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Innovating Curriculum Systems for Railway Intelligence: Construction and Practice of the AITL Layered Model

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Abstract: With the rapid advancement of artificial intelligence (AI), traffic engineering is undergoing a critical transformation that requires restructuring both its knowledge framework and talent cultivation model. Traditional railway-related curricula struggle to address highly complex and real-time problems such as transportation organization, train control, and capacity prediction, resulting in fragmented competencies, outdated modules, and misalignment between instructional content and operational needs. As a data-intensive and safety-critical subsystem, modern railway operations increasingly rely on AI for train control, dispatch scheduling, operational optimization, and digital infrastructure management, calling for systematic curriculum reform. In response, this study examines global teaching practices and technological trends and proposes the AITL Layered Curriculum Model, a three-stage competency pathway encompassing technology internalization, scenario transfer, and intelligent creation. The model establishes an integrated instructional content chain, a task-driven mechanism, and an AI-enabled experimental platform embedded in representative railway scenarios. Multi-scenario virtual teaching experiments verify that the AITL model effectively mitigates fragmented curriculum organization, insufficient task embedding, and unclear competency progression, providing a systematic, transferable, and evaluable framework that aligns with the intelligence-oriented transformation of railway traffic engineering and offers broader applicability to transportation education.

Keywords: Artificial intelligence; AITL layered curriculum model; Railway systems; Traffic engineering; Curriculum reform

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1. Introduction

With the rapid integration of artificial intelligence (AI) into railway transportation systems, core operational processes, such as train scheduling, traffic control, signal management, and equipment maintenance are undergoing profound transformation. A technological system centered on intelligent construction, smart equipment, and intelligent operations is reshaping the fundamental logic of railway transportation. Consequently, the pedagogical paradigm of traffic engineering is shifting from traditional rule-based and experience-driven control models toward data-driven and intelligence-oriented operational modes. This paradigm shifts places higher demands on the cultivation of traffic engineering talent particularly in railway-oriented programs in the areas of data modeling, algorithm development, system integration, and real-time decision-making. As a result, existing curricula still dominated by theoretical instruction and static models urgently require structural reconstruction to address the emerging needs posed by AI-enhanced railway systems [1].

However, faced with the rapid iteration of AI technologies, curriculum updates in current university traffic engineering programs remain slow and insufficient. Course content is still centered on traditional theoretical instruction, and knowledge related to AI applications in railway scenarios has not yet formed a coherent and systematic chain. This leads to fragmented capability development: although students acquire basic knowledge in train operation organization, signal interlocking, and similar subjects, they lack the ability to integrate AI technologies into real-world railway operational problems for modeling and deployment [2]. Existing research indicates that establishing a “course–competency–task” mapping mechanism, supported by knowledge graphs, can significantly enhance the adaptability of traffic engineering curricula in the era of intelligentization [3].

At the policy level, General Secretary Xi Jin ping emphasized the need to accelerate the deep integration of AI with education in his congratulatory letter to the International Conference on Artificial Intelligence and Education [4]. National strategic documents such as China’s Education Modernization 2035 and the 14th Five-Year Plan for Railway Science and Technology Innovation explicitly call for the adoption of AI and other frontier technologies to systematically traffic engineering and to optimize talent cultivation systems in the railway sector [5,6].

In terms of pedagogical practice and theoretical exploration, a growing body of domestic and international research has proposed innovative pathways, focusing on task-driven mechanisms, multimodal interactive platforms, and the integration of deep learning models. For example, Yang et al. (2025) developed a three-layer nested task chain driven by large language models to construct a progressive competency structure [3]. Zhang et al. (2025), using a multimodal teaching platform, conducted comparative experiments demonstrating the positive impact of AI-assisted tools on higher-order cognitive abilities [2]. Agrahari et al. (2024), in their comprehensive review of AI-driven adaptive traffic signal control, highlighted AI-supported optimization mechanisms as a central component of intelligent traffic and railway systems [7]. Schleiss et al. (2024), from the perspective of systemic education reform, argued that AI curriculum integration must involve coordinated adjustments of organizational mechanisms, competency goals, and adoption strategies, and emphasized the need for transferable analytical frameworks to support continuous educational evolution [8].

Although these studies collectively point toward emerging paradigms characterized by task-driven learning, multimodal interaction, and deep-learning-based system integration, existing efforts are mostly confined to isolated instructional elements or tool applications. They fall short of offering a comprehensive reconstruction of railway traffic engineering curricula grounded in a progressive competency-generation logic, nor do they provide validated models for systematic curriculum redesign.

To address these shortcomings, this paper proposes the “AITL Layered Curriculum Model” tailored to railway traffic engineering, a three-stage competency development framework consisting of technology internalization, scenario transfer, and intelligent creation. The model systematically integrates curriculum structure, task chains, and platform-support mechanisms, offering a holistic pathway for restructuring traffic engineering curricula in the context of AI-driven railway innovation.

2. Core problem analysis and structural diagnosis

2.1. Lag in educational system responsiveness

With the accelerated penetration of emerging technologies such as intelligent connectivity, the transportation industry is placing increasingly stringent competency requirements on practitioners [9]. However, a systemic mismatch has emerged between the traditional instructional paradigm and the professional abilities now required in intelligent railway operations, specifically real-time perception, dynamic decision-making, and multi-objective coordinated optimization. This mismatch signals an urgent need for structural transformation in higher education.

Yet, current railway-oriented curricula in universities remain dominated by static methodologies and exhibit pronounced lag and misalignment.

At the technical level, instruction continues to rely on classical four-step models and associated tools (e.g., TransCAD in "Transportation Planning"), focusing primarily on long-term OD forecasting and route planning. These tools are inherently ill-suited for intelligent railway systems, which demand minute-level dispatching and real-time responsiveness.

At the pedagogical level, most courses still follow a linear "teacher-lecture → verification experiment" approach (e.g., TrainPlan-based timetable exercises). Learning tasks are largely limited to rule reproduction and computational exercises, offering little support for developing competencies in dynamic strategy generation under complex operational scenarios.

At the assessment level, grading remains centered on final examinations and static lab reports, lacking continuous observation of student performance in model development, parameter tuning, and real-time decision-making, the key abilities in AI-enhanced railway systems.

This lag in educational response results in a widening gap between industry demands and academic preparation, undermining the cultivation of high-quality railway transportation professionals.

2.2. Structural fragmentation in current curriculum systems

Against the backdrop of railway system intelligentization, deep structural fragmentation has emerged across content organization, competency development, instructional scenarios, and technical platforms. This fragmentation is not merely a surface-level misalignment; it reflects a systemic disharmony that constrains the development of competent, interdisciplinary transportation engineers.

(1) Fragmented knowledge architecture

Artificial intelligence, big data analytics, and related critical knowledge remain insufficiently integrated into core railway courses such as Railway Transportation Organization, Train Operation Control, and Railway Signaling Systems. These elements typically appear as isolated or "inserted" content modules, lacking vertical continuity and horizontal integration. Consequently, students fail to develop a coherent cognitive framework for understanding railway systems as complex, intelligent infrastructures.

(2) Misaligned competency development

Existing instructional tasks continue to prioritize static knowledge transfer and rule verification, rather than problem-driven and scenario-based learning. Although students master foundational theories and operational skills, they lack training in crucial areas such as model construction, algorithm adaptation, and system deployment, limiting their progression from "tool use" to "system-level problem solving".

(3) Inadequate instructional scenario designs

Most laboratory environments still rely on static timetable software incapable of simulating dynamic operational conditions such as passenger surges or equipment failures. This restricts students' exposure to real-world uncertainties and diminishes their ability to develop dynamic, adaptive strategies.

(4) Lack of integrated teaching platforms

Existing platforms are technologically siloed. Many university labs adopt closed tools (e.g., TrainPlan), making it difficult to integrate mainstream AI frameworks (TensorFlow, PyTorch) or railway simulation tools (RailSys, OpenTrack). This creates a disconnect between algorithm development and operational simulation, hindering the translation of academic learning into engineering practice.

Based on the diagnosis above, this study proposes the AITL Layered Curriculum Model, which integrates a three-stage competency generation pathway, technology internalization, scenario transfer, and intelligent creation, to restructure teaching content, task mechanisms, and platform support for railway traffic engineering education.

3. AI-Driven structured design of the traffic engineering curriculum system

In the context of the deep integration of artificial intelligence into railway transportation systems, the reform of traffic engineering curricula can no longer rely on fragmented or localized adjustments; instead, it requires comprehensive, systematic, and structurally coherent reconstruction. Based on the AITL (AI-Traffic Layered) three-stage curriculum model, this chapter proposes a structured design scheme for railway-oriented traffic engineering programs from three dimensions: curriculum system construction, instructional organization and platform support, and multi-dimensional evaluation combined with industry–academia collaboration. The overall design scheme is presented in **Table 1**.

Table 1. AI-driven curriculum design for railway engineering

Reform dimension	Three-stage AITL curriculum system	Teaching organization & platform support	Evaluation & industry collaboration
Core content	-Technology internalization layer: building mathematical foundations & AI literacy -Scenario transfer layer: algorithm adaptation & railway system integration -Intelligent creation layer: innovative modeling & multi-objective optimization	-Cross-disciplinary collaboration -Task-driven organization -Full-process guidance; integrated "AI + railway" lab platform -Learning-behavior analysis	-Stage-based evaluation -Comprehensive assessment -Industry expert feedback

3.1. Construction of the AITL three-stage curriculum system

3.1.1. Technology internalization layer: Building mathematical foundations & AI literacy

The technology-internalization stage serves as the starting point of the AITL curriculum system. Its central objective is to guide students in shifting from traditional traffic-engineering modes of thinking toward intelligent, algorithm-driven problem-solving paradigms. To achieve this, courses at this stage must strengthen foundational knowledge in mathematics, statistics, and physics, while also helping students develop a systematic understanding of core AI tools and methods. This foundation is essential for supporting subsequent modeling tasks and system-integration activities in complex railway scenarios.

3.1.2. Scenario transfer layer: Algorithm adaptation & railway system integration

The scenario-transfer stage represents the intermediate phase of the AITL curriculum system. Its core objective is to enable students, after having mastered foundational AI techniques, to transfer these methods into specific railway operation and dispatching scenarios and establish a closed-loop capability of "technology–scenario–feedback". This stage places strong emphasis on aligning algorithms with the operational logic of railway systems so that students not only know how to use models but are also able to adapt algorithmic structures and tune parameters according to real operating environments and constraints.

In terms of course arrangement, this stage can be integrated into the mid-to-late instructional segments of Traffic Control and Management, Railway Transportation Organization, and Traffic Simulation. Learning tasks are designed around representative railway operation scenarios, such as improving sectional capacity, optimizing strategies for delay recovery, and dynamically adjusting marshalling yard operation plans. Supported by simulation platforms such as RailSys or OpenTrack together with AI frameworks like TensorFlow and PyTorch, students complete the full workflow from data prediction and control-strategy training to system deployment and validation.

3.1.3. Intelligent creation layer: Innovative modeling & multi-objective optimization

The intelligent-creation stage constitutes the highest level of the AITL curriculum model. Its central aim is to cultivate students' abilities to independently tackle open-ended and complex railway-system problems that involve system innovation, integration, and multi-objective coordinated optimization. At this stage, instruction no longer prescribes fixed algorithmic frameworks or predetermined data-handling procedures; instead, students are required to begin from the global operational logic of railway systems and complete the entire process from problem abstraction to model development, solution implementation, and performance evaluation.

In practice, this stage can be incorporated into the advanced modules of courses such as Railway Transportation Organization, Traffic System Modeling, and Urban Rail Transit Operation Management, and may also serve as the core component of graduation projects or innovation-training programs. Typical project themes include multi-route coordination optimization in high-speed railway networks, coordinated signal control in urban rail transit systems, and developing digital-twin-based platforms for railway operation simulation and prediction. During this process, students are expected to apply advanced techniques such as deep learning, graph neural networks, and multi-agent reinforcement learning to conduct system-state modeling, dynamic prediction, intelligent control, and holistic optimization.

3.2. Teaching organization & platform support pathway

To ensure the effective implementation of the AITL three-stage curriculum system within railway-transportation programs, it is essential to integrate cross-disciplinary collaboration, task-driven learning, and unified experimental platforms into a coherent instructional architecture. A virtual-simulation teaching platform needs to be developed accordingly [10]. The overall framework is shown in **Figure 1**.

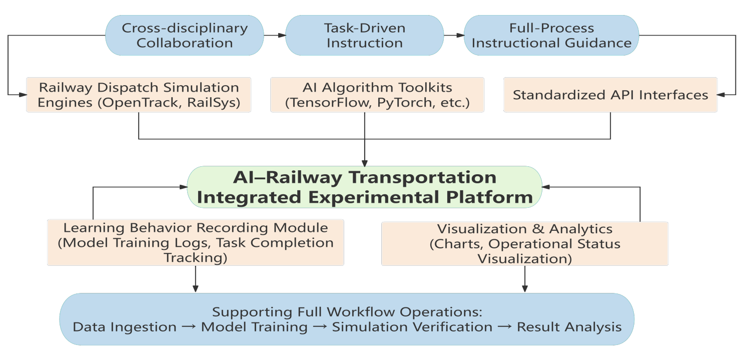

Figure 1. Teaching and platform framework.

In terms of instructional organization, the system adopts an approach characterized by "cross-disciplinary collaboration, task-driven design, and full-process guidance". Cross-disciplinary collaboration refers to the joint participation of faculty from railway transportation engineering, computer science, and control engineering in designing and delivering courses, ensuring both theoretical depth and technological relevance. Task-driven design takes complex problems drawn from real railway operations as the primary project carriers and embeds them throughout the semester in alignment with the three stages of the AITL curriculum model. Full-process guidance is achieved through a cyclical mechanism of task assignment, staged feedback, and final presentation, offering students targeted support and technical scaffolding at key learning milestones.

With respect to platform development, an integrated experimental environment combining AI technologies with railway-transportation scenarios is constructed. By integrating railway simulation software such as OpenTrack and RailSys with AI frameworks such as TensorFlow and PyTorch, and equipping the system with a visualization interface, the platform supports full-range laboratory operations. It provides standardized data interfaces for timetables, real-time operational data, and sectional capacity information, while also supporting custom algorithm embedding, thereby enabling seamless linkage between algorithmic models and railway operational scenarios.

Additionally, the platform incorporates a module for learning-behavior tracking and visualization. This module records students' complete operational traces during model development, parameter tuning, and task execution. It furnishes instructors with process-based evaluation data while simultaneously generating personalized learning-feedback reports for students, thereby forming a data-driven instructional cycle of "task release–process monitoring–iterative feedback".

3.3. Multi-dimensional evaluation & industry collaboration

In the implementation of the AITL curriculum system, evaluation serves not only as a means of measuring learning outcomes but also as a mechanism for driving continuous pedagogical improvement and fostering capability development. To achieve the systematic aims of curriculum reform, this study establishes a multi-dimensional evaluation pathway centered on “stage-based evaluation, comprehensive assessment, and industry–academia collaborative feedback”. The structure of this evaluation pathway is shown in **Figure 2**.

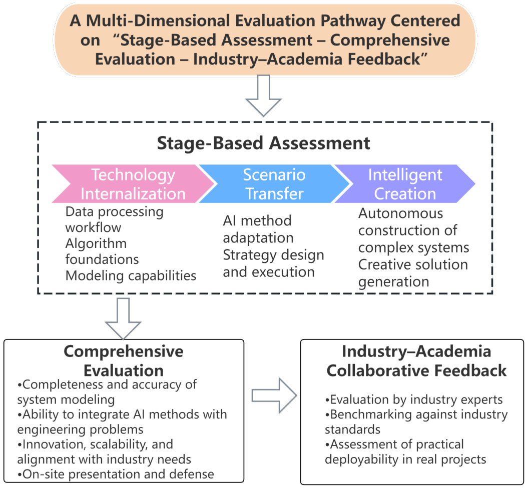

Figure 2. Multi-dimensional evaluation pathway.

Stage-based evaluation runs throughout all three stages of the AITL model, aligning closely with the competency goals of each phase. In the technology-internalization stage, evaluation focuses on students’ grasp of data-processing workflows, algorithmic principles, and problem modeling. In the scenario-transfer stage, assessment emphasizes students’ ability to adapt AI methods to actual railway operating conditions, with particular attention to the rationality of strategy design and operational performance. In the intelligent-creation stage, evaluation targets students’ capacity for autonomous system construction and innovative problem solving. Forms of assessment include process logs, model documentation, simulation analysis, and group presentations, emphasizing procedural, holistic, and traceable evaluation to encourage iterative refinement of methods and solutions.

Comprehensive project assessment is typically conducted at the end of the semester or upon completion of major milestone tasks and requires student teams to complete system-level projects encompassing solution design, algorithm implementation, and simulation-based validation. Evaluation considers performance in operational efficiency, energy consumption, and system stability, while also emphasizing scalability, deployability, and alignment with industry requirements. Project presentations and oral defenses foster communication and collaborative skills while providing precise feedback for instructional enhancement.

The AITL evaluation system incorporates an industry–academia collaboration Feedback mechanism, establishing sustained partnerships with railway enterprises and research institutes. Industry experts participate in scheme evaluations and task design at key instructional stages, offering professional guidance and industry-oriented feedback, while also supporting pilot testing and applied transformation of outstanding student projects. This mechanism strengthens the linkage between educational objectives and industry needs and promotes the integration of the “education chain, talent chain, and industrial chain”, thereby providing institutional support for the sustained optimization and practical impact of railway traffic engineering education.

4. Teaching reform practice strategies: implementation of the AITL model for railway traffic engineering

This chapter centers on the core theme of "reconstructing the railway traffic engineering curriculum system under AI empowerment" and provides a systematic exposition based on the three-stage capability development pathway of the AITL model. The main content includes an in-depth analysis of the operational characteristics and talent requirements of the railway industry under intelligent transformation, followed by a clarification of the direction for deeply integrating teaching reform with the intrinsic features of railway systems. Guided by the sequence of "technology internalization–scenario transfer–intelligent creation", the chapter systematically establishes an implementation plan for curriculum-content chains, task sequences, and instructional-support mechanisms, ultimately forming a promotable and assessable pedagogical reform paradigm.

4.1. Alignment of reform orientation with railway industry characteristics

To align with the operational logic of the railway industry and its competency requirements for future professionals, this section focuses on the restructuring of instructional organization. Under the framework of the AITL three-stage model, teaching shifts from traditional "linear instruction" centered on isolated knowledge modules to "task-chain–oriented instruction" driven by complex problems and anchored in capability development.

Specifically, the restructuring of instructional organization is reflected in three aspects: course content is adjusted around representative railway-system problems so that the same category of problem forms a coherent pathway of knowledge expression and capability training across multiple courses; task design evolves from isolated knowledge-point exercises to systematic engineering problem-solving, emphasizing consistency in task objectives, data interfaces, and evaluation criteria; and laboratory systems are integrated into a unified technological platform so that all teaching activities take place within a consolidated environment, effectively resolving platform fragmentation and improving instructional feedback efficiency and validation accuracy.

The following sections unfold how the teaching task chain is embedded within specific courses and how competencies are progressively achieved along the three stages of the AITL model, as illustrated in **Figure 3**.

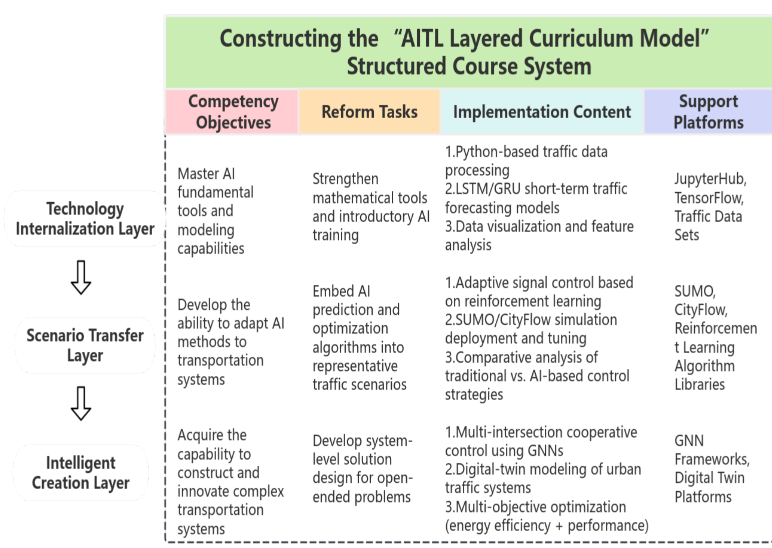

Figure 3. Structure of the AITL layered curriculum model.

4.2. Implementation pathway for staged teaching tasks

Driven by competency goals, teaching reform must overcome the limitations of traditional organizational models and promote systematic restructuring of task design and evaluation mechanisms. Based on this, and grounded in the three-stage AITL model, this section presents an instructional task-chain implementation scheme suitable for railway traffic engineering programs.

4.2.1. Technology internalization stage: Curriculum and task structure

The technology-internalization stage is generally scheduled for the first to third semesters. It is centered on core courses such as Traffic Engineering, Railway Transportation Organization, and Railway Signaling and Control, supplemented by laboratory components in Traffic Control and Management. The emphasis is placed on cultivating students' ability to express railway-system logic mathematically and on introducing them to the initial use of AI tools. Instruction focuses on training students to analyze railway problems through a data-oriented perspective. Representative tasks include performing timetable data cleaning and structural processing using Python and the Pandas library; applying LSTM models to predict peak-hour traffic density; and using Matplotlib or Plotly to visualize bottleneck sections in train operations.

Through these tasks, students are expected to comprehend the essential operational rules of railway systems and transform them into computational and analytically tractable problem models. The teaching platform records students' full workflows, including data processing steps, model-training logs, and visualization outputs, serving as the primary basis for process-oriented evaluation and ensuring mastery of foundational competencies in "structured representation of railway problems".

4.2.2. Scenario transfer stage: Curriculum and task structure

This stage is scheduled for the fourth to fifth semesters and is integrated with courses such as Traffic Simulation, Dispatching Command and Control, and Traffic Big Data Analytics. Its main objective is to cultivate students' ability to transfer and apply modeling skills to representative railway operating scenarios. Learning tasks emphasize "strategy adjustment under operational constraints". For example, students construct a high-density train-dispatching simulation environment in RailSys and apply reinforcement learning methods (such as DQN) to optimize departure intervals and route allocations. In designing reward functions, they must incorporate real-world constraints such as block signaling rules, station-platform resource utilization, and response delays in train-control systems.

Students compare AI-optimized solutions with fixed-timetable strategies on the platform and conduct quantitative evaluation using metrics such as punctuality rate, sectional saturation, and mean delay time. The platform provides automated performance comparison and disruption-recording functions to track students' development in strategy transfer and rule adaptation. This stage aims to help students understand the systemic significance of "railway rules as algorithmic constraints", enabling a cognitive shift from "being able to build models" to "being able to model within constraints".

4.2.3. Intelligent creation stage: Curriculum and task structure

This stage is concentrated in the sixth semester and the graduation design phase, involving advanced courses such as Traffic System Modeling, Urban Rail Transit Operations Management, and Intelligent Decision-Making for Integrated Transportation. Students are guided to construct railway-system optimization models with real deployment potential. Tasks are oriented toward "system-level complex problems" and are characterized by a high degree of openness and uncertainty. Typical project themes include developing a high-speed railway network state-prediction model based on graph neural networks; designing an integrated dispatching strategy that balances energy consumption, punctuality, and system resilience using multi-agent reinforcement learning; and building a simulation platform for coordinated operation between urban rail transit and intercity railway systems.

This stage emphasizes cultivating students' abilities in system integration and cross-module thinking. The platform requires students to submit comprehensive deliverables integrating "data flow–model logic–simulation feedback", and incorporates peer review and industry expert evaluation to enhance assessment objectivity and professionalism. Final outcomes should demonstrate both innovation and verifiability, marking the key transition from academic learning results to "quasi-engineering products".

5. Conclusion

This study takes AI-enabled educational reform in railway transportation engineering as its starting point and reconstructs the logic of competency formation through the development of the AITL (AI-Traffic Layered) curriculum model tailored to the needs of the railway industry. Centered on the progressive sequence of "technology internalization–scenario transfer–intelligent creation", the model restructures and optimizes the curriculum system for railway transportation programs, redesigns the task chain, and systematically constructs the framework for instructional content, project-driven mechanisms, and integrated experimental platforms, thereby achieving deep alignment between pedagogical concepts and engineering practice.

The research outcomes are reflected in three main aspects:

(1) It proposes a structured reconstruction scheme for the railway transportation curriculum system based on the logic of competency development, breaking through the limitations of isolated modules and outdated content in traditional curricula.

(2) It develops an experimental environment that integrates railway simulation platforms with AI algorithm frameworks, providing technological support for realism, interactivity, and process-oriented evaluation in teaching.

(3) It establishes a multi-stage task chain that spans from basic tool usage to system-level innovation, offering a transferable and assessable operational paradigm for future curriculum reform.

Future work may be further advanced in the following four directions.

(1) Promoting empirical teaching research by implementing small-scale trials in real classroom settings, integrating student behavioral data with process-based evaluation to develop a quantitative assessment system, and scientifically verifying the effectiveness and scalability of the AITL model;

(2) Strengthening the platform's data-integration capabilities by enabling data interoperability between the teaching platform and operational systems such as railway dispatching and equipment monitoring, thereby constructing an integrated cycle of "data–model–decision–feedback" to enhance the real-time and authentic nature of instructional training;

(3) Exploring vehicle–infrastructure coordination and multimodal transport scenarios under the framework of intelligent transportation systems, extending instructional scenarios from railway transportation alone to integrated transport systems, and cultivating students' abilities in system-level planning and coordinated optimization for future multimodal environments [11].

(4) Deepening interdisciplinary teaching mechanisms by refining collaborative-teaching models involving university faculty and industry experts, systematically exploring pathways for integrating AI technologies into railway-specialty courses, and promoting dynamic optimization and systematic upgrading of the curriculum.

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References

[1] Li P, Liu Y, Shao S, et al., 2025, Digital Transformation and Intelligent Development Pathways of Railways. Transport Research, 11(04): 2–10.

[2] Zhang S, Wu Y, Wang J, 2025, A Comparative Study of AI-Driven Multimodal Digital Teaching and Traditional Teaching Models. China Agricultural Education, 26(02): 30–36.

[3] Yang Y, Huang H, Chen X, et al., 2025, AI-Enabled Curriculum System Construction and Instructional Design Reform for Traffic Engineering. Journal of Traffic Engineering, 25(06): 106–112.

[4] Xi J, 2019, Congratulatory Letter to the International Conference on Artificial Intelligence and Education. Chinese Journal of Health Information Management, 16(03): 247.

[5] The Central Committee of the Communist Party of China, The State Council, 2019, China Education Modernization 2035, visited on June 15, 2025, https://www.gov.cn/zhengce/2019-02/23/content_5367987.htm.

[6] Wang H, Li J, Zhang L, et al., 2024, Strategies and Recommendations for Empowering High-Quality Development of Transportation Through AI-Driven New Productive Forces. Transport Research, 10(02): 11–19.

[7] Agrahari A, Gupta S, Fekri F, 2024, A Comprehensive Review of Adaptive Traffic Signal Control with Artificial Intelligence. IEEE Access, 12: 45678–45695.

[8] Schleiss J, Utschig-Utschig C, Wirth R, 2024, Integrating AI Education in Disciplinary Engineering Fields: Toward a System and Change Perspective. European Journal of Engineering Education, 49(3): 456–472.

[9] Rong Y, Wang X, Li F, et al., 2024, Reform and Exploration of Application-Oriented Talent Cultivation Models for Transportation Under the Background of Intelligent Connectivity. Education Informatization Forum, 12: 66–68.

[10] Chen L, Tong F, Wang J, et al., 2025, Exploring Reform Pathways for Virtual Simulation Experiment Teaching in Railway Engineering Programs. Journal of Traffic Engineering, 25(03): 94–98.

[11] Xing L, Wu W, Liu W, et al., 2023, Exploring Curriculum Reform Methods for Transportation Engineering Disciplines Oriented Toward Smart Transportation. Innovation and Entrepreneurship Theory Research and Practice, 6(18): 35–38, 84.

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