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Survey paper

Advancing intelligent transportation through digital twin: Challenges, models, and future prospects

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ABSTRACT

As a transformative technology in next-generation digital innovation, digital twin is instrumental in enhancing the efficiency and safety of traffic management while driving advancements in intelligent transportation systems. To this end, we systematically examine the primary challenges associated with the implementation of digital twin technology in transportation and introduce a novel 5 + 2 digital twin model tailored for this domain. Additionally, a comprehensive five-layer architecture is proposed to support the development of digital twin transportation. We further investigate the potential applications of digital twins in critical areas, including traffic flow management, intelligent transportation planning, resource allocation of Internet of Vehicles, traffic safety control, and assisted autonomous driving. Alongside these discussions, we provide an in-depth analysis of the current technological limitations and identify key areas requiring further research. Finally, we explore future development trajectories and the broader impact of digital twin transportation, offering new perspectives and insights to propel the evolution of intelligent transportation systems.

1. Introduction

With the rapid acceleration of global urbanization, urban population densities are increasing at an unprecedented rate. This trend has placed significant strain on urban transportation systems, presenting complex challenges for planners and policymakers. Moreover, the growing demand for personalized transportation solutions, coupled with the increasing intricacy of urban infrastructures, has exposed the limitations of traditional traffic management and planning methods. These constraints underscore the urgent need for modernization, intelligent upgrades, and a comprehensive approach to transportation system management.

In response to these challenges, digital twin (DT) technology has emerged as a promising solution [1–3]. As a transformative digital technology that integrates the physical and virtual worlds, DT enables the creation of digital replicas of physical entities and leverages multi-source data to continuously monitor and assess their real-world counterparts [4,5]. The fundamental strength of DT technology lies in its data-driven methodology and advanced modeling capabilities. By aggregating data from diverse sources, such as traffic monitoring cameras, sensors, GPS, and GIS, DT constructs detailed digital representations of key transportation components, including vehicles, roadways, human activity, and environmental factors. This data extends beyond traffic flow and vehicle parameters to encompass critical contextual elements such as weather conditions, road status, and passenger behavior. By synchronizing real-world conditions in real-time, DT facilitates precise analytical modeling, enables predictive insights, and enhances decision-making processes in urban transportation management.

The deep integration of DT technology with transportation systems not only enhances decision-making processes but also offers distinctive advantages in addressing critical urban traffic management challenges. *First*, DT-enabled traffic systems can quantitatively assess a city's overall traffic conditions, facilitating precise route planning and optimized resource allocation [6,7]. For instance, by continuously monitoring traffic flow and road conditions in real time, these systems can dynamically adjust traffic signal timing and optimize public transportation routes, thereby mitigating congestion.

Second, DT technology enables the visualization and real-time control of urban traffic dynamics within a high-fidelity virtual environment [8]. This capability allows traffic managers to observe and analyze operational patterns, simulate various scenarios, and implement proactive strategies, significantly improving traffic management efficiency. Moreover, DT-based simulation models provide an advanced

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predictive framework for analyzing traffic incidents and their potential disruptions [9,10]. For example, when assessing the impact of accidents or adverse weather conditions, the system can simulate multiple variables to support the development of emergency response strategies, minimizing disruptions to urban mobility.

Third, DT technology facilitates real-time reconstruction of real-world traffic scenarios, creating an immersive experimental environment that accelerates the testing and deployment of emerging transportation technologies, such as autonomous driving [11]. By simulating complex traffic interactions in a virtual space, autonomous driving systems can undergo extensive testing in a risk-free environment, thereby reducing development timelines and enhancing reliability. Collectively, these capabilities position DT technology as a transformative tool for improving the efficiency, safety, and sustainability of transportation networks. Its growing role in traffic planning, management, and infrastructure maintenance underscores its significance in shaping the future of intelligent transportation systems [12].

Recognizing the profound impact of DT technology on transportation, urban management, and related domains, universities and research institutions worldwide have increasingly focused on its applications. This paper aims to provide a comprehensive review of DT applications in transportation, offering insights into their potential to revolutionize current systems. The key contributions of this study include:

- We propose a structured 5 + 2 digital twin model to systematically examine the core components and key characteristics of DT technology in transportation management.
- We propose a novel five-layer architecture for digital twin transportation and analyze its application framework from three critical perspectives: data acquisition, modeling and simulation, and intelligent optimization.
- We assess the practical value and constraints of DT technology in various transportation scenes, including intelligent traffic management, infrastructure maintenance, and vehicular network resource scheduling. Additionally, we explore future research directions to provide a more holistic understanding of DT's potential impact on transportation systems.

2. Digital twin fundamentals

DT has become prevalent in numerous sectors, such as energy, smart manufacturing, and healthcare [13–17]. However, these application scenarios are relatively simple. In this section, we focus on revealing the core challenges faced by digital twin technology in the transportation field, propose a 5+2 digital twin model applicable to transportation systems, and conduct a systematic analysis and discussion of this model. Furthermore, we introduce the fundamental implementation steps for applying digital twin technology in transportation and ultimately design a five-layer architecture for digital twin transportation.

2.1. The challenges of digital twin transportation

Digital twin technology in transportation primarily integrates information from various sensors and data sources to accurately construct a virtual replica of the transportation system, enabling deep insights and intelligent management. Although DT has begun to be researched and applied in the transportation sector in recent years, the inherent characteristics of transportation scenarios – open, complex, dynamic, and random – make applying DTs in this field particularly challenging. The challenges of DTs in transportation can be categorized into four main areas, as shown in Fig. 1.

Challenges of Data Integration and Management: The primary challenge faced by DTs in the transportation domain is data integration and management. This challenge mainly arises from integrating a large amount of real-time data from multiple sources during the DT modeling and interaction process. These data sources may include road sensors, traffic cameras, onboard systems, and weather information, each with different formats and characteristics. To guarantee the precision and efficacy of DT models, it is necessary to confirm that the collected data is comprehensive but also accurate and reliable. Therefore, data processing and analysis require efficient data processing capabilities and robust computing resources.

Challenges of Scale and Complexity: The transportation system is a vast and complex network with numerous interacting elements such as vehicles, roads, traffic signals, and pedestrians. To accurately simulate and predict the entire system's behavior, it is necessary to build and maintain a detailed model that covers all these elements and their interactions. This not only requires a large amount of computing resources to process and analyze data but also requires in-depth expertise to ensure the accuracy and practicality of the model. Moreover, the transportation system is dynamically changing, requiring the model to adapt flexibly to new data and situations, further increasing the complexity and implementation difficulty of digital twin systems.

Challenges of Real-time and Reliability: Real-time reliability is another important challenge faced by DTs in transportation. To ensure that DT models accurately reflect real-world traffic conditions, the models need to be updated in real-time. This means that the system needs to process a large amount of real-time data quickly and ensure the accuracy and reliability of data transmission and processing. Any data delay or error may lead to inaccurate predictions by the model, thereby affecting decision-making effectiveness. Therefore, building an efficient and reliable real-time data processing and analysis system is crucial for achieving effective digital twins.

Challenges of Privacy and Security: Privacy and security are issues that must be taken seriously when applying DT technology in transportation. Since DT systems need to handle a large amount of data involving individuals and vehicles, such as location information and travel trajectories, protecting the privacy of this data is crucial. Any data leakage may lead to serious privacy violations. In addition, the system must be capable of withstanding external attacks to ensure its secure operation. Therefore, security measures such as data encryption, access control, and security monitoring must be considered in the design of DT systems.

2.2. Digital twin 5 + 2 model

After an in-depth analysis of the major challenges faced by the application of digital twin technology in the transportation field, we find that the core issues are interconnected and highly complex. To systematically address problems such as data integration, system scale, real-time performance, and safety-critical requirements, there is an urgent need for a comprehensive framework that can organically integrate various technologies and methods. Based on the inherent need for digital twin technology to evolve from closed static environments to open dynamic ecosystems, this paper proposes a 5+2 digital twin model tailored for the transportation field, as shown in Fig. 2

The fundamental concept of digital twins originally stems from the three-dimensional model proposed by Grieves, which consists of physical entities, virtual entities, and the connections between them. Subsequently, Professor Tao's team made significant expansions to this framework by adding twin data and services [18], proposing the landmark five-dimensional digital twin model, which laid the theoretical foundation for digital transformation and intelligent upgrading in the industrial sector. This model has achieved remarkable success in industrial or smart manufacturing environments, primarily due to the closed and controllable operating environment, highly repetitive processes, and standardized, fixed sensing devices, which ensure consistent data types and controllable quality, greatly reducing implementation difficulty. However, transportation systems, as typical

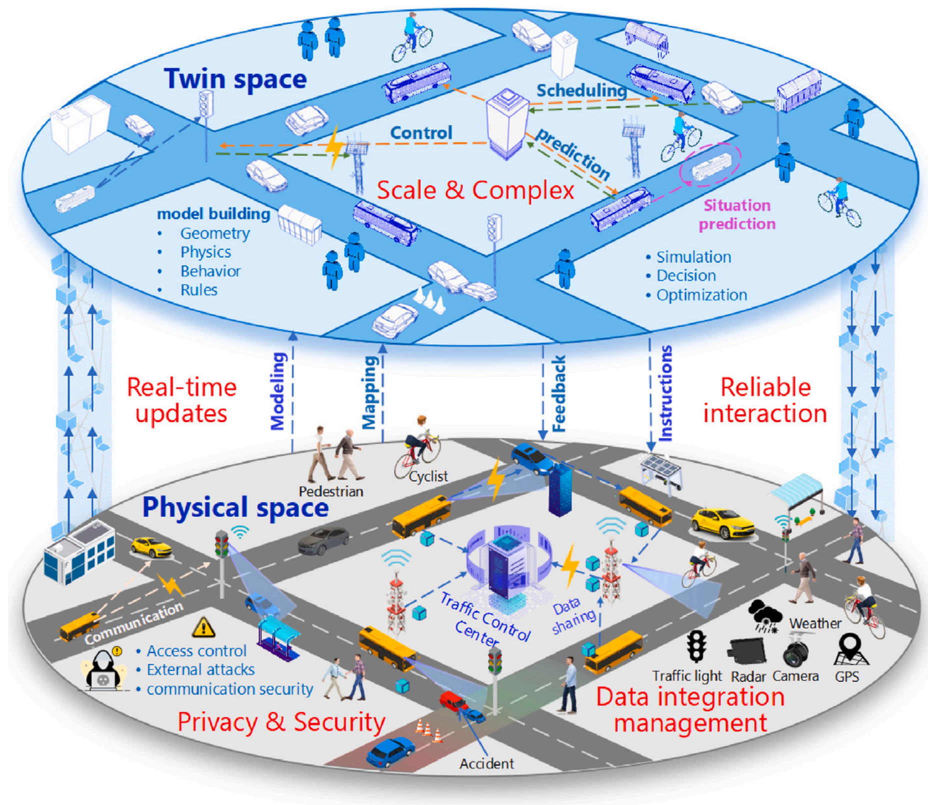

Fig. 1. Digital twin transportation system scenarios and challenges.

cyber–physical–social systems (CPSS), operate in highly open, uncontrollable, and strongly interactive environments, making them highly susceptible to interference from variable weather conditions, mixed traffic flow, human behavior, and other factors. Furthermore, modern transportation systems exhibit distinct "system of systems" (SoS) characteristics, whose successful operation relies on the deep collaboration and integration of multiple subsystems such as connected vehicles, intelligent traffic signal control, and emergency response systems. This evolutionary trend reveals two major limitations of the traditional five-dimensional model in addressing the specific characteristics of the transportation field:

First, as digital twins evolve from closed workshops to open road environments, the deep integration of physical safety and information security becomes essential. Transportation systems involve the dynamic interaction of massive numbers of vehicles, pedestrians, and signaling devices, while handling vast amounts of sensitive data (e.g., personal location and behavioral information), thereby imposing stringent requirements on data protection and privacy. The original five-dimensional model focused primarily on system-internal construction and operation, lacking systematic consideration of both internal and external security threats. Therefore, we introduce the security dimension to ensure the reliability, resilience, and trustworthiness of digital twins in complex open environments.

Second, achieving seamless integration and collaboration across systems and platforms has become an inevitable direction for large-scale digital twin applications. The original "connection" dimension mainly addressed one-way or two-way data transmission and command execution, but lacked unified semantic understanding and interoperability, often resulting in information silos. To overcome this limitation, we introduce the interoperability dimension, aiming to enable cross-platform, cross-standard, and lifecycle-wide integration of models, data, and services, thereby supporting truly collaborative and synergistic digital twin transportation systems.

In summary, the 5+2 digital twin model proposed in this paper is an inheritance and development of the five-dimensional model by Tao et al. designed to systematically address the new demands faced by transportation digital twins in open environments and system integration. Each dimension is specified as follows:

Physical Entity: In the transportation system, physical entities refer to actual transportation infrastructure and participants, such as roads, bridges, tunnels, traffic signals, vehicles (including public transit and private vehicles), and pedestrians. This also includes environmental factors, weather conditions, traffic accidents, or construction areas, directly impacting traffic quality and safety.

Virtual Entity: A virtual entity is a digital representation of a physical entity, such as a three-dimensional model of a traffic network, digital models of vehicles, or traffic flow simulations. These models are used for simulating and analyzing the behavior of the transportation system, for traffic planning, devising traffic management strategies, and reconstructing traffic accidents. In this paper, they are also referred to as twin models.

Services: It refers to various applications and functionalities based on the digital twin model, such as traffic management and optimization, real-time navigation, accident prevention, and congestion forecasting. These services can be oriented towards government sectors for urban traffic management or the public for real-time traffic information.

Twin Data: It supports the operation of virtual entities, including real-time traffic data, historical traffic flow data, traffic accident records, and environmental monitoring data. These data are collected through sensors, surveillance cameras, and vehicle systems and are used to update and maintain the accuracy of virtual entities.

Connections: It refers to the interactions and data flow between physical and virtual entities and between them and services. In the transportation system, this may include real-time data transmission mechanisms, information sharing platforms, and decision support systems, ensuring an efficient flow of information between physical and virtual entities.

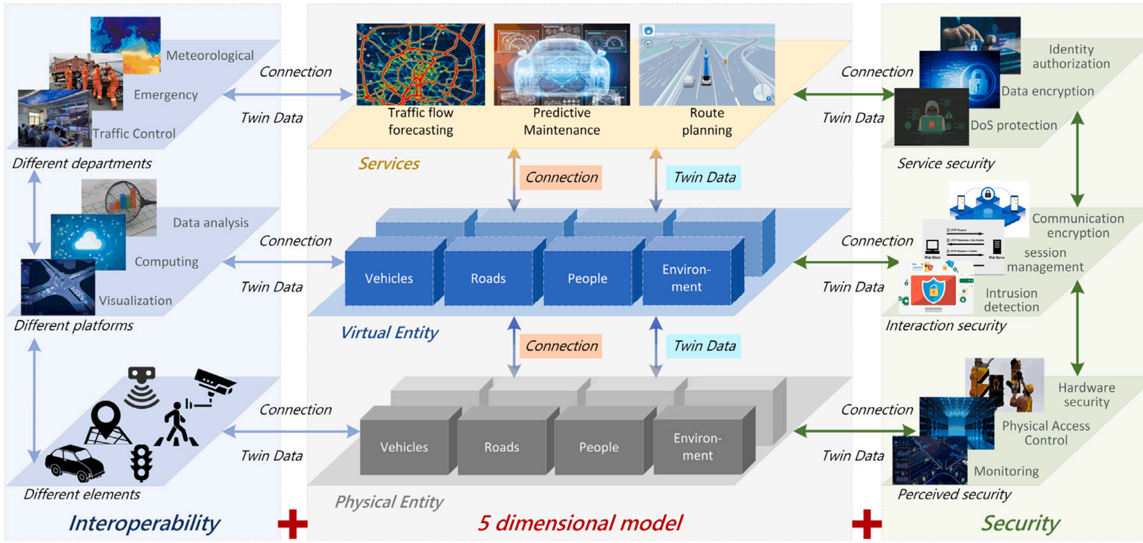

Fig. 2. Conceptual graph of digital twins 5+2 model in transportation systems.

Security: It ensures the safety of all data and information during interaction processes, protects privacy, and guards against malicious attacks. Using encryption and secure protocols, data interception and tampering are prevented, sensitive information is limited to authorized access, and transportation system functionality and user security are maintained.

Interoperability: It emphasizes seamless data exchange and functional collaboration among diverse transportation system components. In DT traffic systems, achieving high compatibility and coordination across devices, systems, and platforms, along with standardizing data formats, is fundamental for comprehensive traffic management and optimization.

By incorporating the dimensions of security and interoperability, the digital twin model provides comprehensive, dynamic, real-time mapping capabilities, enhances system security, and improves the efficiency of collaboration between different systems and devices.

2.3. Analysis and discussion of the 5 + 2 model

This section aims to conduct an in-depth analysis and discussion of the 5+2 digital twin model. We first examine the generality of the model, then evaluate its complexity and scalability, and finally explore its mapping relationship with international Intelligent Transportation Systems (ITS) standards, thereby comprehensively demonstrating the theoretical and practical value of the model.

2.3.1. Generality of the 5+2 model

The proposed 5+2 model not only addresses the challenges of complexity and openness in transportation systems but also exhibits cross-domain applicability. The seven dimensions emphasized by the model correspond to the common requirements faced by all complex cyber–physical–social systems (CPSS) during their evolution from “local–closed–single-scenario” architectures to “global–open–cross-system” paradigms. Among them, the five dimensions of physical entity, virtual entity, twin data, services, and connections ensure the fundamental construction logic of digital twins, while the two additional dimensions – security and interoperability – directly respond to the pervasive issues of privacy protection, cyberattack defense, and cross-platform collaboration in open environments. Therefore, the model not only provides architectural support for digital twin development in transportation but is also applicable to other critical domains such as energy, healthcare, and urban governance, which are characterized by complex interactions and cross-domain collaboration. For example, in smart energy systems, distributed generation units, microgrids, and regional dispatching platforms require real-time collaboration across hierarchical levels and vendors; the security dimension ensures that dispatching data cannot be tampered with, while the interoperability dimension guarantees that heterogeneous devices can consistently interpret and execute data and control information. In the field of smart healthcare, patient imaging and medical records need to be shared across hospitals and diagnostic systems; security ensures the privacy protection of sensitive information, while interoperability enables standardized exchange and semantic consistency across platforms. In smart cities, the integration of transportation, energy, water, and emergency response systems represents a typical “system-of-systems” scenario, where the 5+2 model can serve as a unified reference framework for cross-departmental and cross-industry city-scale digital twins. Consequently, the model not only demonstrates domain-specific value for transportation but also reveals cross-sectoral potential, positioning itself as an important theoretical foundation for future research and practice of digital twins in open and complex systems.

2.3.2. Complexity and scalability analysis

To comprehensively evaluate the practical deployment performance of the 5+2 digital twin model, this section conducts analysis from three perspectives: systemic metrics, network complexity, and functional dimensions, systematically comparing the differences and advantages between the 5D model and the 5+2 model. The results are shown in Table 1.

Communication Bandwidth: The total bandwidth required for message exchange depends on the number of nodes V, the message transmission frequency λ (Hz), and the message size S_0 (bytes) in the 5D model. Adding security and interoperability headers increases the message size by ΔS. The bandwidth can be calculated as:

$$B_{5D} = V \cdot \lambda \cdot S_0, \tag{1}$$

$$B_{5+2} = V \cdot \lambda \cdot (S_0 + \Delta S). \tag{2}$$

Node Processing Overhead: Each node processes incoming messages with a baseline computational cost p_0 (seconds per message). Security verification and interoperability mapping introduce additional computation. The per-node processing cost is:

$$C_{\text{node}} = \lambda \cdot (p_0 + p_{\text{sec}} + p_{\text{interop}}), \tag{3}$$

where p_{sec} represents the extra time for encryption and signature verification, and p_{interop} represents the additional time for semantic translation and cross-platform handling.

Table 1
Comparison of 5D and 5+2 digital twin models.

Metric	5D Model	5+2 Model
Message Size per Packet	S_0	$S_0 + \Delta S$
Node Processing Overhead	p_0	$p_0 + p_{\text{sec}} + p_{\text{interop}}$
End-to-End Latency	$\frac{S_0}{R} + p_0 + L_{\text{prop}}$	$\frac{S_0+\Delta S}{R}$ $+(p_0 + p_{\text{sec}} + p_{\text{interop}})$ $+L_{\text{prop}}$
Network Complexity	$O(V^2)$ or $O(V \cdot k)$	Same as 5D
Security	Weak, vulnerable to attacks	Strong, supports PKI and privacy protection
Interoperability	Weak, fragmented data formats	Strong, aligns with ITS standards
Scalability	Poor, prone to isolation	Good, cross-domain support
Long-term Feasibility	Low	High

Table 2
Mapping of 5+2 model dimensions to ITS standards.

5+2 Dimension	ITS/CPSS Standard	Mapping Description
Physical Entity	SAE J2735 BSM	Vehicle state (position, speed) mapped to standard fields
Virtual Entity	Cloud/Edge ID	Unique ID for virtual objects
Twin Data	DATEX II/ISO 14825	Standardized storage and exchange of traffic flow, events, and data
Services	ETSI ITS Service API/OMA LwM2M	Service requests and responses mapped to standardized interfaces
Connections	DSRC/ITS-G5/5G V2X	V2I and V2V communication
Security	PKI/IEEE 1609.2/TLS	Message encryption, authentication, and signature verification
Interoperability	SAE J2735/DATEX II/ETSI ITS-G5	Format and semantic alignment for cross-platform data exchange

End-to-End Latency: The cumulative effect of larger messages and extra processing affects the end-to-end delay L_{E2E} per message:

$$L_{\text{E2E}} = \frac{S_{\text{msg}}}{R} + C_{\text{node}} + L_{\text{prop}}, \tag{4}$$

where S_{msg} is the message size (S_0 for 5D, $S_0 + \Delta S$ for 5+2 model), R is the network link rate in bytes per second, C_{node} is the per-node processing time, and L_{prop} is the propagation delay in the network.

Network Complexity: Network complexity reflects the scalability of message exchanges as the number of nodes increases. In a fully connected network, the message exchange complexity is $O(V^2)$; in practice, each node typically communicates with k neighbors, resulting in a reduced complexity of $O(V \cdot k)$. Although the 5+2 model increases the message size per exchange, it does not alter the topological complexity compared to the 5D model.

From a functional perspective, the 5+2 model demonstrates clear advantages over the 5D model in terms of security, interoperability, scalability, and long-term feasibility. Specifically, it enhances security by integrating cryptographic mechanisms, PKI-based authentication, and privacy-preserving techniques, thereby mitigating threats such as message forgery and replay attacks. In terms of interoperability, the 5+2 model aligns with ITS standards and introduces interoperability headers, which enable seamless data exchange across heterogeneous platforms and infrastructures, overcoming the fragmented formats of the 5D model. Regarding scalability, the 5+2 model supports standardized interfaces and semantic translation, allowing for consistent performance in large-scale, cross-domain deployments where the 5D model tends to form isolated subsystems. Finally, in terms of long-term feasibility, the 5+2 model provides stronger adaptability and sustainability, as it can evolve with new technologies and standards at lower cost, while the 5D model requires frequent upgrades. These improvements make the 5+2 model a more robust and future-proof framework for intelligent transportation systems.

2.3.3. Mapping with international ITS standards

To ensure practical feasibility and cross-platform interoperability, each dimension of the 5+2 model is mapped to widely adopted ITS and CPSS standards. This mapping facilitates consistent data exchange, standardized service interfaces, and secure communication in real-world deployments. Table 2 summarizes the mapping between the 5+2 model dimensions and current ITS standards. This table highlights how each 5+2 model dimension aligns with widely adopted ITS standards, ensuring both interoperability and practical deployment feasibility. Although the standard versions differ, all represent the mainstream protocols currently applied in industrial ITS systems and academic research.

2.4. Digital twin transportation

We can understand the fundamental components of integrating DTs with the transportation sector based on the above concepts. The following section will introduce the implementation steps of applying DT technology to the transportation field, which include data collection and integration, model building and updating, intelligent analysis and simulation, decision dispatch, and execution. Subsequently, feedback data collected after implementing the decisions are gathered to calibrate further and optimize the digital twin model, thus forming an optimized closed loop. We specifically analyze this entire closed-loop process in the context of the transportation sector applications, as illustrated in Fig. 3.

Data Collection and Upload: The timeliness of data and the variety of sources are crucial. Data must first be gathered from sensors, system logs, and user inputs. This data may include information about physical entities' structure, performance, and operational status. For instance, data on location and speed can be collected from vehicle GPS systems. Traffic cameras and sensors are used to monitor vehicle flow and traffic conditions. Operational data from public transit systems, such as schedule times and load factors, are collected. Weather information is gathered to understand its potential impact on traffic. Data on road maintenance, accidents, and other incidents are also collected. Subsequently, ensuring that data collection and upload are synchronized in real-time is vital. To achieve this, edge computing can perform preliminary data analysis and processing near the data sources, reducing communication costs and alleviating the load on central servers.

Model Construction and Updating: To construct a twin model that corresponds one-to-one and provides a complete mapping for entities in physical space, it is necessary to obtain real-time data from smart devices. This data can primarily be categorized into four types: geometric, physical, behavioral, and regulatory, as shown in Fig. 4. Otherwise, depending on the specific application scenario and requirements, there are multiple options for where to deploy the twin model. Priority can be given to placing twins requiring substantial real-time and low latency on edge servers. This arrangement brings the model nearer to the data source, reducing delays and increasing interaction efficiency. For scenarios that require analyzing global data and issuing global decisions, the twin model can be deployed on central servers, where cloud computing platforms are used for data analysis and decision-making. The twin model can be deployed on onboard devices or mobile edge nodes, adapting to resource distribution and

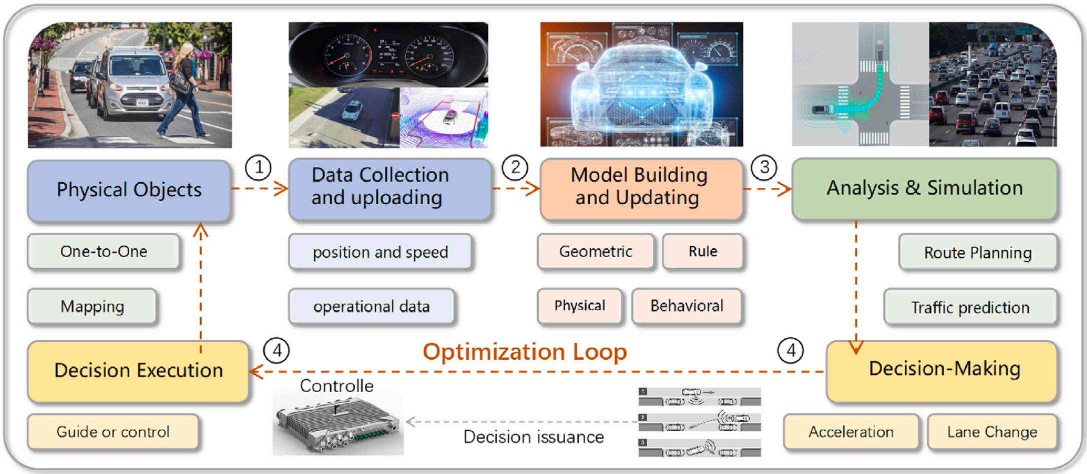

Fig. 3. Digital twin transportation optimization closed-loop.

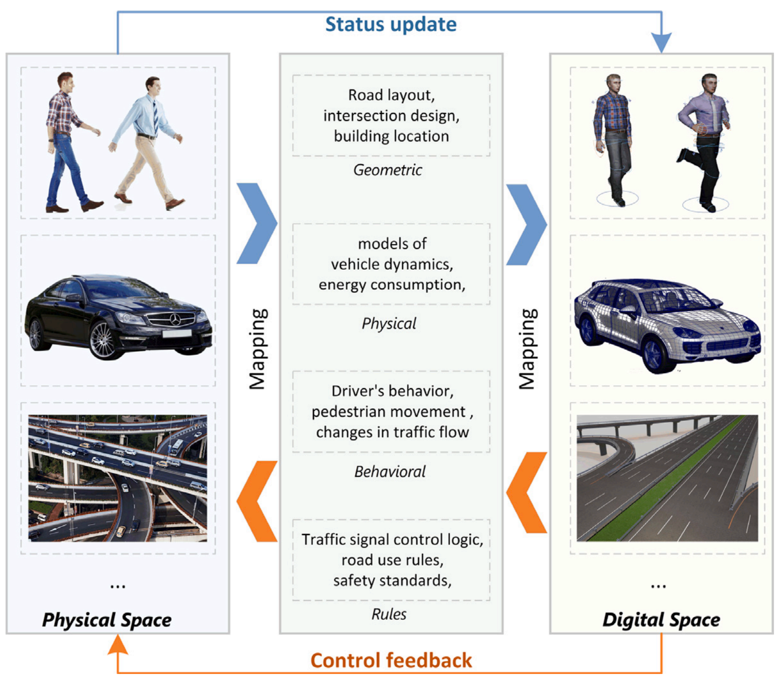

Fig. 4. Construction of digital twin transportation model.

physical-twin distance for timely and efficient data transmission and processing.

Intelligent Analysis and Simulation: Digital twin models can analyze data or results using advanced computational methods, enabling the testing of different hypotheses and decisions without impacting the physical entities. For instance, simulations can be conducted to observe changes in traffic flow under various conditions, such as peak times or adverse weather, analyze traffic patterns, and predict congestion points. However, the traffic system is a vast and complex dynamic system that faces numerous computation-intensive and latency-sensitive tasks. Therefore, sufficient computing resources are necessary during the analysis and simulation processes to ensure the timeliness of decisions.

Decision Making and Execution: Decisions are made based on analysis and simulations, such as adjusting traffic light timings, planning lane usage, devising traffic diversion plans for special events (like large-scale events or emergencies), and optimizing public transportation scheduling strategies to enhance efficiency and service quality. These decisions are then transmitted to the physical entities to guide or control their behavior and state. Specifically, the issuance of decision instructions can be broadly categorized into two types: direct decision issuance, where the twin model directly links with the control systems of the physical entities (such as route adjustments and speed control), suitable for scenarios with high automation and connectivity. The other type is indirect decision issuance, where decisions generated by the twin model are first sent to a central control platform (like a traffic management center) and then disseminated or broadcasted to the relevant physical entities. To enhance the transparency, reliability, and traceability of decisions, a unified Explainable AI (XAI) and audit mechanism can be integrated. For any generated decision, such as signal timing plans, reroute suggestions, or lane-change warnings, the decision optimization layer outputs the instruction. At the same time, it generates machine-readable explanatory metadata, which includes the decision rationale (e.g., key data states such as “queue length > threshold”), the reasoning objective (e.g., optimization of “total delay minimization”), and confidence levels. The application service layer can convert this metadata into operator-facing natural language explanations, for example, ”This signal timing plan aims to alleviate

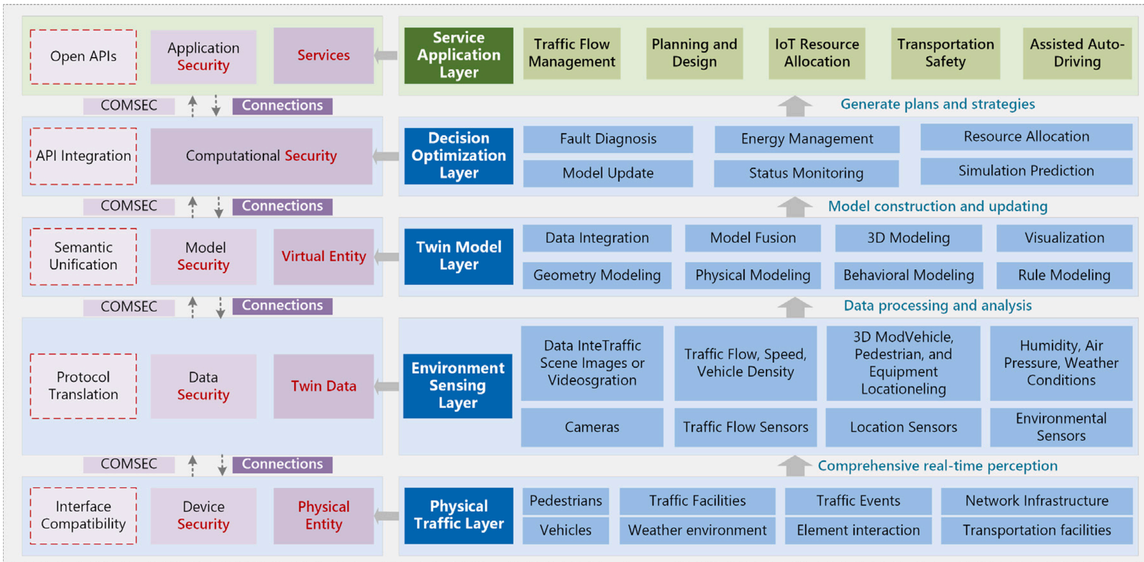

Fig. 5. Five layer framework of digital twin transportation.

the expected congestion in the northeast direction caused by an accident", and display it on the control interface. Meanwhile, all decision processes are recorded in a standardized audit log, including timestamps, decision IDs, input data hashes, model versions, output results, and explanatory rationale, enabling full traceability across application scenarios and facilitating post-hoc auditing, model optimization, and accountability. With this design, decisions within the closed loop not only guide the actions of physical entities but also allow operators to understand the rationale behind the decisions and provide data support for continuous system improvement.

Finally, based on the outcomes of the implemented decisions and new feedback data, the digital twin model is continuously adjusted and updated to reflect new traffic regulations and infrastructure changes. The model's accuracy is regularly assessed through these steps, and necessary calibrations are made, enabling the DT traffic system to achieve dynamic, real-time management and optimization. This effectively addresses the complexity and evolving challenges of urban traffic.

2.5. Five-layer framework for digital twin transportation

Based on the above concepts, we propose a five-layer framework for digital twin transportation, as shown in Fig. 5.

This framework consists of the Physical Traffic Layer, the Environment Sensing Layer, the Twin Model Layer, the Decision Optimization Layer, and the Service Application Layer. At the same time, it illustrates the dynamic mapping between the 5+2 model, the five-layer architecture, and key application scenarios. Specifically, the Physical Traffic Layer hosts the real-world traffic environment and underlying communication infrastructure, corresponding to the "Physical Entity" in the 5+2 model; the Environment Sensing Layer is responsible for data collection and preprocessing, serving as the primary source of twin data in the 5+2 model; the Twin Model Layer corresponds to the "Virtual Entity" in the 5+2 model and standardizes the collected data; the Decision Optimization Layer generates strategies and issues control instructions based on the preceding information; and the Service Application Layer corresponds to the "Service" in the 5+2 model, executing the instructions from the Decision Optimization Layer in the actual traffic system to support traffic flow management, traffic planning and design, vehicular network resource allocation, traffic safety, and assisted autonomous driving. Furthermore, the newly added "Security" dimension in the 5+2 model covers all layers, including device security, data security, model security, computational security, and application security. The "Interoperability" dimension guarantees interface compatibility, unified data formats, and consistent semantic protocols across layers, thereby supporting efficient coordination and reliable communication among different components and modules within the system.

3. Application of digital twins in the transportation

With the rapid advancement of urbanization and the growing demand for transportation, traditional traffic systems are facing significant challenges. Relying on manual methods to collect and analyze traffic data, using expert knowledge to design road networks, and applying static traffic models for simulation are becoming insufficient in dealing with complex and dynamic traffic conditions. Although modern traffic systems have improved in data collection, monitoring, and management, such as adopting intelligent traffic signal control and real-time monitoring technologies, they still struggle with data fragmentation, limited automation, and inefficient resource allocation. Improving the accuracy of traffic management, enhancing adaptability, and optimizing resources remain key challenges in the field of transportation.

In response to these challenges, digital twin technology has become an important tool for advancing intelligent traffic systems. By enabling high-precision simulation and real-time traffic analysis, digital twins improve system responsiveness, predict traffic patterns, and optimize transportation strategies. This provides strong support for the planning and management of smart transportation. The following sections examine digital twin roles and their influence on transportation innovations.

3.1. Traffic flow management

The DT system plays a key role in optimizing traffic flow management, as it enables accurate simulation of urban transportation networks and integrates real-time traffic data to optimize various traffic management tasks. Digital twins not only improve the accuracy of traffic flow prediction but also support applications such as traffic signal optimization, collision avoidance, route planning, and trajectory tracking, thereby enhancing the overall intelligence of transportation systems.

In the field of traffic flow prediction and optimization, researchers have proposed various strategies based on digital twin technology to

Table 3
Characteristics and limitations of different traffic flow prediction methods.

Methods		Characteristics	Limitations
Early methods	Empirical/ Statistical [19]	Simple mathematical models, easy to understand	Dependent on expert experience and Based on linear assumptions
Model development period	Classical traffic flow theory [20]	Intuitively simulates the physical process of traffic flow	Sensitive to initial conditions
	Spatio-temporal analysis [21]	Considers the effects of time and space relationships on traffic flow	Inability to predict complex traffic patterns and unexpected events
Intelligent method period	Neural network [22]	Capable of capturing non-linear relationships in traffic data	Black box characteristics make the results poorly interpreted.
	Support vector machine [23]	Based on nonlinear prediction	Limited by the choice of parameters and kernel functions
Advanced method period	Deep learning [24]	Capable of automatically extracting complex spatio-temporal features	Cannot be applied to non-Euclidean space
	Graph neural network [25–27]	Uses the graph structure to simulate the traffic networks	Generalizability and interpretability

improve prediction accuracy and optimization efficiency. However, traditional traffic flow prediction methods, as well as many recently developed approaches, still face several challenges in practical applications. These include a high dependence on expert knowledge, sensitivity to model parameters, and a lack of interpretability, as summarized in Table 3. Digital twin technology has demonstrated great potential in addressing these issues. For example, Anniciello et al. proposed a traffic flow management strategy that integrates digital twins with trajectory mining [28]. This data-driven approach enhances traffic flow management by leveraging in-depth traffic data analysis. For highway traffic flow prediction, Zhang et al. [29] introduced a Dual-State Traffic Factor State Network (DS-TFSN) model, incorporating Long Short-Term Memory (LSTM) networks to simultaneously consider both macroscopic traffic conditions and microscopic vehicle movement patterns. The maximum mean absolute percentage error (MAPE) of the prediction results was reduced by 6.2%. However, these methods rely heavily on high-quality real-time data, and if sensors are unevenly distributed (e.g., in mountainous areas or urban highways) or environmental conditions are harsh, incomplete data collection may reduce the effectiveness of traffic flow prediction.

To fix this limitation, Hu et al. created a real-time traffic data prediction framework leveraging digital twin technology [30]. This approach utilizes Locality-Sensitive Hashing (LSH) and data processing techniques in 5G environments to effectively handle missing data. By incorporating temporal contextual information, the method significantly enhances prediction accuracy and computational efficiency. Equally important, precise traffic accident prediction enhances the accuracy of traffic flow forecasting. Ji et al. developed a model-free traffic accident prediction strategy [31], which employs macroscopic road network imagery and Convolutional LSTM networks to predict the spatiotemporal dynamics of traffic incidents without requiring explicit traffic dynamics modeling. Simulation results show that, compared with model-based methods and LSTM network models, the proposed approach significantly improves prediction accuracy. This strategy provides a novel perspective for predicting spatiotemporal congestion caused by accidents from a macroscopic viewpoint. However, these advanced prediction methods typically require significant computational resources, particularly for large-scale urban traffic networks, making them dependent on efficient computing infrastructure and 5G connectivity.

Traffic flow prediction provides valuable decision support for traffic management; however, effectively integrating such predictions with real-time control systems remains a key challenge in enhancing urban traffic efficiency. As a crucial tool for regulating traffic flow, adaptive traffic signal control (ATSC) systems are increasingly incorporating digital twin technology to enable more intelligent and flexible management. For instance, Wagner et al. proposed a DT-based ATSC scheme leveraging vehicle-to-infrastructure (V2I) communication via SPaT/MAP messages to facilitate efficient interaction between traffic signals and vehicles [32], thereby optimizing overall traffic flow. However, this study assumes complete synchronization between the twins and its entities system, without considering the impact of computational constraints on signal control decisions. To resolve this challenge, Zhu et al. introduced a DT-ATSC scheme incorporating grid search, genetic algorithms, and Bayesian optimization to minimize total intersection delay under limited synchronization conditions [33]. Meanwhile, research [34] explored DT-based ATSC strategies from a user experience perspective, proposing two approaches: one focused on reducing delays for vehicles approaching a target intersection, while the other extended optimization to account for delays at neighboring intersections. Although these studies effectively improve traffic efficiency, they primarily emphasize travel time reduction while paying relatively little attention to mitigating environmental impacts such as emissions and fuel consumption. To address this limitation, study [35] proposed a DT-based adaptive signal control method utilizing multi-agent DDPG. This approach optimizes traffic signal timing to simultaneously reduce vehicle delay and minimize emissions and energy consumption. However, most existing research focuses on homogeneous traffic conditions and lacks adaptability to mixed traffic flows involving. To address this issue, Adarbah et al. introduced a DT-based signal control strategy integrating the BIRCH clustering algorithm. This method dynamically adjusts traffic light durations in response to mixed traffic flow conditions, optimizing vehicle idling time and fuel consumption [36].

Although traffic flow prediction and signal control contribute to traffic optimization, complex traffic environments often involve challenges such as congestion, unexpected incidents, and high-density traffic conditions. In this context, collision avoidance is a key factor

Table 4
Comparison of digital twin-based traffic flow management.

Ref.	Method	Dataset	Metrics	Constr.	Comp. Cost	Edge Dep.
[39]	DT/ Trajectory Planning	MAT LAB	Collision rate, trajectory smoothness, latency	Dynamics and communication constraints	Low	Yes
[41]	DT/PID	Carsim/ Simulink	Lateral error, yaw rate, lateral, speed	high-precision sensors	Low	Yes
[31]	DT/Conv-LSTM	Traci/ SUMO	Prediction accuracy, loss	Image-based only	Med.	Yes
[35]	DT/ MADDPG	SUMO	CO_2 emission rate, fuel consumption, average travel time	CV-only, Fixed spacing	Med.	Partial
[29]	DT/EM Alg./multivariate LSTM	Chinese city highway	MAPE, MAE/ RMSE, Accuracy	Sparse sensor	Low	Yes
[33]	DT/Cell Transmission Model	SUMO	Average delay, control effectiveness	Uncertain Constr.	Low	Yes

in advancing automated traffic management. Huang et al. proposed a Proximity-Aware Longitudinal Lane-Change (PALLC) model, which improves lane-change safety and stabilizes edge-assisted DT systems by simplifying lane-change behavior modeling and theoretically analyzing collision risks [37]. Building on this foundation, Tang et al. explored collision avoidance from a distributed training perspective and developed a DT-assisted collision warning framework incorporating a Semi-Federated Learning with Adaptive Asynchronous Parameters scheme. This approach enhances distributed training efficiency in intelligent driving systems, enabling more accurate collision risk prediction [38]. While federated learning improves distributed computation efficiency, its computational overhead may impact real-time performance. While federated learning improves distributed computation efficiency, its computational overhead may impact real-time performance, especially under high-density traffic or network latency. To expand the applicability of DT-assisted collision avoidance, Du et al. investigated a queue-based cooperative automated vehicle (CAV) collision avoidance framework [39]. In this approach, a DT system is deployed on the leading vehicle while DT monitoring systems are used on the assisting vehicles. Simulation results demonstrate that the DT-based scheme shows significant performance advantages in sudden obstacle avoidance. Compared with existing approaches, it can reduce collisions by 95% and pass unexpected obstacles about 10% faster. However, this approach heavily relies on communication infrastructure, making it vulnerable to information loss in high-noise or low-bandwidth environments. Finally, Zhao et al. focused on collision avoidance for unmanned ground vehicles (UGVs), integrating the A-star algorithm with quadratic programming for collision-free trajectory planning [40]. By employing bidirectional tracking control, this method ensures synchronization between virtual and physical vehicles, thereby enhancing autonomous vehicle safety and driving stability.

Beyond collision avoidance strategies, high-precision path planning and trajectory tracking are also crucial for ensuring traffic efficiency [42]. Hu et al. proposed a DT-based trajectory projection method that integrates advanced control frameworks, and an improved proportional–integral–derivative (PID) algorithm to optimize both lateral and longitudinal control, thereby enhancing trajectory tracking accuracy and driving stability [41]. Experimental results show that this method reduces lateral error by more than 60%. Compared with the model-based longitudinal PID algorithm, the longitudinal velocity error is reduced by at least 38%, and the oscillation amplitudes of the wheel angle and yaw angle are also significantly reduced. However, the effectiveness of this approach depends on the synchronization accuracy of DT data, which may lead to information latency issues in complex scenarios. The improved accuracy is largely dependent on precise DT synchronization; in scenarios with high traffic density or delayed updates, lateral and longitudinal control performance may deteriorate, suggesting the need for robust data handling mechanisms. To address potential data synchronization challenges, Tang et al. introduced a DT-assisted distributed federated reinforcement learning framework for cooperative path planning [43]. This framework compensates for missing data during DT synchronization, ensuring high-fidelity modeling and improving trajectory optimization. Simulation results demonstrated its effectiveness in optimizing vehicle speed utilization and reducing collision rates. However, the computational cost of distributed reinforcement learning remains high, posing challenges for real-time applications. Additionally, In [44], the authors proposed an autonomous driving cooperation mechanism based on social value orientation (SVO), incorporating a DT-enabled traffic guidance architecture to improve traffic efficiency under high-load conditions. Nonetheless, this method was mainly tested in fully autonomous driving, and its potential in mixed traffic warrants more investigation.

To more intuitively compare the applications of digital twins in traffic flow management, Table 4 summarizes the core information of relevant studies, including their objectives, methodologies, datasets, and evaluation metrics. It can be observed that while digital twins have significantly enhanced the intelligence of traffic management, three common challenges persist in practical applications. First, there is a real-time synchronization issue: solutions such as DT-ATSC signal optimization and trajectory tracking all depend on real-time physical–virtual synchronization. However, most existing studies are based on idealized assumptions, which often lead to decision biases in scenarios characterized by sparse sensors or data latency. Second, a contradiction exists in computational efficiency: although deep learning models improve prediction accuracy, they require balancing model complexity against edge computing capabilities. Additionally, the computational overhead associated with approaches like federated learning may become a bottleneck for real-time decision-making. Third, there is insufficient adaptability to mixed traffic conditions: most methods are designed for homogeneous traffic flows and exhibit poor adaptability to mixed scenarios involving pedestrians and non-motorized vehicles. Only limited studies have attempted optimization in this regard, and a comprehensive global framework remains absent.

Future research could achieve breakthroughs in the following areas. First, construct a hybrid traffic digital twin model that integrates

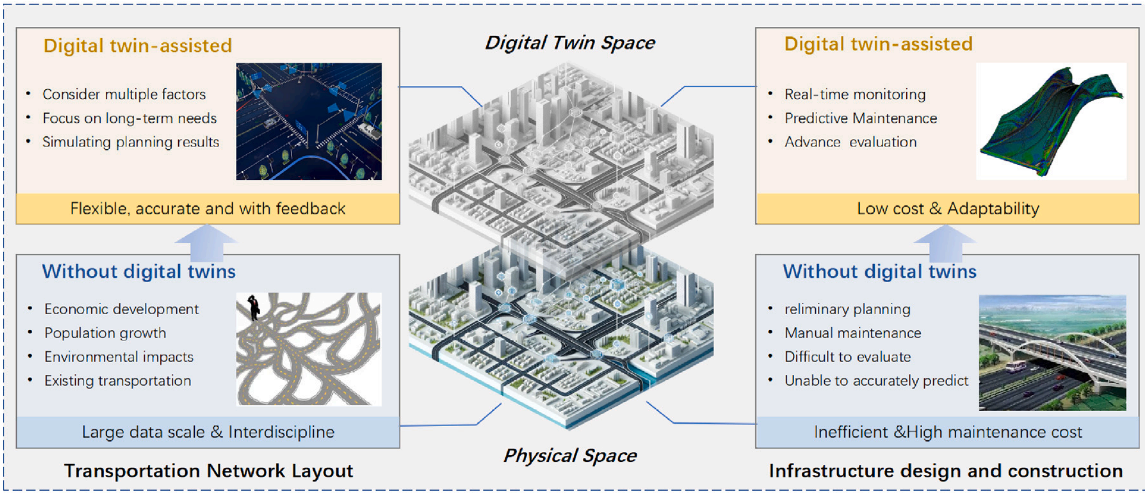

Fig. 6. Digital twin assisted transportation planning and design.

upstream and downstream lanes, pedestrian and non-motorized vehicle data, connected vehicles and non-connected vehicles, thereby addressing the current gap in modeling complex traffic elements. Second, integrate multi-source data fusion and dynamic event prediction technologies, and balance model accuracy with operational efficiency through edge computing and distributed optimization strategies to mitigate the computational burden of real-time decision-making. Finally, incorporate energy consumption constraints into signal control and trajectory planning, and explore adaptive reinforcement learning techniques to further enhance the real-time performance of traffic flow prediction and the overall intelligence of traffic management systems.

3.2. Transportation planning and design

Transportation planning plays a crucial role in urban development, with transportation network planning and infrastructure design at its core [45–47]. Traditional planning methods often rely on empirical knowledge, making it difficult to comprehensively account for multiple factors such as economic growth, population expansion, environmental impact, and existing traffic conditions. Consequently, the accuracy and adaptability of such approaches remain limited. DT enables the simulation of urban transportation systems, assisting planners in optimizing road network layouts and evaluating the impact of new infrastructure (e.g., roads, bridges, intersections) on traffic, as illustrated in Fig. 6. Compared with conventional approaches, DT technology integrates real-time data, dynamically adjusts planning strategies, and predicts long-term traffic demand, making planning processes more precise and efficient. Furthermore, DT technology can simulate traffic flow variations and environmental impacts under different scenarios during the planning phase, facilitating the development of more scientific and sustainable transportation plans.

To mitigate the drawbacks of traditional transportation planning techniques, DT has been increasingly explored for urban transportation system optimization. [48,49]. In [50], the authors examined the evolution of DT from physical to social systems, emphasizing its extensive applications in urban planning and management. The study illustrated DT's critical function in understanding, anticipating, and designing real-world cities. Building on this foundation, Jiang et al. proposed an urban road planning framework that integrates DT, multi-criteria decision-making, and GIS [51]. This framework considers factors such as traffic congestion, land use, and air quality to generate functionally optimized, cost-effective, and environmentally sustainable urban planning solutions, demonstrating the potential of DT in complex multidimensional urban systems. Expanding on this concept, Kumalasari et al. developed a generative design process aimed at enhancing walkability in urban environments by incorporating factors such as pedestrian comfort, street greenery, and public facilities, ultimately offering a more human-centered urban planning approach [52]. In practical applications, Aloupogianni et al. introduced an innovative digital twin framework for Singapore's urban transportation system. By integrating real-time traffic and weather data with artificial intelligence techniques, this framework enhances traffic safety under adverse weather conditions [53]. Additionally, [54] proposed an Urban Digital Twin (UDT) framework tailored to the complex urban system of Matera, Italy. Driven by artificial intelligence, the framework integrates urban sensor networks and historical data to achieve real-time monitoring and multi-objective dynamic optimization of traffic flow, air quality, infrastructure health, and emergency response. However, due to the significant variations in transportation patterns, climatic conditions, and infrastructure across different cities, the generalizability and adaptability of these methods require further validation and optimization. These studies demonstrate the potential of DT applications across various urban environments, but they also reveal limitations due to a high reliance on high-quality sensor networks and real-time data, which restricts their applicability in areas with sparse data or underdeveloped infrastructure. Furthermore, it is necessary to further examine these limitations, such as the impact of different urban climates, infrastructure conditions, and data availability on the applicability of the methods, as well as the scalability of different digital twin frameworks in practical deployment.

With the steady growth of digital twin solutions, its applications in transportation infrastructure management are expanding. Li et al. introduced an ontology-based digital twin modeling framework for infrastructure, which incorporates five essential elements: scenarios, virtual models, physical entities, relationships, and components. This framework aims to facilitate interdisciplinary collaboration, increase transparency, and enhance infrastructure safety, particularly in managing system complexity and uncertainty [55]. In real-world applications, Shen et al. developed a high-performance asphalt pavement modeling solution based on the Semi-Analytical Finite Element Method (SAFEM) for evaluating pavement responses in road infrastructure [56]. Chen introduced a laser-scanning-based digital twin technique, combining tree segmentation, modeling, and parameter optimization for efficient large-scale urban tree representation [57]. Moreover, digital twin technology has demonstrated notable advantages in urban drainage system applications [58,59], combining real-time data and simulation techniques to enhance drainage efficiency, improve emergency response capabilities, and optimize the overall performance of urban infrastructure. However, the effectiveness of DT applications varies across different types of infrastructure: for example, drainage systems focus

Table 5
Comparison of digital twin applications in urban planning and infrastructure.

Ref.	Objective	Method	Dataset	Feature	Metrics	Lim.
[51]	Multi-objective road planning	DT/ MCDM	Mortlake area, London	3D building data, real-time traffic flow, air quality	Relocation cost savings	Limited generalizability
[52]	Urban walkability optimization	DT/ MOGA	Krastova, Vada Lozenets	Building data, walking preferences, aerial imagery	Facility accessibility, segmented NDVI scores, relocation cost	Untested in dense networks
[54]	Full-element urban monitoring	DT/ Linear Prog./ DMD	Matera case study	Terrain, vehicle detection, environment	Occupancy prediction accuracy	Weather not integrated
[55]	Road infrastructure DT	DT/ SAFEM	Full-range testing and on-site measurements	Tire contact stress, asphalt viscoelastic behavior	Simulation accuracy, computation time, storage usage	Multi-scale modeling incomplete
[60]	Cable-stayed bridge lifecycle assessment	DT/ CAD/ CAE	Lab-scale bridge model	geometry, material, connections, coordinates	Model fidelity, DT prediction error	Fidelity depends on sensor quality

on real-time response and efficiency optimization, whereas pavement and greenery management place greater emphasis on model accuracy and long-term maintenance prediction. The frequency, accuracy, and integration methods of data collection have a significant impact on the reliability of simulation results, representing key areas for further optimization in future research.

As urban transportation systems become increasingly complex and intelligent, the application of DT in lifecycle management and predictive maintenance is emerging as a key research focus. By constructing digital twin models of transportation infrastructure, it becomes feasible to oversee the full lifecycle of transportation systems, spanning design, building and maintenance. This approach optimizes decision-making processes and enhances overall system performance. Gao et al. emphasized that DT technology significantly improves the efficiency of transportation infrastructure planning, design, construction, operation, and safety management [61]. Guo et al. proposed a DT-based lifecycle management framework for cable-stayed bridges. The framework utilizes data exchange and fidelity metrics to validate the consistency between the digital model and its physical counterpart, thereby significantly enhancing the accuracy of condition monitoring. Furthermore, it can accurately capture the dynamic response of cable-stayed bridges under moving loads, effectively overcoming the limitations of traditional techniques such as finite element model updating [60]. Tu et al. integrated digital twin technology with Data Envelopment Analysis (DEA) to evaluate the performance of transportation facilities in 12 cities, demonstrating that this model offers more precise efficiency assessments compared to traditional methods [62]. Vodyaho et al. developed a three-layer cyber–physical lifecycle model for metro stations, leveraging sensor data and machine learning techniques to enhance event detection accuracy [63]. Finally, the paper [64] introduced a municipal pipeline network lifecycle management framework, underscoring the critical role of high-fidelity digital twins in pipeline network management. These studies illustrate the growing significance of DT in the lifecycle management and predictive maintenance of infrastructure.

Table 5 summarizes representative studies on the application of digital twins in urban planning and infrastructure. While these studies demonstrate the potential of digital twins in enhancing traffic management, improving urban walkability, and optimizing the full-lifecycle monitoring of infrastructure, several common limitations remain. First, the generalizability of traffic and urban road planning is insufficient: most existing studies are designed and validated for a single region, failing to fully account for the impacts of road network characteristics, climatic conditions, and network infrastructure capacities across different countries and regions. This limitation restricts their generalization during cross-scenario migration. Second, adapting to the heterogeneity of transportation infrastructure poses a challenge: different facilities (e.g., roads, drainage systems, and green vegetation) have distinct requirements for data update frequency, accuracy, and adaptation methodologies. Current planning practices lack a unified framework for integrating heterogeneous elements, which often results in a discrepancy between simulation outcomes and real-world conditions.

Future research should advance the development of open digital twin platforms and establish cross-scenario standardized protocols to define data collection specifications under varying conditions; tailor modeling and update strategies to address the heterogeneity of infrastructure, thereby achieving efficient integration; and investigate fault-tolerant and error-correcting algorithms for data gaps or inconsistencies to enhance the reliability and scalability of the model.

3.3. Internet of vehicles resource allocation

Ensuring the efficient and secure operation of transportation systems requires optimal network resource management and task scheduling. By optimizing network topology, data transmission paths, and traffic management strategies, communication latency can be reduced, transmission rates can be improved, and accurate information acquisition can be ensured. A well-designed task scheduling strategy further optimizes resource allocation and enhances system efficiency, particularly in emergency situations, enabling rapid response and ensuring safety [65–71]. However, traditional caching and offloading optimization methods in vehicular networks mainly rely on geographical location, content popularity, and user behavior patterns. These methods are often based on local information and lack a global system perspective, making resource allocation more challenging.

Digital twin technology enables rational allocation of vehicular network resources from a global perspective, as illustrated in Fig. 7. By creating a virtual replica of the transportation network, digital twin technology provides a comprehensive view to accurately simulate vehicle mobility, user behavior, and network conditions, thereby facilitating more precise caching and offloading decisions [72–77]. Existing research on network resource optimization utilizing DT can be categorized into deep reinforcement learning-based approaches, deep optimization methods combined with federated learning, and approaches incorporating novel algorithms. Each of these methods has

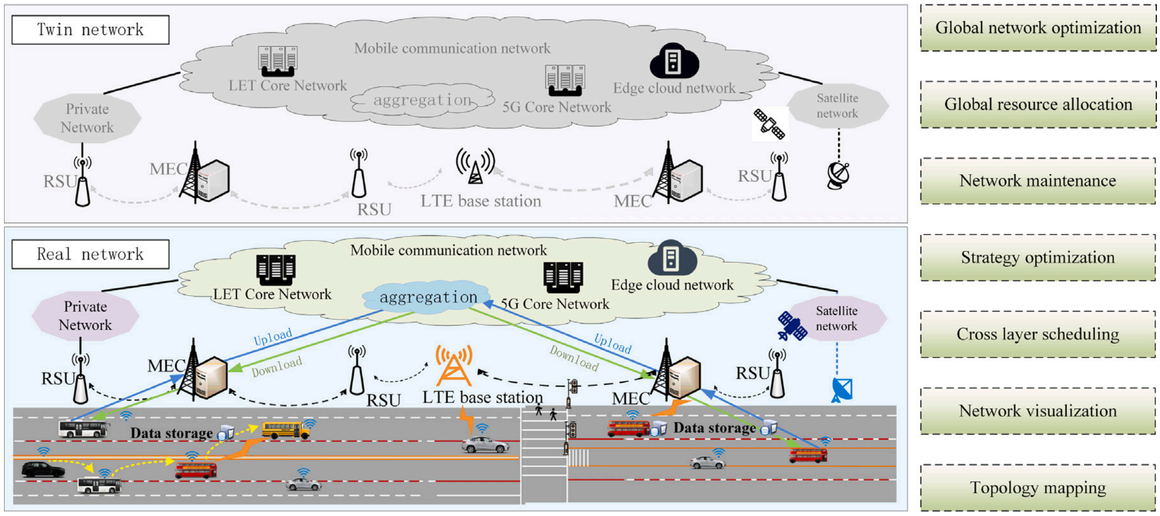

Fig. 7. Digital twin-assisted resource optimization for the internet of vehicles.

its specific focus, offering intelligent solutions for vehicular network resource management.

In dynamic network environments, deep reinforcement learning (DRL) provides an efficient solution for real-time resource allocation [78–80]. For instance, in [81], to mitigate the issues of high mobility and dynamic environments in vehicular edge computing, a framework integrating digital twin technology was proposed. This framework combines the non-orthogonal multiple access protocol with A2C algorithm to optimize offloading decisions, subchannel allocation, and RSU association, aiming to maximize computation rates and minimize task latency. However, the synchronous update mechanism of A2C is inefficient in large-scale tasks. To overcome this limitation, research in [82,83] proposed an asynchronous advantage actor–critic (A3C) algorithm based on a digital twin architecture, significantly improving computational efficiency through an asynchronous update mechanism. Moreover, in [84], A3C was further integrated with graph attention networks to dynamically incorporate network information, significantly enhancing task throughput and stability, thus providing an efficient and reliable solution for resource allocation in complex dynamic environments. Additionally,Xu et al. introduced a DQN-based service offloading method, which effectively optimizes offloading decisions [85]. However, DQN may suffer from Q-value overestimation and slow convergence when handling complex tasks. To address these challenges, Chen et al. proposed a DDQN, which decouples action selection from value estimation, further improving the accuracy and stability of caching decisions, Simulation results demonstrate that the proposed algorithm reduces request latency by 2.62%, 3.06%, and 3.95%, and energy costs by 26.07%, 47.05%, and 49.90% respectively [86]. The transition from synchronous to asynchronous update mechanisms and from DQN to DDQN reflects methodological advancements, enabling more effective handling of dynamic resource allocation challenges in vehicular networks empowered by edge computing and digital twin technology.

In studies combining deep reinforcement learning with other technologies, numerous innovative approaches have emerged. For example, in [87], a Lyapunov-assisted multi-agent deep federated reinforcement learning (MADFRL) was proposed to optimize CPU frequency, the number of digital twins, and energy harvesting, minimizing execution costs and privacy overhead. Similarly, in [88], a two-tier network offloading architecture assisted by digital twin technology was designed, incorporating a federated deep reinforcement learning scheme. In this approach, local agents train offloading decisions while a global agent optimizes resource allocation. Numerical results demonstrate the effectiveness of the proposed joint DT framework, achieving up to 67.1% reduction in system costs compared to baseline methods. However, these methods adopt synchronous update mechanisms, requiring all distributed nodes to update the model at the same time, which results in computational inefficiencies. To address this limitation, studies in [89,90] proposed a digital twin-based resource allocation method that integrates asynchronous federated learning with multi-agent DRL, improving task success rates, energy efficiency, and response times in unmanned aerial vehicle-assisted vehicular networks. Furthermore, Paul et al. proposed an innovative integration of quantum computing and DRL, leveraging the parallel processing capabilities of quantum computing to enhance DRL algorithms [91]. The study employed a LSTM to predict future network states, enabling real-time synchronization and adaptive strategy optimization. Additionally, a multi-agent framework based on Nash equilibrium strategies was introduced, incorporating incentive and penalty mechanisms to refine decision-making. These studies illustrate the deep integration of DRL with federated learning, quantum computing, Lyapunov optimization, and other advanced techniques, providing diverse and efficient solutions for resource allocation in complex dynamic environments. This interdisciplinary fusion not only expands the application boundaries of DRL but also opens new research directions for intelligent system optimization in the future.

To provide a more comprehensive understanding of existing digital twin-based task offloading methods for the IoV, Table 6 summarizes the objectives, methodologies, datasets, evaluation metrics, and limitations of representative studies. As indicated in the preceding context and Table 6, most methods rely on simulation environments or scenario-specific datasets, which restricts their cross-environment generalizability and efficiency in large-scale task processing. Considering the practical research context, the core issues center on two aspects. First, balancing real-time performance and reliability remains challenging: whether in DRL-based offloading optimization or asynchronous federated learning for resource scheduling, the trade-off between real-time decision-making and reliable data transmission persists. Network latency or node heterogeneity often leads to deviations in resource allocation. Second, there is a lack of a global optimization perspective: existing methods primarily focus on local resources (e.g., single edge nodes) and lack global collaboration among vehicle–road–cloud systems and auxiliary devices such as UAVs, intelligent reflecting surfaces, and satellites. This leaves room for improving resource utilization under high-load scenarios.

These issues suggest that while progress has been achieved in digital twin-assisted IoV optimization, practical deployment still necessitates designing multi-objective joint optimization strategies for digital twin

Table 6
Comparison of digital twin-based task offloading approaches.

Ref.	Obj.	Method	Dataset	Metrics	Lim.
[81]	Improve formic acid efficiency, reduce latency	DT/ NOMA/ A2C	omnet++/ Veins sim	Task latency, drop rate, throughput, resource usage	Sync updates inefficient for large tasks
[82]	Reduce task delay and energy	DT/ DNN/ A3C	SUMO/ omnet++ /Veins sim	Latency, energy	–
[83]	Fast convergence, low cost	DT/ A3C	Python	Runtime, avg. cost, failure rate	Comm. overhead ignored
[85]	Improve service quality	DT/ DQN	Nanjing IoV requests	Response time, QoS, throughput	Tasks indivisible; partial offload gains ignored
[80]	Minimize offload delay, maximize throughput	DT/ DDPG/ MFG	CARLA/T-Drive	Avg. reward, offload scale, trans. MSE, avg. delay	Ignores DT-vehicle comm. latency; sim differs from reality

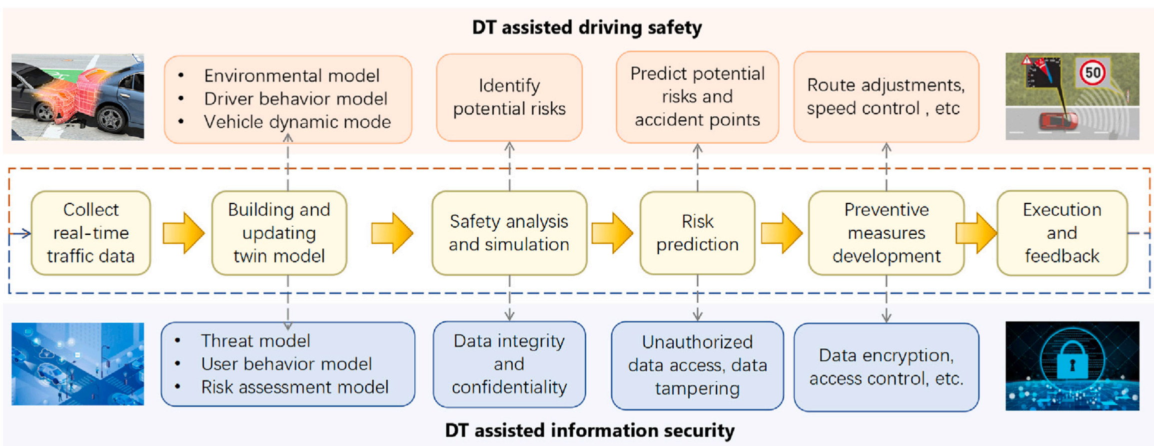

Fig. 8. Digital twin-assisted flowchart for transportation safety.

migration to enhance the generalizability, real-time performance, and robustness of the methods. It is also essential to establish an integrated global scheduling framework for vehicle–road–cloud–auxiliary devices, optimize the reliability of data transmission and the efficiency of real-time decision-making, and ultimately realize efficient, flexible, and reliable IoV resource management.

3.4. Transportation safety

In intelligent transportation systems, driving safety and information security are core issues for ensuring smooth traffic flow and user safety. Driving safety concerns the condition of the driver, vehicle operation, and the reliability of critical components, while information security guarantees the authenticity and integrity of traffic information, preventing tampering and cyber-attacks. DT is indispensable in both aspects by delivering real-time monitoring and intelligent analysis [92–95]. Fig. 8 illustrates the application process of digital twin technology in traffic safety, Table 7 systematically compares typical application schemes of digital twins in the field of IoV security.

In intelligent transportation systems, driving safety impacts user lives and system efficiency. Digital twin technology offers novel solutions to enhance driving safety. Ma et al. proposes a driver digital twin (DDT) framework that integrates Transformer-based action recognition, temporal localization modules, and emotion recognition to improve the accuracy and robustness of distraction detection [102]. Siddiqi et al. introduces a Web 3.0-based drunk driving detection method, leveraging digital twins to process state information and employing DRL to predict drunk driving behavior, Experimental results demonstrate that the DT-integrated solution achieves a 96% accuracy rate in detecting drunk driving incidents [96]. Additionally, Chen et al. presents a driving behavior twin model framework that utilizes data sharing between connected vehicles to predict the future behavior of surrounding vehicles, thereby improving driving safety [103]. In more complex driving scenarios, predicting personalized driving behaviors becomes particularly important. To address this, Liao et al. developed a lane-changing behavior prediction method based on DDT, which integrates an edge–cloud architecture and historical data to enhance the accuracy of lane-changing strategy predictions [104]. Furthermore, to ensure vehicle safety, Wang et al. proposed a digital twin-based vehicle stability monitoring system in [105], utilizing the PSO-LSTM algorithm to accurately monitor vehicle sideslip angles under various operating conditions. The management of vehicle hardware also plays a crucial role in driving safety, particularly in predictive maintenance. In [97], authors introduces a method that combines digital twins with DDPG for electric vehicle battery performance evaluation. This method records battery status and health indicators using digital twins and employs a DDPG model to predict battery capacity degradation. Experimental results demonstrate its effectiveness in assessing battery performance decline and improving battery safety and reliability. The paper [98] further proposes an integrated predictive maintenance framework incorporating digital twins, machine learning, and blockchain to identify potential failures before they occur, thereby reducing safety risks. As driving processes involve multiple disciplines such as traffic engineering, data science, artificial intelligence, and even psychology, despite the advantages digital twin technology offers for driving safety, a comprehensive understanding of driving behavior and safety risks has yet to be fully achieved. Therefore, further research should focus

Table 7
Comparison of digital twin applications in transportation security.

Ref.	Problem	Method	Expt.	Trace	Innov.	Lim.
[96]	IoV security detection	Web3.0/ DT/DNN /Blockchain	Simulation	Strong	Vetaverse concept, multi-chain security	Complex deployment
[97]	Battery management	DT/DDPG	Simulation/ Expt.	No	DT with RL for SoH estimation	Lack of large-scale application
[98]	Predictive maintenance	DT/ML /Blockchain)	PoC implementation	Strong	Integration of DT, ML, and Blockchain	Prototype stage
[99]	Vehicle Handover Security	Blockchain/ handover authentication	Ethereum testnet	Partial	Smart contracts reduce vehicle overhead	Lack of real-vehicle validation
[100]	IoV-DT communication security	Blockchain	Security analysis	Strong	Intra/Inter dual-layer authentication	Limited empirical validation
[101]	High blockchain cost	DT/Blockchain /DDPG	Simulation	Partial	Dynamic DT construction /RL	Lack of real-vehicle validation

on interdisciplinary expert training, the development of generalizable driving risk mitigation strategies across different scenarios, and more advanced fault prediction models.

In addition, information security is a critical aspect of ensuring the stable operation of intelligent transportation systems, as maintaining data authenticity, integrity, and resistance to tampering is essential. Given the complexity of network environments and multi-party data interactions, leveraging digital twin technology to enhance information security in transportation systems has become a key research focus. For instance, The research [106] addresses security challenges in communication and authentication within DT networks by proposing a multi-factor user authentication scheme called READ, which integrates advanced encryption techniques and security assessments to provide efficient and secure authentication and communication solutions. Gautam et al. design a blockchain-powered handover authentication protocol for vehicular digital twin networks (VDTN) to mitigate the security challenges of inter-regional vehicle handovers in dynamic topologies [99]. This protocol leverages digital twin technology to reduce computational overhead for vehicles while improving the efficiency and security of the handover process. In [100], the authors proposes a blockchain-based distributed identity authentication framework that ensures data integrity and auditability between twin nodes using blockchain's immutability while optimizing computational and communication costs through lightweight encryption techniques. Additionally, The paper [107] presents the STIoV framework, which integrates mutual identity authentication and credit management mechanisms to establish an end-to-end security protection system covering identity, behavior, and data.

Once the identities of communication participants are verified and interaction security is ensured, the next critical challenge is securing data sharing and privacy protection in dynamic network environments. This requires the integration of fine-grained access control, privacy-enhancing technologies, and standardized data governance frameworks to establish an end-to-end data security lifecycle management system. Li et al. design a lightweight data-sharing solution for vehicular DT networks, employing trust-based filtering to eliminate unqualified twins and a proxy-based protocol for secure verification and key exchange [108]. Wang et al. introduces a flexible and secure data-sharing scheme that utilizes a knowledge signature protocol to protect vehicle identities, an intelligent contract algorithm for accountability mechanisms, and a verification control mechanism to support flexible data sharing [109]. Meanwhile, consistent-state digital twins can anonymize sensitive information to ensure data privacy and synchronization. However, most of these approaches heavily rely on blockchain technology, which may lead to significant communication and computational resource consumption. To mitigate this problem, Chai et al. proposes a DT-based dynamic vehicular blockchain framework that incorporates a DT migration mechanism and a communication-efficient Local Perceptual Multi-Agent DDPG algorithm, significantly reducing communication costs and latency [101]. Xu et al. further optimizes blockchain consensus processes in network spaces by introducing a lightweight d2BFT scheme. This approach utilizes a multi-agent dual actor–critic (MADAC) algorithm to jointly optimize task allocation, communication bandwidth, computational frequency, and blockchain stability, effectively reducing resource overhead while enhancing system efficiency [110].

Building upon the demonstrated potential of DT to enhance driving safety and information security, it remains necessary to systematically analyze system security. This section introduces a threat model for DT-based transportation systems, proposes a lightweight security stack tailored for vehicular and edge environments, and summarizes typical trade-offs between security and performance.

In DT-based transportation systems, protection targets include not only vehicles and road infrastructures but also data flows in the perception layer, virtual entities in the model layer, and control strategies in the decision and application layers. Key assets in such systems include vehicle control units (ECUs), real-time telemetry data such as speed, location, and sensor states, driver identity and privacy information, as well as the integrity of the twin models. The potential adversaries consist of external attackers such as hackers, internal malicious nodes including compromised vehicles or forged twins, and untrusted third-party services. The attack surfaces encompass physical–network interfaces connecting sensors, in-vehicle units, and road infrastructures, edge–cloud communication links such as V2X and V2I channels, and the processes of data synchronization or migration between digital twins. Based on this threat model, possible attacks may include data tampering that leads to erroneous decisions, identity forgery to impersonate legitimate vehicles, denial-of-service attacks that affect system real-time performance, privacy breaches exposing sensitive driver or vehicle information, and cross-layer attacks exploiting the closed loop between virtual and physical systems.

To counter these threats, we design a lightweight security stack emphasizing modularity and low overhead, aiming to provide end-to-end protection without compromising real-time performance:

- **Authentication & Authorization:** Lightweight schemes (e.g., ECC with one-time signatures) reduce computation compared with traditional PKI. Multi-factor approaches, including behavioral features, strengthen resistance to impersonation. Fine-grained role- and attribute-based access control ensures only legitimate entities gain access.

Table 8
Security vs. performance trade-off matrix.

Security Mechanism	Security Strength	Performance Impact/Notes
Encryption (AES/RSA/ECC)	High	Increases computation latency, consumes more in-vehicle/edge resources
Blockchain verification	High auditability	Increases communication overhead and latency, especially with frequent synchronization
Differential privacy	Medium	Reduces risk of sensitive information leakage, may slightly reduce model accuracy
Federated learning	High	Avoids centralized data leakage, adds extra communication overhead
Lightweight signatures/ECC	Medium	Reasonable security with low computational overhead
Trusted Execution Environment	High	Provides hardware-level protection for critical modules, may increase initialization latency
Access Control	Medium	Controls access permissions, adds system configuration complexity
Secure OTA updates	Medium	Ensures update integrity and authenticity, may consume extra bandwidth
Hash chains/Merkle trees	Medium	Protects data integrity and traceability, with slight storage and computation overhead

- **Key Management:** Group negotiation and rapid session key updates support highly dynamic vehicular environments. One-time session keys and short rotation cycles reduce risks while limiting resource costs.

- **Secure Updates:** OTA processes are safeguarded with encryption, digital signatures, and integrity checks. Differential updates and hierarchical verification mitigate bandwidth and computation overhead, while TEE or sandboxing protect critical modules.

- **Telemetry Protection:** Lightweight MACs or hash chains, combined with challenge–response schemes, secure real-time data. Edge-level anomaly detection further guards against false data injection.

- **Privacy & ML Security:** Differential privacy and federated learning with lightweight cryptography prevent sensitive data leakage during model training. Parameter compression and approximate secure computation adapt these methods to resource-constrained devices.

- **Extensibility:** The modular "plug-in" design enables flexible deployment and adaptation to evolving threats and varying application contexts such as V2X, autonomous driving, or traffic management.

To assist system design and deployment decisions while balancing security and performance, Table 8 summarizes typical trade-offs between security mechanisms and system performance in DT transportation systems. The "Security Strength" column uses qualitative ratings such as High or Medium, based on factors including the scope of protection for critical assets, resistance against potential attacks, immutability/auditability, and technical maturity. Designers can select appropriate mechanisms according to application scenarios, e.g., lightweight encryption and signatures for real-time decision-making, and blockchain verification when auditability and security are prioritized.

In summary, digital twins provide a comprehensive framework for enhancing driving safety and information security within ITS. By integrating real-time monitoring, predictive analytics, and lightweight security mechanisms, digital twin technology can proactively mitigate risks while preserving system efficiency. The proposed threat models and security stacks also offer a structured reference for identifying vulnerabilities, implementing protective measures, and balancing security with performance. However, current research solutions rely heavily on blockchain technology. While blockchain can ensure data security and privacy, it tends to incur substantial communication and computational resource overhead. A critical direction requiring urgent breakthroughs is how to safeguard system efficiency while strengthening privacy and security protection, and further optimize the security architecture to achieve lightweight deployment. Second, multi-modal risk perception is insufficient: existing solutions (e.g., collision warning, battery health monitoring) are primarily designed for single risk sources (e.g., vehicle malfunctions, malicious attacks) and demonstrate weak responsiveness in scenarios involving coexisting multiple risks, as they lack a unified risk assessment framework to integrate multi-dimensional threat information.

Future research should focus on addressing the aforementioned bottlenecks: on the one hand, exploring lightweight security technology pathways to reduce the resource consumption of technologies such as blockchain while ensuring robust security protection; on the other hand, developing a unified risk assessment framework that covers multiple risk sources to enhance the system's capability to perceive and respond to complex overlapping risks. Ultimately, this will facilitate the secure and efficient deployment of digital twins across diverse in-vehicle and edge computing environments.

3.5. Assisted autonomous driving

With the rapid development of autonomous driving technology, comprehensive and rigorous testing can reduce potential safety risks and ensure that vehicles respond correctly under various road and traffic conditions. The standard methods for autonomous driving testing mainly include real-world road tests, closed-loop tests, and simulation tests. Among them, real-world road tests are conducted in actual road environments, providing authentic driving experiences and feedback. However, covering all possible road and traffic scenarios is costly and challenging. Closed-loop testing is conducted in controlled environments, offering higher safety but potentially lacking the complexity of real-world situations. In contrast, simulation testing takes place in virtual environments, simulating various complex scenarios, but there are still limitations in terms of accuracy and realism [111–113].

Digital twin technology provides an efficient and comprehensive solution for autonomous driving testing [114]. By constructing detailed virtual environments and simulating real traffic conditions, digital twin technology allows for extensive and in-depth testing in a safe virtual space. This approach not only reduces testing costs and minimizes the risks of real-world road tests but also simulates various extreme and rare traffic scenarios, ensuring a more comprehensive test coverage. With digital twin technology, autonomous driving systems can undergo rigorous simulation tests before official deployment, significantly enhancing their safety and performance in real applications, as shown in Fig. 9.

In recent years, the application of digital twin technology in autonomous driving testing has gradually expanded from closed environments to more complex settings, demonstrating its powerful potential. Hu et al. reviewed the application of DT in autonomous driving testing, focusing on the differences between virtual simulation and the real world, and analyzed the challenges and applications of three major technologies: Sim2Real, DT, and parallel intelligence [115]. Based on this research, Gao et al. developed a method leveraging digital twins for autonomous driving testing in limited environments, achieving real-world testing through virtual simulation, providing a preliminary framework for testing in closed scenarios [116]. Building on this, Niaz et al. further proposed an intelligent connected autonomous driving testing framework, combining digital twin technology and LTE/5G communications, achieving real-world testing in complex virtual road scenarios, providing a more comprehensive technical foundation for autonomous driving testing. Moreover, experimental verification shows that compared with other classical algorithms, the established digital twin-based model achieves an accuracy of approximately 85.80%, with

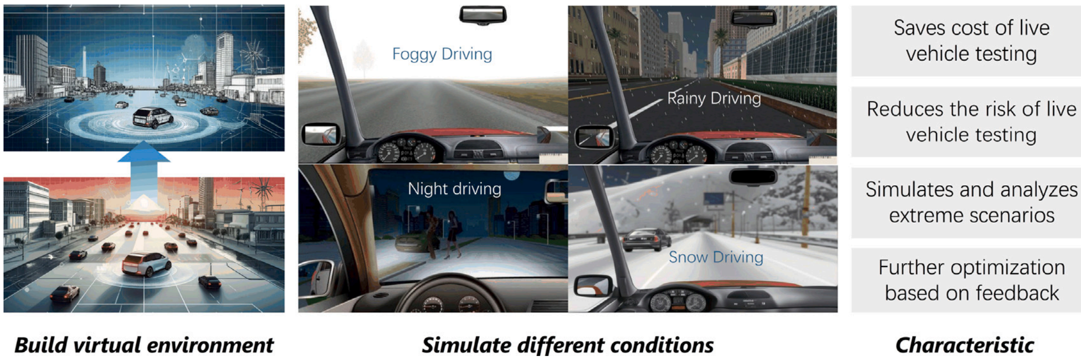

Fig. 9. Digital twin assisted autonomous driving applications.

Table 9
Comparison of digital twin applications in autonomous driving.

Ref.	Problem	Method	Exp.	Metrics	Innov.	Lim.
[115]	Reduce sim-to-real gap	Sim2Real /DT/Parallel Intelligence	CARLA/ LGSVL/SUMO	–	Summarize three simulation paths	Lack unified modeling framework
[116]	Hybrid-reality DT testing	DT/ Collision /Virtual Scene	Unity3D /BYD EV /Changan Univ.	Traj. consistency/ Collision accuracy/Packet loss	Real-time interaction with virtual traffic	Stability under high sampling rates
[117]	High cost	DT/RL /Scenario Sim.	MATLAB/ Simulink /CANoe	Braking dist. /Growth /Degradation time	Auto-adjust model precision by scenario	Low frame rate in complex scenes
[119]	Image segmentation	DT/ Neural Network	PASCA LVOC/ NYUDv2 /Real Scenes	Train time /Inference /SpeedUp	Hybrid addressing strategy	Needs pre-labeled data

training time reduced to 107s and testing time to 0.70 s, demonstrating a significant acceleration rate [117]. However, most of these methods focus on specific communication conditions or constrained scenarios. How to extend them to larger-scale and highly dynamic open road environments remains a critical challenge that requires urgent resolution. With the growing demand for testing, Shoukat et al. developed an open digital twin testing platform, integrating simulation tools, communication devices, and real-world test vehicles, creating a test environment combining the virtual and real, further expanding the application scope of digital twins [118]. Meanwhile, Lv et al. optimized image segmentation models in autonomous driving environments using deep learning and digital twin technology, enhancing visual recognition and information processing capabilities in complex scenarios, demonstrating the strong role of digital twins in algorithm optimization [119]. Additionally, Kaur et al. designed a DT-based vehicle performance evaluation and prediction model, integrating Naive Bayes, spatio-temporal mining, regression analysis, and recurrent neural network techniques, achieving high-precision, low-latency real-time performance evaluation, providing important support for the performance optimization of autonomous vehicles [120]. This series of studies gradually established the foundation for digital twin testing, from closed scenarios to complex environments, covering performance evaluation, algorithm optimization, and real-time prediction, providing strong support for the verification and optimization of autonomous driving technology. It is evident that current research primarily focuses on the feasibility of methods and localized optimizations. However, there remains a lack of long-term stability validation and universality in complex interactive scenarios, which also presents avenues for future research expansion.

To better illustrate the characteristics of representative studies, Table 9 summarizes the comparative analysis of digital twin applications in autonomous driving. As observed from the table, these applications primarily focus on three directions: simulation-to-reality verification, physical–virtual integrated testing, and perception-decision optimization. Existing studies have also achieved significant improvements in model accuracy and testing efficiency via strategies such as multi-path simulation and real-time virtual interaction. However, beyond issues including the lack of a unified modeling framework, insufficient stability under high sampling rates, low frame rates in complex scenarios, and reliance on pre-annotated data, current research still confronts two key challenges. First, virtual testing has limitations: pure virtual scenarios struggle to replicate the dynamic interaction characteristics of real-world roads, and the mechanism for physical–virtual joint testing requires further refinement. Second, large-scale high-dynamic scenarios face a data validity issue: data redundancy or gaps often arise during scenario construction, and solutions for ensuring data validity remain underdeveloped.

These issues underscore the core bottlenecks, which demand efficient module integration, enhanced algorithm versatility, and improved environmental perception. It is also essential to strengthen the data processing capability of cloud–edge computing optimization while achieving breakthroughs in physical–virtual joint testing and large-scale scenario data governance technologies. Additionally, system integration and algorithm versatility should be further polished to support efficient and secure testing in complex autonomous driving scenarios.

3.6. Research gaps and open challenges

Based on the analysis of digital twin applications in the five key areas of transportation in Section 3, current research on digital twin transportation systems has achieved breakthroughs in local scenarios. However, from the perspectives of technology implementation and system upgrading, there remain cross-domain common gaps and urgent open challenges, which can be specifically summarized into the following four categories.

3.6.1. Data credibility and synchronization bottleneck

Signal optimization in traffic flow management, physical–virtual joint testing for assisted autonomous driving, and resource scheduling in the IoV all take the credible integration and real-time synchronization of physical–virtual data as the core prerequisite. The accurate mapping of physical entities by digital twins highly relies on data fidelity, which stems from the consistency and reliability of data throughout the entire process from collection to application. Once data credibility or synchronization is insufficient, it will directly lead to disconnection between the virtual model and the physical scenario, thereby rendering subsequent decisions valueless. Current research has two major shortcomings. First, the integration of multi-source data is incomplete: data sources such as traffic flow sensors, V2X devices, and autonomous driving simulation platforms exhibit heterogeneous formats and inconsistent semantics. Moreover, in scenarios with sparse sensors (e.g., mountainous road sections) or missing data, a full-link credible mechanism covering collection, verification, and privacy protection has not been established. Second, balancing synchronization accuracy and efficiency is challenging: in dynamically complex and open road environments, data transmission latency tends to exceed the decision-making tolerance threshold. Meanwhile, secure synchronization technologies such as blockchain introduce additional computational overhead, further exacerbating the contradiction between synchronization requirements and system security.

3.6.2. Model generalization and adaptation under complex scenarios

Existing digital twin models are mostly designed for single scenarios or homogeneous conditions, lacking universal adaptability to complex transportation environments. On one hand, the cross-scenario migration capability of models is weak: road network models developed for a single city in transportation planning cannot be well adapted to regions with different climates and road network characteristics. In assisted autonomous driving, the accuracy of simulation models developed for closed test fields decreases significantly in mixed traffic flows on open roads, and a unified modeling framework to support scenario migration is lacking. On the other hand, the accuracy-efficiency contradiction in large-scale scenarios is prominent: when deep learning models for traffic flow management and global resource scheduling models for the IoV cover large-scale road networks or multiple auxiliary devices (e.g., UAVs, satellites), they need to balance model complexity and edge computing power. Existing distributed optimization solutions still struggle to meet the real-time requirements of large-scale scenarios while ensuring model accuracy, making it difficult for models to fully function in practical deployment.

3.6.3. Lack of multi-dimensional collaborative protection

Although studies in the field of transportation security have introduced technologies such as blockchain and lightweight encryption, most focus on single-dimensional protection and fail to form a full-stack security system covering physical entities, virtual models, and data privacy. For example, some studies only focus on encryption protection in the data transmission link but ignore the tamper resistance of virtual models and the security protection of physical entities (e.g., vehicle ECUs), resulting in global security vulnerabilities in the system. In addition, the ability to respond to overlapping multi-risks is weak: existing solutions are mostly designed for single risk sources; when facing scenarios with multiple vehicles and coexisting multiple risks, a unified risk assessment framework to integrate multi-dimensional threat information is lacking, making it difficult to accurately identify the correlation and impact scope of risks, and thus unable to formulate effective collaborative protection strategies.

3.6.4. Standardization and integration gap

The large-scale application of digital twin transportation systems needs to overcome the constraints of domain barriers and lack of standards. On one hand, cross-domain collaboration is insufficient: the integration of digital twins is weak in transportation planning with those in fields such as energy and environment, and an integrated transportation-city optimization paradigm has not been formed. For instance, the planning of electric vehicle charging infrastructure is not fully combined with the dynamic adjustment of traffic flow, leading to low resource allocation efficiency. In IoV resource scheduling, the global collaboration framework is yet to be improved for vehicle–road–cloud–auxiliary devices, leaving room for enhancing resource utilization under high-load scenarios. On the other hand, the technical standard system is lacking: specifications for digital twin model construction and data interaction protocols vary across different studies, making it difficult to reuse simulation models for traffic flow management and testing platforms for autonomous driving. This not only increases repeated investment in technology research and development but also significantly raises the cost of large-scale implementation of digital twin transportation systems.

4. Digital twin transportation future outlook

Although DT has already demonstrated tremendous potential in the current transportation field, the application scenarios and opportunities for innovation will become even more expansive and profound with the continuous advancement of technology. Next, we will explore the future development directions of DT technology in transportation systems and discuss potential technological breakthroughs and application scenarios.

Multi-dimensional Development: Although there has been discussion on applying DT in simulation and testing for autonomous driving, we can further explore how AI can be deeply integrated with DT. For example, future DT models will simulate traffic flow and vehicles and learn and optimize behavior patterns through AI, providing more intelligent traffic management and decision-making systems. These advanced digital twins will possess self-learning and adaptive capabilities, continuously optimizing models based on changes in real traffic conditions.

As DT technology progresses, edge computing will become increasingly important. Current discussions focus on cloud computing and high-performance computing. However, we can further explore how edge computing enables local real-time processing and analysis, alleviating central server load, cutting latency, and enhancing decision-making efficiency. For instance, edge nodes can optimize routes and traffic signals through real-time computation to address sudden incidents in autonomous driving and intelligent traffic management.

Multi-dimensional Collaboration and Integration: In the transportation field, DT is not just about technological innovation; it requires deep collaboration with urban planning, environmental science, sociology, and other disciplines. In the future, transportation DT can integrate with other fields of DT technologies (e.g., energy, communications, and environmental monitoring) to form cross-industry integration. For instance, transportation DT can be combined with energy twins to optimize the deployment of electric vehicle charging infrastructure and energy management, achieving cross-industry collaborative optimization and improving the sustainability and intelligence of overall city systems.

It is not just about optimizing individual twins; future DT systems can explore how to achieve cross-tier collaboration, that is, coordination between different levels of twins (e.g., vehicles, traffic facilities, city management centers). By leveraging data flows and control strategies across different tiers, a more comprehensive traffic management system can be realized, improving the overall efficiency of urban traffic.

Personalized Services and New Business Models: DT technology can combine real-time traffic data with personalized user demands to provide customized travel services. For example, future transportation systems can optimize public transportation and offer optimal route planning for personal vehicles and shared mobility services, adjusting strategies based on real-time traffic conditions. The most optimal travel plan can be offered to each user through DT's real-time simulation capabilities.

The widespread application of DT technology will also drive new business models in the transportation field. For example, the Transportation as a Service (TaaS) model based on DT allows users to no longer own vehicles but instead use shared transportation tools or services in real-time through DT system scheduling and predictive capabilities. DT technology can provide insights into vehicle demand, optimal scheduling, and business maintenance strategies, improving efficiency and reducing operational costs.

Deep Data Privacy and Security Challenges: As more and more traffic data is collected, stored, and utilized by DT technology, data privacy and cybersecurity will become critical challenges. Future discussions can delve into how DT systems can ensure data privacy and security, especially when dealing with connected vehicles and large-scale traffic flow monitoring, addressing complex cyber-attacks and data breach risks. Blockchain and other distributed technologies may be a potential solution for the future, ensuring data security and privacy protection through decentralized methods.

Public trust in transportation DT systems will be key to widespread adoption. In the future, more transparent data usage and decision-making processes may need to be developed to ensure users' trust in the system. For example, developing a visualized DT interface could allow users to see how the twin system makes decisions and how their data is protected.

Enhancing Interaction and Experience: As DT systems become more complex, how to enable users to interact with the system intuitively and conveniently will become a key issue to be addressed in the future. Discussions can focus on developing intelligent user interfaces (e.g., AR/VR technologies) to provide convenient tools for traffic managers, policymakers, and the general public, facilitating real-time visualization and predictive analysis of complex traffic systems.

Future DT systems should have robust real-time feedback capabilities. By collecting user feedback data, the management and services of the traffic system can be dynamically optimized. For example, users can report traffic conditions via mobile devices or smart terminals, and the system can respond in real-time by adjusting traffic signals or travel suggestions, thereby improving user experience and system efficiency. Conclusion

Overall, DT technology will be a powerful tool in the future of transportation, building safer, more efficient, and sustainable systems while driving the industry toward greater intelligence and data-driven operations. As technology advances, DTs are anticipated to increasingly contribute to addressing transportation challenges and enhancing urban sustainability.

5. Conclusion

Digital twin technology, as an emerging technological tool, has demonstrated significant potential in the transportation sector. Through our research, we have delved into the basic concepts of DT technology, constructed a 5 + 2 model for digital twin transportation, and proposed a five-layer architecture for digital twin transportation. We conducted an in-depth literature review on the application of DT in various aspects of transportation. These applications cover various facets of transportation systems, providing transportation management authorities with more intelligent and precise management methods, thereby enhancing transportation systems' operational efficiency and safety. However, the application of DT technology in the transportation sector still faces numerous challenges, including multi-dimensional collaboration and cross-industry integration, personalized services, deep privacy protection. Therefore, further in-depth research and exploration are needed to address these challenges and promote the widespread application of DT in the transportation domain.

CRediT authorship contribution statement

Ling Xing: Supervision, Funding acquisition, Conceptualization. **Bing Li:** Writing – review & editing, Writing – original draft, Data curation. **Kaikai Deng:** Methodology, Investigation, Formal analysis. **Jianping Gao:** Supervision, Project administration, Conceptualization. **Honghai Wu:** Supervision, Formal analysis, Conceptualization. **Huahong Ma:** Methodology, Investigation, Formal analysis. **Xiaohui Zhang:** Resources, Methodology, Investigation, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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