Technical Path and Design of Dynamic Teaching Driven by Intelligent Archives

Technical Means: Construct an artificial intelligence-based student learning archive data system. All types of data are collected, sorted and input into the system, with detailed information collection elaborated below, forming a complete system through continuous dynamic updates.

Teaching Design: Five dimensions including stratified teaching planning design, stratified teaching objectives, stratified teaching contents, stratified teaching methods and stratified assessment evaluation are comprehensively planned to deeply integrate stratified teaching with application-oriented talent training and highlight the distinctive features of application-oriented undergraduate education.

The architectural framework of the overall scheme design is shown in Figure 1.

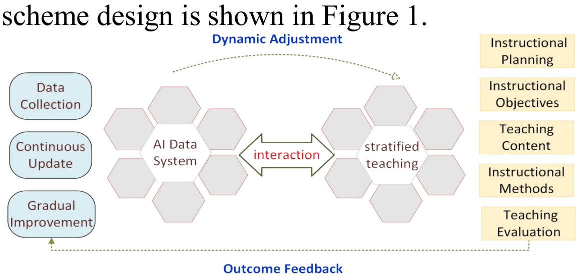

Figure 1. Overall Technical Architecture

3.1 Establish Rational Teaching Planning

Combining quantitative and qualitative methods, this paper proposes a student characteristic-based stratification standard to achieve accurate grouping tailored to student conditions.

Key stratification indicators include students' origin, college examination type and math scores, placement test results, majors, learning interests and development plans. On this basis, a mathematical evaluation and classification model is built for precise student stratification. Relevant data are imported into the admission database to establish electronic student files for dynamic updating.

For practical implementation, students are divided into three tiers:

Basic Weak Tier (Tier C, 30%–35%): Students with poor math foundations and self-learning ability, oriented toward direct post-graduation employment. The curriculum prioritizes basic major-related math skills and course qualification.

Intermediate Tier (Tier B, 50%–55%): Students with moderate math foundations and learning capacity, who intend to pursue postgraduate studies or improve professional skills. This tier focuses on knowledge consolidation and practical ability training to support long-term career development.

Advanced Tier (Tier A, 10%–20%): Students with solid math foundations, strong self-learning capability and proactive learning attitudes, preparing for postgraduate study or high-end technical positions. The curriculum broadens and deepens professional knowledge and fosters students' inquiry and innovation abilities.

A dynamic adjustment mechanism is adopted to match students' evolving learning status and development needs. Each semester, comprehensive evaluations covering examinations, assignments, classroom performance and student feedback are conducted to update student tier placement in a timely manner.

This study digitizes students' learning and developmental experiences, including academic scores, specialized coursework, campus participation, competitions, honors, disciplinary records, internships and employment outcomes. All data are standardized and archived into digital student growth files. Leveraging machine learning and big data analysis, the system precisely captures students' learning demands and academic performance. Dynamic teaching adjustment is implemented to align stratified instruction with individual development and application-oriented talent training goals[9].

The implementation path of dynamic stratified teaching driven by the intelligent data system is shown in Figure 2.

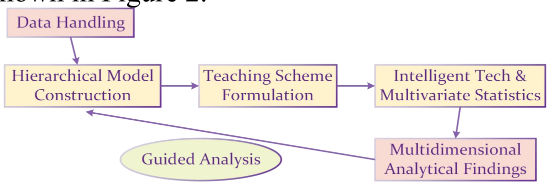

Figure 2. Technical Implementation Framework

3.2 Formulate Stratified Teaching Objectives

Students' academic and developmental data, including grades, campus activities, awards, disciplinary records, internships and employment information, are digitally archived into individual growth files. Data analysis identifies students' learning status and needs, supporting dynamic stratified teaching adjustment for personalized and application-oriented talent training.

Tier C: This tier strengthens basic mathematical competencies to meet course requirements. Students master core advanced mathematics knowledge for basic calculations and simple applications, reducing learning difficulties and passing assessments. They maintain over 75% exercise accuracy and complete fundamental major-related tasks, such as basic accounting for economics and management majors and elementary integrals for engineering majors.

Tier B: This tier stresses mathematical practical application. It consolidates students' mathematical knowledge and logical thinking to integrate mathematics with professional learning. With over 83% exercise accuracy, students are capable of medium-difficulty professional work, including economic data analysis and engineering computational design.

Tier A: This tier adopts in-depth and expanded learning to cultivate students' mathematical modeling, exploration and innovation skills for postgraduate study and high-end technical jobs. Achieving over 92% exercise accuracy, students solidly grasp advanced mathematics theories, solve practical mathematical problems independently, and build advanced competencies for further academic and professional development.

3.3 Adjust Stratified Teaching Contents

This study designs tier-specific teaching content and adjusts textbook usage to improve practicality for different student groups.

Tier C: Teaching centers on textbook fundamentals, removing cumbersome theoretical proofs and supplementary readings to emphasize practical, easy-to-grasp knowledge. For example, complex multi-variable integral proofs are skipped, focusing instead on basic calculations and simple practical applications.

Tier B: Teaching links mathematical knowledge to professional practice with discipline-specific cases. Economics and management students learn statistical methods for data analysis and economic modeling, while engineering students apply calculus to practical computational scenarios.

Tier A: Teaching covers full textbook content with extended, inquiry-focused learning materials, including mathematical modeling, numerical calculation and postgraduate exam-related knowledge. It fosters students' independent exploration and innovation, incorporating derivative applications in machine learning and artificial intelligence.

3.4 Stratified Application of Teaching Methods

Teaching approaches are tailored to individual needs and application-oriented training objectives. Multiple practical teaching modes are adopted according to student proficiency for targeted instruction:

Tier C: Lectures and interactive guidance are used alongside online basic tutorials, exercises and explanatory videos. Daily and discipline-related cases clarify abstract ideas—charging speed illustrates limits, and supermarket discounts explain derivatives to sustain student interest.

Tier B: Lectures, seminars and practical work are combined. Learning platforms supply advanced exercises and professional cases. Group discussions and one or two practice sessions help students apply mathematics to discipline-specific problems.

Tier A: Inquiry, project and competition-driven learning are implemented. Supplementary resources, postgraduate materials and modeling cases are offered. Students carry out collaborative modeling projects to build innovative thinking and teamwork. Supported by competition coaching, they are encouraged to join national mathematics and modeling contests to prepare for further study.

3.5 Scientific Assessment and Evaluation

Data analysis results of intelligent student Learning archives enable comprehensive, objective evaluation of student performance and generate learner profiles. Teachers and administrators can keep abreast of students' real-time learning progress. Meanwhile, cross-disciplinary student feedback reflects teaching quality, helping faculty identify instructional shortcomings and offering reliable evidence to improve talent cultivation. This elevates teaching standards and academic performance, supporting the development of well-rounded capable learners.

Real-time updates to student archives, together with feedback from intelligent teaching platforms, support timely understanding of learning dynamics. Teaching strategies can then be adjusted to align with student traits and application-oriented training requirements. Differentiated assessment tasks and criteria are accordingly designed to emphasize practical competence.

Tier C: Focus on progress and pass rates, with priority given to mastery of basic mathematical tools and improvement of learning attitudes.

Tier B: Emphasize command of basic knowledge and practical application capabilities, focusing on students' comprehensive mathematical application skills and post matching competence.

Tier A: Prioritize innovation and inquiry capabilities. Students with a comprehensive score above 85 and innovative achievements such as modeling works or competition awards are rated excellent, with evaluation focusing on inquiry potential and postgraduate competitiveness.

An artificial intelligence-based multi-dimensional evaluation system is established, covering teacher evaluation, student self-evaluation, peer evaluation and professional practice supervisor evaluation to ensure comprehensive and objective assessment aligned with application-oriented talent training objectives. Based on students' actual learning levels reflected in learning archives, continuous analysis and research are carried out to explore effective improvement strategies for stratified teaching implementation schemes, so as to optimize stratified curriculum design, teaching contents and teaching methods of Advanced Mathematics, strengthen the novelty, practicality and major integration of teaching contents, improve the quality and development of stratified Advanced Mathematics teaching, and meet the requirements of cultivating application-oriented talents.

Combined with the inherent characteristics of Advanced Mathematics teaching and the data collected by the intelligent data system, a comprehensive evaluation system is constructed. Primary indicators and appropriate sub-indicators can be selected, as shown in Table 1 below. All indicators can be properly adjusted according to the specific issues of statistical analysis.

Let the comprehensive evaluation score be defined as S:

$$S = \sum_{i=1}^{3}\sum_{j=1}^{3} w_{ij}x_{ij} \quad (1)$$

Where x_{ij} and w_{ij} denote the evaluation score and weight of the corresponding secondary indicator B_{ij}, respectively, i=1,2,3,4; j=1,2

Table 1. Indicators of Comprehensive Evaluation System

Evaluation Indicators	Secondary Indicator	Weight of Secondary Indicator	Weight of Primary Indicator
Teacher Evaluation (A_1)	Teaching Model (B_{11})	0.3	0.35
	Teaching Effect (B_{12})	0.5	
	Implementation Level (B_{13})	0.2	
Student Evaluation (A_2)	Content Satisfaction (B_{21})	0.4	0.35
	Learning Initiative (B_{22})	0.3	
	Demand Satisfaction (B_{23})	0.3	
System Evaluation (A_3)	Data Precision (B_{31})	0.4	0.3
	Application Matching (B_{32})	0.4	
	Data Update Latency (B_{33})	0.2	

4. Analysis and Practice

4.1 Analysis and Practice

Structured data including students' learning behaviors, scores, interactions and evaluation records collected by the intelligent archive system can be processed via descriptive statistics and correlation statistics for basic data analysis to explore data distribution and indicator correlation rules:

Descriptive Statistics: Calculate central tendency, dispersion and distribution characteristics of numerical fields in the database such as learning duration, test scores, evaluation marks and access frequency to intuitively grasp the overall data level.

Cross-tabulation (Grouped Statistics): Group data by classified fields including grade, major and curriculum type, and compare the mean values and frequencies of each group to distinguish indicator gaps among different groups.

Correlation Statistics: Adopt Pearson correlation coefficient and Spearman rank correlation to analyze the linear correlation strength between two continuous variables (*e.g.*, learning duration vs. test scores, academic performance vs. evaluation scores).

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad (2)$$

Cluster analysis is further conducted to divide homogeneous groups according to multi-dimensional sample features, realizing student learning stratification, behavior classification and personalized feature identification. The K-Means clustering algorithm is widely adopted due to its efficient operation and easy system implementation for massive structured learning data in databases.

Core Principle: Samples with similar multi-dimensional feature spatial distances are automatically divided into the same cluster with high intra-cluster similarity and significant inter-cluster differences. Euclidean distance is used to measure sample discrepancies, and Within-Cluster Sum of Squares (WCSS) evaluates clustering effects [10,11].

Auxiliary methods include the elbow method to determine the optimal cluster number K and silhouette coefficient to verify the rationality of cluster division. Clustering results are interpreted with statistical indicators to identify feature characteristics of each student group.

Application Scenarios: Stratify students by learning efficiency (high-efficiency, intermediate and low-efficiency learners), mine characteristic features of different learning behavior groups, and provide grouping basis for personalized learning resource recommendation.

4.2 Practical Effects

Our university has carried out practical exploration on dynamic stratified teaching of

Advanced Mathematics based on intelligent student archives, and optimized teaching strategies aligned with application-oriented talent training objectives, achieving remarkable results as follows:

Students' learning enthusiasm and academic performance have improved significantly. Students of all tiers receive teaching contents and methods matching their own demands, their confidence in mathematics learning is strengthened, and the failure rate has decreased sharply. Statistics show that after the implementation of stratified teaching, the failure rate of Advanced Mathematics dropped by approximately 5%, and the average score increased by 4 to 8 points. Tier A students participated in college mathematics competitions and achieved outstanding results among peer universities. Mathematical modeling training was launched for students to take part in National College Mathematical Modeling Contests, with the highest award-winning rate reaching 54% in the past two years including national-level prizes. In addition, the postgraduate admission rate of Tier A students is significantly higher than that of other tiers.

5. Conclusion

Based on the current teaching status of Advanced Mathematics in universities, this study establishes a student learning data archive system with artificial intelligence technologies, which can better adapt to student source characteristics and connect with application-oriented talent training objectives, provide personalized learning resources and training schemes for curriculum teaching, and improve the level of stratified teaching of Advanced Mathematics. The system can better cultivate students' practical capabilities and innovative awareness, realizing in-depth integration between Advanced Mathematics teaching and application-oriented talent training.

Future research can further align with regional economic development demands and specialized talent training objectives, continuously optimize stratified teaching strategies, promote in-depth integration of stratified teaching with specialized teaching and practical teaching, make Advanced Mathematics a core basic curriculum supporting the cultivation of application-oriented talents in universities, provide strong guarantees for cultivating high-quality application-oriented talents, and facilitate high-quality educational development.

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