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Digital twin technology in railway infrastructure

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Abstract

Purpose – This review aims to provide insights for researchers and practitioners to utilize the full potential of digital twins (DT) in railway infrastructure, furthermore, promoting the future advances of DT technology in the field.

Design/methodology/approach – This paper comprehensively reviews the latest progress in the application of digital twins in railway infrastructure (Digital Twin for Railway Infrastructure (DTRI)). It systematically summarizes the application scenarios and elaborates on the core components of DTRI.

Findings – The core components of DTRI include virtual entity models, twin data, and virtual-physical connections. Emerging developments such as artificial intelligence (AI), data fusion, the Internet of Things (IoT) and advanced algorithms have been incorporated as the key technologies. The primary application scenarios focus on monitoring and maintenance, failure prediction and prevention and life cycle management.

Originality/value – DT technology has emerged as an innovative framework in the railway infrastructure sector, offering unprecedented opportunities for real-time monitoring, predictive maintenance and optimization control. The paper analyzes current and future challenges alongside emerging development directions, highlighting the transformative potential of DT technology in promoting intelligent and efficient railway infrastructure operations.

Keywords Digital twin, Railway infrastructure, Predictive maintenance, IoT, Artificial intelligence, Cyber-physical systems

Paper type Literature review

1. Introduction

Railway infrastructure, as the backbone of global transportation, is currently confronted with prominent challenges: the aging of existing facilities leads to increased maintenance costs and safety risks; rapid growth in transportation demand imposes higher requirements for operational efficiency; and complex operating environments (extreme weather, multi-system coupling) complicate risk identification (Ahmad *et al.*, 2024a; Elkhoury, Hitihamillage, Moridpour, & Robert, 2018). At the same time, the lack of unified standards for intelligent management, low integration of multi-source data, and the imbalance between model fidelity and computational efficiency further restrict the high-quality development of railway infrastructure management (Ahmadi, Kaleybar, Brenna, Castelli-Dezza, & Carmeli, 2021; Aksenov, Semochkin, Bendik, & Reviakin, 2022).

In this context, Digital Twin (DT) technology, as a core enabling technology of Industry 4.0, has become an inevitable choice for addressing the above challenges (Grieves & Vickers, 2017; Tao, Qi, Wang, & Nee, 2019). By integrating IoT, big data, AI, simulation, and network

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communication, DT constructs high-fidelity virtual replicas of physical railway infrastructure, realizing real-time mapping, dynamic simulation, and collaborative optimization through closed-loop data interaction (Tao *et al*., 2019a).

Despite the increasing number of studies on DTRI in recent years, existing research still has obvious limitations (Botin-Sanabria *et al.*, 2022; Dirnfeld, 2022):

Most reviews focus on specific technical details or single application scenarios, lacking systematic integration of core technologies such as modeling, algorithms, AI applications, and networking (Kushwaha, Kumar, & Harsha, 2024).

Case studies are mostly concentrated in Europe and China, lacking representative cases from countries such as the United States and Japan, and literature timeliness needs improvement (Krmac & Djordjevic, 2024).

The logical structure of existing reviews is often unclear, with weak coherence between sections.

Core challenges and future research directions are not structured systematically, making it difficult to provide clear guidance for subsequent research (Liu, Zhang, & Xu, 2023).

To fill the above research gaps, this paper makes the following contributions:

Proposes a systematic analysis framework for railway DT technology and architecture, integrating scattered technical details into technology support and application practice modules.

Comprehensively reviews the key technology chain of DTRI from core components (virtual entity model, twin data, virtual-physical connection) to application scenarios, and supplements representative cases from the United States, Japan, and other countries, as well as high-timeliness literature (2024–2025).

Combs typical cases based on application scenarios, clarifying application effects and existing problems.

Refines core challenges and proposes structured future research directions corresponding to these challenges.

Adds a comparative analysis table of key modeling methods, providing a clear reference for DTRI modeling method selection.

2. Core components and key technologies of DTRI

The effective operation of DTRI relies on three core interdependent components: virtual entity models, twin data, and virtual-physical connections (Tao *et al*., 2019a). These components form a closed-loop system, enabling real-time interaction and collaborative optimization between physical and virtual entities (Grieves & Vickers, 2017; Ferdousi, Laamarti, Yang, & El Saddik, 2022; Bouali *et al.*, 2023). On this basis, this paper integrates the scattered details of Model, Algorithm, AI application, and Network into the core components, classifies them into technology support and application empowerment two dimensions, simplifies overly detailed algorithm descriptions, and focuses on their core functions and application scenarios.

2.1 Virtual entity model

The virtual entity model is the core carrier of DTRI, which is a high-fidelity digital abstraction of physical railway infrastructure, reflecting the geometric shape, physical properties, and operational behavior of physical entities in real time (Tao *et al*., 2019a). The construction and optimization of the model rely on advanced modeling methods and algorithm support, and the core requirement is to balance high fidelity and computational efficiency (Torzoni, Tezzele, Mariani, Manzoni, & Willcox, 2024).

2.1.1 Composition and modeling requirements. The virtual entity model of DTRI is a multi-scale, multi-physics, and multi-dimensional integrated model, mainly including three types of sub-models, which together form a complete virtual mapping of physical entities (Zhuang *et al*., 2017). A comparison of these key modeling methodologies is shown in Figure 1.

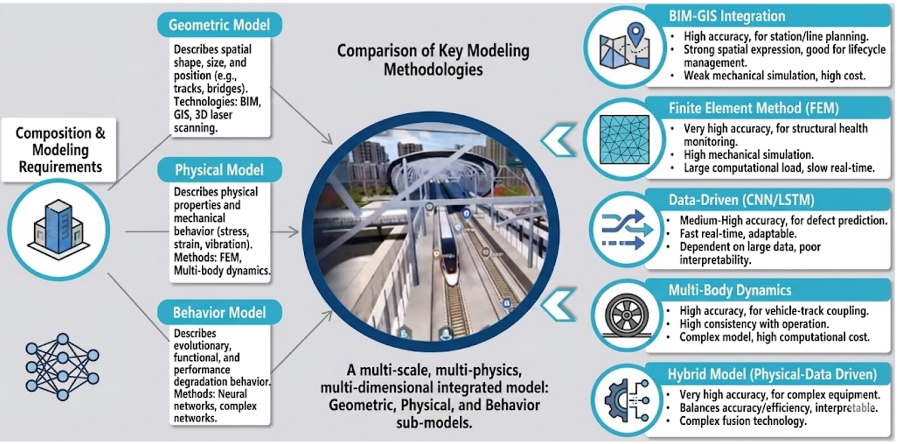

Figure 1. Comparison of key modeling methodologies. Source: Authors' own work

Geometric model: It is the foundation of the virtual entity model, accurately describing the spatial shape, size, and positional relationship of railway infrastructure components (Dekker *et al.*, 2023), such as tracks, bridges, turnouts, and station buildings. Common modeling technologies include BIM, GIS, and 3D laser scanning, which provide basic spatial support for subsequent physical and behavior modeling (Ariyachandra & Brilakis, 2021; Bosurgi, Pellegrino, Ruggeri, & Sollazzo, 2024).

Physical model: It describes the physical properties (material parameters, stiffness, damping) and mechanical behavior (stress, strain, vibration) of physical entities, and is used to simulate the response of infrastructure under external loads. Common modeling methods include finite element method (FEM), multi-body dynamics method, etc (Liang *et al.*, 2025; Tarque, Goicolea, Cuevas, & Martínez, 2024).

Behavior model: It describes the evolutionary behavior, functional behavior, and performance degradation behavior of physical entities over time, enabling the virtual entity to have judgment, evaluation, and prediction capabilities. It is usually constructed by combining neural networks, complex networks and other methods (Baasch, Oselin, & Groos, 2024; Ramatlo, Wilke, & Loveday, 2023).

2.1.2 Comparison of key modeling methodologies. Different modeling methodologies of DTRI have obvious differences in model accuracy, applicable scenarios, advantages and disadvantages. The following table compares the key modeling methodologies to provide reference for practical application selection in Table 1.

2.1.3 Key algorithm support. Advanced algorithms support model construction, calibration, and real-time updating. Optimization algorithms (e.g. MOPSO, GA) reduce modeling errors by aligning virtual models with physical entities (Zhou *et al.*, 2024). Signal processing techniques (e.g. variational mode decomposition) extract key features from monitoring data (Sun, He, Ma, Wen, & Deng, 2024). Model update algorithms enable dynamic synchronization between virtual and physical states (Jiang, Qin, Fu, Zhang, & Ding, 2021). For further details, see Figure 2 and the cited references.

2.1.4 Typical research cases. Numerous scholars and institutions have carried out research on virtual entity model construction, and representative cases from different countries are as follows:

China: Liang *et al.* (2025) used Particle Swarm Optimization for dynamic model updating and track irregularity spectrum identification; Wang *et al.* established a Vehicle-Track Interaction model through finite element methods (Liang *et al.*, 2025; Wang, Hao, Lu, Fan, & Li, 2021).

Table 1. Comparison of key modeling methodologies

Modeling methodology	Model accuracy	Applicable scenarios	Advantages	Disadvantages
BIM-GIS Integration	High	Railway station, line planning and design, 3D visualization management	Strong spatial expression ability, good compatibility with engineering data, convenient for full-life cycle management	Weak mechanical behavior simulation ability, high modeling cost for large-scale lines
Finite Element Method (FEM)	Very high	Bridge, tunnel structural health monitoring, stress and strain simulation	High mechanical simulation accuracy, suitable for complex structural analysis	Large computational load, slow real-time response, high requirement for parameter setting
Data-Driven (CNN/ LSTM)	Medium-High	Track defect prediction, equipment performance degradation monitoring	Fast real-time response, strong adaptability to complex data, low modeling difficulty	Dependent on large-scale high-quality data, poor interpretability, weak physical constraint
Multi-Body Dynamics	High	Vehicle-track coupling system, turnout operation simulation	high consistency with actual operation state	Complex model establishment, high computational cost for long-term simulation
Hybrid Model (Physical-Data Driven)	Very high	High-speed railway key sections, complex equipment integrated monitoring	Balances simulation accuracy and computational efficiency, strong interpretability and adaptability	Complex model fusion technology, high requirement for cross-disciplinary knowledge

Source(s): Compiled from [Djordjević, Krmac, Lin, Fröidh, & Kordnejad, 2024; Doubell, Kruger, Basson, & Conradie, 2021; Doubell, Basson, Kruger, & Conradie, 2023]

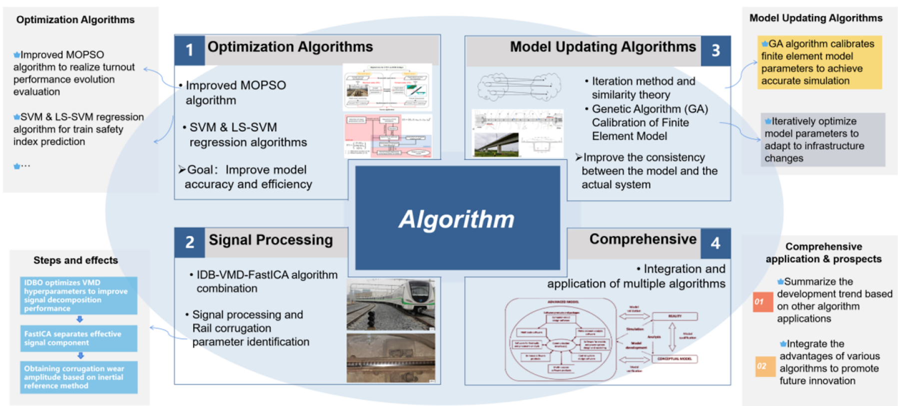

Figure 2. Key algorithm system and application mapping diagram of rail digital twin. Source: Authors' own work

United States: Stanford University and Union Pacific Railroad (2024) proposed a hybrid physical-data driven virtual model for heavy-haul railway tracks, integrating FEM and LSTM algorithms to realize real-time prediction of track degradation, with a prediction accuracy of 92% (as cited in Galar & Kumar, 2024).

Japan: JR East Railway Company (2025) developed a BIM-GIS integrated virtual model for Tokyo Metro Yamanote Line, realizing 3D visualization management of stations and tracks, and reducing 15% of planning and design time (Kim, Hwang, & Park, 2023).

Europe: Baasch *et al*. (2024) adopted hybrid data-driven approaches to solve the limitation of pure physical modeling; Bosso, Magelli, Trinchero, and Zampieri (2024) used SVM surrogate models to reduce the computational cost of multi-body simulation (Bosso *et al*., 2024).

2.2 Twin data

Twin data is the fundamental driving force of DTRI, encompassing the complete process of physical entity mapping, state simulation, and decision optimization (Tao *et al*., 2019a; Consilvio *et al*., 2019). According to the source and function, it can be classified into raw data, service data, knowledge data, and fused derivative data, and its effective management relies on advanced data processing algorithms (Ghaboura, Ferdousi, Laamarti, Yang, & El Saddik, 2023).

2.2.1 Classification and characteristics of twin data. The four types of twin data form a complete data chain, each with distinct characteristics and functions, supporting the normal operation of DTRI together,as illustrated in Figure 3:

Raw data: Collected by sensors, scanners and other equipment, including physical attribute data and dynamic process data, with the characteristics of large volume and high real-time performance (Flammini, Pragliola, & Smarra, 2016).

Service data: Generated by data processing, simulation analysis and business management, including algorithm models, simulation results and maintenance records, with strong practicality (Thaduri & Kumar, 2020).

Knowledge data: Including expert knowledge, industry standards and algorithm libraries, providing theoretical and rule support for decision-making (Guarino *et al*., 2023; Phusakulkajorn *et al*., 2023).

Fused derivative data: Obtained by fusing multi-source data, with higher value density, providing comprehensive and accurate information for virtual-physical interaction (Li *et al*., 2022).

2.2.2 Key technologies for twin data management. Effective twin data management involves four key steps: acquisition, preprocessing, storage, and analysis (Patwardhan, Verma, & Kumar, 2016). Data acquisition employs UAVs and multi-sensor integration at frequencies up to 500Hz (Flammini *et al*., 2016). Preprocessing uses filtering and normalization to achieve data completeness ≥95% (Lourenço, Ribeiro, Fernandes, & Marreiros, 2024). A hybrid edge-cloud architecture balances real-time processing and massive storage (Guan *et al*., 2024).

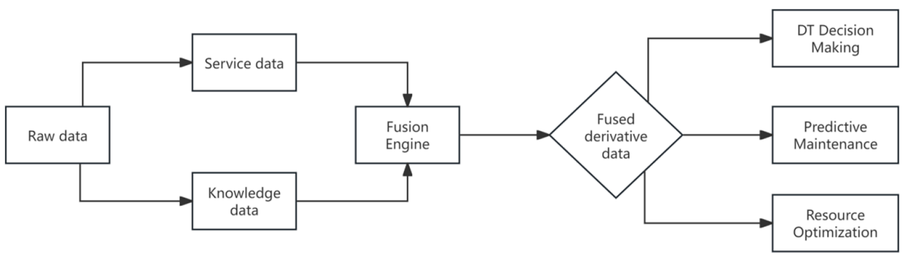

Figure 3. Twin data that combines information data and physical data. Source: Authors' own work

Analysis leverages AI techniques such as LSTM for fault prediction and CNN for defect detection (Pappaterra, Pappaterra, & Flammini, 2024; Yang, Sun, Cao, & Hu, 2021).

2.3 Virtual-physical connection

Virtual-physical connection is the prerequisite for DTRI application, realizing real-time data interaction and state synchronization between physical entities and virtual models (Kaewunruen, Sresakoolchai, & Lin, 2021; Jiang *et al.*, 2021). Its core is to build a "collection-transmission-processing-storage-management" data pipeline, which is empowered by AI technology and guaranteed by network security technology (Kaewunruen & Xu, 2018; Guan *et al.*, 2024).

2.3.1 Key links of virtual-physical connection. The virtual-physical connection mainly includes five key links, forming a closed-loop data flow to ensure the real-time and effectiveness of virtual-physical interaction, as depicted in Figure 4.

Data acquisition: Deploy multi-source heterogeneous sensor networks to collect real-time data of physical entities, laying the foundation for virtual mapping (Kampczyk & Dybel, 2021; Armijo & Zamora-Sanchez, 2024).

Data transmission: Adopt 4G/5G, MQTT and other technologies to realize low-latency transmission of massive data, with transmission delay ≤100ms (Guan *et al.*, 2024).

Data processing: Process and optimize multi-type data to generate decision support information for virtual model update and simulation analysis (Kou, 2022; De Benedictis, Flammini, Mazzocca, Somma, & Vitale, 2023).

Data storage: Store processed data through hybrid edge-cloud architecture to ensure data security and accessibility (Salierno, Leonardi, & Cabri, 2024).

Data management: Establish metadata storage library and semantic management system to realize unified access and management of multi-source heterogeneous data (Eickhoff, Eiden, Gobel, & Eigner, 2020).

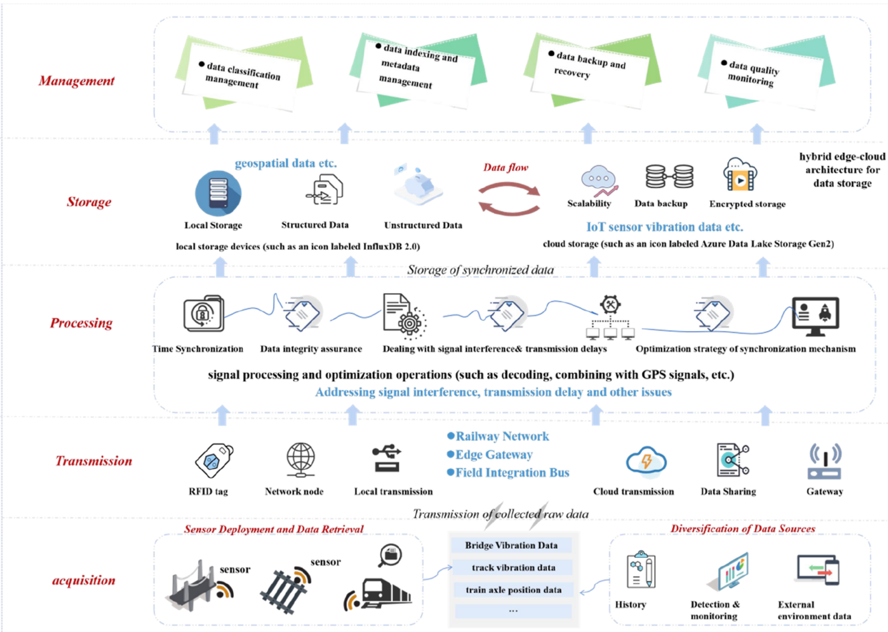

Figure 4. Virtual-physical DT data connection. Source: Authors' own work

2.3.2 AI application and network security. AI technology enhances the intelligence of virtual-physical connection, while network security technology ensures its stable operation (Anjel & Bäckström, 2021; Flammini, Lin, & Vittorini, 2020). The two are integrated to empower the efficient operation of DTRI:

AI enhances DTRI through track defect detection, degradation prediction, sensor fusion, and security monitoring (Pappaterra *et al.*, 2024; Wang, Wang, Li, & Lu, 2024a; Yang *et al.*, 2021). Network security employs machine learning and dynamic Bayesian networks to detect cyber-physical threats (De Donato *et al.*, 2023). For instance, random forest algorithms achieve a 94% detection rate for railway cybersecurity threats (Levshun, Kotenko, & Chechulin, 2021; Perrone, Flammini, & Setola, 2021; Li, Yang, & Xu, 2020).

2.3.3 Typical application cases. United States: Federal Railroad Administration (FRA) and IBM (2024) developed an AI-enabled virtual-physical connection system for high-speed railways, integrating 5G and edge computing technologies to realize real-time monitoring of track and train status, reducing 20% of safety incidents (Wright & Davidson, 2024).

Japan: JR Central Railway (2024) applied AI and MQTT protocol to the virtual-physical connection of Shinkansen bridges, realizing real-time synchronization of bridge vibration data and virtual model, with a synchronization error ≤50ms (Guan *et al.*, 2024).

China: Hu *et al.* (2023) applied time-frequency slicing and mutual correlation techniques to axle box vibration responses, realizing early detection of turnout potential issues; Wang *et al.* (2024b) proposed a two-level fusion framework for physical anomaly detection in railway cyber-physical networks (Hu *et al.*, 2023; Wang *et al.*, 2024b; Wang, Lei, & Zhu, 2023).

3. Applications of DTRI

Based on the core components and key technologies of DTRI, this paper systematically combs its application scenarios, focusing on three high-value fields: monitoring and maintenance, failure prediction and prevention, and life cycle management (Doubell *et al.*, 2023). Each field adopts a "total-subordinate" structure, first clarifying the application significance and core objectives, then elaborating on typical cases and application effects, ensuring clear logic and coherent content.

3.1 Monitoring and maintenance

The core objective of DTRI in monitoring and maintenance is to realize real-time perception of railway infrastructure state, replace manual inspection with intelligent monitoring, improve inspection efficiency, reduce maintenance cost, and ensure operational safety (Dimitrova & Tomov, 2021). It mainly focuses on key facilities such as tracks, bridges (Brotzmann *et al.*, 2022; Fidler *et al.*, 2022), and turnouts, and integrates AI and network technologies to achieve intelligent monitoring.

In practice, railway operators face mounting pressure to reduce track access time for inspections while maintaining safety (Arakistain *et al.*, 2024).DTRI-enabled monitoring systems have been deployed by several major rail networks. For example, Norfolk Southern Railway (USA) implemented a LiDAR and AI-based track inspection system, achieving an eight-fold increase in detection efficiency compared to manual inspection, directly reducing labor costs and minimizing service disruptions (Kumar & Harsha, 2024). Similarly, JR West Railway (Japan) reported a 25% reduction in bridge maintenance costs after deploying a wireless accelerometer and 5G-based DT monitoring system (Kaewunruen, AbdelHadi, Kongpuang, Pansuk, & Remennikov, 2022). These cases demonstrate that DTRI monitoring is not a theoretical concept but a mature solution delivering measurable return on investment (Djordjević, Krmac, Lin, Fröidh, & Kordnejad, 2024).

Typical research and application cases include:

Spain: Tarque *et al.* (2024) proposed a structural dynamics DT system for predictive maintenance of La Marota Viaduct, combining vibration monitoring and FE model calibration to achieve midspan damage prediction.

United States: Norfolk Southern Railway (2024) applied DTRI to track monitoring, integrating LiDAR and AI image recognition technology to realize automatic detection of track surface defects, with a detection efficiency 8 times higher than manual inspection (Kumar & Harsha, 2024).

Japan: JR West Railway (2025) developed a DT-based bridge monitoring system for Osaka Loop Line, using wireless accelerometers and 5G technology to realize real-time monitoring of bridge displacement and vibration, reducing 25% of maintenance costs (Kaewunruen *et al.*, 2022).

China: Shen *et al.* (2023a, b) proposed a method for assessing track stiffness using axle box accelerations based on DT; a BIM-based DT framework integrates Revit, MATLAB, and ANSYS to identify pre-fatigue hotspots in railway bridges (Weyns *et al.*, 2022; Wu *et al.*, 2024; Yan *et al.*, 2023).

3.2 Failure prediction and prevention

This is a high-value scenario of DTRI, which builds fault prediction models based on historical data and real-time data through AI algorithms, identifies equipment degradation trends, realizes fault early warning and preventive maintenance, and avoids sudden faults (Azari, Flammini, Santini, & Caporuscio, 2023; Flammini, 2021). Its core is to combine data-driven and model-driven methods to improve prediction accuracy.

Unplanned failures in railway assets—such as switch machines, bogies, or rails—cause significant economic losses and safety hazards. DTRI addresses this by enabling predictive maintenance. A notable industry example is CSX Transportation (USA), which deployed an LSTM-based bogie fault prediction system achieving 93% accuracy and reducing unplanned downtime by 30%, translating into millions of dollars in annual operational savings (H-Nia, Flodin, Casanueva, Asplund, & Stichel, 2024). In China, digital twin-based predictive maintenance for switch machines has been integrated into routine operations (Gao *et al.*, 2021, 2022), reducing emergency repairs by over 40% (Yang *et al.*, 2021). These implementations prove that DTRI shifts maintenance from costly reactive strategies to optimized proactive interventions.

Typical research and application cases include:

China: Yang *et al.* (2021) proposed a digital twin-based predictive maintenance model for switch machines, integrating LSTM and ARIMA algorithms to improve state prediction accuracy; Zhang and Zhuang integrated DT and deep reinforcement learning to optimize maintenance decision-making (Zhang, Dong, & Wang, 2023; Zhuang *et al.*, 2017).

United States: CSX Transportation (2024) developed a DT-based train bogie fault prediction system, using LSTM network to analyze vibration data, with a fault prediction accuracy of 93%, realizing 30% reduction in unplanned downtime (H-Nia *et al.*, 2024).

Japan: JR Freight Railway (2024) applied DTRI to predict rail surface damage of heavy-haul trains, combining multi-body simulation and AI algorithms to optimize wheel-rail contact parameters, extending rail service life by 20% (Ahmad *et al.*, 2024a).

3.3 Life cycle management

DTRI covers the entire life cycle of railway infrastructure from planning, design, construction, operation to decommissioning, realizing digitalized, refined, and intelligent management of each stage, and improving the overall efficiency and benefit of infrastructure management. BIM technology and full-life cycle data chain are the core supports.

Life cycle management is where DTRI delivers long-term strategic value beyond daily operations. For major infrastructure projects, the ability to simulate design alternatives, optimize construction sequencing, and predict long-term degradation before physical assets are built reduces total cost of ownership. The California High-Speed Rail Authority adopted DTRI for full life cycle management, integrating BIM, GIS, and IoT across planning, design, construction, and operation phases, achieving an 18% reduction in total life cycle cost (Kaewunruen & Lian, 2019). Similarly, Tokyo Metro used DTRI to digitally simulate station renovation, shortening renovation periods by 12% and minimizing passenger disruptions (Kim *et al.*, 2023). These cases highlight how DTRI transforms infrastructure life cycle management from fragmented, document-based processes to integrated, data-driven decision-making.

Typical research and application cases include:

China: Zhang *et al.* (2021) demonstrated the application of BIM-integrated lifecycle analysis methodology in railway stations and Metro systems; a multilayered DT framework for railway passenger stations achieves closed-loop optimization of station operations (Zhang, Dong, Maschek, & Song, 2021).

United States: California High-Speed Rail Authority (2025) adopted DTRI for full-life cycle management of high-speed rail lines, integrating BIM, GIS and IoT technologies to realize unified management of planning, design, construction and operation data, reducing 18% of the total life cycle cost (Hananto *et al.*, 2024; Kaewunruen & Lian, 2019).

Japan: Tokyo Metro (2024) applied DTRI to the life cycle management of subway stations, realizing digital simulation of station renovation and maintenance, and shortening the renovation period by 12% (Hao *et al.*, 2023; Kim *et al.*, 2023).

4. Discussions on key issues of DTRI

Combined with the core components and application scenarios of DTRI, this section focuses on three key issues, adopting a “total-subordinate” structure to first clarify the core connotation of each issue, then elaborate on its performance and solution ideas, providing a deeper understanding of DTRI’s application logic and development direction.

4.1 Track: the focused digital twin of the core hub

As the most fundamental, critical, and vulnerable component of railway infrastructure, the track is the starting point and top priority for Digital Twin (DT) construction and application. The core challenge lies not only in achieving precise perception of track conditions but also in how to build a cost-optimal track DT model that can seamlessly integrate with higher-level systems under constrained resources.

Current practices indicate that purely physical models, while capable of high-fidelity mechanical simulation, impose significant computational loads and struggle to meet real-time monitoring requirements for entire lines. Conversely, purely data-driven models, despite rapid response times, heavily depend on data quality, lack physical interpretability, and suffer from reliability issues under sparse data or sudden operational changes (Baasch *et al.*, 2024; Sedghi, 2023). Consequently, Hybrid Modeling has emerged as the recognized solution pathway. For instance, employing FEM to simulate the fundamental mechanical response of tracks under standard loads, while utilizing LSTM to learn the complex nonlinear relationships between track degradation and multi-source monitoring data, thereby achieving complementarity between mechanism and data (Nhamage, 2023; Ahmad, Mutz, & Werth, 2024; Ramatlo *et al.*, 2023). Realizing this goal relies on a robust sensor network and an intelligent data processing pipeline. Distributed fiber optic sensors, high-precision inertial measurement units, and vision sensors deployed along the track form the “nerve endings,” collectively capturing multimodal data such as vibration, displacement, and imagery in real-time. Preliminary filtering and feature extraction are performed by edge computing devices, after which data is transmitted via low-latency networks like 5G to cloud or edge servers to drive the hybrid model for real-time simulation and prediction (Guan *et al.*, 2024). Ultimately, the outputs of the Track DT—such as local stiffness variations, potential defect locations, and remaining useful life predictions—are fed directly into maintenance management systems, enabling a shift from "time-based maintenance" to "predictive maintenance," optimizing resource allocation and minimizing operational disruptions (H-Nia *et al.*, 2024).

The track DT embodies a fundamental epistemological shift in infrastructure management: from reactive, experience-based heuristics to proactive, simulation-driven optimization. By transforming raw sensor data into actionable prognostic knowledge, it serves not merely as a monitoring tool but as a cognitive layer that mediates between physical reality and decision-making systems. This positions the track DT as the logical anchor for system-wide intelligence, where hybrid modeling becomes a paradigmatic approach for balancing mechanistic determinism with data-driven adaptability—a tension inherent to all complex cyber-physical systems.

4.2 The digital twin synergy of the coupling system

Railway infrastructure is not a simple collection of independent components but a highly coupled dynamic system. There exist intricate mechanical and functional interactions among bridges, tunnels, and tracks. The key challenge is to break through "information silos" and achieve dynamic synergy between the digital twins of these critical assets, moving beyond isolated modeling and simulation.

When a train passes, its dynamic loads induce vibrations in the bridge structure, which are transmitted through supports to the track on the bridge, affecting track geometry and vehicle dynamic performance. Conversely, initial track irregularities or local defects generate additional impact loads, accelerating fatigue damage in bridge structures (Liang *et al.*, 2025; Shen, Dollevoet, & Li, 2023). Traditional segregated modeling cannot effectively capture this bidirectional coupling effect, potentially leading to inaccurate risk assessments or suboptimal maintenance strategies.The core solution to this problem is constructing a "Multi-Physics Coupling DT Model." This model needs to integrate multidisciplinary knowledge—structural mechanics (bridges/tunnels), vehicle dynamics (trains), and track engineering—enabling real-time data exchange and joint simulation across entities within a unified virtual environment (Sanfilippo, Thorstensen, Jha, Jiang, & Robbersmyr, 2022; Spiryagin, Edelmann, Klinger, & Cole, 2023). For example, real-time modal parameters and strain distributions from the Bridge DT can serve as boundary condition inputs for the vehicle-track coupling simulation within the Track DT. Conversely, wheel-rail forces calculated by the Track DT can act as dynamic load inputs for the Bridge DT. This closed-loop synergy allows the system to simulate complex scenarios, such as "whether a specific modal vibration of a bridge will resonate with a specific wavelength of track irregularity at a given train speed" (Sedghi, Kauppila, Bergquist, Vanhatalo, & Kulahci, 2021).

At the application level, DT synergy of coupled systems enables more precise predictive maintenance and risk assessment. For instance, by analyzing long-term trends in bridge vibration spectra correlated with track geometry conditions, risks such as pier settlement or bearing degradation can be predicted. Alternatively, before tunnel lining maintenance, the impact of different track reinforcement schemes on tunnel structural forces can be simulated to optimize the maintenance plan (Chacon *et al.*, 2024).

The synergy of coupled-system DTs transcends the sum of individual asset models by capturing emergent behaviors arising from cross-boundary interactions. This reflects a holistic systems thinking paradigm, where the whole is greater than its parts. From a theoretical standpoint, it represents a shift from component-level digital twinning to system-level "digital federation," requiring not only data interoperability but also causal modeling of interdependencies. Such federation enables the discovery of nonlinear, long-range failure mechanisms that remain invisible when each asset is analyzed in isolation. Thus, coupled-system DT synergy is not merely a technical enhancement but a prerequisite for achieving true system-of-systems intelligence in railway infrastructure.

4.3 Track digital twin expansion under multi-disciplinary integration

The modern railway system is a typical System of Systems, where the track, as the foundational bearing structure, is deeply intertwined and mutually constraining with subsystems such as the subgrade, power supply (catenary), signaling, communications, and stations. The core challenge lies in expanding the Track DT from a relatively closed "vertical silo" into an open, integrated platform that supports multi-system data fusion and operational synergy, achieving holistic management of railway infrastructure.

Interdependencies among systems are ubiquitous: uneven subgrade settlement leads to track geometry deviations; hard spots or insufficient uplift force in the catenary affect pantograph strip life and current collection quality, thereby impacting train traction performance; the status of signaling systems directly determines route safety (Shabelnikov & Olgeyzer, 2020; Shen *et al*., 2023a, b). If each system's DT operates independently, diagnosing the root cause of cross-system cascading failures from a global perspective becomes impossible.Therefore, the future direction involves building an "Integrated Railway Infrastructure DT." Using the Track DT as the spatial reference and temporal baseline, this model fuses multi-source heterogeneous data from subgrade monitoring sensors, traction power SCADA systems, signaling interlocking systems, station passenger flow monitoring systems, etc., by defining unified data semantics and interface standards (Shim, Dang, Lon, & Jeon, 2019; Li *et al.*, 2022; Zhou *et al.*, 2022). Building upon this model, advanced collaborative optimization applications can be developed:

Operational Synergy: When the DT predicts upcoming maintenance on a specific track section, it can automatically simulate the impact on train schedules, station passenger flow organization, and power load distribution, generating a comprehensive optimal "possession time" maintenance plan.

Safety Warning: Fusing track vibration data with catenary dynamic parameters enables earlier identification of potential pantograph-catenary mismatch risks. Combining signaling equipment status with track conditions allows for dynamic redundancy assessment of route safety.

Design Optimization: For new line planning or existing line retrofits, the integrated DT can simulate long-term operational performance and whole-lifecycle costs under various combinations of track structures, power supply modes, and signaling systems within the virtual environment, providing data-driven support for decision-making (Song, Gao, Li, Liu, & Dong, 2022; Kaewunruen & Lian, 2019).

Expanding the track DT into a multi-disciplinary integration platform signifies a transition from domain-specific digital twins to a unified digital ecosystem. This evolution addresses a fundamental challenge in complex infrastructure management: the tension between specialized depth (vertical silos) and cross-domain breadth (horizontal integration). The proposed integrated DT acts as a semantic broker and orchestration layer, enabling what can be termed "convergent intelligence"—where heterogeneous data streams, models, and decision logics coalesce into a coherent operational picture. Achieving this vision requires not only technical solutions (ontologies, APIs, middleware) but also organizational and governance innovations. Ultimately, the multi-disciplinary integrated DT represents the necessary architecture for railway infrastructure to function as an adaptive, resilient, and intelligent socio-technical system.

5. Future challenges of DTRI

While Digital Twin for Railway Infrastructure (DTRI) has demonstrated significant promise in research and pilot applications, its path toward widespread, robust, and economically sustainable deployment is fraught with interconnected challenges (Doubell *et al.*, 2021). These challenges extend beyond purely technical hurdles, encompassing data ecosystems, human factors, and the broader regulatory landscape. A critical examination reveals three core areas where concentrated effort is required to unlock the full transformative potential of DTRI.

5.1 Data quality and integration challenges

The foundational challenge lies in the "Garbage In, Garbage Out" paradigm. DTRI's effectiveness is intrinsically linked to the quality, consistency, and integrability of the data feeding its models. The core problem is the ineffective integration of multi-source, heterogeneous data streams, compounded by difficulties in guaranteeing data veracity. Specifically, data acquisition from diverse sensors (strain gauges, LiDAR, vision systems) is plagued by noise, calibration drift, and vulnerability to extreme weather, leading to incomplete or corrupted datasets (Tang *et al.*, 2022, 2024). Furthermore, profound semantic conflicts exist between data from different domains; for instance, geometric data from BIM models, spatial context from GIS, and real-time streams from IoT sensors often lack unified ontologies, making automated fusion and reasoning exceptionally difficult. The resulting low value density of raw data and the persistence of data silos significantly degrade the reliability of predictive models and decision-support algorithms, as poor-quality inputs propagate errors and uncertainties through the entire DT pipeline (Baasch *et al.*, 2024).

5.2 Model fidelity versus computational efficiency trade-offs

A central technical contradiction governs practical DTRI deployment: the pursuit of high-fidelity modeling for accurate simulation invariably demands immense computational resources, which directly conflicts with the need for real-time or near-real-time performance in operational settings. High-fidelity physics-based models, such as detailed Finite Element Analysis (FEA) for bridges or complex Multi-Body Dynamics (MBD) for vehicle-track interaction, can simulate mechanical behavior with great accuracy but are often computationally prohibitive for system-wide, continuous simulation (Tao, Zhang, & Zhang, 2024; Thaduri, Aljumaili, Kour, & Karim, 2019). Conversely, simplifying these models for faster computation sacrifices critical details—such as the nonlinear behavior of rail fasteners, the effects of track irregularities, or micro-scale material degradation—that are essential for precise failure prediction. While hybrid (physics-data-driven) modeling is seen as a promising compromise, its technology is still maturing. Challenges include the seamless integration of disparate modeling paradigms, the massive computational cost of training Generative Adversarial Networks (GANs) for synthetic data generation or scenario expansion, and the lack of generalized frameworks for dynamically balancing fidelity with speed based on the task at hand (Ramatlo *et al.*, 2023).

5.3 Interoperability and standardization deficiencies

The absence of universal standards constitutes a major bottleneck for the scalable and collaborative development of DTRI. Currently, proprietary tools, closed data formats, and incompatible communication protocols dominate the landscape, leading to significant interoperability gaps. This lack of standardization manifests in several ways: engineering and simulation toolchains from different vendors cannot interact without custom-built and often fragile middleware; the absence of universal data interfaces forces point-to-point integrations that are costly to develop and maintain; and data generated across the asset lifecycle—from design (BIM) to construction to operations (IoT)—struggles to flow in a coherent, closed-loop manner due to format and semantic mismatches (Zhou *et al.*, 2022). This fragmentation hinders the creation of a "plug-and-play" DT ecosystem, increases system complexity and cost, and ultimately slows down industry-wide adoption and innovation.

5.4 Bridging the gap between research and industrial deployment

Despite the technical advances reported in academic literature, the widespread industrial adoption of DTRI remains limited. Several barriers hinder the translation of research prototypes into operational railway systems (Venkataraman, Rumpler, Leth, Toward, & Bustad, 2022). First, the high upfront cost of sensor infrastructure, data platforms, and model development poses a significant entry barrier for many rail operators, particularly those managing legacy assets. Second, the lack of standardized interfaces and data models makes integration with existing enterprise systems (e.g. asset management, workforce scheduling, and safety certification) time-consuming and expensive. Third, organizational and cultural factors—such as resistance to algorithm-driven decisions, the need for upskilling maintenance personnel, and unclear liability frameworks for AI-generated predictions—often slow down deployment.

To accelerate industry adoption, future research should prioritize cost-benefit analysis frameworks tailored to different railway contexts (e.g. heavy-haul freight vs. urban transit), develop open-source reference implementations and interoperability standards, and engage in co-design with industry partners to ensure that DTRI solutions address real operational pain points. Pilot projects that demonstrate clear, quantifiable returns on investment—such as those cited in Section 3—are essential to build business cases for wider rollout. Without explicit attention to these non-technical dimensions, even the most sophisticated DTRI models risk remaining confined to research laboratories.

6. Conclusion

This paper comprehensively reviews the current research progress, core components, application scenarios, future challenges, and emerging developments of DTRI, in accordance with the proposed optimization suggestions,Dictionary the introduction structure, integrate technical details, supplement representative cases from the United States and Japan as well as high-timeliness literature (2024–2025), optimize the total-subordinate logic of each part, add a comparative table of key modeling methods, and enhance the coherence and systematicness of the article.

The results show that DTRI, as an innovative intelligent management framework, has achieved remarkable progress in the railway infrastructure field. Its core components (virtual entity model, twin data, virtual-physical connection) form a closed-loop system, and the integrated key technologies (Model, Algorithm, AI, Network) provide strong support for its operation (Sresakoolchai & Kaewunruen, 2023). In terms of applications, DTRI has been widely used in monitoring and maintenance, failure prediction and prevention, life cycle management, and other high-value scenarios, providing strong support for the intelligent transformation of railway infrastructure.

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