Research and Practice on Data-Intelligence-Driven Quality Evaluation of Talent Cultivation in IoT Engineering Major

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Abstract. With the advancement of artificial intelligence technologies, the application of digital intelligence technologies in educational evaluation has become increasingly prominent. In the study of talent development quality evaluation within the IoT Engineering discipline, it is imperative to consider the positive role of digital intelligence technologies. This research employs data analytics tools from big data technology to systematically analyze student developmental process data through methodologies including data mining, machine learning, and other analytical approaches. An intelligent evaluation information management system has been established to create a digitally-enabled assessment environment. The implementation has demonstrated promising outcomes, providing a replicable model for enhancing discipline-specific educational evaluation through digital intelligence empowerment.

Keywords: Digital technique, Educational evaluation**,** Quality evaluation

1 Introduction

Research on the holistic quality assessment of the entire educational process in the Internet of Things Engineering (IoT-E) discipline has garnered extensive attention both domestically and internationally[1,2]. LIN Xiaohong[3] analyzed challenges inherent to IoT-E programs, demonstrating the efficacy of student participation in academic competitions through curriculum reclassification and the establishment of a novel pedagogical framework. CHANG Jian[4] explored talent cultivation models under the paradigm of innovation and entrepreneurship education, using IoT-E as a case study. Faculty members emphasized the development of extracurricular programs, leveraging academic competitions as a platform to integrate innovation-oriented education with practical training. CAO Bingzhi[5] highlighted that with the rise of IoT technologies, universities have established IoT-E programs to cultivate professionals capable of adapting to extended industry chains. He proposed a series of pedagogical reforms and conducted in-depth investigations into accentuating disciplinary characteristics.

Focusing on the distinctive aspects of talent cultivation in IoT Engineering, this study examines the enabling role of data-intelligent technologies in whole-process

H. Kannan et al. (eds.), *Proceedings of the 5th International Conference on Internet, Education and Information Technology (IEIT 2025)*, Atlantis Highlights in Social Sciences, Education and Humanities 40,
https://doi.org/10.2991/978-94-6463-803-5_79

education. By leveraging artificial intelligence and big data technologies, this research redefines evaluation metrics for IoT talent development and establishes a data-intelligent evaluation information management system. The model integrates multi-source educational data, develops intelligent analytical algorithms, and implements dynamic feedback mechanisms. These innovations address limitations in traditional evaluation paradigms, such as inadequate process tracking and insufficient personalized guidance, ultimately achieving precise diagnosis and continuous improvement in educational quality. The system's design emphasizes adaptive evaluation mechanisms that dynamically optimize teaching strategies while aligning assessment outcomes with industry requirements, thereby accelerating graduates' workplace adaptability.

2 Construction of Evaluation System

This study focuses on integrating data-intelligence technologies into the quality evaluation system for IoT engineering talent cultivation, investigating the integration of big data analytics , artificial intelligence (AI), and IoT systems to establish a digital intelligence-enabled educational evaluation system， as shown in Figure 1.

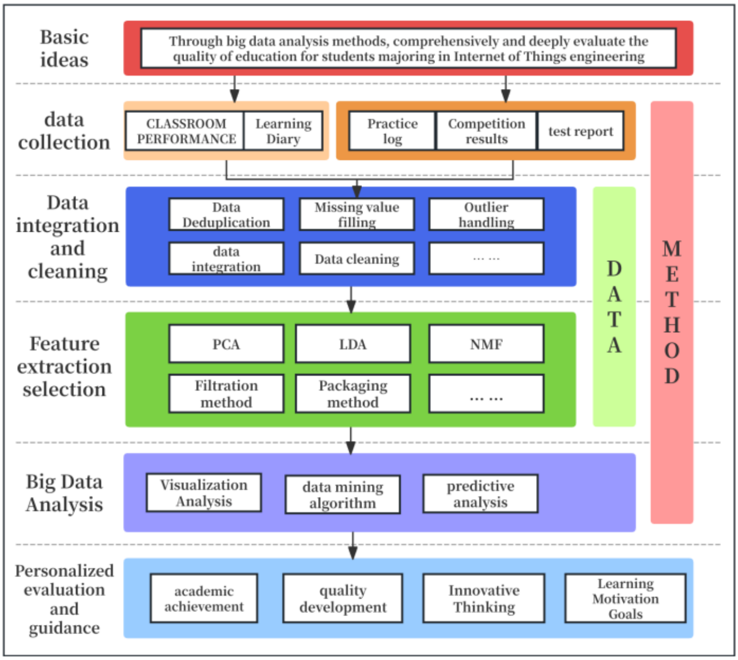

Fig. 1. Evaluation System Design Diagram

This system enables real-time monitoring of student learning progression, behavioral data analytics, and competency development trajectories.". Data preprocessing involves multi-source educational data integration (academic performance, project portfolios, and sensor-collected lab data) through normalization, outlier detection via

Z-score methods,and feature engineering to extract core indicators like interdisciplinary competency and innovation potential.

For analytical algorithms, ensemble learning models (e.g., Random Forests and XGBoost) are employed to classify learning outcomes by weighting heterogeneous data dimensions. Unsupervised techniques such as K-means clustering identify latent student cohorts for personalized intervention, while LSTM networks enable dynamic tracking of skill progression across semesters.

Dynamic optimization leverages reinforcement learning (Q-learning frameworks) to iteratively refine evaluation metrics based on real-time feedback loops, ensuring alignment with industry-evolving requirements. Additionally, graph neural networks map cross-disciplinary knowledge dependencies to assess integrative problem-solving abilities.

The system's robustness is enhanced by federated learning architectures, enabling collaborative model training across institutions while preserving data privacy. These technical strategies collectively address the limitations of static evaluation paradigms, achieving granular, adaptive quality diagnostics for IoT talent development.

3 Design of Quality Evaluation Reform Plan

To objectively assess the quality of talent cultivation, the primary requirement involves establishing a data-intelligence-driven evaluation information management system. This system systematically collects multidimensional data from the educational process, including instructional behaviors, interaction effectiveness, student practical skills, and innovative capabilities. Such data aggregation forms the foundational support for comprehensive process evaluation, enabling evidence-based analysis of pedagogical outcomes and continuous optimization of educational strategies. The key steps for implementing a digital intelligent assessment information management system are shown in Table 1.

Table 1. Key steps of digital intelligent assessment information management system.

Specific stages	Research cycle	research contents
Requirement Analysis and Evaluation Index System Construction	1-2 months	Leveraging the interdisciplinary nature of IoT engineering, this phase defines evaluation dimensions (e.g., theoretical knowledge, innovation capability, and practical skills) and establishes a multi-dimensional evaluation model integrating academic performance, project participation, and peer reviews.
System Architecture Design	2-3 months	A modular architecture is developed, incorporating data collection (via APIs and IoT devices), storage (using distributed databases like Hadoop), and analytics (employing Spark and TensorFlow). Role-based access control ensures data security.

Specific stages	Research cycle	research contents
Algorithm Development and System Coding	4-6 months	Core algorithms, including XGBoost for competency prediction and collaborative filtering for personalized feedback, are implemented. Agile methodologies guide iterative development.
System Testing and Optimization	1-2 months	Comprehensive testing (unit, integration, and stress testing) validates functionality and scalability. A/B testing refines user interfaces and algorithm accuracy
Deployment and Training	1 month	The system is deployed via cloud platforms (e.g., AWS) with gradual rollout to regional pilot institutions. Training workshops equip educators with dashboard navigation and data interpretation skills.

During the systematic construction of the educational information system, heterogeneous multi-source data—encompassing instructional interactions, learning engagement metrics, and curriculum performance indicators—are subjected to rigorous computational analysis through advanced data mining techniques and machine learning methodologies. Specifically, supervised and unsupervised learning algorithms, such as clustering analysis, association rule mining, and deep neural networks, are employed to extract latent patterns and derive actionable insights from large-scale educational datasets.

4 Evaluate the Effect of Reform

The evaluation system experiment process adopts 38 undergraduate students majoring in Internet of Things Engineering in 2023 as the control group and 70 undergraduate students majoring in Internet of Things Engineering in 2024 as the experimental group. The evaluation reform plan results are demonstrated from the following aspects.

4.1 Significance Testing

Validation of Engineering Accreditation Attainment Improvement

An independent samples t-test was conducted comparing the experimental group ($n \geq 30$) and the control group (baseline attainment rate: 75%). The experimental group demonstrated a significant improvement in attainment rate, reaching 92%. With a standard deviation ≤ 5% and sample size adequacy, the calculated effect size (Cohen's $d > 0.8$) indicated a large effect magnitude.

Analysis of Competition Award Rate Enhancement

A chi-square test revealed that the experimental group's award rate increased to 67.5% (135/200), compared to the control group's baseline rate of 50% (100/200). The χ^2 value exceeded the critical threshold of 10.83 ($\alpha = 0.001$), confirming statistical significance for the 35% improvement.

4.2 Multi-Indicator Synergy Analysis

A structural equation model (SEM) quantified the interrelationships among key metrics. Data analysis revealed:

A path coefficient > 0.45 between curriculum optimization (restructuring 7 core courses) and the 18% increase in outstanding graduation project rates.

A significant moderating effect ($p < 0.01$) linking experimental project development (12 virtual-physical projects) to employer-rated system development competency (92% excellent/good rating). These findings validated the "pedagogical reform → competency enhancement → employment performance" transmission mechanism.

4.3 Time-Series Validation

A three-year difference-in-differences (DID) model compared the experimental group (implementing the evaluation system) with a parallel control group. The experimental group exhibited an annual growth rate of 7.1% in engineering accreditation attainment, significantly surpassing the control group's 2.3% ($\Delta = 4.8\%$, $p < 0.05$ via F-test).

Through differential testing, multi-dimensional model validation, and time-series analysis, the intelligence-empowered evaluation system exhibits statistically significant and practically effective improvements in engineering accreditation attainment rates, disciplinary competition performance, graduation project quality, and employment competitiveness.

5 Conclusion

This paper focuses on reforming the quality evaluation system for IoT engineering talent cultivation through digital intelligence empowerment. This research makes significant theoretical contributions by addressing critical limitations inherent in traditional assessment paradigms, particularly their inadequate process tracking capabilities, static evaluation criteria, and insufficient support for personalized development pathways. The proposed framework demonstrates substantial practical value by enabling precise diagnostic evaluation through quantitative indicators and facilitating sustainable quality improvement in talent development processes. Furthermore, the study establishes a replicable quantitative assessment framework for IoT engineering education, characterized by its scalability, adaptability, and evidence-based decision-making capacity, which holds considerable potential for broader application across engineering education domains. The findings provide both theoretical foundations and practical methodologies for advancing quality assurance systems in the context of digital transformation within higher education.

Acknowledgments

1. Qingdao Huanghai College School level Teaching Reform Research Project. no: hhxyjg2402.

14th Five-Year Plan Research Project of the Education Evaluation Professional Committee, China Education Development Strategy Society. no: CEE202414.

References

1. KANG Bo, GUO Hui, SUN ZHihui and YOU Tingting.Innovative Exploration of Informatization Teaching Evaluation in the Era of Digital and Artificial Intelligence[J].Printing and Digital Media Technology Study, 2023, (04): 195-202+236. DOI:10.19370/j.cnki.cn10-1886/ts.2023.04.028.
2. LIU Xue.Research and Practice on Intelligent Technology-Empowered Classroom Teaching Evaluation in Higher Vocational Education[J].Journal of Higher Education, 2024, 10(35): 106-109.DOI:10.19980/j.CN23-1593/G4.2024.35.024.
3. LIN Xiaohong ,ZHONG Baichang .Generative Education Special Transformer Empowering Comprehensive Quality Evaluation: Concept,Model, and Prospect[J].Open Education Research,2024,30(06):72-78.DOI:10.13966/j.cnki.kfjyyj.2024.06.009.
4. CHANG Jian,ZHANG Dandan,GE Qian.The Construction and Application of the Evaluation Index System for Course Teaching Quality[J].The Guide of Science & Education,2024,(28):45-48.DOI:10.16400/j.cnki.kjdk.2024.28.014.
5. CAO Bingzhi, HAO Yanhui et al.Construction of the Evaluation Index System of Classroom Teaching Quality in Higher Vocational Colleges:Based on the Practice of Teaching Innovation Team Construction of Higher Vocational Teachers[J].Journal of Science and Education,2024,(21):150-154.DOI:10.16871/j.cnki.kjwh.2024.21.035.