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The Path and Strategy of Empowering the Construction of Internal Quality Assurance System in Higher Vocational Education with Smart Campus under the Background of "Double High"

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Abstract: In the era of exponential big data technology advancement, fostering the establishment and refinement of vocational colleges' internal quality assurance frameworks holds paramount importance for enhancing educational standards and fostering industry-education alignment. Aligned with the "dual excellence" initiative-emphasizing elevated educational prowess and seamless industry-education fusion-the smart campus blueprint has been reinvigorated with a pivotal role in advancing vocational institutions' internal quality safeguards. This essay delves into the multifaceted avenues and inventive methodologies for bolstering the internal quality assurance constructs in higher vocational education, leveraging smart campus infrastructures. It introduces an AI-powered information governance and teaching quality assessment mechanism, which harnesses cutting-edge technologies like big data analytics and machine learning (ML) to optimize teaching resource allocation, refine educational process management, and ensure meticulous teaching quality evaluation. Experimental outcomes underscore the system's prowess in dramatically enhancing the efficacy and precision of teaching quality oversight, thereby furnishing a robust technological backbone for the iterative enhancement of vocational colleges' internal quality assurance ecosystem.

1. Introduction

Amidst the technological revolution of the 21st century, Information Technology (IT) fosters unparalleled transformations across diverse sectors, notably education [1]. As the Internet landscape broadens and intensifies, the notion of "Internet-integrated education" has proliferated rapidly, emerging as a pivotal catalyst for educational innovation and advancement [2]. Vocational institutions, vital elements within the vocational education architecture, undertake the mission of nurturing proficient technical and skilled professionals, with their instructional excellence intimately linked to the foundations of national economic growth and societal advancement [3]. Consequently, establishing a robust, efficient, and adaptable internal quality assurance framework holds paramount significance in elevating teaching standards and safeguarding the quality of talent development in vocational colleges [4]. Amid contemporary educational reforms, vocational colleges are progressively acknowledging the essence of teaching quality and are actively delving into strategies to optimize it [5]. Nevertheless, enhancing teaching quality necessitates a well-structured quality assurance system as its cornerstone, a journey that necessitates patience and persistence.

The comprehensive teaching system ought to encompass every facet of the educational journey, spanning from resource allocation, content crafting, methodology innovation, to assessment and feedback mechanisms, creating a circular framework that fosters relentless enhancement of instructional excellence [6]. Pivotal to its realization stands the development of smart campuses, a testament to the profound convergence of IT and education. These smart environments harness cutting-edge technologies like IoT, cloud computing, big data, and AI to grant a holistic understanding of the campus environment, orchestrate resource allocation intelligently, refine teaching administration meticulously, and tailor learning experiences uniquely for each individual [7]. Within the realm of vocational education's internal quality assurance system construction, smart campuses transcend mere technological enablers; they furnish a robust data-driven foundation for teaching quality oversight and assessment, leveraging deep data mining and analytical prowess [8]. Illustratively, leveraging big data analytics empowers stakeholders to quantify student learning patterns and teacher performance benchmarks, swiftly pinpointing and addressing teaching challenges. Furthermore, AI-driven decision support systems offer managers strategic insights, fostering a scientific and nuanced approach to teaching management, thereby enhancing overall educational outcomes [9].

Concurrently, as big data technology continues to mature and broaden its application scope, its significance in the realm of education has significantly intensified. Positioned as a pivotal strategic asset in contemporary society, big data encompasses vast volumes of information, coupled with real-time analytical prowess and predictive insights, underpinning robust decision-making frameworks in education, teaching assessments, learning analytics, and various other aspects [10]. In the context of fostering smart campus ecosystems within vocational colleges, the deployment of big data serves as a catalyst for enhancing the efficiency of teaching resource allocation, fostering greater transparency and auditability in the teaching lifecycle, and fostering the innovation and modernization of teaching methodologies, thereby advancing teaching quality across dimensions. Thus, the present study delves into the multifaceted avenues and creative approaches for empowering the development of internal quality assurance systems within higher vocational education, leveraging the smart campus paradigm. The core objective is to investigate the practical implementation of smart campuses in this educational sector and conceive an AI-driven information management and teaching quality assessment framework. This proposed system capitalizes on the strengths of both big data and AI technologies, harmoniously integrating advanced capabilities like big data analytics and ML, to attain optimal teaching resource distribution, meticulous teaching process governance, and precise teaching quality evaluations.

2. Methodology

2.1 System Construction

In the context of the current digital transformation of education, vocational colleges, as important bases for cultivating high skilled talents, have particularly important information construction and the improvement of their teaching quality evaluation system [11]. Deploying a smart campus platform is not only a profound transformation of traditional education management models, but also a key measure to promote educational modernization, improve teaching quality, and optimize resource allocation [12]. This article will explore in depth the construction of an AI based information management and teaching quality evaluation system from the aspects of system architecture design, key technology selection, functional module implementation, and implementation effects. Figure 1 shows the structure of the system in this article. The construction of a smart campus platform should follow the principles of "unified planning, resource integration, data sharing, and highlighting applications", aiming to break down information silos and achieve seamless integration and efficient utilization of various resources on campus. The platform adopts a layered architecture design, including infrastructure layer, data resource layer, service support layer, business application layer, and user access layer.

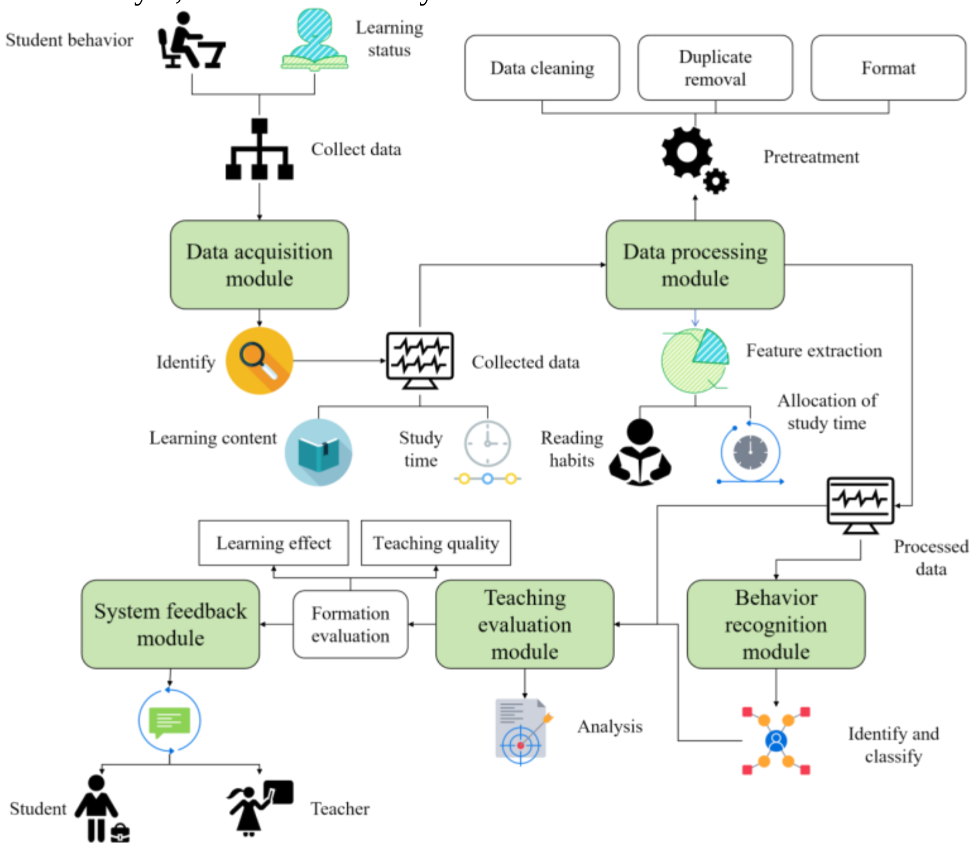

Figure 1: System Structure

The infrastructure layer provides infrastructure support such as cloud computing and big data; The data resource layer achieves unified standards, centralized storage, and sharing of data through data governance; The service support layer provides general services such as identity authentication and message push; The business application layer includes multiple subsystems such as teaching management, student management, and teaching quality monitoring; The user access layer provides convenient access points for teachers and students. By utilizing technologies such as ML and DL, intelligent recognition and analysis of student learning behavior and teacher teaching activities can be achieved, providing scientific basis for teaching quality evaluation. Using big data technology frameworks such as Hadoop and Spark, efficiently process and analyze massive teaching data, and explore potential value. Deploy sensors, RFID and other devices in smart classrooms to monitor the classroom environment, student attendance, teacher-student interaction, and provide real-time data for teaching quality monitoring. Through cloud computing platforms, we can achieve elastic expansion and on-demand allocation of resources, reduce system operation and maintenance costs, and improve system stability and availability.

The data collection module utilizes multiple sources of data such as IoT devices and teaching management systems to automatically collect student learning behavior data, teacher teaching activity data, course evaluation data, etc., ensuring the comprehensiveness and accuracy of the data. The data processing module cleans, converts, and integrates the collected data, uses data analysis models for deep mining, identifies learning patterns, predicts learning outcomes, and evaluates teaching quality. The behavior recognition module is based on video analysis, speech recognition and other technologies to automatically recognize students' behavior in the classroom, such as attention concentration, participation, etc., providing teachers with real-time feedback on students' status. The teaching evaluation module combines formative evaluation and summative evaluation to construct a multidimensional and comprehensive teaching evaluation system. Through intelligent algorithms, automatically generate electronic student growth portfolios, record students' learning trajectories, changes in grades, and ability development, providing a basis for personalized teaching. The system feedback module automatically generates feedback reports based on the evaluation results of teaching quality, providing improvement suggestions to teachers, students, and management. Meanwhile, establish a closed-loop feedback mechanism to ensure timely response and resolution of issues.

2.2 Algorithm Principle

To improve the convenience and comparability of statistical data in subsequent processing, we adopted the min max normalization method to convert the raw data into a dimensionless standardized form. This process is achieved by applying the following normalization transformation formula:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

Among them, the maximum value in the sample is $x_{\max}$ and the minimum value is $x_{\min}$.

By using advanced ML algorithms, we can deeply analyze students' learning behavior and learning status, construct accurate analysis models, comprehensively evaluate teachers' teaching effectiveness, and propose targeted improvement strategies based on this. When using the powerful tool of decision tree algorithm, the key is to perform detailed splitting processing on each feature, aiming to find the optimal splitting point to optimize model performance. In this process, evaluation indicators such as information gain and information gain rate play a crucial role, providing scientific basis for the selection of splitting points. Taking information gain as an example, as one of the important indicators to measure the quality of feature splitting, its calculation method focuses on evaluating the degree of reduction in information uncertainty before and after feature splitting. Specifically, information gain is quantified by comparing the difference between the information entropy of the pre split dataset and the weighted information entropy of each subset after splitting. The larger the difference, the greater the contribution of the feature split to reducing dataset uncertainty (i.e. improving classification purity), and therefore more likely to be selected as the optimal splitting point.

$$Gain(D, A) = Entropy(D) - \sum_{v \in Values(A)} \frac{|D|}{|D^v|} Entropy(D^v) \tag{2}$$

In the formula, D is the dataset, A is a certain feature, D^v is the subset of feature A at the value v, and is the entropy of dataset D.

In the process of extracting students' learning behavior characteristics, K-means clustering method has become an effective analysis tool due to its characteristic of grouping samples based on similarity between samples. This method typically uses Euclidean distance as a metric to quantify the similarity between any two samples in the dataset. For a given dataset $S=\{s_1,s_2,s_3,\cdots,s_n\}$, the Euclidean distance between any two samples X and Y can be accurately calculated as follows:

$$dist(X,Y)=\sqrt{\sum_{i=1}^{n}(x_i-y_i)^2} \tag{3}$$

Among them, n is the number of samples in dataset S.

In the initial stage of cluster analysis, we assume that k subsets have been formed, represented as $C_k = \{C_1, C_2, \cdots, C_k\}$, which are the initial set of cluster centroids. Subsequently, based on the Euclidean distance formula, we systematically evaluate the similarity between each remaining sample and these centroids. For any given sample $X = \{x_1, x_2, x_3, \cdots, x_p\}$, its similarity (or distance) to any initial centroid can be accurately calculated using the following formula:

$$dist(X, C_k) = \sqrt{\sum_{i=1}^{n}(x_{pi} - c_{ki})^2} \tag{4}$$

Divide the sample into clusters that are most similar to it based on the results. Therefore, the objective convergence function of K-means is:

$$E=\sum_{i=1}^{k}\sum_{x\in C_j}|x-\mu_i|^2 \tag{5}$$

Among them, μ_i is the mean of C_j.

Intelligent speech recognition nodes, as a type of intelligent unit dedicated to audio information processing, play a core role. Specifically, HMM (Hidden Markov Model) speech recognition technology is fundamentally rooted in an efficient probabilistic computing framework, characterized by its ultra fast recognition speed and excellent dynamic adjustment ability, ensuring accurate and real-time recognition. The HMM model, represented by a parameter set, can be formally expressed as the following formula:

$$\begin{cases}\lambda=\{\pi, A, B\}\\ \pi_i = p_r(q_0 = s_i), i=1,\cdots,N\\ A=\{a_{ij}\}_{N\times N}\\ B=b_i(x)\end{cases} \tag{6}$$

In the formula, N is the number of states; π_i is the initial distribution vector; A is the state transition probability matrix; B is a probability density function that describes the distribution of state characteristic vectors; M is the size of the vector quantizer codebook.

3. Result Analysis and Discussion

To verify the performance of the system in this article, a comparative experiment will be conducted between the system and traditional teaching quality evaluation methods based on expert systems. Fig. 2 visually presents the significant advantage of our system in evaluating accuracy compared to traditional methods. As can be seen from the figure, as the samples are presented one by one, we can see that whether it is a micro analysis of a single course or a macro evaluation of the entire teaching system, the system presented in this article has demonstrated evaluation accuracy far exceeding that of traditional expert systems. This significant improvement is due to the powerful data processing capability, complex pattern recognition ability, and real-time adaptive optimization mechanism of AI systems. It can capture and analyze subtle differences and trends that are difficult to detect under traditional teaching modes, thus making more accurate and comprehensive judgments on teaching quality. Specifically, AI systems use ML algorithms to automatically extract features from massive teaching data and construct refined evaluation models. This not only identifies the strengths and weaknesses of teachers' teaching methods, but also evaluates feedback on students' learning outcomes and the overall impact of the teaching environment.

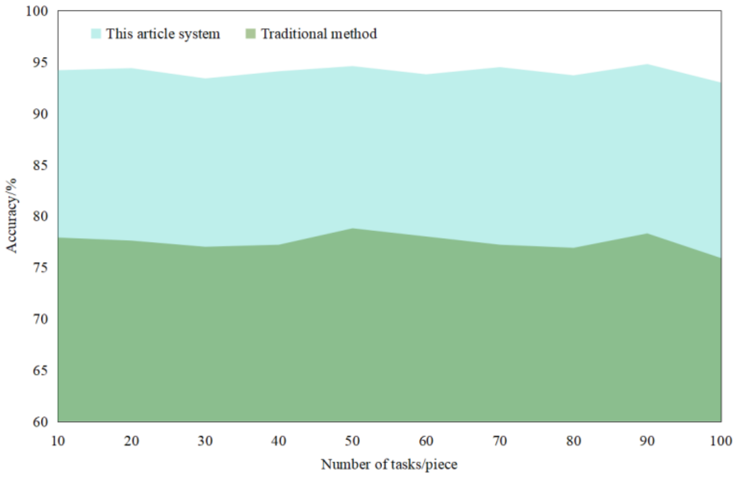

Figure 2: Comparison of Evaluation Accuracy

Fig. 3 provides a visual and powerful comparison of the time required for processing teaching quality evaluation tasks between the system proposed in this paper and traditional methods. From the figure, it can be seen that the system presented in this article exhibits significant time efficiency advantages and significantly shortens the task processing cycle. As the complexity of tasks increases or the amount of tasks accumulates, traditional expert systems often experience significant delays in processing time due to the need for manual intervention and cumbersome decision-making processes. In contrast, AI systems, with their efficient parallel processing capabilities, automated decision-making mechanisms, and intelligent optimized algorithm designs, can quickly respond to and process a large number of evaluation tasks, greatly reducing waiting time and processing cycles. This leap in time efficiency not only improves the timeliness of teaching quality evaluation, but also enables faster feedback of evaluation results to both teaching parties, promoting continuous improvement of teaching quality; At the same time, it also reduces the workload of academic management personnel, allowing them to devote more energy to in-depth analysis and strategy formulation of teaching quality.

Fig. 4 deeply reveals the significant advantages of the system proposed in this article in terms of user satisfaction compared to traditional methods. From the figure, it can be clearly seen that users' satisfaction with the AI system designed in this article is much higher than that of traditional expert systems. This result is not accidental, it stems from the AI system fully considering user needs and experience from the beginning of its design. AI systems greatly enhance user convenience and interactivity through intelligent interface design, personalized evaluation reports, and instant feedback mechanisms. Teachers can quickly receive comprehensive feedback on their teaching performance, students can have a clearer understanding of their learning status, and educational administrators can make more scientific and reasonable decisions based on real-time data. In addition, AI systems also have strong self-learning and optimization capabilities, which can continuously adjust evaluation models and algorithms based on user feedback, ensuring the accuracy and fairness of evaluation results, thereby further enhancing user trust and satisfaction.

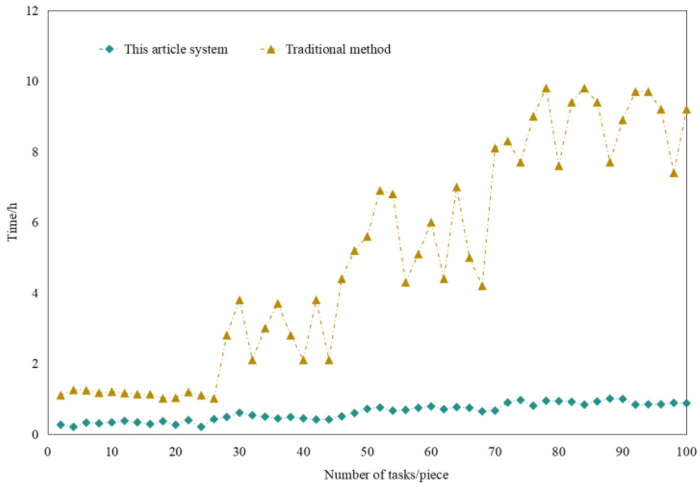

Figure 3: Comparison of Task Processing Time

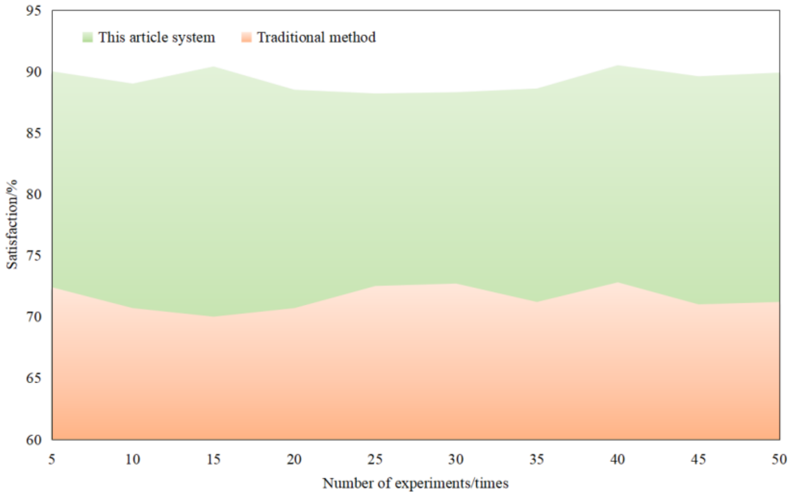

Figure 4: Satisfaction Comparison

Fig. 5 provides a detailed comparison of the performance of our system and traditional methods in evaluating the key indicator of recall rate. From the figure, it can be clearly seen that the AI system designed in this article demonstrates significant advantages in recall rate, that is, the system can more comprehensively identify and evaluate actual teaching quality issues, reducing omissions. As one of the important indicators for evaluating system performance, recall rate directly reflects the coverage of the target problem by the system. In Figure 5, with the diversification and increasing complexity of teaching quality evaluation scenarios, traditional expert systems are often limited by manually set rule libraries and expert experience, making it difficult to comprehensively capture all potential issues, resulting in relatively low recall rates. And the AI system in this article has constructed a more intelligent and flexible evaluation model through the integration and application of advanced technologies such as ML. This model can deeply understand various data features in the teaching process, automatically identify and evaluate various teaching quality issues, thereby achieving a higher recall rate.

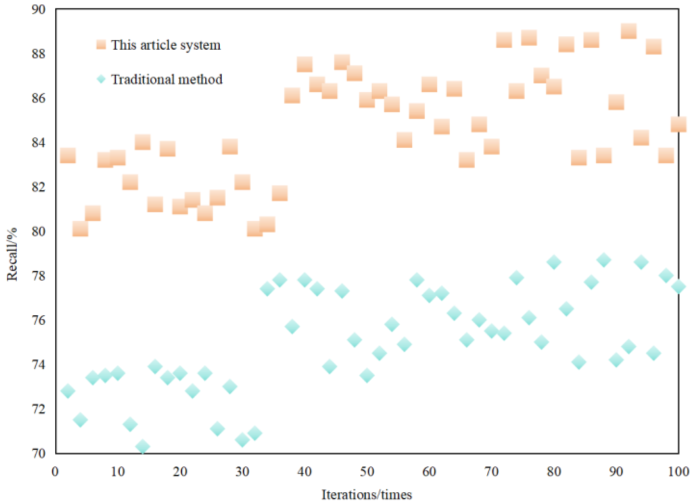

Figure 5: Comparison of Recall Rates

4. Conclusion

After comprehensively analyzing the multidimensional path and innovative strategies for constructing the internal quality assurance system of higher vocational education under the background of smart campus, this article creatively proposes an information management and teaching quality evaluation system that integrates AI technology. This system not only deeply integrates cutting-edge technologies such as big data analysis and ML, but also successfully achieves intelligent configuration of teaching resources, fine monitoring of teaching processes, and precise quantitative evaluation of teaching quality, building an efficient, intelligent, and comprehensive quality assurance system for vocational colleges. The significant results of the experimental data strongly demonstrate the enormous potential of the system in improving the efficiency and accuracy of teaching quality management, injecting new vitality into the sustainable development of vocational colleges. However, while acknowledging the advantages of the system, we should also be aware of its shortcomings. Firstly, the widespread deployment and application of the system require a large amount of high-quality data support, and currently some vocational colleges still have shortcomings in data collection, organization, and standardization, which may limit the full utilization of system efficiency. Secondly, the rapid development of AI technology requires systems to have continuous learning and iteration capabilities to cope with constantly changing teaching environments and demands, and the maintenance and upgrade costs of the system are also key considerations for the future.

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