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A Multimodal Learning Analytics and Instructional Optimization Study for the Data Structures Course in Smart Classrooms

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Abstract: In the context of smart education, the singularity and hysteresis of traditional learning analysis methods have become a bottleneck hindering the improvement of teaching quality. To address this issue, this study takes the Data Structures course as a practical vehicle to construct a multimodal learning analysis model based on the smart classroom. This model systematically integrates five-dimensional data—namely, students' class performance, lab results, attendance, task completion, and chapter quizzes—to achieve precise characterization of the learning process and outcomes. Through the correlation analysis of multimodal data, this study can not only dynamically diagnose knowledge weaknesses at both group and individual levels but also reveal the intrinsic connections between learning behaviors and academic performance, thereby generating personalized learning diagnostic reports. Ultimately, based on data-driven insights, the study proposes targeted teaching optimization strategies, aiming to achieve a shift from "experience-driven" to "data-driven" precision teaching and to provide a replicable pathway for enhancing the teaching quality of engineering courses.

1. Introduction

Jiandong Yang et al. [1] suggest that collecting and analyzing student learning data enables instructors and educational administrators to gain deeper insights into student learning behaviors, habits, and outcomes, thereby facilitating the development of more personalized and precise teaching strategies. They utilized big data technology to conduct learning analysis, consequently optimizing teaching approaches.

Li, Jian et al. [2] examine the role of artificial intelligence in learning analytics and precision teaching strategies within the context of ideological education. They indicate that AI tools assist in evaluating student behavior, emotional states, and academic progress, allowing for the customization of personalized learning experiences based on individual needs. By providing real-time feedback, teachers can identify gaps in knowledge, emotional engagement, and academic performance, and adjust their teaching methods accordingly.

Based on case studies, teaching effectiveness, and practical pathways of blended learning in higher education, Yaozhen Feng [3] integrated the Chaoxing platform, along with student questionnaires and individual interviews, to design a blended teaching model focused on learning diagnosis, learning supervision and intervention, and timely, accurate evaluation and feedback. His findings demonstrate that this approach not only enhances students' abilities to analyze and solve problems but also improves learning attitudes and stimulates motivation for self-directed learning.

Learning Analytics plays a pivotal role in the instructional process, serving as both the foundation for developing teaching plans and a critical factor in enhancing educational quality. Defined as instructional design based on the comprehensive understanding and evaluation of students' current learning status, this process involves in-depth investigation and assessment of multiple dimensions including academic performance, learning habits, motivation, interests, personality characteristics, and cognitive patterns. Through systematic collection and analysis of this information, educators can more accurately diagnose students' learning conditions and consequently design instructional schemes that better align with actual needs. This approach enables teachers to assess students' foundational knowledge and learning capabilities, thereby establishing a solid reference framework for subsequent teaching activities. Furthermore, it facilitates timely identification of potential challenges and obstacles encountered during the learning process, allowing for proactive guidance and targeted support.

Learning analytics further enables educators to adapt teaching methodologies and instructional content flexibly, based on students' learning characteristics and needs, with the aim of achieving optimal educational outcomes. This personalized teaching approach can better cater to individual learning needs and promote students' holistic development.

The significance of learning analytics lies not only in its capacity to provide a more comprehensive understanding of students but also in serving as a critical prerequisite and foundation for effective instruction. By gaining an in-depth understanding of students' learning conditions, educators can more effectively address learning needs and facilitate overall progress. This involves the objective analysis of students' knowledge base, cognitive abilities, learning styles, and disciplinary characteristics to accurately reflect both the collective profile and individual differences, thereby anticipating potential instructional challenges.

However, educators frequently encounter a significant challenge in classroom instruction: the lack of effective capabilities and methodologies for assessing student learning. This deficiency may prevent instructors from obtaining timely insights into students' learning progress and conceptual understanding, consequently compromising both teaching quality and learning outcomes. The problem primarily stems from the following factors:

(1) Deficiency in Assessment Awareness: Some educators fail to recognize the critical importance of evaluating student learning. Their pedagogical focus remains predominantly on knowledge delivery and classroom exposition, while neglecting systematic assessment of learning effectiveness.

(2) Limited Assessment Modalities: The prevailing approach relies excessively on summative evaluations such as quizzes and examination scores, while largely overlooking formative assessment practices. This restricted assessment repertoire proves inadequate for obtaining comprehensive, accurate, and dynamic understanding of students' learning status and competency development.

Smart Classrooms, as a crucial component of educational innovation, utilize modern information technologies and intelligent tools to reshape traditional teaching models. This transformation enhances both educational quality and instructional efficiency while creating broader societal impacts. Conventional teaching content and methods often struggle to adapt to this shift. For instance, many curricula remain heavily dependent on teacher-centered lectures, lacking interactive components and failing to accommodate diverse personalized learning needs. The smart classroom paradigm requires educators to dynamically adjust instruction based on student learning data and implement differentiated teaching strategies—presenting significant challenges to conventional pedagogical approaches.

Nevertheless, research indicates that the current instructional quality in Smart Classrooms remains suboptimal. Key challenges include: (1) The requirement for teachers to possess digital teaching competencies—such as developing digital courseware and operating intelligent terminals—where insufficient technological proficiency impedes effective implementation; (2) Monotonous instructional content and methods in some Smart Classrooms that lack diversity, failing to stimulate student engagement, coupled with overreliance on technological tools leading to neglect of proven traditional teaching methods; (3) The prerequisite of active student participation to realize the advantages of Smart Classrooms, whereas limited student engagement in practice hinders effective utilization of these learning environments.

Intelligent assessment systems present transformative solutions:

Resolving Traditional Evaluation Dilemmas: By establishing a tripartite "Knowledge-Ability-Competency" intelligent evaluation framework, we can transcend the limitations of conventional quantification methods. Through real-time collection of learning behavior data—including pre-class preparation assessments, in-class learning capability evaluations, and post-instructional outcome analyses—this system provides precise decision-making support, ultimately forming a closed-loop teaching optimization model: Intelligent Assessment → Learning Diagnosis → Instructional Improvement.

Facilitating Personalized Learning: Student competency profiles constructed from behavioral data enable identification of differential needs between foundational learners and advanced programming contestants. Through tiered resource allocation and early warning mechanisms (e.g., academic failure prediction), pedagogical intervention evolves from post-hoc remediation to proactive prevention, significantly enhancing learning efficacy.

Optimizing Teaching Effectiveness: By relieving instructors from repetitive evaluation tasks, the system reorients their focus toward instructional design innovation and competency development. Data-driven learning analytics reports empower educators to dynamically adjust teaching strategies, thereby increasing classroom targeting precision and student engagement.

2. Toward a Multimodal Learning Analytics Framework for Data Structures Courses in the Smart Classroom

Against this backdrop of smart teaching platforms, traditional evaluation methods based solely on final grades fail to support precision teaching. This research develops an integrated multimodal learning analytics instrumentation, incorporating both process-oriented and outcome-based data. It delivers an omnidirectional and stereoscopic portrayal and diagnosis of student learning behaviors, knowledge assimilation, and ability progression through five analytical dimensions: in-class performance, practical lab achievements, attendance records, chapter-based task accomplishment, and quiz results.

2.1. Classroom Performance Analysis

Classroom performance serves as a key indicator for measuring students' class participation, cognitive engagement, and immediate learning states.

Data is sourced from interaction logs within the smart classroom system, including but not limited to: frequency of questions raised and answered, quality and frequency of discussions in online forums, participation rates and accuracy in real-time quizzes/polls, and task contribution levels in group collaborations (analyzed through platform logs). Dimension-based analysis and its implications are outlined below:

Participation Analysis: By quantifying the frequency of students' initiation and responses to classroom interactions, we can measure their engagement levels. Students exhibiting consistently low participation may indicate insufficient learning interest, difficulties in comprehending knowledge points, or introverted characteristics.

Real-time Feedback Analysis: Instant quiz results provide immediate insights into students' grasp of core concepts (e.g., "differences between stacks and queues", "binary tree traversal"), enabling instructors to dynamically adjust teaching pacing.

Intelligent Evaluation Implementation: The system automatically generates classroom performance heatmaps and individual participation reports, assigning performance ratings (e.g., active, average, inactive) and flagging students requiring special attention.

As illustrated in the **Figure 1** and **Figure 2**, the data reveal that Zhang Ye has a total participation score of 16 and an average class participation score of 0; Liao Songlin has a total participation score of 17 and an average class participation score of 0; and Cheng Yiming has a total participation score of 15 and an average class participation score of 3. These students' total participation and average class participation scores are significantly below the class average, indicating a relatively passive classroom presence and lower levels of engagement.

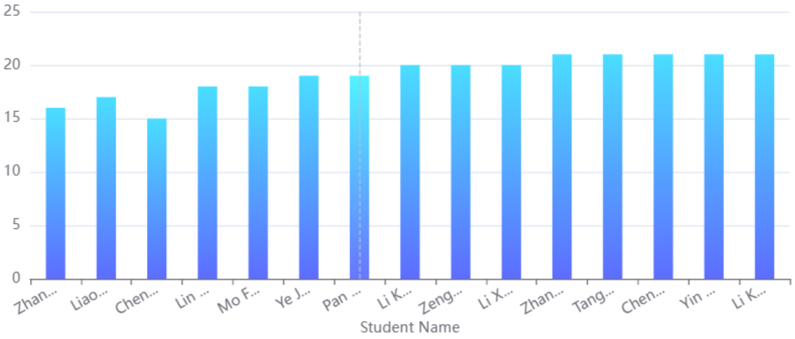

Figure 1: Total Participation

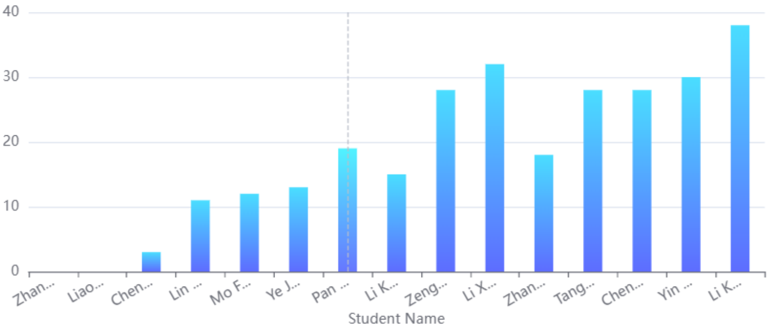

Figure 2: Average Class Participation Score

2.2. Laboratory Performance Analysis

As a highly practical course, Data Structures necessitates that laboratory performance directly reflects students' capacity to translate theoretical knowledge into functional code and practical problem-solving.

Data are derived from online judging systems (such as Chaoxing and Educoder) or manually graded assignments, encompassing metrics like code accuracy, completion time, coding style, and algorithmic efficiency (e.g., time and space complexity measured via test cases). Instructors can perform dimensional analysis as follows:

Knowledge Application Analysis: Laboratory results directly evaluate students' implementation proficiency with specific data structures (e.g., linked lists, trees, graphs) and algorithms (e.g., sorting, searching). Suboptimal performance typically indicates either insufficient theoretical comprehension or inadequate programming fundamentals.

Problem-Solving Capability Analysis: By examining students' attempt frequency, debugging processes, and ultimate algorithmic strategies for complex problems, we can assess their logical reasoning, debugging skills, and innovative thinking.

Intelligent Evaluation Implementation: The system not only delivers final scores but also generates diagnostic reports of error patterns (e.g., boundary condition mishandling, pointer misuse, recursive logic flaws) and produces personalized competency radar charts evaluating dimensions like logical rigor, code standardization, and algorithmic optimization capability.

As shown in the **Figure 3** and **Figure 4**, the data indicate that Cheng Yiming has completed only 5 assignments, which is significantly lower than the class average of 8.79. Moreover, his average score stands at 46 points, well below the class average of 78.02. These results suggest that Cheng Yiming faces substantial challenges in both assignment completion and academic performance, necessitating targeted intervention.

Although Zhang Ye has completed all 9 assignments, his average score of 56.56 points remains below the class average. This may be attributed to subpar assignment quality or insufficient mastery of the course material.

As for Yin Yuming and Mo Fengming, both students have completed a number of assignments meeting the class average; however, their average scores are 64.67 and 65.11 points respectively, still falling short of the class average. This indicates room for improvement in the quality of their submitted work.

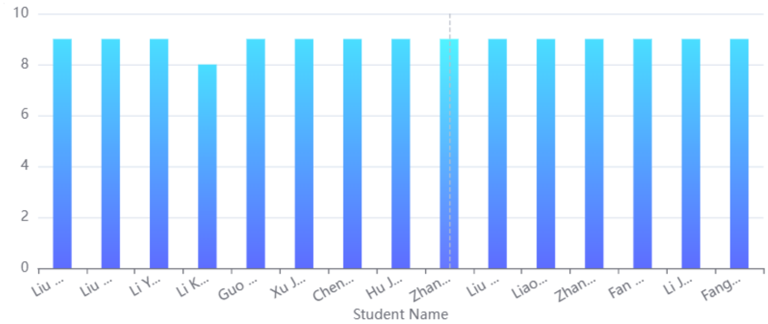

Figure 3: Number of Assignments Completed

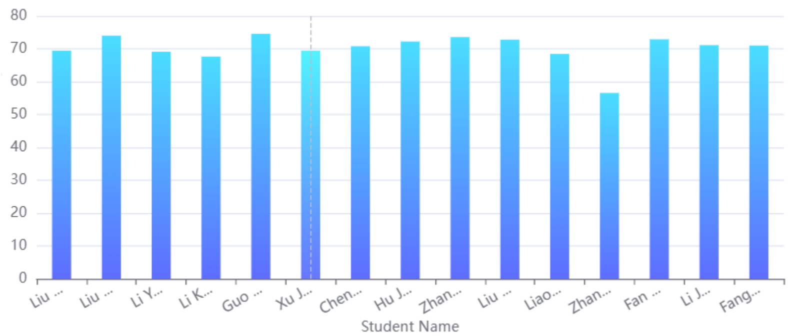

Figure 4: Average Assignment Score

2.3. Attendance Analysis

Attendance serves as the most fundamental indicator of learning discipline and attitude. In the smart classroom context, its analytical value extends beyond simple "class participation rates."

Data is collected through classroom check-in records (e.g., GPS-based check-ins, QR code scans). Teachers can conduct dimensional analysis based on student data as follows:

Learning Discipline Analysis: Regular attendance is a prerequisite for maintaining learning continuity. Frequent absences or early departures serve as crucial early warning signals of academic risk, typically associated with declining learning interest, gaming addiction, or personal affairs.

Learning Pattern Correlation Analysis: Correlative analysis between attendance data and chapter quiz results/final exam performance can validate the positive relationship between attendance rates and academic achievement. Furthermore, it provides insights into special cases such as "high achievement with low attendance" or "low achievement with high attendance." The latter scenario may indicate ineffective in-class engagement despite physical presence, necessitating attention to learning quality.

Intelligent Evaluation Implementation: The system automatically calculates attendance rates, establishes warning thresholds, and sends automated alerts to both instructors and students when thresholds are breached. Simultaneously, it generates class attendance trend charts to help teachers monitor overall learning climate dynamics.

As illustrated in the **Figure 5**, the attendance rates for the following students are as follows: Zhang Ye, 76.47%; Liao Songlin, 76.47%; Cheng Yiming, 76.47%; and Lin Yukai, 82.35%. All of these attendance figures fall below the class average of 94.52%.

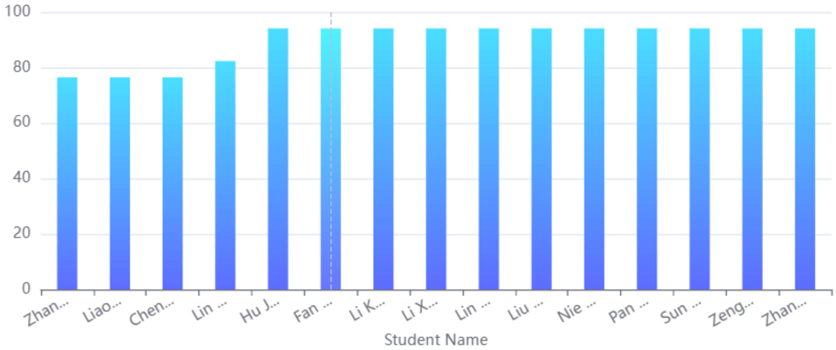

Figure 5: Attendance Rate

2.4. Chapter Task Completion Analysis

Chapter task completion reflects students' self-directed learning progress and planning capabilities, serving as a core component of process evaluation.

Data are sourced from the Chaoxing system records tracking each student's completion of predefined tasks, including lecture video viewing completion rates, courseware/document download and browsing duration, and click-through rates on extended reading materials. Dimensional analysis by instructors reveals:

Learning Initiative Analysis: Whether students complete learning tasks ahead of schedule, on time, or with procrastination directly demonstrates their planning competence and self-directed learning initiative. Significant differences in knowledge internalization effectiveness are observed between concentrated "task-binging" behavior patterns and regular, distributed learning practices.

Knowledge Preparation/Review Analysis: By analyzing timestamps, we can determine whether students view instructional videos before or after class sessions, thus evaluating their preparatory and review habits.

Intelligent Evaluation Implementation: The system generates task completion progress indicators and learning path visualizations, automatically alerts students demonstrating lagging progress, and provides instructors with macroscopic perspectives on class-wide learning advancement.

As illustrated in the **Figure 6**, the data regarding task completion reveal that 13 students – including Pan Weishen, Guo Ziying, and Liu Botao – have completed all 112 learning tasks, representing the highest completion rate. In contrast, Cheng Yiming and Liao Songlin completed the fewest tasks, with only 72 each. Overall, the majority of students demonstrated satisfactory task completion, with the class averaging 103.38 completed tasks and an average completion progress of 92.3%.

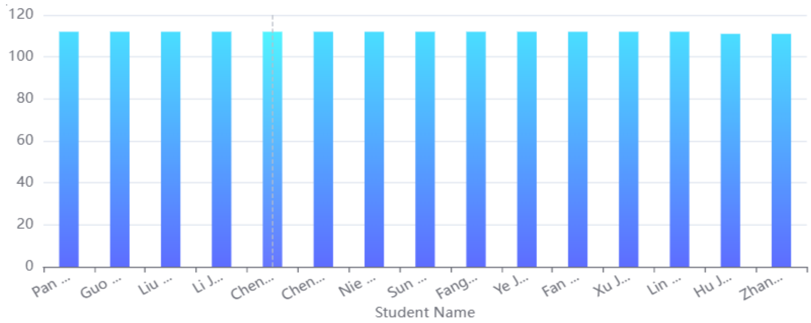

Figure 6: Number of Completed Learning Tasks

2.5. Chapter Quiz Analysis

Chapter quizzes serve as a standardized assessment tool for evaluating knowledge comprehension at formative stages, with their results holding significant diagnostic value.

The data are derived from online quiz scores administered upon the completion of each instructional chapter. These quizzes typically comprise objective items and short constructed-response questions, with the system recording response details for every item. Teachers can conduct dimensional and value-based analysis on this student data:

Analysis of Knowledge Point Mastery: By examining the accuracy rate for each test item, common areas of weakness across the class can be precisely identified (e.g., "conversion between adjacency list and adjacency matrix," "non-recursive implementation of quicksort"). This provides a direct basis for instructors to conduct targeted review sessions and focused instruction.

Diagnosis of Individual Knowledge Gaps: For each student, the system analyzes the specific knowledge points associated with incorrectly answered questions, generating a personalized knowledge gap profile. This helps pinpoint the specific areas where the student requires remedial learning.

Implementation of Intelligent Evaluation: The system automatically generates class-wide quiz analysis reports, which include metrics such as average score, highest and lowest scores, score distribution, and mastery rates for each knowledge point. Additionally, it compiles personalized sets of incorrect questions for each student and can intelligently recommend relevant review materials and practice exercises based on their identified knowledge gaps.

3. Teaching Optimization Strategies Based on Multimodal Learning Analytics Data

Leveraging the multimodal analysis across the aforementioned five dimensions, instructors can transition from "experience-driven" to "data-driven" teaching optimization.

(1) Implementing Precision Teaching Interventions:

To help students with inactive classroom performance but adequate quiz results, it is recommended that they be encouraged to participate through online discussion forums or assigned as group representatives to build confidence gradually.

Students demonstrating poor laboratory performance coupled with low chapter task completion may struggle with foundational gaps and learning inertia. These cases warrant one-on-one counseling and the provision of fundamental programming exercises and tutoring.

Students with satisfactory attendance but consistently low scores across all assessments require focused attention on their in-class engagement efficiency and learning methodologies. Recommendations may include improving note-taking strategies or seeking academic advising.

(2) Dynamic Adjustment of Teaching Content and Pacing:

When chapter quiz data reveals that class-wide mastery of a specific knowledge point (e.g., "B-tree") falls below 60%, instructors should revisit the concept in subsequent sessions and design targeted practice exercises.

Lecture pacing should be promptly modulated and deeper explanations should be given to commonly misunderstood topics, based on real-time feedback from in-class assessments.

(3) Constructing Personalized Learning Pathways:

The system can utilize students' "personal knowledge gap maps" (derived from chapter quizzes) and "learning style preferences" (identified through chapter task analysis) to curate personalized review packages and extended learning resources, actualizing the "one student, one plan" approach.

(4) Refining the Comprehensive Evaluation Mechanism:

Data from all five dimensions will be incorporated into the final course grade according to a specified weighting scheme (e.g., classroom performance 10%, laboratory results 30%, attendance 20%, chapter task completion 20%, chapter quizzes 20%). This establishes a more scientific and equitable process-oriented assessment system, incentivizing students to value consistent learning and cumulative knowledge building.

4. Conclusion

This study addresses the teaching and evaluation challenges in the Data Structures course within the context of smart education by successfully constructing a multimodal learning analytics framework integrating five dimensions: **classroom performance, laboratory results, attendance, task completion, and chapter quizzes**. This framework transforms fragmented learning behaviors from traditional instruction into quantifiable, correlatable, and diagnosable precise learning profiles, achieving a transition from macro-level perception to micro-level insight.

The core contribution of this research lies in establishing a **data-driven closed-loop teaching optimization model**. This model enables precise identification of group knowledge weaknesses and individual learning obstacles, providing scientific evidence for instructors to implement **targeted interventions, dynamically adjust teaching strategies, and construct personalized learning pathways**. This effectively promotes a paradigm shift in course instruction from "experience-driven" to "data-driven" approaches.

Although this study has limitations regarding data completeness, integration of subjective factors, and long-term strategy effectiveness, future research can be enhanced by exploring more advanced data fusion algorithms, incorporating affective computing technologies, and ultimately developing adaptive learning systems. This research provides a clear and transferable practical pathway for reforming Data Structures and related engineering courses in smart classroom environments.

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