

Design of a Personalized Teaching Path for the Intelligent Sports Engineering Micro-major Based on Big Data Analysis

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Abstract: With the accelerated digital transformation of the sports industry and the increasingly prominent demand for personalized higher education, the Intelligent Sports Engineering Micro-major, as an interdisciplinary educational model, urgently requires the establishment of a data-driven teaching paradigm. Supported by big data analysis as the core technology, this study aims to construct a personalized teaching path for the Intelligent Sports Engineering Micro-major. The research first explains the integration mechanism and theoretical foundation combining the Intelligent Sports Engineering Micro-major with big data technology, analyzing its interdisciplinary essence and theoretical bases such as constructivism and connectivism. It then systematically examines the key elements of personalized teaching based on big data analysis, including multi-dimensional learner profile construction, dynamic competency model establishment, and adaptive resource delivery mechanisms. Finally, addressing implementation challenges such as data quality, model accuracy, and systematic support, the study proposes dynamically optimized strategies based on feedback loops to form a sustainable evolutionary teaching path design. This provides theoretical reference and practical paradigms for talent cultivation in the field of intelligent sports engineering.

Keywords: Intelligent Sports Engineering; Big Data Analysis; Personalized Teaching Path; Learner Profile; Dynamic Competency Model

Introduction

The intelligent transformation of the sports industry has imposed higher requirements for the cultivation of professional talent. Traditional standardized teaching models struggle to meet the diverse needs of students in terms of knowledge structures, skill development, and innovative capabilities. As a cutting-edge, interdisciplinary field, the Intelligent Sports Engineering Micro-major urgently requires the construction of a new, data-driven, and learner-centered teaching system. Big data analysis technology provides the methodological foundation for achieving this goal. By collecting and analyzing learning data throughout the entire process and across multiple dimensions, it can accurately identify student characteristics, diagnose learning bottlenecks, and dynamically adapt teaching strategies, thereby enhancing teaching efficiency and quality. This study aims to systematically explore the design of a personalized teaching path based on big data analysis. Its significance lies in promoting the evolution of Intelligent Sports Engineering education from being experience-dominated to data-driven, and from uniform provision to precise empowerment, thereby providing essential theoretical support and practical pathways for teaching innovation in the field of intelligent sports within higher education.

1. Integration Mechanism and Theoretical Basis of the Intelligent Sports Engineering Micro-major and Big Data

1.1 Core Essence and Contemporary Characteristics of the Intelligent Sports Engineering Micro-major

The establishment of the Intelligent Sports Engineering Micro-major represents a direct response

from higher education to the strategic demands of the digital and intelligent transformation of the sports industry. Its core essence transcends the boundaries of traditional sports science, constructing an interdisciplinary knowledge system driven by data and supported by intelligent technologies. This system deeply integrates multiple disciplinary fields, including sports human science, biomechanics, computer science, electronic information engineering, and data science. It aims to systematically address complex engineering problems encountered in competitive sports, public fitness, and the sports industry. The teaching content focuses on cutting-edge areas such as intelligent sensing technology, sports data mining, human movement modeling, intelligent equipment design, and virtual simulation training, demonstrating distinct engineering and informatization characteristics.

The contemporary characteristics of this micro-major are primarily reflected in its high degree of cutting-edge nature and agility. Confronted with the accelerating pace of technological iteration in the sports field, the micro-major, with its compact curriculum modules and flexible organizational structure, can rapidly integrate emerging technological achievements and dynamically update the knowledge system. This effectively compensates for the shortcomings of traditional major programs, which often have long setup cycles and slow update speeds^[1]. This training model is designed to cultivate inter-disciplinary talent who possess data-driven thinking, master intelligent technologies, and can innovatively apply them in practical sports scenarios. Consequently, it precisely meets the urgent demand for specialized professionals across various segments of the industry chain, ranging from high-end sports equipment research and development to scientific training guidance.

1.2 Theoretical Basis for Big Data-Driven Transformation of Educational Models

The transformation of educational models led by big data technology is underpinned by profound theoretical foundations in pedagogy and cognitive science. From the perspective of constructivism, learning is viewed as a process in which learners actively construct meaning based on their existing experiences. Big data technology, through the comprehensive and multi-dimensional collection and analysis of learners' cognitive behaviors, skill practice trajectories, and interaction data, makes it possible to reconstruct a learner-centered teaching environment. It can build precise "cognitive scaffolding" for each learner, supporting their individualized knowledge construction path.

Connectivism provides another crucial theoretical support for the application of big data in education. This theory defines learning as a process of establishing connections within specialized networks. Big data analysis can reveal the complex, non-linear associative networks between knowledge elements, and between learners and learning resources. This optimizes the pathways and efficiency of knowledge flow, assisting learners in constructing more efficient and stable personal knowledge networks. Simultaneously, cognitive load theory emphasizes that instructional design must fully consider the limitations of human working memory. Big data analysis based on learning behaviors and physiological data can accurately assess students' cognitive load states during complex motor skill learning. This enables the dynamic adjustment of content granularity, presentation sequence, and instructional feedback strategies, effectively managing intrinsic and extraneous cognitive load to enhance learning efficiency. Together, these theories form a solid foundation for the transformation of the educational paradigm from "uniform instruction" to "precision empowerment".

1.3 Deep Integration Mechanism of Data Intelligence and Sports Engineering Teaching

The deep integration of data intelligence and sports engineering teaching essentially involves constructing a closed-loop intelligent system that covers the entire teaching lifecycle^[2]. The starting point of this integration mechanism lies in the comprehensive perception and seamless integration of multi-source heterogeneous data. This encompasses physiological and biochemical indicators captured by wearable devices, motion posture sequences based on computer vision, sports environmental parameters, and behavioral logs from online learning platforms, collectively forming a three-dimensional foundational data set for student digital profiles.

Building upon data aggregation, the core of the integration mechanism resides in utilizing data modeling and intelligent algorithms to achieve precise mapping and decision-making optimization of the teaching process. By applying machine learning and deep learning algorithms to analyze processed feature data, the system can construct dynamically updated student competency models. These models not only assess current motor skill levels and knowledge mastery but also diagnose learning styles, technical deficiencies, and even potential injury risks. These models drive the intelligent generation of subsequent teaching decisions, including the setting of adaptive learning objectives, the planning of

personalized training programs, and the precise delivery of targeted learning resources and instructional feedback.

Ultimately, this integration mechanism forms a self-evolving, continuously optimized "perception-decision-execution-evaluation" closed loop. New data generated during the teaching execution process continuously flows back to the data platform, where it is used to evaluate the effectiveness of previous decisions and retrain the algorithmic models. This dynamic adjustment mechanism, based on real-time feedback, enables the teaching system to continuously approximate the optimal development path for each learner. This achieves a fundamental transformation of the teaching system from static pre-setting to dynamic generation, and from experience-driven to data-driven, signifying the advancement of intelligent sports engineering teaching towards a higher-order adaptive and self-organizing form.

2. Analysis of Key Elements for Personalized Teaching Based on Big Data Analysis

2.1 Data Collection and Construction of Multi-Dimensional Learner Profiles

Multi-dimensional learner profiles serve as the logical starting point and core data foundation for achieving personalized teaching. The construction process relies on the systematic collection and integrated processing of multi-modal data streams. The scope of data collection must extend beyond traditional academic scores and attendance records to comprehensively encompass multi-source information from students' learning processes within the Intelligent Sports Engineering Micro-major. This includes high-precision motor skill data collected through inertial measurement units, surface electromyography sensors, and optical motion capture systems; physiological indicator data reflecting cardiopulmonary function and metabolic state; behavioral data recorded on online learning platforms, such as course video viewing duration, interactive quiz completion rates, and virtual simulation operation sequences; as well as cognitive style and learning preference data obtained through scales and interactive tasks. To ensure the spatiotemporal consistency of multi-source data, it is necessary to establish unified timestamp sequences and data synchronization mechanisms, which are crucial for subsequent analysis of the coordinated evolution of motor skills and cognitive processes^[3].

The heterogeneity of raw data determines the complexity of the construction process, requiring preprocessing steps such as data cleaning, noise reduction, and standardization. Building on this, key indicators are extracted through feature engineering; examples include movement technique economy, movement pattern stability, knowledge point mastery trajectories, and learning engagement levels. By comprehensively applying statistical analysis, clustering algorithms, and deep learning models, these discrete feature points are integrated into a structured, time-dimensioned dynamic digital profile. This process places particular emphasis on mining correlations between features to identify potential coupling relationships between different competency dimensions. The final constructed profile provides a panoramic depiction of the learner's comprehensive state across skill, cognitive, and behavioral dimensions. It continuously updates as the learning process advances, providing reliable data support for subsequent precise teaching decisions.

2.2 Establishment of Personalized Teaching Objectives and Dynamic Competency Models

The formulation of personalized teaching objectives stems from an in-depth interpretation of learner profiles, with its core principle being the decomposition of macro-level course goals and their mapping into micro-level developmental steps aligned with the individual's current competency state. In the field of Intelligent Sports Engineering, this necessitates creating a progressive set of objectives tailored for each student, ranging from the mastery of fundamental theories to the ability to solve complex engineering problems. The setting of these objectives is not static but is tightly coupled with a dynamically evolving competency model, forming an objective-competency co-evolution mechanism.

This dynamic competency model serves as a quantitative representation of a student's position along their professional development path. It typically consists of a multi-level, multi-indicator competency map, where the base layer comprises specific, observable behavioral indicators, and the upper layers integrate into higher-order comprehensive competency dimensions. By continuously incorporating new evidence from the learner profiles, the model utilizes Bayesian updating or online learning algorithms to adjust the probability estimates of proficiency levels across various competency dimensions in real-time. For instance, when the system detects a student's sustained improvement in operational accuracy within a "Sports Biomechanics Simulation" project, the capability valuation for that specific

skill node is correspondingly increased. This dynamism ensures that teaching objectives remain synchronized with the learner's most recent zone of proximal development. Furthermore, the model integrates psychometric methods such as Item Response Theory to more precisely quantify the trajectory of competency growth. This enables an adaptive objective management mechanism that evolves alongside the learner, effectively avoiding the frustration caused by excessively high goals and preventing learning stagnation resulting from objectives set too low^[4].

2.3 Adaptive Learning Content and Precise Resource Delivery Mechanism

The precise delivery of adaptive learning content and resources constitutes the final execution stage in realizing personalized teaching paths, with its effectiveness directly determining the practical value of prior data analysis and objective setting. The efficient operation of this mechanism relies on two core components: a deeply semantically annotated and structurally processed "learning resource repository," and a "recommendation algorithm engine" serving as the decision-making hub.

Various materials within the learning resource repository, such as theoretical literature, technical videos, simulation software modules, engineering cases, and training projects, all require standardized annotation using ontologies or knowledge graph technologies. This process clearly identifies their corresponding knowledge units, skill requirements, difficulty levels, and teaching contexts. The recommendation algorithm engine then performs intelligent matching and filtering within the resource repository based on the individual learning needs and goal gaps identified by the dynamic competency model. The matching strategy typically involves multi-objective optimization, requiring simultaneous consideration of content relevance, cognitive load appropriateness, learning style compatibility, and knowledge structure coherence. The algorithms employed may combine various techniques, including collaborative filtering, content-based recommendation, and knowledge graph-based sequential recommendation.

The system generates highly personalized learning task sequences and resource lists, delivering them to students through interactive interfaces. More critically, this mechanism embeds a closed-loop optimization circuit based on learning behavior feedback. Student interaction data with the delivered content—such as completion rates, time spent, repeated access patterns, and subsequent performance—is fed back in real-time to the recommendation engine. This data is used to evaluate the effectiveness of the delivery strategy and continuously optimize subsequent recommendation decisions. This self-improving mechanism ensures precise alignment and ongoing adaptation between the supply of teaching resources and students' dynamically changing needs.

3. Implementation Challenges and Optimization Strategies for Personalized Teaching Paths

3.1 Practical Challenges in Data Quality and Model Accuracy

In the transition of personalized teaching paths from theoretical conception to practical application, data quality and model accuracy present primary real-world challenges. Challenges at the data level stem from the complexity and uncertainty inherent in multi-modal data collection. During motor skill assessment, raw data from inertial sensors and optical capture systems are susceptible to environmental noise, equipment errors, and individual physiological variations, leading to a reduced signal-to-noise ratio in extracted movement features^[5]. Physiological data exhibit significant intra-individual and inter-individual variability, imposing stringent requirements for data standardization. Learning behavior data, characterized by its sequential and high-dimensional nature, presents substantial issues with sparsity and missing values. These factors collectively compromise the completeness and accuracy of the constructed learner profiles.

Challenges regarding model accuracy manifest at the algorithmic level. Assessing cognitive and skill states in the intelligent sports engineering domain represents a typical dynamic, non-linear modeling problem. Existing machine learning models, particularly those relying on supervised learning with large volumes of high-quality annotated data, demonstrate significantly diminished generalization capability and robustness when sample sizes are limited or annotation consistency is inadequate. Models may overfit the data characteristics of specific populations or scenarios, failing to accurately capture the subtle progressions of individuals engaged in complex skill acquisition. Furthermore, insufficient model interpretability constitutes an additional barrier. A "black-box" model whose decision-making logic cannot be traced, even if its predictive accuracy is acceptable, struggles to gain the full trust of teaching practitioners and learners, thereby limiting the depth and breadth of its

adoption.

3.2 Systematic Support Conditions for the Implementation of Personalized Teaching

Overcoming the aforementioned challenges and achieving the routine operation of personalized teaching paths requires the construction of a multi-level, integrated set of systematic support conditions. Technical support forms the cornerstone of the entire system, centered around an intelligent teaching platform that integrates a data mid-platform, an algorithm engine, and business applications. This platform must possess robust capabilities for real-time data ingestion and processing, provide a standardized algorithm model library tailored for educational scenarios and flexible application programming interfaces, while ensuring the scalability and security of the overall system architecture. The systematic development and knowledge-based encapsulation of high-quality digital learning resources constitute another critical support; without a well-structured, accurately content-rich, and properly annotated resource repository, personalized delivery becomes a fountain without a source.

Beyond technology, organizational management and professional talent support are equally indispensable. Implementing personalized teaching requires the teaching team to possess data literacy, enabling them to understand model outputs and make collaborative decisions with the intelligent system, rather than relying solely on traditional experience. This necessitates a shift in the teaching team's role from pure knowledge transmitters to designers of learning processes, collaborators in data analysis, and providers of personalized guidance. Correspondingly, the modular restructuring of the curriculum system, adaptive adjustments to teaching management processes, and continuous technical maintenance and pedagogical support collectively form an ecological environment that ensures the stable and efficient operation of this new teaching model.

3.3 Dynamic Optimization Strategy for Teaching Paths Based on Feedback Loops

The fundamental strategy for ensuring the long-term efficacy of personalized teaching paths lies in establishing a feedback loop optimization mechanism that runs throughout the entire process and is driven bidirectionally. This mechanism treats the implementation of the teaching path itself as a continuous, measurable, intervenable, and optimizable experimental process. Its operation relies on a multi-dimensional, fine-grained evaluation of the effects of teaching interventions. The evaluation data includes not only final learning outcomes such as grades and skill mastery rates but also, and more critically, focuses on process indicators. These include student acceptance of delivered content, time spent on task completion, frequency of seeking help at difficult nodes, and the growth trajectories across various dimensions of their dynamic competency model^[6].

These process and outcome data are systematically collected and fed back to the data mid-platform to drive optimization at two levels. At the micro individual level, the system uses online learning algorithms to adjust the estimation of the learner's competency state in real-time. Based on their latest feedback behaviors—such as preferences for certain resource types or repeated failures in specific tasks—the system instantly updates the recommendation strategy, enabling fine-tuning and calibration of the teaching path. At the macro system level, periodic aggregate analysis is conducted on the overall effectiveness of the recommendation algorithms, the coverage and quality of the resource repository, and even the structural validity of the competency model itself. Methods such as A/B testing are employed to compare the effects of different teaching strategies, leading to iterative upgrades of algorithm parameters, model features, and even pedagogical rules based on empirical evidence. This closed loop, which moves from "data to decision" and then "feedback on effectiveness back to data," enables the teaching system to evolve from a static program into an organic entity capable of self-improvement, thereby achieving the continuous enhancement and sustainable development of personalized teaching quality.

Conclusion

This study addresses the personalized teaching requirements of the Intelligent Sports Engineering Micro-major by systematically constructing a teaching path design framework based on big data analysis. The framework encompasses three core dimensions: the integration mechanism, key elements, and implementation strategies. Research demonstrates that constructing dynamic learner profiles through multi-modal data fusion, combined with adaptive recommendation and closed-loop feedback mechanisms, can effectively achieve precise and personalized configuration of teaching paths.

However, the comprehensive implementation of this path still faces multiple challenges, including data quality, algorithm reliability, and system integration. Future research should focus on the standardized processing of cross-modal data, the introduction of explainable artificial intelligence models, and the optimization of human-computer collaborative teaching decision-making mechanisms. These efforts will further advance personalized teaching systems towards greater intelligence, adaptability, and sustainability.

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