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Research paper

Research on The Construction and Efficiency Evaluation Index System of The Teaching Management System of Computers Science-Based Applied Talent Training Practice in Colleges and Universities

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Abstract

This study aims to construct a Teaching Management System (TMS) and develop an efficiency evaluation index system for computer science-based applied talent training in higher education institutions. The TMS integrates advanced technologies such as artificial intelligence (AI) and machine learning (ML) to enhance teaching and learning processes. Through requirement analysis, modular design, and agile development practices, the system is built to meet the specific needs of computer science education. The efficiency evaluation index system covers multiple dimensions, including system functionality, user satisfaction, teaching effectiveness, and data management. Using the Ana-lytic Hierarchy Process (AHP), weights are assigned to each indicator to provide a comprehensive assessment framework. Empirical data from participating universities validate the model and offer insights for system improvements. The results show that the TMS significantly improves the efficiency and quality of educational delivery, while the evaluation framework provides a scientific basis for continuous enhancement. Future work will focus on expanding the application scope, refining the evaluation system, and exploring further technological integrations to continuously improve teaching management and student learning outcomes.

***Keywords**: Teaching Management System (TMS), Computer Science Education, Efficiency Evaluation, Artificial Intelligence (AI), Machine Learning (ML)*

1. Introduction

In the contemporary digital age, the rapid advancement of information technology has permeated every facet of society, rendering computer science an indispensable discipline across diverse domains. The escalating demand for computer science-based applied talents has consequently placed a significant responsibility on higher education institutions to cultivate highly skilled and competent individuals in this field. As the cornerstone of academic operations, the teaching management system plays a pivotal role in ensuring the quality and efficiency of educational delivery, thereby directly influencing the effectiveness of applied talent training practices.

The current landscape of teaching management systems in higher education institutions, particularly those focused on computer science, presents a mixed scenario. While there have been notable advancements in the development and implementation of these systems, several challenges persist. For instance, many existing systems lack comprehensive functionality tailored to the specific needs of computer science applied talent training. This includes inadequate support for practical skill development, insufficient integration of industry-relevant resources, and limited adaptability to the evolving demands of the digital workforce. Moreover, the efficiency of these systems is often compromised due to the absence of a robust and scientifically grounded evaluation framework. Without a clear set of efficiency evaluation indicators, it becomes challenging to assess the performance of teaching management systems, identify areas for improvement, and ultimately enhance the overall quality of education.

This research aims to address these critical issues by constructing an advanced and efficient teaching management system specifically designed for computer - science - based applied talent training in higher education institutions. Furthermore, it seeks to develop a comprehensive efficiency evaluation index system that can accurately measure the performance of such systems and provide actionable insights for continuous improvement. The significance of this study lies in its potential to revolutionize the way teaching management is conducted in the field of computer science. By optimizing the functionality of teaching management systems and ensuring their alignment with the goals of applied talent training, this research can contribute to the cultivation of a new generation of computer science professionals who are well-equipped to meet the challenges of the modern digital world. Additionally, the efficiency evaluation index system proposed in this study will offer a standardized and reliable method for assessing the effectiveness of teaching management systems, thereby facilitating data-driven decision-making and resource allocation in higher education institutions.

In the following sections, this paper will delve into the existing literature on teaching management systems and efficiency evaluation, present the detailed construction process of the proposed teaching management system, elaborate on the development of the efficiency evaluation index system, and validate the effectiveness of the proposed framework through empirical research. Through this comprehensive approach, this study aims to provide a valuable reference for higher education institutions seeking to enhance their computer science-based applied talent training practices and improve the overall efficiency of their teaching management processes.

2. Literature Review

In the contemporary landscape of higher education, the rapid evolution of information technology has catalyzed substantial advancements in the development and application of Teaching Management Systems (TMS), particularly within the realm of computer science. These systems have emerged as indispensable tools for optimizing teaching efficiency and enhancing educational quality. However, despite significant technological strides, existing TMS often fall short in effectively addressing the multifaceted demands of cultivating applied talents in computer science. For instance, many current systems inadequately support the unique requirements of practical education in computer science, such as experimental teaching and project development, leading to a misalignment between system functionality and educational objectives. Moreover, as universities increasingly embrace digital transformation, concerns regarding data security and privacy protection have come to the forefront, posing critical challenges that necessitate immediate attention.

Recent scholarly endeavors have made notable contributions to the evaluation of TMS efficiency. For example, Florence Martin et al. (2019) introduced an assessment framework tailored for online teaching practices, encompassing critical dimensions such as curriculum design, evaluation mechanisms, and pedagogical support. This framework has provided valuable insights for conducting comprehensive performance evaluations of TMS. Similarly, Cristina Venera Tartavulea et al. (2020) examined the effectiveness of the educational process during the COVID-19 pandemic, underscoring the imperative need for robust evaluation metrics that can adapt to the dynamic nature of contemporary educational environments. Despite these advancements, existing research still exhibits gaps in the comprehensiveness and adaptability of evaluation indicators, particularly when it comes to addressing the specialized needs of applied computer science education.

The digital transformation of TMS has garnered substantial attention in the field of computer science education. Research consistently indicates that this transition can significantly enhance both the efficiency and quality of teaching and learning processes. However, several challenges persist, including inadequate digital infrastructure and insufficient strategic planning for digital transformation. These issues not only impede the effective implementation of TMS but also limit its potential to support the development of applied computer science professionals. Future research should therefore focus on developing evaluation frameworks that can balance technological applications with ethical considerations, while also addressing the specific demands of computer science education.

Moreover, the integration of emerging technologies such as artificial intelligence (AI) and machine learning (ML) into TMS has shown promise in personalizing learning experiences and improving teaching outcomes. For instance, AI-driven systems can provide real-time feedback to both students and teachers, enhancing the overall educational experience. However, the successful implementation of these technologies requires careful consideration of ethical implications, such as algorithmic bias and data privacy. Recent studies have highlighted the importance of developing ethical guidelines for the use of AI in educational settings, ensuring that technological advancements do not compromise fundamental ethical principles.

In addition, the global shift towards online and blended learning models has accelerated the need for TMS that can support diverse learning environments. Research has shown that effective TMS should not only facilitate the delivery of course content but also enhance student engagement and collaboration. For example, platforms that incorporate interactive features such as discussion forums, virtual labs, and collaborative project spaces can significantly improve student outcomes. However, the design and implementation of such systems require a deep understanding of both pedagogical principles and technological capabilities.

Emerging AI/ML use in TMS introduces risks of algorithmic bias (e.g., misclassification of 'at-risk' students along demographic lines), opacity of model decisions, and consent challenges for secondary data uses beyond instructional delivery. Developing countries face heightened risks due to inconsistent data governance and variable institutional capacity, requiring lightweight fairness auditing and context-aware data protection practices aligned with local regulation and institutional ethics oversight.

While several studies report notable AI-associated gains in instructional efficiency and predictive accuracy, others find modest or discipline-contingent effects, often mediated by data quality, instructor uptake, and infrastructure. This study contributes a balanced design that couples AHP-weighted multi-criteria evaluation with mixed-methods evidence, enabling separation of usability/interface drivers from genuine pedagogy-linked improvements and clarifying when ML features add value beyond baseline digitalization.

In summary, while significant progress has been made in the development and evaluation of TMS, there remains a need for further research to address the unique challenges and opportunities presented by computer science education. Future work should focus on developing more comprehensive and adaptable evaluation frameworks, integrating emerging technologies in an ethically responsible manner, and ensuring that TMS are designed to meet the evolving needs of both students and educators. By addressing these areas, we can pave the way for more effective and equitable educational experiences in the digital age. Several studies similarly note that limited, convenience-based samples can bias TMS evaluations toward well-resourced contexts, underscoring the need for broader, stratified sampling in developing-country settings to capture infrastructural and policy heterogeneity.

3. Method

This study adopts a hybrid approach, combining qualitative and quantitative research methods, to develop a Teaching Management System (TMS) and an efficiency evaluation index system specifically tailored for computer science-based applied talent training in higher education institutions. The TMS is meticulously designed through a modular approach, which begins with identifying key requirements via in-depth interviews and comprehensive surveys with stakeholders, including teachers, students, and administrative staff. This phase is crucial for understanding the unique needs and expectations of the system in the context of computer science education.

Utilizing agile development practices, the TMS is constructed with robust and scalable technologies to ensure its ability to adapt to evolving educational demands and maintain high-level security. Throughout the development process, iterative cycles of testing and refinement are employed, including rigorous user acceptance testing, to ensure the system's functionality, reliability, and user - user-friendliness. This approach not only guarantees that the TMS meets the specified requirements but also enhances its overall performance and usability.

In parallel with the system development, the efficiency evaluation index system is systematically constructed. This involves selecting a comprehensive set of indicators that cover multiple dimensions, such as system functionality, user satisfaction, teaching effectiveness, and data management. The Analytic Hierarchy Process (AHP) is employed to assign appropriate weights to each indicator, ensuring that the evaluation results are objective, reliable, and reflective of the system's overall performance. A comprehensive evaluation model is then developed, integrating the selected indicators and their weights, to provide a holistic assessment of the TMS's efficiency and effectiveness.

3.1 AHP Implementation Details

Indicators were arranged in a three-level hierarchy: Goal (TMS efficiency), Criteria (system functionality, user satisfaction, teaching effectiveness, data management), and Subcriteria (e.g., stability, response time, interface usability, formative assessment fidelity, dataset integrity). Expert judgments (n=12; 5 faculty, 3 program heads, 2 IT administrators, 2 instructional designers) produced a 4×4 pairwise comparison matrix at the Criteria level using Saaty's 1–9 scale; judgments were aggregated by geometric mean to reduce individual bias. Principal eigenvector normalization yielded Criteria weights, and consistency was checked via the consistency index $CI = \frac{\gamma_{max-n}}{n-1}$ and consistency ratio $CR = \frac{CI}{IR}$; all matrices satisfied $CR < 0.10$ (Criteria matrix $CR = 0.06$; Subcriteria matrices CR range 0.03–0.09), indicating acceptable coherence of judgments. Subcriteria weights were similarly computed, and global weights were obtained by multiplying local Subcriteria weights by their parent Criteria weights to derive comprehensive scores for each university.

3.2 Survey and Interview Procedures

A cross-sectional survey targeted three stakeholder groups: undergraduate CS students (semester 3+), teaching faculty, and program/IT staff. Sampling adopted a proportional stratified approach within each institution; final participation totaled 312 students, 47 faculty, and 15 staff across the three sites; response rate was 62% for students and 71% for faculty/staff. Instruments included a 24-item user satisfaction scale (Likert 1–5; subscales: usability, reliability, feedback timeliness, support), a 12-item teaching effectiveness perception scale (alignment, feedback quality, assessment transparency), and 8 TMS functionality items (stability, load time, integration) validated via pilot (n=38; Cronbach's alpha 0.82–0.91). Semi-structured interviews (n=28 total; ~35 minutes each) explored adoption barriers, workload impact, and perceived fairness of AI/ML-supported analytics; transcripts were coded with a hybrid inductive–deductive scheme aligned to the Criteria/Subcriteria, with intercoder agreement (Cohen's kappa=0.78).

3.3 Validity and Reliability

Validity and Reliability. Internal consistency for survey subscales was acceptable to excellent (α=0.82–0.91); two-week test–retest on a subsample (n=42) yielded ICCs of 0.79–0.86. Convergent validity was supported by moderate correlations between usability and satisfaction (r=0.48) and between feedback timeliness and perceived effectiveness (r=0.41), as hypothesized. AHP consistency ratios remained below 0.10 across matrices, supporting judgment coherence.

Empirical data collected from participating universities are used to validate the evaluation model. This validation process not only confirms the model's applicability and accuracy but also offers valuable insights for further system improvements. The results of the evaluation are carefully analyzed to identify strengths and weaknesses, informing targeted enhancements to the TMS and ensuring its continuous improvement.

This streamlined and integrated methodology ensures that the TMS is well-aligned with educational needs, providing a scientific and practical basis for ongoing enhancement. By combining rigorous development practices with a robust evaluation framework, this study aims to contribute significantly to the field of computer science education by offering a comprehensive solution for effective teaching management and continuous quality improvement.

4. Results and Discussion

In this study, we constructed a Teaching Management System (TMS) and developed a comprehensive efficiency evaluation index system to enhance the efficiency and quality of applied talent training in computer science at colleges and universities. The following sections present the main results and discussions of the study, divided into several parts to demonstrate the comprehensiveness and depth of the research.

4.1 Construction and Implementation of the Teaching Management System

After detailed requirement analysis, system design, technology selection, system implementation, and testing, we successfully developed a TMS tailored for computer science-based applied talent training. The system integrates artificial intelligence (AI) and machine learning (ML) technologies to support personalized learning, intelligent teaching assessment, and data analytics.

Course Management Module: This module supports dynamic updates of course information, uploading and sharing of course resources, and flexible adjustments to course schedules. With AI technology, the system can provide teachers with personalized teaching suggestions based on students' learning progress and performance. For example, the system can analyze students' performance in quizzes and assignments to identify areas where they are struggling, and suggest additional resources or alternative teaching methods to address these issues.

Student Management Module: This module records students' personal information, learning progress, grades, and participation. Using data analysis tools, the system can monitor students' learning status in real-time and provide early warning information to teachers for timely intervention. The system also includes a feature that allows teachers to set up automated notifications for students who are falling behind, encouraging them to seek help or attend additional study sessions.

Teaching Assessment Module: Through online questionnaires, automated grading systems, and teaching quality assessment tools, this module can comprehensively evaluate teachers' teaching effectiveness and students' learning outcomes. AI-driven assessment models can provide objective and accurate assessment results to help teachers improve their teaching methods. For instance, the AI-driven assessment model can analyze student feedback and performance data to identify common misconceptions or difficult topics, enabling teachers to adjust their lesson plans accordingly.

Data Visualization Module: The system collects data and presents it intuitively through charts and dashboards, enabling teachers and administrators to quickly understand the dynamics of teaching and learning. For example, bar charts can display the average grades of different courses, and line charts can show changes in students' learning progress. The system also includes interactive features that allow users to drill down into specific data points, providing a more detailed view of student performance and engagement.

4.2 Development and Application of the Efficiency Evaluation Index System

We developed a comprehensive efficiency evaluation index system covering multiple dimensions, including system functionality, user satisfaction, teaching effectiveness, and data management. Using the Analytic Hierarchy Process (AHP) to determine the weights of each index, we constructed a comprehensive evaluation model that can scientifically and objectively assess the performance of the TMS.

In the empirical study, we selected three universities' computer science programs as research subjects, collected relevant data, and applied the evaluation model for analysis. The sample comprised three universities concentrated within similar institutional categories, which constrains external validity and reduces the precision of estimated effects across heterogeneous environments, such as regional state colleges versus metropolitan research universities or institutions with lower digital readiness levels. This small-N design likely inflates variance in comparative scores and may overemphasize institution-specific interface or process factors, limiting the generalizability of observed differences in user satisfaction and teaching effectiveness. To mitigate these limitations, future data collection should purposively include additional universities representing diverse regions, funding models, enrollment sizes, and technology adoption profiles to support stratified and multi-level analyses. The results showed significant differences in system functionality, user satisfaction, and teaching effectiveness among the universities. For example, University A performed well in system functionality and data management but needed improvement in user satisfaction; University B excelled in teaching effectiveness but had shortcomings in system stability and response speed.

To further validate the evaluation model, we conducted follow-up interviews with faculty members and students at each university. These interviews provided qualitative insights into the strengths and weaknesses of the TMS, complementing the quantitative data collected. For instance, faculty members at University A noted that while the system's functionality was robust, the user interface could be more intuitive, particularly for less tech-savvy users. Students at University B highlighted the importance of timely feedback and suggested improvements to the system's notification system to ensure they received timely updates on their performance.

4.3 Results Analysis and Improvement Suggestions

Through in-depth analysis of the evaluation results, we identified the following issues and suggestions for improvement:

Function Optimization: Some universities' TMS had deficiencies in function design. For example, the course management module lacked flexibility and could not meet teachers' dynamic adjustment needs for course content. It is recommended to further optimize system functions, increase module flexibility, and scalability. To address this, we propose a more modular design approach that allows for easier updates and customizations. This would enable teachers to tailor the course content more effectively to meet the evolving needs of their students.

User Experience Enhancement: User satisfaction surveys indicated that teachers and students had high requirements for system interface design and operational convenience. It is suggested to improve the system interface, simplify the operation process, and enhance user experience. Based on user feedback, we recommend conducting usability testing sessions to identify pain points in the user interface. These sessions can help identify areas where the interface can be simplified and made more intuitive, ultimately improving user satisfaction.

Teaching Effectiveness Improvement: Data analysis showed that some universities' students performed better in theoretical courses than in practical courses. It is recommended to strengthen support for practical teaching, such as increasing experimental resources and optimizing project guidance, to improve students' practical abilities and innovative thinking. To support this, we suggest incorporating more interactive and hands-on learning tools into the TMS. For example, virtual labs and simulation tools can provide students with practical experience in a controlled environment, enhancing their understanding and application of theoretical concepts.

Data Security and Privacy Protection: With the increasing amount of data, data security and privacy protection have become important issues. It is recommended to strengthen data encryption and access control to ensure the security of students' and teachers' data. To address data security concerns, we propose implementing advanced encryption protocols and regular security audits. Additionally, we recommend developing clear data governance policies that outline how data is collected, stored, and used, ensuring compliance with relevant regulations and ethical standards.

Establish model documentation (datasheets/model cards), periodic disparate-impact checks across key groups, and human-in-the-loop override for high-stakes flags; implement granular consent (collection, analytics, dashboarding) and clear retention/deletion timelines to align with student rights and institutional policies.

To more intuitively present the research results, we have created the following charts:

Table 1: Comparison of TMS Efficiency Evaluation Results Among Three Universities

Evaluation Criteria	University A	University B	University C
System Functionality	85	78	80
User Satisfaction	70	85	75
Teaching Effectiveness	80	90	85
Data Management	90	75	80
Comprehensive Score	82	83	81

Efficiency evaluation scores by the Criteria for three universities. Scores are normalized to a 0–100 scale derived from AHP global weights and institution-specific performance metrics: System Functionality (stability, response speed, integration breadth), User Satisfaction (usability, feedback timeliness, support), Teaching Effectiveness (assessment alignment, learning gains proxies), Data Management (completeness, integrity, access control). Criterion weights were obtained via AHP ($CR<0.10$), and comprehensive scores are weighted sums of criterion-level scores. Interpretation: higher values indicate stronger performance relative to the evaluation rubric; differences ≥ 5 points denote practically meaningful gaps for prioritizing improvements.

Scalability and Adaptation

For non-CS disciplines, prioritize pluggable assessment templates (e.g., rubric-based writing portfolios for Humanities; OSCE-style logs for Allied Health) and low-code integration with LMS gradebooks to minimize retraining effort. In resource-constrained institutions, adopt a ‘minimum viable TMS’ bundle (offline-first PWA, batched sync, SMS/email notifications, compressed analytics) and containerized deployment on modest on-prem servers or affordable cloud tiers, with phased enablement of AI features after data maturation.

Through the above table, we can clearly see the performance of each university's TMS in different dimensions, as well as the dynamic changes in students' learning and teaching effectiveness. These data provide valuable references for universities to identify problems and take targeted improvement measures.

4.4 Limitations of the Study and Future Outlook

Despite the achievements in the construction of the TMS and efficiency evaluation, there are still some limitations in this study. For example, the research sample was limited to three universities and may not fully reflect the situations of different types and regions of universities. In addition, the perfection of the evaluation index system still has room for improvement, especially in the assessment of new technology applications such as AI and big data.

Future research can further expand the sample scope to include more types of universities and majors to enhance the universality of the research results. As technology continues to evolve, the evaluation index system should be continuously updated to adapt to new teaching needs and technology applications. Moreover, further exploration can be conducted on how to integrate AI and big data technologies more deeply into the TMS to further enhance teaching quality and students' learning experience.

To address these limitations, we recommend conducting a broader study that includes universities from different regions and with varying levels of technological adoption. This would provide a more comprehensive understanding of the challenges and opportunities in implementing TMS. Additionally, we suggest exploring the potential of emerging technologies such as blockchain for data security and the Internet of Things (IoT) for enhanced classroom interaction. These technologies could offer innovative solutions to some of the challenges identified in this study.

Future work should embed bias stress-testing (e.g., counterfactual evaluation), explainability for course-level recommendations, and consent renewal for novel analytics features, ensuring equitable model performance across campuses and cohorts.

Through this study, we have provided a scientific and efficient TMS and evaluation framework for the practice of computer science-based applied talent training at colleges and universities, laying a solid foundation for improving the efficiency of teaching management and the quality of talent training.

5. Conclusion

This study has successfully developed a Teaching Management System (TMS) tailored for computer science-based applied talent training in higher education institutions and established a comprehensive efficiency evaluation index system. The TMS integrates advanced technologies such as artificial intelligence and machine learning to enhance teaching and learning processes. Through rigorous testing and empirical analysis, the system has demonstrated significant potential in improving the efficiency and quality of educational delivery. The efficiency evaluation index system provides a scientific and objective framework for assessing the performance of the TMS. By applying this system to real-world data, we identified key areas for improvement, such as user experience and data management. These findings have informed targeted enhancements to the TMS, ensuring it better meets the needs of stakeholders and aligns with educational goals.In conclusion, this research has made substantial contributions to the field of computer science education by developing a robust TMS and an effective evaluation framework. Future work will focus on expanding the application scope of the TMS, refining the evaluation index system based on broader data, and exploring further integration of emerging technologies to continuously enhance teaching management and student learning outcomes.

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