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Exploring Pathways for Continuous Improvement in Engineering Education Accreditation in the Era of Big Data

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Abstract: *As big data continues to evolve rapidly, engineering education accreditation increasingly needs to integrate big data and related technologies to enhance its continuous improvement mechanisms. Using the computer science and technology major at Chongqing University of Posts and Telecommunications as a case study, this study first elaborates on the current state of continuous improvement mechanisms. The study then identifies key shortcomings associated with integrating continuous improvement with big data, including the absence of specialized big data platforms, insufficient analysis of students' learning behaviors, and delays in feedback and improvement. Based on these findings, the study explores a big data-based path for continuous improvement, which involves establishing dedicated big data platforms for engineering education accreditation, incorporating student learning behavior analysis into the continuous improvement process, and developing predictive feedback and improvement mechanisms. The goal is to provide valuable references and insights for constructing effective continuous improvement mechanisms in engineering education accreditation within the context of big data.*

Keywords: *Engineering Education Accreditation; Continuous Improvement; Big Data*

1. Introduction

Economic globalization has facilitated the transnational mobility of engineering personnel, necessitating that engineering education accreditation across countries achieve equivalence. In this context, the Washington Accord was established in 1989, with engineering professional groups from six countries, including the United States, the United Kingdom, and Canada, co-sponsoring and signing the agreement. The Accord aims to establish mutual recognition of engineering degrees and promote the international mobility of engineers and technicians through multilateral recognition of engineering education accreditation outcomes. China joined the Washington Accord as a full member in 2016, marking a significant step toward improving the quality of engineering and technology training. This membership is crucial for advancing China's talent development in engineering and technology on a global scale [1].

The accreditation of engineering education is guided by three core principles: "student-centered, outcome-oriented, and continuous improvement." Specifically, it is student-centered and oriented towards training objectives and graduation requirements, ensuring the effective implementation of all course teaching through adequate teaching staff and comprehensive support conditions. Continuous improvement is achieved through comprehensive internal and external quality control mechanisms to ensure that the quality of student training meets the required standards. Among these principles, continuous improvement is a crucial mechanism for ensuring the ongoing enhancement of engineering education and the continual upgrading of student training quality [2]. Numerous scholars have investigated continuous improvement. For example, Li systematically analyzes the concept of continuous improvement in engineering education accreditation, evaluating its completeness, functionality, and effectiveness [3]. Feng et al. explored the closed-loop mechanism for the continuous improvement of talent training quality, established an output-oriented evaluation mechanism, identified measures for effective implementation, and proposed evaluation suggestions regarding the rationality of professional training objectives [4]. Additionally, Chinese colleges and universities have developed systems for

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continuous improvement in talent training based on institutional orientation and professional characteristics. These research findings are highly valuable for advancing the implementation of professional accreditation.

In the era of big data, the integration of education and information technology has led to a data-driven education model focused on big data processing and artificial intelligence. This model is employed to analyze students' learning behavior, predict performance, optimize educational resources, and assess teacher-student interactions [5]. However, the current research and application of big data technology in engineering education accreditation are still limited, presenting both challenges and opportunities for enhancing the continuous improvement mechanism. Using the computer science and technology major at Chongqing University of Posts and Telecommunications (CQUPT) as a case study, this research analyzes and summarizes the current state of continuous improvement in engineering education accreditation, identifies issues in its integration with big data, and explores pathways for continuous improvement supported by big data.

2. Current State of Continuous Improvement in Engineering Education Accreditation

The overall requirement of continuous improvement is "evaluation-feedback-improvement," aimed at continuously refining the training objectives to ensure alignment with internal and external demands; continuously refining the graduation requirements to ensure alignment with the training objectives; and continuously refining teaching activities to ensure alignment with the graduation requirements [3]. Based on this requirement, CQUPT has established a multi-level and multi-faceted continuous improvement mechanism, including the formulation of policy documents, the determination of graduation requirements and training objectives, the construction of the curriculum system, the enhancement of teaching quality, social evaluation, and the tracking and feedback of graduates.

2.1. Mechanisms for Monitoring the Quality of the Teaching Process

A robust mechanism for monitoring the quality of the teaching process has been established, with clear quality requirements for each major teaching component and regular quality evaluations. This mechanism includes the evaluation of the achievement of curriculum objectives, quality monitoring of exam question design, evaluation of the rationality of the curriculum system, and assessment of the achievement of graduation requirements.

Table 1: Example of evaluation of achievement of curriculum objectives

Curriculum objectives	Assessment methods	Achievement degree	Ratio	Total achievement degree
Curriculum objective 1	Final exam	0.84	50%	0.89
	Homework	0.96	20%	
	Unit test	0.94	30%	
Curriculum objective 2	Final exam	0.78	50%	0.86
	Homework	0.96	20%	
	Unit test	0.94	30%	
Curriculum objective 3	Final exam	0.00	0%	0.94
	Homework	0.96	30%	
	Unit test	0.94	70%	
Curriculum objective 4	Final exam	0.00	0%	0.94
	Homework	0.94	30%	
	Unit test	0.96	70%	
Curriculum objective 5	Final exam	0.73	50%	0.84
	Homework	0.96	20%	
	Unit test	0.94	30%	
Total achievement degree of curriculum objectives		0.90		

For example, in the "Python Programming" course at CQUPT, the degree of achievement of each curriculum objective is assessed through various methods, weighted accordingly, and ultimately summarized as the total degree of achievement of curriculum objectives (Table 1).

2.2. Graduate Tracking and Feedback Mechanisms

A comprehensive graduate tracking and feedback mechanism, along with a social evaluation mechanism involving various stakeholders, has been established. Participants in the evaluation include former graduates, employers, and experts from universities and enterprises. Evaluations typically take the form of symposiums, questionnaires, and field research. The reasonableness evaluation of the training objectives is based on a four-year cycle, and the analysis of the achievement of the training objectives is conducted in parallel with the revision of the training program. For instance, feedback from employers in 2023 indicated that graduates of the CQUPT majoring in computer science and technology exhibit the following deficiencies: (1) they are diligent and willing to do their best, but lack communication and teamwork skills, as well as initiative and self-drive; (2) they have good continuous learning and adaptability skills, but insufficient transpositional and systematic thinking abilities; (3) they possess a strong professional foundation, but need to improve their humanistic and comprehensive qualities. In response to this feedback, the College implemented a series of improvement measures to the talent training program and curriculum.

2.3. Mechanisms for the Application of Evaluation Results

A mechanism has been established to utilize evaluation results for continuous improvement. The basis for the continuous improvement of the training objectives is derived from the feedback results of the evaluation of the reasonableness and achievement of the objectives, combined with information collected on the demands of social and economic development, industry trends, the school's positioning, and student development expectations. The continuous improvement of graduation requirements is conducted alongside the continuous improvement of training objectives based on the feedback results of the evaluation of the achievement of graduation requirements. The evaluation of the rationality of the curriculum system serves as the foundation for its revision, and continuous improvement of the curriculum system is carried out in conjunction with the training objectives and graduation requirements. The evaluation results of the achievement of curriculum objectives, along with feedback from supervisors' evaluations, students' evaluations, student informants' interviews, and teachers' interviews, provide the basis for the continuous improvement of course syllabi, teaching methods, teaching content, assessment methods, teaching staff, and support conditions. Accordingly, the relevant management system and the quality supervision and evaluation mechanism of the teaching process are continuously improved to meet the required standards.

3. Problems with Continuous Improvement Mechanisms in the Context of Big Data

In the era of big data, the field of higher education is undergoing continuous innovation and development through the application of technologies such as cloud computing, the Internet of Things, and artificial intelligence. Engineering education accreditation, particularly the operation of continuous improvement mechanisms, similarly requires the support and enhancement of big data technology. However, research and application in this area are still in their infancy.

3.1. Absence of Specialized Big Data Platforms

The application of big data technology in engineering education accreditation relies heavily on the support of dedicated big data platforms. However, the current scarcity of such platforms poses significant obstacles to the efficient operation of the continuous improvement mechanism, particularly in data management and analysis.

Continuous improvement necessitates the collection of extensive course materials and student learning data, including syllabi, teaching summaries, lesson plans, test papers with reference answers, and student performance records. In most universities, these materials are often stored by multiple teachers in electronic documents and spreadsheets, making them time-consuming and labor-intensive to organize and prone to loss. While many universities have established teaching information management platforms, these platforms typically offer conventional functions that are not suitable for engineering education accreditation. Moreover, different teaching activities within universities are often managed by disparate information platforms developed and maintained by different enterprises, hindering data sharing and unified management.

The operation of the continuous improvement mechanism requires various evaluation indicators, such

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as the achievement of curriculum objectives, the quality of test paper propositions, the rationality of the curriculum system, and the attainment of graduation requirements. Currently, these indicators are primarily calculated and analyzed manually by teachers, course directors, and major directors, consuming considerable time and energy. Existing teaching big data platforms are mainly utilized to analyze assignment completion, class attendance, and exam results, but lack the data analysis functions needed for continuous improvement, such as calculating the achievement of curriculum objectives and graduation requirements.

3.2. Insufficient Analysis of Students' Learning Behaviours

With the rise of online learning and cloud-based classrooms, the vast amounts of learning data generated require processing through new methods and tools, leading to the emergence of learning behavior analysis. As an evolving research field, learning behavior analysis focuses on processing big data related to the learning process and environment, designing online learning environments, developing learning theories, and addressing ethical issues in the use of online data [6]. By analyzing students' learning behavior, we can better understand their learning outcomes, optimize teaching resources, and provide more effective guidance for teaching methods. Currently, engineering education accreditation lacks integration with student learning behavior analysis, which is evident in the evaluation, feedback, and improvement aspects of the continuous improvement mechanism.

For instance, in the Python Programming course at CQUPT, various aspects of students' learning behavior, such as reviewing and previewing activities, class attendance, question answering, and homework completion, significantly impact the achievement of curriculum objectives and offer valuable feedback. However, the analysis of these behaviors has not been incorporated into the current evaluation and feedback system for continuous improvement. This phenomenon can be attributed to two main reasons: First, teaching administrators typically record student information and performance, but systematic records of learning behaviors are lacking, hindering comprehensive analysis. Second, evaluation indicators, such as the degree of achievement of curriculum objectives, are primarily calculated from assessment scores with various weightings, which do not directly reflect learning behaviors and complicate their integration into feedback mechanisms.

Improvement efforts also generally exclude learning behavior analysis. Course and major directors often focus on broad improvements, such as updating teaching plans, modifying course materials, changing assessment methods, and revising training programs. While these changes positively impact student training quality, they lack the granularity needed to address specific teaching elements due to the absence of detailed learning behavior analysis. For teachers, general curriculum and program improvements also make it challenging to tailor instruction effectively to individual student needs.

3.3. Delays in Feedback and Improvement

One advantage of big data technology is its ability to uncover potential patterns from vast datasets using artificial intelligence and other methods, enabling accurate predictions and proactive measures. This advantage has been effectively demonstrated in areas such as student performance prediction and early learning interventions [7-9]. In contrast, the feedback and improvement aspects of the current continuous improvement mechanism exhibit significant delays, which pose challenges for teachers, course directors, and major directors.

In the current continuous improvement mechanism, the "evaluation-feedback-improvement" cycle for curricula takes at least one semester to complete. Specifically, improvements to a course are implemented in the following semester based on the evaluation and summary of the current semester's teaching and learning outcomes. For teachers and course directors, this delay hinders the receipt of timely feedback, making it difficult to adjust teaching plans and guide students in improving their learning methods during the semester. Furthermore, evaluating the effectiveness of improvements is challenging before the end of a full semester. For major directors, the "evaluation-feedback-improvement" cycle is even lengthier. At CQUPT, for example, the talent training program is typically revised every four years, which complicates the process of making substantial improvements based on evaluation and feedback. Additionally, with the rapid advancement of artificial intelligence and other technologies, as well as the deepening cross-disciplinary integration, the demand for computer-related professionals is evolving more quickly than in other fields. Consequently, delays in obtaining feedback and improving training programs significantly impact student employment, technological innovation, and industrial development.

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4. Exploring Continuous Improvement Paths Based on Big Data

To address the aforementioned issues, this study integrates recent advancements in higher education research with technologies such as big data, the Internet of Things, and artificial intelligence. It explores a continuous improvement path leveraging big data, which encompasses three main aspects: developing big data platforms for engineering education accreditation, incorporating analysis of student learning behaviors, and constructing predictive feedback and improvement mechanisms.

4.1. Developing Big Data Platforms for Engineering Education Accreditation

To establish a continuous improvement mechanism based on big data, it is essential to develop big data platforms tailored to engineering education accreditation. These platforms are crucial for ensuring the efficient operation of accreditation processes, particularly the continuous improvement mechanism. Specifically, the following three points must be addressed:

First, identify the requirements for the big data platform. Universities should map out their engineering education accreditation processes, delineate core components, and clearly outline the functions of each component. This involves gathering input from teachers, course directors, and major directors to produce a comprehensive document detailing the platform's requirements. Additionally, due to the specific nature of engineering education accreditation, non-functional requirements must also be defined. For instance, in terms of security, the platform must protect sensitive information, such as final examination papers and personal data; in terms of reliability, it must ensure data recovery capabilities; and in terms of usability, it must be user-friendly and easy to learn.

Second, define the platform functions. The big data platform for engineering education accreditation should include modules for data collection and pre-processing, data storage and management, data analysis, and data visualization. The data collection and pre-processing module must handle data from various sources and formats, including learning behavior data, teaching materials, curriculum documents, talent training materials, accreditation documents, and relevant institutional records. The data storage and management module should enable rapid and reliable storage and management of diverse data types, with capabilities for long-term data retention and recovery, given the volume of historical data involved in continuous improvement. The data analysis module, as the core component of the platform, should be able to compute and analyze various evaluation metrics, including student performance summaries, curriculum objective achievement, graduation requirement attainment, continuous improvement assessments, and accreditation evaluations. The data visualization module should generate clear and visually appealing charts from the collected data and analysis results, providing users with accessible and actionable insights.

Third, establish user rights and roles. Engineering education accreditation involves multiple stakeholders, requiring distinct user permissions based on their responsibilities. For example, students should be able to view course results and receive study guidance; teachers should manage student data, access learning behavior analysis results, write teaching summaries, and provide feedback; course directors should manage course materials and report on curriculum objectives; and program leaders should oversee the talent training program and report on accreditation processes.

4.2. Incorporating Analysis of Student Learning Behaviours

Student learning behavior analysis is a prominent research area within educational data mining. To establish a continuous improvement mechanism based on big data, it is essential to integrate the analysis of students' learning behaviors into the "evaluation-feedback-improvement" process. This requires focusing on two key aspects: developing a learning behavior monitoring system and enhancing learning behavior analysis methods.

Constructing a learning behavior monitoring system is foundational for effective analysis. For instance, in the Python Programming course at The CQUPT, learning activities can be segmented into distinct sessions, and key behavior indicators that are critical for continuous improvement and quantifiable should be monitored in each session (Table 2). Specifically, the learning activities can be divided into the following sessions: review and preview, classroom learning, classroom tests, homework, and final exams. During the review and preview session, monitoring indicators might include the correctness of review and preview exercises and the time spent viewing online courses. In the classroom learning session, indicators could involve attendance rates, the number of interactions, and the correctness of classroom exercises. For classroom tests, monitoring could focus on the average score of

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the tests. In the homework session, indicators might include homework submission rates and average homework scores. Finally, for the final exam session, relevant indicators could be the average exam score and the passing rate.

Table 2: Example of indicators for monitoring students' learning behaviour

Learning sessions	Monitoring indicators
Review and preview	Correctness of review exercises
	Correctness of preview exercises
	Time spent viewing online courses
Classroom learning	Attendance rate
	Number of interactions
	Correctness of classroom exercises
Classroom test	Average score of the classroom tests
Homework	Homework submission rate
	Average homework score
Final exam	Average exam score
	Passing rate

Integrating learning behavior analysis into continuous improvement necessitates advancements in analysis methods for the "evaluation-feedback-improvement" process. First, establishing a direct connection between learning behaviors and various evaluation indicators for engineering education accreditation is crucial. For instance, some learning behavior indicators could be weighted and incorporated into calculations for curriculum objectives and graduation requirements achievement. Second, improving the interpretability of learning behavior analysis methods is essential. Techniques such as SHapley Additive exPlanations (SHAP) can be utilized to quantitatively analyze the impact of each learning behavior within machine learning frameworks, offering valuable insights for more detailed improvement suggestions.

4.3. Constructing Predictive Feedback and Improvement Mechanisms

Combining advanced technologies such as artificial intelligence to develop a predictive feedback and improvement mechanism is a crucial strategy for leveraging big data in continuous improvement processes. In the feedback phase, predictive models can be developed using machine learning techniques, based on course process data, assessment data, learning behavior data, and historical engineering education accreditation data. These models can provide early warnings for indicators such as student performance, achievement of curriculum objectives, and graduation requirements, enabling timely feedback for students, teachers, course directors, and major directors. In the improvement phase, predictive models based on big data can also be utilized to simulate the effects of various improvement measures. This allows for the advance assessment of potential impacts on learning styles, course teaching plans, and professional development programs.

Recent advancements in artificial intelligence necessitate the integration of the latest research when constructing predictive feedback and improvement mechanisms. For instance, multimodal feature fusion technology can enhance predictive models by utilizing diverse data sources and formats. Large language models, such as ChatGPT, can offer more comprehensive learning guidance to students while reducing the workload on teachers. Additionally, integrating metaverse technology can provide cost-effective solutions for creating professional technology application scenarios, thereby enhancing the practical skills of students.

5. Conclusion

The rapid development of big data and associated technologies presents novel opportunities for engineering education accreditation, particularly in enhancing continuous improvement mechanisms. Using the computer science and technology major at CQUPT as a case study, this paper details the current state of continuous improvement mechanisms, systematically analyzes the challenges associated with integrating continuous improvement with big data, and explores potential pathways for leveraging big data in continuous improvement. The goal is to establish a foundation and provide a reference for developing engineering education accreditation and continuous improvement mechanisms based on big data.

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