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Review

Digital Twin Technology in Transportation Infrastructure: A Comprehensive Survey of Current Applications, Challenges, and Future Directions

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Abstract: Transportation infrastructure is central to economic development and the daily lives of citizens. However, rapid urbanization, increasing vehicle ownership, and growing concerns about sustainable development have significantly heightened the complexity of managing these systems. Although digital twin (DT) technology holds great promise, most current research focuses on specific areas, lacking a comprehensive framework that spans the entire lifecycle of transportation infrastructure, from planning and construction to operation and maintenance. The technical challenges of integrating different DT systems remain unclear, which to some extent limits the potential of DT technology in the management of transportation infrastructure. To address this gap, this review first summarizes the fundamental concepts and architectures involved in DT systems for transportation infrastructure, such as roads, bridges, tunnels, and hubs. From a lifecycle perspective, DT systems for transportation infrastructure are categorized based on functional scope, data integration methods, and application stages, and their key technologies and basic frameworks are outlined. Subsequently, the potential applications of DT in various lifecycle stages of transportation infrastructure—planning and construction, operation and maintenance, and decommissioning and renewal—are analyzed, and current research progress is reviewed and discussed. Finally, the challenges and future directions for achieving a full lifecycle DT system for transportation infrastructure, encompassing technical, operational, and ethical aspects, are discussed and summarized. The insights gained herein will be valuable for researchers, urban planners, engineers, and policymakers.

Keywords: transportation infrastructure; digital twin (DT); project lifecycle; DT use

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1. Introduction

Transportation infrastructure is at the core of an economy's development and the general life of civic societies. At the same time, rapid urbanization, the growing ownership of vehicles, and concerns for sustainable development have led to a rise in complications in managing these systems. For example, the transportation network in China comprises approximately 5.35 million kilometers of roads and 155,000 km of railways. All these put together create a vast network that faces many challenges, like the severe congestion of traffic, inequalities in the standards of infrastructure, and increasing maintenance costs [1]. The population and number of vehicles have registered a steep increase, especially in urban areas, putting a heavy burden on the available infrastructure. The need for such infrastructure far exceeds the supply, causing traffic jams that continue to worsen day by day, which are a waste of time and energy and are also contributory factors to environmental pollution. Added to this is the abominable condition of the roads, insufficient public transport systems, and inefficient traffic management that further worsen the problem [2]. However, traditional methods of infrastructure management are for the most part reactive; for instance, the damage or congestion of roads usually must reach a critical level before any attempt is made to resolve it. This has been a very costly and inefficient practice that can affect the lifespan and safety of infrastructure [3]. With increasing complexity and scale in transport systems, the need has emerged to adopt more innovative approaches, like digital twin (DT) technology, which may help enhance transportation infrastructure management, monitoring, and maintenance.

1.1. Digital Twin Technology in Transportation Infrastructure

Originally developed for product lifecycle management, DT technology has since evolved into a versatile tool with extensive applications across various sectors, including manufacturing, healthcare, and notably, transportation infrastructure. In recent years, advancements in this technology have facilitated more efficient and data-driven management of complex systems [4]. A DT is, in principle, a virtual twin of a physical object capable of interacting with real-time data to provide simulations and predictive models. This solution upgrades an integrated approach to the entire asset lifecycle management in an active, data-driven style for critical transportation infrastructure, such as roads, bridges, tunnels, and railways [5]. Compared to traditional transportation infrastructure management technologies, DT technology offers advantages such as real-time capabilities, digitization, and proactive features, enabling more efficient optimization of transportation system operations and bringing positive impacts to national economic and environmental sustainability [6,7]. For instance, most traditional transportation infrastructure relies on routine inspections and manual repairs, which often fail to promptly address sudden failures. For critical structures like bridges and tunnels, DT technology can provide lifecycle data, leveraging historical data analysis and machine learning algorithms to identify potential safety hazards in real time and predict aging and damage trends [8,9]. This allows for proactive maintenance and early estimation of repair needs, avoiding sudden shutdowns or severe failures. Not only does this extend the service life of transportation infrastructure, but it also further reduces maintenance costs. Additionally, DT technology for transportation infrastructure can provide multi-dimensional information queries and early warnings regarding road network operation status, bridge and road construction status, sudden safety incidents, and air visibility through cloud platforms, helping travelers save time on their journeys [10]. Undoubtedly, this significantly contributes to reducing energy and water consumption, raw material extraction, and greenhouse gas emissions [11].

Hitherto, most of the research on DT technology for transport infrastructure has focused on four key areas, including infrastructure modeling and simulation [12–16], real-time monitoring and management [17–20], predictive maintenance [21–23], and safety management [24–27]. Based on the literature summarized above, a schematic diagram of the urban transportation infrastructure digital twin platform architecture was developed and is presented in Figure 1. In terms of infrastructure modeling, over the years, 3D models of roads, bridges, tunnels, and railways that can simulate real conditions to support infrastructure design and planning optimization have been developed by researchers [12–16]. These models allow planners to predict traffic flows, identify bottlenecks, and assess the possible achievements of different construction and maintenance strategies [5,12]. Equally important is the real-time monitoring and management of transportation systems using DT technology. There is increased utilization of sensor networks and the Internet of Things (IoT) to capture data on real-time traffic conditions, vehicle speeds, and the usage of roads [17,18]. All this information is then integrated into digital models to continuously monitor the performance of transportation infrastructure and provide insights into areas that require maintenance or improvement. Advanced machine learning techniques in predictive analytics allow for proactive decision-making that may reduce downtime and improve overall system efficiency [19,20]. Another key research area is that of predictive maintenance, whereby models of DTs are used to simulate the condition of diverse transportation assets. Through real-time data analysis, DT can identify whether and when an asset—a bridge or a tunnel—is likely to fail or require maintenance, thus enabling timely interventions that can prevent expensive repairs and minimize accidents. This proactive approach to infrastructure maintenance can significantly reduce the cost for maintenance and enhance safety [21–23]. Finally, safety management is a continuously covered field of research. DT technology allows for the simulation of accidents and dangerous situations in traffic, thus giving an impressive view of potential risks. This helps authorities take necessary precautions to avoid those risks by adjusting the timing of traffic lights, redirecting the flow of vehicles, or improving the conditions of the roads [24–27].

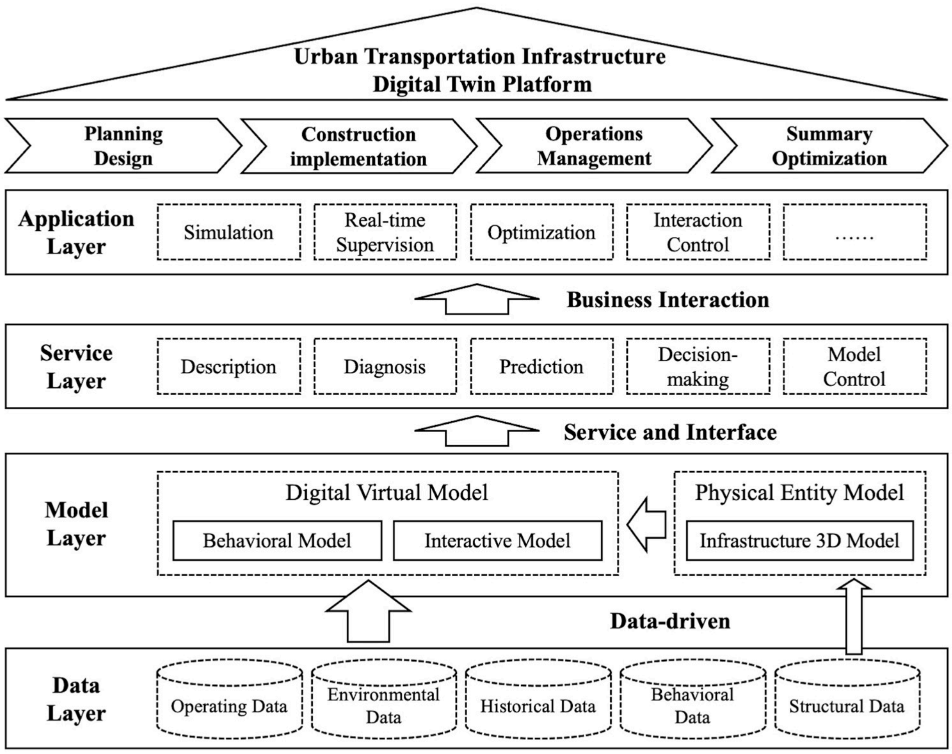

Figure 1. Schematic diagram of urban transportation infrastructure digital twin platform architecture (inspired by and summarized from the literature [12–27]).

1.2. Motivation and Research Gap

Although DT technology holds immense promise, its implementation to date is in its relative infancy regarding transportation infrastructure. Large measures of most of the ongoing studies address specific areas of interest, such as either traffic management systems or monitoring infrastructure health, with studies being confined for the most part to individual components of the transportation network [28,29]. For example, some DT models simulate road conditions to predict bottlenecks or hotspots of congestion, while applications continuously monitor the structural health of bridges and tunnels. In addition, most current implementations are narrow and focus more on specific use cases than on providing an overall integrated solution for managing transportation infrastructure [30]. DTs will need to be developed further through collaboration among researchers, policymakers, and stakeholders on strategic issues like data integration, real-time processing, and standardization [31]. This collaboration among several stakeholders is very important in the context of this research in overcoming specific technical and logistical problems associated with the implementation of DT systems. The approach would be much more comprehensive if it considered all aspects of the lifecycle of transportation systems—from urban planning and construction to ongoing operation and maintenance. However, to realize the full potential of DT technology, more research is needed on the integration of such systems across all phases of infrastructure development and operation. In such a holistic approach, there will be the opportunity to better coordinate various stages in managing the transportation system, thereby developing more effective strategies for planning, construction, and maintenance. DT technology can facilitate optimal resource allocation, reduce downtime, and thus drastically cut lifecycle costs by incorporating insights from various stages of transportation infrastructure management.

1.3. Objectives and Organization of the Review

This review seeks to address this gap by delivering an in-depth analysis of the present state of DT applications in transportation infrastructure. It examines the conceptual framework, key components, challenges, and future directions of DT technology, providing valuable insights for researchers, urban planners, engineers, and policymakers. A full lifecycle perspective is adopted to ensure a thorough understanding of both the broad benefits and limitations associated with DTs in transportation systems.

The rest of this paper is organized as follows: Section 2 introduces the literature review method (SLR), search strategy, and eligibility criteria adopted in this study. Section 3 provides a conceptual overview of DTs in transportation infrastructure, defining key principles and assessing the current state of these systems. Section 4 introduces a new taxonomy tailored for transportation-related DT systems, detailing their diverse applications. It also explores the core components of DTs, such as data integration, simulation models, 3D visualization, and system architecture. Section 5 discusses how DT technology manages assets throughout their lifecycle. Section 6 reviews current applications of DTs in urban planning, traffic management, and infrastructure maintenance, supported by case studies. Section 7 addresses the main challenges of DTs in transportation infrastructure and highlights future research directions. Section 8 concludes the survey by summarizing key insights and implications for future developments.

2. Methodology

This study adopts a systematic literature review (SLR) to explore the applications of digital twin (DT) technology across different stages of transportation infrastructure. By adhering to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [32], we ensure a transparent, rigorous, and reproducible process. Both quantitative and qualitative methods are applied to locate, assess, and synthesize the existing body of knowledge.

2.1. Research Design

The SLR identifies, screens, and evaluates academic publications on DT technology in transportation infrastructure, focusing on various phases of the infrastructure lifecycle—namely, planning, construction, operation and maintenance (O&M), and decommissioning or renewal [33,34]. Through its structured approach, the SLR aims to reduce selection bias and enhance reproducibility [35]. The framework offers both a high-level statistical overview and a more detailed thematic synthesis, thereby covering the breadth of DT research and the depth of technical and thematic insights across multiple lifecycle stages [36,37].

2.2. Search Strategy

This study employed a multi-database search strategy to comprehensively capture the interdisciplinary scope of digital twin (DT) applications in transportation infrastructure [35]. Specifically, we searched Scopus, Web of Science, and IEEE Xplore—well-established databases recognized for their wide coverage of peer-reviewed journals and conference proceedings [38]—and supplemented these results with Google Scholar to address any potential gaps. Building on prior conceptual analyses of DT technology, transportation infrastructure, and lifecycle management [4,36,39], we constructed a Boolean search query that combined terms like "digital twin*" and "information system*" with infrastructure-related keywords (e.g., "transportation infrastructure", "structure maintenance") and lifecycle concepts (e.g., "planning", "maintenance"). We imposed no strict date limits in order to include both foundational DT concepts and recent advancements (2020–2024) [4] and then performed an initial screening of the articles to confirm their relevance to DT applications in transportation infrastructure.

2.3. Eligibility Criteria

To refine the initial pool of literature, we established inclusion and exclusion criteria to ensure the selection of high-quality, thematically relevant studies. Specifically, we included peer-reviewed articles, conference papers, and recognized book chapters that explicitly focus on DT technology within transportation infrastructure—covering roads, bridges, tunnels, and railway systems [10,40–42]—and that are published in English to maintain conceptual consistency. Documents in other languages were excluded to avoid potential linguistic issues, as were purely theoretical studies lacking empirical or case-based evidence. Similarly, research focusing on manufacturing, healthcare, or aerospace was omitted unless it clearly connected to transportation. In addition, any material lacking accessible full-text or critical data was excluded. By applying these criteria, we ensured that only well-founded and relevant investigations of DT applications in transportation infrastructure across multiple lifecycle stages were retained [33,34].

2.4. Paper Selection

Following the PRISMA guidelines [35], we implemented a multi-phase screening process. An initial search across Scopus, Web of Science, and IEEE Xplore produced 1582 records. After removing 327 duplicates—using both EndNote's automated tool and manual checks—1255 unique items remained. A preliminary review of titles and abstracts then led to the exclusion of 862 studies that lacked a clear emphasis on DT or transportation infrastructure. From the 393 articles eligible for full-text review, 287 were excluded due to insufficient technical focus, limited transportation relevance, or the absence of a lifecycle perspective. A backward and forward citation analysis of key articles [10,41] uncovered 28 additional publications that met our inclusion criteria, culminating in a final corpus of 134 articles for in-depth study. Through this systematic, step-by-step filtering, we ensured that the corpus aligned closely with the scope of DT-focused transportation research.

3. Conceptual Overview of DTs in Transportation Infrastructure

3.1. Definition and Core Concepts

The concept of digital twin (DT) was first introduced by Michael Grieves [4]. A digital twin is a special type of physical entity or process that is realized through data linkages, ensuring a certain degree of consistency between the physical and virtual states.

It provides a comprehensive perspective on the entire lifecycle of the entity or process, thereby aiding in overall performance optimization. A digital twin uses digital means to create a virtual representation of a physical entity, leveraging algorithmic models, historical data, and real-time data to simulate, predict, validate, and control the entity throughout its lifecycle [33].

In the conceptual model proposed by Michael Grieves [4], the digital twin comprises three core components: the physical product entity in the real world, the virtual product in the virtual space, and the data and information links that connect the virtual and physical products. In the context of transportation infrastructure research and applications, this study defines the core elements as follows: the physical transportation infrastructure in the real world, the virtual model in the information space, and the communication link connecting the two. "Physical transportation infrastructure in the real world" refers to existing or planned infrastructure such as roads, bridges, tunnels, and traffic signal equipment. "Virtual model in the information space" refers to the computer-generated model of transportation infrastructure in the information space, i.e., the digital twin, which not only reflects the appearance, dimensions, and textures of the physical infrastructure but also demonstrates its functions, operational status, and behaviors. The "Communication link connecting the two" serves as the bridge enabling data communication and interaction between the physical infrastructure in the real world and the virtual model in the information space, facilitating real-time data synchronization and information exchange.

In transportation, DTs result in a virtual model, an exact replica of critical physical infrastructure assets. The virtual model is continuously updated with real-time data flows. Consequently, it reflects the current condition of the physical asset at any given moment and can even estimate future conditions [43]. Unlike static models, DTs are dynamic. They evolve continuously as new data from sensors, IoT devices, and weather monitoring systems are integrated [44]. This dynamic nature reveals the condition of the asset at any instant and supports predictive modeling and decision-making related to infrastructure [40].

Furthermore, DT in transportation infrastructure exhibits two core characteristics. The first is lifecycle integration, which means that it supports every phase of infrastructure management, from initial planning to construction, operation, and maintenance. The second equally vital characteristic is real-time interaction. By connecting DTs with sensors embedded in physical assets, real-time reflections of infrastructure conditions are achieved [45]. This capability enables early warnings and proactive measures beyond mere monitoring. The DT technology stack includes machine learning algorithms, AI, cloud computing, and 3D modeling [39]. Advanced data analytics enable DTs to process vast amounts of information from diverse sources, creating opportunities for real-time decision-making and predictive maintenance.

3.2. Six-Dimensional Structure of the DT of Transportation Infrastructure

The DT of transportation infrastructure typically features a six-dimensional structure, as shown in Figure 2. It integrates physical entities and virtual models through a DT engine to enable real-time data interaction, simulation optimization, and predictive analysis. It represents the physical transportation assets with a very high degree of accuracy in an interactive way. The system allows for the function of real-time data interaction, simulation optimization, and prediction through the DT engine. It covers all aspects of transportation infrastructure, ranging from planning, design, and construction to operation, maintenance, and renewal. In this way, the system provides powerful technical support for the sustainable, intelligent, and efficient development of urban transportation.

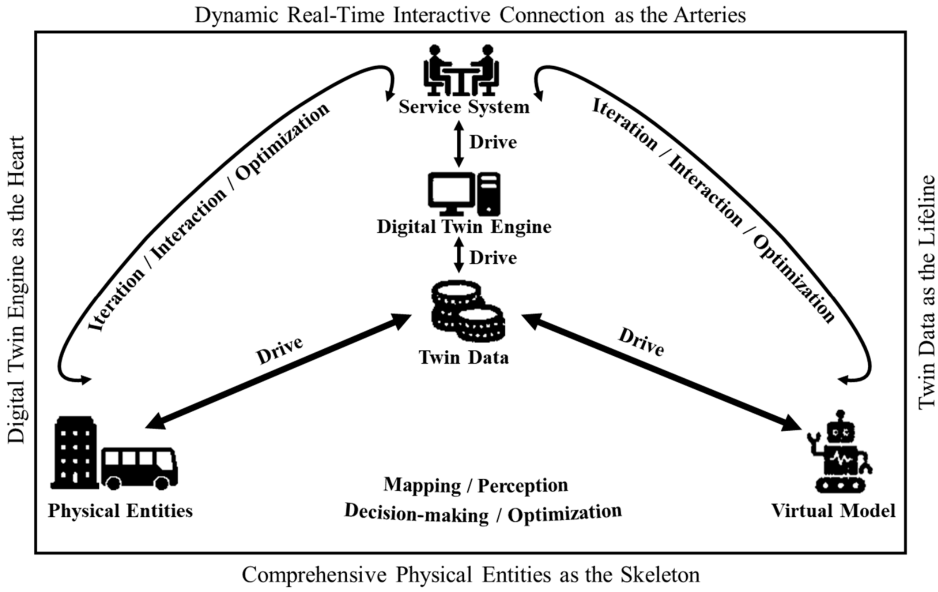

Figure 2. Six-dimensional structure of DT of transportation infrastructure.

At the center could be the physical entity, the backbone of transportation infrastructure in the DT. These include all the transportation-related facilities in the real world: roads, bridges, tunnels, vehicles, bus stations, traffic signs, and more. Each physical entity has specific attributes. For example, a bridge has specific materials, load-bearing capacities, and special lifespan characteristics, while a road differs in width, materials, traffic flow, and maintenance history. Vehicles have model types, speeds, passenger capacity, and emission standards. In fact, these are not just static structures but active dynamic elements closely connected to the life and economic vibrancy of the city through essential data input into the digital model. The DT can thus provide a reflection of the real world in real time using sensors, including cameras, infrared sensors, GPS, accelerometers, and temperature sensors.

The virtual model constitutes the core of the DT, hence providing a very precise DT of physical infrastructure. The virtual model emulates the behaviors, attributes, and interactions of physical entities that enable dynamic simulations of infrastructure performance. The virtual model is not just a simple static 3D representation but encompasses dynamic behavior, mechanical performance, material properties, and environmental interactions of physical entities. This integration enables simulations ranging from traffic flow predictions and congestion forecasting for specific places and times to the performance and reaction of structures under certain loads, as well as long-term maintenance needs. Furthermore, the virtual model is open to connections with other digital models, data sources, and applications, interlinking to constitute an overall digital ecosystem.

Data from twins are basically the lifeblood of this DT system, representing the state, behavior, and environmental context of each physical entity, as well as predictions and feedback that fundamentally drive the whole system. The data also include real-time, continuous input, such as the status of traffic flow, vehicle behavior, and environmental data, which enable the DT to reflect the real world with high precision. Twin data are diverse, heterogeneous, and large-scale in nature since it comes from different sensors and devices, each with different formats and structures. Advanced data processing and analysis capabilities are required to manage and extract meaningful insights from this data, ensuring that the system functions effectively.

The DT engine serves as the driving force for the whole system. Essentially, it processes, analyzes, and interprets data from the twins to realize the real-time synchronous operation of physical entities with virtual models. Simulations, traffic flow optimizations, predictions about future conditions, and intelligent insights will be run on this engine. Advanced algorithms, together with large-scale data analytics, are employed to provide predictive capabilities, thereby allowing for the optimization of signal control and route planning, along with other operational capabilities of the transport system.

The service layer of the DT transforms these capabilities into useful applications for users. The decision support tools and services housed here include traffic monitoring, congestion prediction, accident response, and urban planning. Further services that allow transportation managers and the public to interface with the DT to gain valuable insights into real-time conditions also include traffic monitoring, congestion prediction, accident response, and urban planning. APIs enable the integration of other entities into the system with the help of third-party applications, thus providing flexibility to developers to create new tools based on data and functionality stemming from the DT.

Lastly, the connectivity layer acts as the communication bridge between the physical world and the virtual model, ensuring a seamless flow of data across various system components. This layer maintains real-time synchronization, allowing the DT to accurately reflect the current state of the physical infrastructure. It is responsible for data integrity and accuracy, utilizing robust protocols and technologies to manage large volumes of data transmission with minimal delay and loss.

Together, these six components form a cohesive network that powers the DT of transportation infrastructure, providing substantial technological support for the continuous, intelligent, and efficient evolution of urban transportation systems.

4. Classification and Core Components of DT Systems in Transportation Infrastructure

4.1. Classification of DT Systems in Transportation Infrastructure

A clear classification would be useful for understanding the diverse nature and applications of DT systems in transportation infrastructure. Most of the existing literature classifies DTs on the basis of either functions or data sources, or even specific application domains [46]. However, these classifications normally render them very limited and do not fully present the potential of DT applications in the transport sector. The new taxonomy to classify DT systems according to functional scope, data integration methods, and application stages is introduced in the following section, providing a well-structured overview. To provide a concise overview of how digital twin (DT) systems are classified in transportation infrastructure, Table 1 summarizes both the functional scope and data integration methods.

Table 1. Classification of digital twin (DT) systems in transportation infrastructure.

	Classification	Key Features	Example	Key Challenges	Refs
By Functional Scope	Monitoring and Control	- Focus on real-time data (sensors, cameras, GPS) - Manages traffic flow and signal timing in real time	Urban traffic control centers dynamically adjusting signal timing [47]	Data heterogeneity, latency in handling large volumes of real-time data [48]	[47–49]
	Simulation and Analysis	- Models and analyzes transportation scenarios (e.g., adding a BRT line) - Requires large datasets and computing	Simulating new BRT routes for road congestion impact [50]	Computational intensity; high-quality input data needed [36]	[36,50]
	Predictive Maintenance and Optimization	- Uses real-time sensor data (stress, vibration) plus historical trends - ML algorithms forecast failures	Bridge health monitoring with embedded sensors [13]	Data integration complexity; need for accurate ML models [41]	[5,13,41]

Table 1. *Cont.*

	Classification	Key Features	Example	Key Challenges	Refs
By Data Integration	Static Data-Based DTs	- Relies on design specs, geographical info, and historical data - Suitable for long-term planning and design	Evaluating new road layouts and materials based on historical usage [51]	Limited adaptability to real-time changes; slower to reflect realities [52]	[51,52]
	Dynamic Data-Based DTs	- Continuously updated from IoT sensors, GPS, weather data, etc. - Enables real-time traffic management	City-wide sensor-driven traffic control and congestion alerts [53]	Ensuring data consistency and low latency at large scales [54]	[53–55]
	Hybrid Data-Based DTs	- Combines static (blueprints) and dynamic (sensor) data - Provides a holistic view for complex networks	Railway DT integrating design data with real-time loads [3]	Complex system integration; requires standard data formats [53]	[3,53]

4.1.1. Functional Scope

DTs in transportation infrastructure can be divided into three main categories based on their primary functions: Monitoring and Control, Simulation and Analysis, and Predictive Maintenance and Optimization.

1. Monitoring and Control

This category deals with the gathering and visualization aspects of real-time data for monitoring infrastructure conditions and managing traffic flow. For example, a DT utilized in an urban traffic management center collects real-time data from IoT sensors, cameras, and GPS devices regarding current traffic conditions to dynamically adjust the timings of traffic signals [31]. Other environmental factors that may also be integrated into DTs for monitoring include weather conditions and public transit schedules, which contribute to a comprehensive view of traffic operations [30]. While these methods effectively aim to reduce congestion, challenges associated with data variety and latency arise during the implementation of such systems [32].

2. Simulation and Analysis

Simulation and analysis-centric DTs allow urban planners and engineers to model different transportation scenarios and analyze the impact of interventions. For example, the transportation department in a city may want to use a DT to simulate the effect of adding a new bus rapid transit (BRT) line on existing road traffic. By taking into account various factors such as passenger demand, road capacity, and traffic signal timings, a DT can provide approximate pre-information on congestion and enable optimizations of route design [33]. However, this requires substantial computational resources to generate simulation models with high-quality input data [36].

3. Predictive Maintenance and Optimization

Predictive maintenance digital twins (DTs) utilize real-time sensor data and historical trends to evaluate infrastructure asset conditions and forecast maintenance requirements. A notable application involves DTs in bridge health monitoring, where embedded sensors collect stress, vibration, and temperature data. Machine learning algorithms process and analyze these data streams to predict structural failures, facilitating proactive maintenance interventions [13]. Real-time sensor data in such systems are typically derived from strategically positioned sensors (e.g., strain gauges, accelerometers, and temperature sensors), which deliver continuous, high-resolution insights into structural integrity. Raw sensor data undergo cleaning and normalization to ensure suitability, followed by feature extraction to identify critical indicators of deterioration. Machine learning models, such as regression algorithms and neural networks, then analyze the processed data to generate predictive outputs. However, predictive maintenance DTs encounter challenges, including data integration, model accuracy, and the computational intensity of real-time large-scale dataset processing [5,41]. These challenges emphasize the necessity for resilient data processing frameworks and scalable analytical tools to develop high-accuracy predictive models.

4.1.2. Data Integration Methods

1. Static Data-Based DTs

These DTs rely heavily on static information, such as design specifications, geographic data, and historical usage patterns. In new infrastructure planning and design, the static data-based DT may simulate the long-term implications of different design choices, such as road layout and material selections [51]. However, these models react poorly to real-world, real-time changes and do not capture the true dynamic nature of these transportation systems [52].

2. Dynamic Data-Based DTs

Dynamic DTs make use of real-time data streams from sensors, IoT devices, GPS systems, and more. They have become vital for every traffic management system, which requires minute-by-minute updates on traffic conditions, the state of the weather, and accidents on roads [53]. The main challenges regarding the integration of dynamic data include the consistency of data, reduction in latency, and handling voluminous real-time data efficiently [54]. Among these problems, edge computing has been proposed to serve the purpose of enabling the local processing of data near the source and reducing constant transmissions to higher-end centralized servers [55].

3. Hybrid Data-Based DTs

Hybrid DTs are built on an integrated view of both static and dynamic data within a more holistic transportation system. For example, a railway network DT might integrate design blueprints, static data, with real-time data on train loads and track conditions to evaluate system health and predict maintenance needs [3]. The net effect is more accurate and flexible modeling, but there is a concomitant increase in integration complexity [53]. Developing standardized data formats and communication protocols is essential for enabling hybrid data integration, although achieving full interoperability remains challenging.

4.2. Core Components of DTs in Transportation

The major development in DT implementation in transport infrastructures can be said to rest on a few core building blocks or components. These components work together in the realization of real-time monitoring, simulation, and prediction. A key issue in discussing how DTs work and challenges in their development and usage is understanding these components. This chapter has identified the main technologies and features that constitute a DT. These include data integration, simulation and prediction models, 3D modeling and visualization, and architecture.

4.2.1. Key Technologies and Features

1. Data Integration and Real-Time Interaction

Data integration provides the backbone for DTs in transportation, merging the physical and virtual worlds. A DT integrates manifold data, which originate from sensors embedded in infrastructure (such as bridges and roads), traffic cameras, GPS devices, and environmental monitoring stations [56]. These different feeds contribute to a clear, real-world perspective on transportation, enabling a holistic lifecycle management approach. Data integration not only serves as the foundation of DTs but also plays a critical role in the lifecycle management of transportation systems. During the design phase, DTs leverage historical and environmental data to optimize system layout and functionality; during the operation phase, real-time data integration provides dynamic updates, enabling real-time monitoring and operational efficiency; during the maintenance phase, data integration supports predictive maintenance, reducing unexpected failures and repair costs; and during the optimization and upgrade phase, data integration offers comprehensive support for decision-making, helping to evaluate system performance and plan future improvements.

Real-time interaction is the two-way flow of data between a physical system and its DT. This ebb and flow allows real-world modifications to be mirrored instantaneously in the DT, which aids in optimizing physical operations through digital insights [57]. For example, a DT with up-to-the-minute data about vehicle flow, road conditions, and weather could automatically adjust traffic signal times and lane usage in traffic light control [58]. Real-time interaction not only enhances operational efficiency but also has a profound impact on other lifecycle phases. During the design phase, real-time interaction enables virtual simulations to test and optimize design solutions; during the operation phase, it allows DTs to dynamically adjust system parameters in response to emergencies; during the maintenance phase, it supports remote monitoring and maintenance, reducing costs and downtime; and during the optimization and upgrade phase, it provides real-time feedback to ensure the effectiveness of improvement measures.

However, one of the significant challenges of data integration is ensuring that this information is accurate and delivered in a timely manner. Wrong or outdated information may lead to incorrect decisions within the transportation system [59], potentially compromising the effectiveness of lifecycle management. For example, inaccurate sensor data may lead to incorrect assessments of bridge structural health, while delayed data may prevent DTs from effectively optimizing traffic flow. Additionally, data consistency issues increase integration complexity, potentially affecting the overall performance of DTs. Advanced techniques, such as machine learning algorithms, are being researched to process real-time data streams for noise filtering and error detection [5]. Edge computing technology can also reduce data transmission delays by distributing data processing tasks to the network edge, thereby improving the efficiency of real-time interaction. Despite these efforts, seamless real-time data integration remains an area needing improvement, as it is critical to achieving the overarching goal of holistic lifecycle management.

2. Simulation and Prediction Models

Simulation and predictive models lie at the heart of how DTs work, enabling the analysis of numerous scenarios and the forecasting of future system states. These models play a critical role in lifecycle management by supporting decision-making across all phases. During the design phase, simulation models allow designers to test and optimize system layouts; during the operation phase, predictive models enable real-time monitoring and optimization; during the maintenance phase, they facilitate predictive maintenance by identifying potential failures; and during the optimization and upgrade phase, they provide data-driven insights for system improvements.

Simulation models have a wide range of applications in lifecycle management. For instance, agent-based models can simulate the behavior of individual vehicles within a road network, enabling transport authorities to predict congestion patterns and test various traffic control strategies [48]. Additionally, simulation models can assess the impact of infrastructure changes, such as the construction of new roads or bridges, on traffic flow. They can also evaluate the effects of environmental conditions, such as weather changes, on transportation systems.

Predictive models are critical for enabling digital twins (DTs) to forecast future scenarios, such as traffic flow volumes, infrastructure degradation, and maintenance or refueling requirements. These models primarily utilize machine learning algorithms—including neural networks, decision trees, and regression models—to identify patterns in historical data and generate actionable predictions. For example, a DT designed for bridge health monitoring integrates real-time sensor data (e.g., stress, vibration, and temperature measurements from strain gauges and accelerometers) with historical maintenance records to predict structural failures, facilitating proactive interventions [35]. The selection of data sources is guided by their capacity to capture long-term degradation trends and real-time operational conditions, which are critical for ensuring prediction accuracy. To ensure reliability, raw sensor data undergo preprocessing steps such as noise removal, normalization, and feature extraction to identify key indicators of structural health, including abnormal vibration frequencies. However, developing robust predictive models requires access to extensive high-quality datasets, significant computational resources for real-time processing, and ongoing calibration to adapt to dynamic environmental and operational conditions [50]. These challenges underscore the need for scalable data pipelines and adaptive algorithms to improve the efficacy of predictive models in DTs. By integrating data from multiple sources, simulation and predictive models provide a holistic perspective on the lifecycle of transportation systems. These models establish connections between different lifecycle phases, enabling seamless transitions from design to operation, maintenance, and optimization. For example, simulation results from the design phase can inform operational strategies, while predictive insights from the operation phase can guide maintenance and upgrade decisions.

3. Three-Dimensional Modeling and Visualization

Three-dimensional modeling and visualization are pivotal in intuitively representing complex infrastructure systems throughout their entire lifecycle. Digital twins (DTs) leverage advanced technologies such as building information modeling (BIM), geographic information systems (GIS), and light detection and ranging (LiDAR) to create highly accurate 3D models of physical assets [30]. These models not only provide a visual representation of infrastructure but also integrate critical data on material properties, structural health, and environmental conditions, enabling comprehensive lifecycle management.

From the design and construction phases to operation and maintenance, 3D visualization transforms these models into interactive tools. Urban planners, maintenance teams, and other stakeholders can navigate and interact with the DT in real-time, exploring its features and functionalities [38]. For instance, a DT of an urban transportation system can utilize 3D models to simulate traffic flow, allowing urban planners to identify bottlenecks and evaluate the potential impact of capital investment plans [60]. This capability facilitates remote inspections, enabling engineers to assess infrastructure conditions without being physically present, thereby saving time and resources.

However, the application of 3D modeling in DTs is not without challenges. Generating precise and accurate 3D models demands high-resolution data from sources like LiDAR scans and satellite imagery, which can be both costly and technically demanding [61]. Moreover, to maintain the accuracy of these models over time, continuous data updates are essential. This requirement can be particularly challenging in dynamic urban environments where changes occur frequently and unpredictably. Addressing these challenges is crucial for ensuring the long-term effectiveness and reliability of DTs in infrastructure management throughout their entire lifecycle.

4.2.2. System Architecture

Interoperability in the architecture of a DT should be designed to ensure smooth data exchange among different tiers and various subsystems [14]. Standard communication protocols, data formats, and application programming interfaces (APIs) enable seamless integration with external systems, which may include urban planning databases, intelligent transportation systems (ITS), and public transit networks. However, achieving a completely interoperable system is often an extremely complex effort that requires significant coordination among many stakeholders and technologies [62].

The architecture of DTs in transportation is typically structured across several layers: data acquisition, data processing, modeling and simulation, and application. Each tier serves a distinct function within the DT, ensuring the seamless integration of physical assets with their digital counterparts.

- Data Acquisition Tier: This tier gathers raw data from diverse sources, including sensors, IoT devices, GPS systems, and monitoring stations. For example, traffic cameras, road sensors, and weather stations continuously collect data, which are then forwarded to the data processing layer [38].
- Data Processing Tier: In this tier, raw data undergo filtering, cleaning, and conversion into analyzable formats. Sophisticated data processing methods, such as machine learning algorithms, are applied to identify patterns, eliminate noise, and pinpoint errors. Edge computing is sometimes employed to handle data locally, minimizing latency and enhancing system responsiveness [62].
- Modeling and Simulation Tier: This tier houses the core models of the DT, encompassing simulation, prediction, and optimization models. It executes simulations, analyzes scenarios, and generates predictions based on the refined data [3]. Continuous updates to the models maintain the accuracy of the DT.
- Application Tier: The final tier includes tools and applications for operators, planners, and maintenance teams. It features user interfaces, visualization tools, and control systems that enable stakeholders to interact with the DT, conduct simulations, monitor infrastructure conditions, and make informed decisions [60].

The architecture of a DT must be interoperable. Seamless data exchange between different tiers and various subsystems can be ensured only when the basic design itself is interoperable [14]. Standardized communication protocols, data formats, and APIs integrate these with third-party systems, such as urban planning databases, ITS, and public transit networks. However, building a fully interoperable system is complex and often involves coordination at multiple levels among several stakeholders and technologies [62].

Considering the core components of a DT, these could include data integration, simulation models, 3D visualization, and system architecture. At this point, it establishes a foundation for providing a well-functioning management and optimization platform for transportation infrastructure. A DT combines real-time data with advanced analytics, thereby offering proactive decision-making that keeps transportation systems safe, efficient, and sustainable [63].

4.3. Basic Framework of DTs of Urban Transportation Infrastructure

As shown in Figure 3, this study provides a comprehensive framework for digital twins (DTs) in urban transportation infrastructure—a "4 Horizontal + 4 Vertical + N" model that spans the entire lifecycle of the infrastructure, from planning and design to operation, maintenance, and decommissioning. The framework ensures not only the functionality of the system but also its adaptability and long-term sustainability. The four horizontal layers are described below in terms of the full lifecycle.

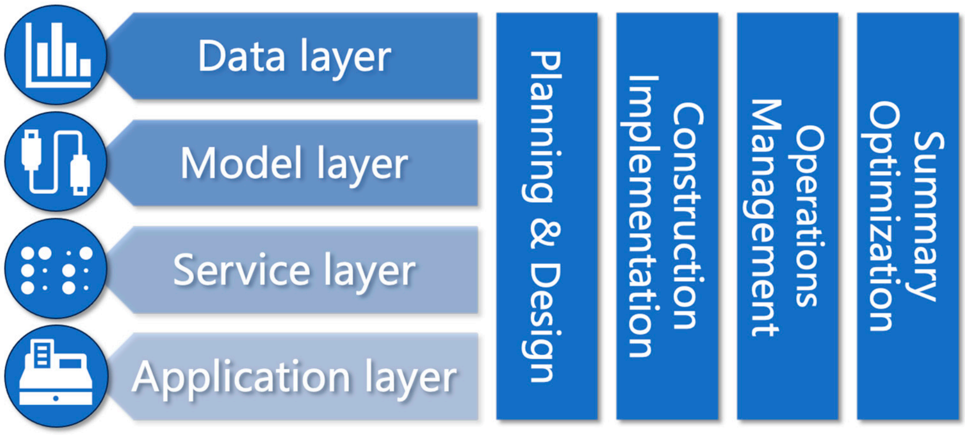

Figure 3. "4 horizontal + 4 vertical + N" DT framework for urban transportation infrastructure.

4.3.1. Four Horizontal Layers

1. Data Layer

The data layer serves as the foundational layer throughout the lifecycle of urban transportation infrastructure. It is responsible for collecting, integrating, and processing both dynamic and static data from physical entities. This layer evolves as the infrastructure progresses through the following lifecycle stages:

- Design and Construction Phase: During this phase, the data layer primarily focuses on structural data, such as the geometric and material properties of bridges, roads, and tunnels, which are critical for ensuring that the infrastructure is built to specifications. Environmental data, such as soil conditions and weather patterns, is also collected to inform design decisions.
- Operation Phase: In this phase, the data layer shifts its emphasis to operational data (e.g., traffic flow, speed, and congestion) and environmental data (e.g., temperature, humidity, and pollution levels) captured by sensors. These datasets provide real-time insights into the performance of the infrastructure and its interaction with the environment.
- Maintenance and Decommissioning Phase: Historical data become crucial here, as they enable trend analysis and predictive maintenance. For example, historical traffic and incident records help identify patterns that inform maintenance schedules. Behavioral data, which record the interaction patterns of traffic participants, are also vital for optimizing traffic management and ensuring safety.

Throughout the lifecycle, the data layer ensures that the virtual models in the DT system are continuously updated with accurate and relevant data, which enables precise predictions, simulations, and decision-making.

2. Model Layer

In the digital twin's model layer, complex virtual models of transportation infrastructure are created and maintained. These models are not just 3D replicas of physical entities but dynamic models that integrate detailed behaviors and interactions to simulate and predict how the transportation system will operate. These model layers take inputs from the data layer, and the data-driven model-based models provide decision-makers with insights through real-time simulation and behavioral predictions to help them understand and anticipate challenges that the transportation infrastructure may face. As the full infrastructure lifecycle progresses, the digital twin's model layers play a critical role at different stages: in the planning and design phase, simulation analysis helps assess the feasibility of different design options and predict traffic bottlenecks or structural weaknesses; in the construction phase, the real-time monitoring of construction progress and quality ensures that the construction complies with design specifications; Confirm, the original text can be modified as follows Confirm, the original text can be modified as follows. The real-time updating and adjustment mechanism of the model layer makes it possible not only to command and optimize traffic flow through the control model but also to intelligently manage the traffic system in a changing environment, ensuring the optimal management of the infrastructure under changing traffic loads and external environments. This dynamic updating mechanism makes the digital twin not only a static monitoring tool but also an intelligent system with predictive capability and adaptive optimization to support the sustainable development of transportation infrastructure and provide decision-makers with full lifecycle management support.

3. Service Layer

The service layer is a critical transformation layer in the digital twin, ensuring that outputs from the model layer can be effectively applied to the application layer. It provides key services and interfaces for translating complex data analysis and model predictions into actionable operations and decision support. The core functions of the service layer include description, diagnosis, prediction, decision support, and control of the digital twin. In the context of full lifecycle management of infrastructure, the service layer is not just an analytical tool but a dynamic system that can directly determine and optimize real-world operations. By integrating data and predictive information from all phases of planning, design, construction, operation, and maintenance, the service layer is able to provide immediate decision support at all lifecycle stages, driving intelligent management of infrastructure. In the planning and design phases, the service layer provides constructive advice to decision-makers through diagnostics and predictive analysis; in the construction phase, it monitors construction progress in real time and proposes optimization solutions; in the operation phase, the service layer ensures the efficient execution of traffic flow, resource allocation, and maintenance operations through real-time data feedback and dynamic decision support; and in the maintenance phase, it analyzes the health status of infrastructures and optimizes resource allocation to achieve proactive maintenance. Through this continuous optimization and decision support, the service layer plays a bridging role in the whole lifecycle of transportation infrastructure, transforming the prediction and control capabilities of the model layer into actual operation and management results.

4. Application Layer

The application layer is the final layer of the digital twin, with which the user interacts directly. It supports functions such as simulation, real-time monitoring, predictive optimization, active control, and virtual testing. In this layer, decision-makers and operators can intuitively apply the data and analytics provided by the service and model layers to optimize the performance and response of the transportation system. The application layer not only translates the digital twin into actionable practices but also ensures that the benefits associated with transportation management are effectively applied in the real world. By using this layer across the entire lifecycle of transportation infrastructure, decision-makers are able to make accurate decisions based on real-time data and predictive information during the planning, design, construction, operation, and maintenance phases. For example, in the planning phase, the application layer supports decision-makers in evaluating the effectiveness of different transportation scenarios; in the operation phase, the application layer helps to optimize traffic flow and resource allocation; and in the maintenance phase, it provides intelligent scheduling and proactive management recommendations to extend the service life of the infrastructure. By translating the predictive analytics and control functions of the modeling and service layers into real-world operations, the application layer facilitates the efficient management of transportation systems at different lifecycle stages and ensures the practical application and sustainability of digital twin technology in urban transportation management.

4.3.2. Four Vertical Phases

The vertical layers represent the four key stages of the DT's lifecycle in urban transportation infrastructure as follows:

DTs simulate different scenarios during planning and design and assess the resultant impacts on improved traffic flow and environmental sustainability. The foundation that is laid at this stage forms the lifecycles of the infrastructure through the provision of tools for informed decision-making in designing new or improved transportation systems.

DTs will also enable the constructor to monitor minute details of progress and quality control in real time during construction to ensure that the infrastructure is built according to the specified design. With sensor data integrated into the DT, it identifies possible issues or deviations from the plan in advance, before these issues become major ones, thereby improving construction efficiency and safety.

Once operational, these infrastructures play a very important role in ongoing monitoring and predictive maintenance with DTs. Through continuous data acquisition and analysis, DTs determine the optimization of the operation of transportation systems, predict maintenance needs, and improve the safety and dependability of infrastructure. Predictive models can reduce operational costs by averting breakdowns and elongating the lifecycle of assets.

The third and final stage is one of continuous improvement—providing feedback throughout the aforementioned stages—of the infrastructure. DT models allow for post-implementation analysis, enabling urban planners to optimize infrastructure performance and make data-driven decisions concerning future upgrades or redesigns. This process helps ensure that transportation infrastructure adapts and evolves in response to the demands for and challenges to long-term sustainability.

4.3.3. "Form-Condition-Mechanism-Tendency" Concept

Alongside the "4 horizontal + 4 vertical + N" framework, the "Form-Condition-Mechanism-Tendency" concept further refines the DT system's ability to manage urban transportation infrastructure as follows:

- Form (Digital Reconstruction): This component describes the infrastructure's physical shape, structure, and geometric properties. High-precision 3D modeling is essential to mirror the physical entities accurately. This phase also develops digital representation rules and databases that retain the unique attributes and characteristics of the infrastructure.
- Condition (Precise Mapping): This layer represents the infrastructure's current operational state, dynamic responses, and performance under specific conditions, such as wear and tear, health status, and potential risk factors. By integrating performance monitoring and holographic sensing technologies, the system provides real-time insights into the health of the infrastructure.
- Mechanism (Mechanistic Deduction): This element analyzes the infrastructure's detailed functioning and performance, including reliability and safety. DTs simulate and predict the infrastructure's response to environmental and load conditions, offering deep insights into performance dynamics.
- Tendency (Integration and Feedback): The tendency phase employs data integration to forecast future trends and identify potential issues, aiding urban planners in anticipat-

ing and addressing future challenges. By synthesizing insights from previous layers, the DT delivers a comprehensive view of the infrastructure's performance trajectory.

Incorporating these concepts into the DT framework equips urban transportation systems with a more detailed understanding of infrastructure performance and potential challenges, thereby ensuring continuous optimization and sustainable management.

5. DT Technology in the Lifecycle of Transportation Infrastructure

The entire lifecycle [64] refers to the complete process a product or system undergoes, from design and manufacturing to testing, operation, and maintenance, covering all stages from conceptualization to decommissioning. During the lifecycle, it is highly important not only to focus on initial design and production but also to continuously monitor operation, maintenance, and upgrades to achieve performance, reliability, and safety. The whole lifecycle for DT systems in urban transportation infrastructure includes all phases, starting from the very beginning with planning and design to construction and implementation, followed by operation and management, maintenance and upgrades, and concluding with decommissioning and replacement. In this lifecycle, DT technology can provide comprehensive intelligent services under real-time conditions for transportation infrastructure management and optimization.

Guidance on integrating the technology of a DT into urban transportation infrastructure includes comprehensive innovations. It helps planners intuitively understand the layout and identify strengths or weaknesses in transportation infrastructure through high-precision virtual models during the early planning and design stages. Additionally, it can simulate various problems that may arise, along with outcomes from several alternate plans during real operation to optimize design decisions. During the construction and implementation phase, DT technology, in conjunction with IoT, sensors, and drones, analyzes continuous feedback data, thereby offering real-time capabilities for monitoring construction status and proactive risk forecasting. This allows for the precise management of engineering quality and schedules while minimizing the possibility of human error.

The operation and management phase mainly involves the real-time monitoring and optimization of dispatching in response to the long operational pressures faced by urban transportation facilities due to rapidly growing traffic flow in modern cities. At this stage, DT technology leverages virtual–physical mapping to facilitate the real-time monitoring and dynamic simulation of transportation infrastructure. This ranges from monitoring the flow of traffic and facility conditions to carrying out safety checks to ensure that the whole operation process is continuous, efficient, and safe. Additionally, DT technology offers structural health monitoring for critical structures such as bridges and tunnels that can support the early detection of potential safety hazards, thereby facilitating preventive maintenance. Considering this, by the time of the maintenance–upgrade phase, most conventional transportation infrastructures rely on routine inspections and manual repairs, which usually fail to enable timely responses to sudden failures. Based on historical data analysis and machine learning algorithms, DT technology can predict the aging and damage trends of facilities and provide precise and appropriate suggestions for maintenance in advance in order to avoid sudden downtime or severe failures. This capability extends the service life of transportation infrastructure and further reduces the cost of maintenance.

DTs in the decommissioning and replacement phase assist the city manager in making an accurate assessment of the current condition and future potential of transportation infrastructure—like bridges, roads, and tunnels—when it approaches its design lifespan, presents safety hazards, or no longer meets the demands of modern urban development. This is achieved through detailed analysis in real time as well as historical data. With the help of DTs' virtual simulation capability, it is possible to simulate the impact of decommissioning on surrounding traffic and urban operations in order to come up with a much more reasonable decommissioning plan that ensures safety throughout the process with minimal impact on the city. Additionally, DT technology will enable the identification and planning of resource reutilization, such as recycling specific construction materials or reusing certain infrastructures, and will surely contribute to sustainable development. Replacement Phase: By applying DTs in this phase, it would be possible to virtually test new facility designs and layouts in pursuit of optimal upgrade plans and seamless integration between old and new systems to enhance overall urban transport efficiency. This approach ensures safety and, due to the use of DT technology, guarantees a scientific basis for decommissioning through intelligent comprehensive evaluation and meticulous management. Furthermore, the valuable experiential data obtained from this field will inform the future development of urban infrastructure.

5.1. Planning and Design Phase

During the planning and design phase, transportation infrastructure design must consider complex factors, including traffic flow, topography, environmental conditions, and socio-economic aspects. Traditional methods, which rely heavily on historical data and experience [34], often fail to accurately predict future usage scenarios, presenting several challenges: (a) the lack of comprehensive, sufficient, and effective lifecycle data support hampers the creation of a useful database for design decisions; (b) the complexity of design models and the difficulty in integrating interdisciplinary models; (c) the absence of precise simulation methods makes design validation challenging and time-consuming. To address these challenges, the adoption of dynamic and flexible DT technology facilitates extensive twin data support for establishing a knowledge database and assisting with modeling tasks. Using high-precision DT modeling technology and model fusion theory, the planning and design of urban transportation projects are transformed from traditional two-dimensional drawings and static analyses into dynamic simulation processes based on three-dimensional virtual environments. Additionally, the realistic simulation environment provided by DTs enhances design verification capabilities, accelerates the design process, and improves design accuracy, offering planners an unprecedented intuitive understanding and optimization of design plans.

DT technology spans from preliminary to detailed design, providing services like virtual facility simulation, multi-dimensional visualization, scenario evaluation and optimization, multi-objective trade-offs, decision support, and collaborative design.

By constructing highly realistic virtual models, planners can simulate urban transportation infrastructure operations under various conditions. These models integrate historical and real-time data, encompassing geometric and structural details of physical facilities, as well as traffic flow, weather, 24 h lighting, and volumetric clouds. This method allows for testing different design schemes within a virtual setting, providing an intuitive observation and assessment of their potential performance. For example, DTs simulate traffic flow distribution for various road layouts, helping planners identify congestion points and traffic bottlenecks [65,66]. By combining dynamic population data with traffic flow information, DTs can evaluate the impact of road designs on traffic efficiency and capacity, offering quantitative results [67]. Ref. [68] suggested DTs for scenario generation in large-scale planning across multiple cities, enhancing decision-making. Their study in Ålesund, Norway, demonstrated the benefits of DTs in urban mobility planning. Visualization features in these models include zooming, orbiting, bird's-eye views, panning, roaming, flying, and querying. They support visual scenarios under various conditions, merge real geographic environmental data, and facilitate the integration and interaction of business data related to urban transport in a DT environment. Compared to Building Information Models (BIM), DTs provide a multi-dimensional view by integrating operational data, environmental impacts, and structural behaviors, along with detailed geometric information.

Scenario optimization is a crucial application of DT technology during the planning phase. It allows planners to balance multiple objectives, such as traffic flow efficiency, pedestrian safety, and environmental impact. Through multiple simulations and feedback from DTs, the optimal design can be determined. Ref. [69] introduced an enhanced framework for ITS that uses DTs for spatiotemporal data mining, capturing human travel patterns, and visualizing intersections. DTs employ AI and machine learning to explore the best solutions through extensive simulations and data analysis. In the design of public transportation hubs [70], DTs assess how layout variations affect passenger flow, transfer times, and satisfaction, thereby guiding decision-makers. This multi-objective consideration is essential in complex urban settings involving multiple stakeholders. DTs provide precise data support for achieving optimal outcomes. Ref. [71] developed a sustainable urban road planning method using a DT-MCDM-GIS framework, considering multidisciplinary factors. They applied different weights to various factors, creating multiple road schemes within the limited space of Bromley, London.

Moreover, DTs facilitate collaborative design and decision-making among multiple stakeholders. They enable urban planners, environmental agencies, and citizen representatives to jointly view and discuss design impacts via a shared platform, enhancing communication and reducing potential conflicts caused by information asymmetry.

5.2. Construction and Implementation Phase

For instance, in transport infrastructure construction, such as roads, bridges, and tunnels, problems always occur when prototype design is disconnected from process design, when the components are complicated to manage, and when 2D process documents are unintuitive. DTs integrate physical construction sites with virtual models, offering strong data support and real-time feedback mechanisms [72]. They help in the monitoring of the construction process of transportation infrastructure and continuously update with progress and the consumption of resources. This helps project managers take an effective approach to resource allocation—manpower, machinery, and materials—to ensure that construction work proceeds in accordance with the design plans. This also enables the forecasting of possible problems, timely intervention, and quality control regarding defects and risks that may arise.

DT systems can provide services such as construction monitoring and progress management, risk warning and on-site safety management, as well as quality control and compliance inspection during the facility's construction and implementation phase.

Sensors can collect data on construction equipment, building materials, and environmental factors like temperature, humidity, and vibration, transmitting that data in real time to the DT platform. Virtual planners and construction managers can virtually see, in real time, what is going on with the construction process. They are able to compare this information against the DT model created during the planning phase, finding variances or warnings regarding potential issues. Feedback from sensor and drone data in the construction of bridges [73] and tunnels [74] enables more effective monitoring of the sections of the construction and ascertains its quality to meet the design standards. In the event of delays or quality issues, the DT system issues warnings in order to aid managers in taking necessary corrective actions and minimizing further delays and quality issues. In addition, the DT can compare historical data with the current status to predict factors that may affect the progress of construction, providing more scientific decision support to managers. It enables project managers to track equipment usage and location in order to optimize equipment utilization and reduce idle time. The DT can also predict possible issues during the construction phase, such as delays in the supply chain or construction errors, thereby allowing preparedness to avoid excessive costs and time consumption [75].

In the construction phase, DT technology manages project progress and provides effective safety risk warnings at construction sites. By analyzing sensor data in real time, it identifies potential risk sources, such as equipment failures, high-risk operation zones, and abnormal environmental conditions. Through intelligent data collection and comprehensive analysis of safety quality, noise, dust, and deformation monitoring, DTs detect and notify stakeholders of safety risks, issue real-time warnings, and support early emergency detection. This technology helps develop an emergency warning system and assesses the impact of emergencies on infrastructure, aiding in the creation and optimization of emergency plans. Ref. [76] developed a multi-information intelligent warning and safety management platform for tunnel construction, characterized by high-risk conditions. A communication network inside the tunnel, established through multifunctional base stations, collects and transmits multisource information. The virtual twin then simulates dynamic construction and surrounding rock conditions, setting up a four-level warning and emergency response system to evaluate the construction status. In projects facing extreme climates, harmful gases, and adverse geology, this system predicted and warned of potential tunnel collapses, facilitating timely emergency actions and ensuring personnel safety. Additionally, tunnel fire accidents and other emergent issues are receiving increased attention. To expedite rescue operations, ref. [77] introduced an IoT-enabled DT system for smart tunnel fire safety management. Using deep learning models trained on Transformer networks and simulation datasets, the system predicts the real-time location and scale of fires, visualizes 3D fire scenarios, and supports evacuation, firefighting, and emergency rescue efforts.

Regarding quality control, DT technology ensures full-process tracking and management of construction quality through real-time virtual mapping of the construction process. When combined with BIM, DTs compare detailed specifications from the design phase with actual operations during construction, thereby guaranteeing adherence to standards. Additionally, DTs track and inspect material quality by integrating supply chain data, ensuring that all materials meet regulatory standards [68]. In road construction, DTs monitor the production, transportation, and pouring of concrete, aligning with design requirements and minimizing the impact of material quality on construction [78]. The construction phase involves multiple teams and stakeholders, such as construction companies, supervisory units, and government departments. DTs provide real-time updates of virtual sites, allowing stakeholders to view progress and collaborate effectively. Construction teams can highlight issues on the shared platform, supervisory units can monitor compliance, and government departments can review key milestones to ensure that projects meet regulatory and quality standards.

5.3. Operation and Management Phase

During the operational phase, transport infrastructures such as roads, bridges, and tunnels are constantly subjected to traffic flow and environmental pressures. Traditional management models mainly depend on periodic inspections and reactive maintenance. These efforts have been handicapped by a serious lack of real-time data, significant theoretical limitations, and post-event maintenance. The DT can accurately monitor and horizontally control the dynamic state of key parameters, including traffic flow and equipment status. The main applications of DTs at this stage involve the real-time monitoring of traffic flow, assessment of equipment status, optimization of maintenance, and support for emergency management. According to the data analysis, it is possible to forecast the wear of infrastructure components to estimate the timing of future failures. The advantage of this approach over traditional regular maintenance is that it allows the maintenance team to intervene only when necessary, thereby reducing unnecessary activities and minimizing downtime.

DT systems in the operation and management phase of infrastructure offer services that include real-time traffic monitoring and dispatch optimization, as well as equipment status monitoring and predictive maintenance.

In road, bridge, and tunnel traffic management, DT technology enables real-time monitoring and management of traffic flow, vehicle speed, and congestion data, thus enhancing traffic efficiency and safety [79]. Ref. [80] highlighted data-driven decision-making approaches, emphasizing the importance of timely and informed decisions based on accurate data, as well as the application of DT technology in infrastructure resilience and disaster management. Traffic facility simulation enables the modeling [81] and optimization [82] of urban traffic networks, identifying bottlenecks and providing congestion simulation and optimization services. By simulating traffic operations under different strategies and scenarios, DTs assess the effects of traffic planning and infrastructure modifications, offering decision support and optimization recommendations to improve traffic fluidity, reduce congestion, and increase operational efficiency.

Transportation infrastructure interconnection entails the integration, interaction, and collaborative connection of multisource heterogeneous data. It links data from various transportation facilities and systems using identifiers like GIS feature codes, geographic entity codes, BIM model codes, and IoT codes. This method associates spatial information and static attribute information of urban transportation infrastructure with related performance state indicators, materials, algorithm output metrics, sensor information, location data, and model spatial structure information, facilitating data sharing and collaboration to enhance traffic management and decision-making. Additionally, this interconnected framework allows for detailed visual modeling of people, vehicles, roads, hubs, auxiliary facilities, and the environment. Through high-fidelity visual representation, simulation models not only accurately replicate traffic flow and behavior but also vividly reproduce the complexity and diversity of the traffic environment. These models aid in situational awareness and dynamic data display, depicting in real time key performance indicators such as vehicle and pedestrian micro-traffic behaviors, traffic flow, speed, waiting time, delays, queue length, signal states, accident information, and the interconnected status of various facilities [67,83,84].

Monitoring equipment status in transportation infrastructure operation is vital for ensuring stability. Data collected by sensors—including bridge vibration frequencies, humidity, and tunnel temperatures [85], along with the conditions of road wear—are transmitted in real-time to the DT model, facilitating the dynamic portrayal of the facility's current state [86]. By juxtaposing this data against historical records, DTs are capable of identifying discrepancies in equipment, foreseeing failure risks, and supporting proactive maintenance efforts. To address fragmented video, severed connections between video and operational data, and missing 2D–3D connections in tunnel operations, ref. [87] introduced a novel methodology for the creation of tunnel DTs that integrates the virtual with the real. Their strategy encompasses the evaluation of digital management demands for tunnel operations, the development of static models that mirror actual tunnel configurations, and the incorporation of real-time video into three-dimensional virtual scenarios. By consolidating data from various sensors, the resulting DT aligns closely with actual traffic operations, improving the efficiency of digital management by supporting smooth traffic, emergency responses, facility oversight, and incident management within tunnels. Concerning the management of bridges within the digital and intelligent sphere—an integral part of the forthcoming smart transportation infrastructure—Ref. [24] engineered a DT system for multiple bridges, integrating traffic load monitoring based on machine vision. This system employs dynamic weighing and machine vision sourced from multiple points across the target bridges, complemented by lightweight sensors that capture structural responses from the bridges. Within the digital realm, a mechanical analysis model is crafted to enhance operational awareness and safety across the bridge network within the regional transportation framework, significantly bolstering the development of an intelligent transportation system. In the realm of innovative smart highways, ref. [88] forged a framework and operational protocol for smart freeways enabled by DTs. By amalgamating control mechanisms from both upstream urban networks and traffic management of freeway segments, the effectiveness of the proposed strategies for freeway control was confirmed, advancing the evolution of smart highway systems.

5.4. Maintenance and Upgrade Phase

As transportation infrastructure ages, its structural components become increasingly susceptible to degradation caused by environmental exposure and operational loads. Traditional maintenance methods, which rely on scheduled inspections and repairs, often fail to account for the actual conditions of the infrastructure, leading to inefficiencies, excessive costs, and unforeseen breakdowns. Digital twins (DTs) transform this paradigm by continuously collecting real-time sensor data from transportation facilities and integrating it into virtual models. This enables facility managers to monitor real-time operational status, assess degradation patterns, and develop responsive maintenance plans. For example, in bridge health monitoring, the integration of real-time sensor data with predictive models supports condition-based maintenance strategies that enhance efficiency and mitigate the risks of abrupt failures [89]. However, the effectiveness of these strategies depends on the quality and quantity of sensor data, as well as the capacity to process and analyze large datasets in real time. Addressing these challenges is critical to unlocking the full potential of DTs in modernizing infrastructure maintenance and alleviating financial burdens associated with unnecessary repairs.

DT technology during the maintenance and upgrade phases offers predictive maintenance capabilities and the assessment of the condition of transportation infrastructure, ensuring more accurate and timely interventions.

Predictive maintenance is an advanced concept in maintenance methodology. It provides dynamic analysis and forecasts of condition information for equipment and infrastructure, which enables the identification of problems and the execution of preventive measures before the occurrence of failures. In this way, it prevents the aggravation of problems. DT technology makes use of real-time integration of multi-type sensor data, such as structural stress, vibration, and temperature, to establish a virtual entity model of the infrastructure, simulate its operating conditions, and evaluate its health status [42]. Assisted by machine learning and data mining algorithms, DTs are capable of analyzing this data [90] for trends that could predict potential failure risks. A necessary contribution to bridge and tunnel maintenance is performed by DTs, which provide data analysis retrieved from devices like vibration sensors and strain gauges to detect minor changes in the structure and offer a prognosis on the timing of the appearance of future damage. With such an analysis, maintenance teams can prepare for certain maintenance plans, such as strengthening inspections in some areas or replacing parts in advance to avoid structural failure. This predictive maintenance approach significantly reduces the incidence of emergency repairs and service interruptions from sudden failures, thereby reducing costs not only in repair expenses but also by enhancing safety and stability in the transportation system.

During the maintenance and upgrade phase, advanced Structural Health Monitoring (SHM) and non-destructive testing (NDT) techniques are critical for accurately assessing infrastructure conditions and predicting potential deterioration [91,92]. For instance, UAV-based crack detection, thermographic imaging, and ultrasonic scanning enable high-resolution data collection from bridge and tunnel structures, ensuring timely interventions and reducing the risk of catastrophic failure. By integrating SHM and NDT datasets into digital twin (DT) platforms, engineers can validate simulation results against real-time measurements, refine predictive maintenance schedules, and optimize resource allocation for refurbishment [93]. Incorporating NDT data—particularly from emerging robotic or drone-based inspection methods—into building information modeling (BIM) and geographic information system (GIS) models significantly enhances condition-based maintenance strategies [94]. These approaches ensure continuous monitoring of structural integrity and load-bearing capacity, enabling infrastructure managers to proactively respond to signs of fatigue, corrosion, or other defects.

In maintaining roads, bridges, and tunnels, the analysis and evaluation of 3D models of transportation infrastructure facilitate the timely identification of road damages and defects, thereby enhancing maintenance efficiency and quality. DT systems capture and deliver real-time, precise data such as traffic patterns, critical driving behaviors, geographic data, and variations in road wear or friction [95]. Utilizing GIS technology, geometric models of transportation infrastructure employ various data fusion algorithms to produce simulations that mimic the physical and operational characteristics of these structures [96]. Ref. [3] performed an extensive analysis incorporating environmental conditions, employing BIM, finite element modeling, and statistical approaches to forecast bridge strain. Ref. [97] proposed a "BIM-based bridge risk inspection model" aimed at minimizing inspection risks by thoroughly evaluating internal, natural, and human-related risks, providing a comprehensive prediction of bridge risks. By leveraging real-time data and the simulation capabilities of DTs, managers can assess the lifespan of infrastructure, calculate the remaining service life of structures, and design life extension strategies tailored to various operational and environmental conditions. This proactive, data-driven method of assessing conditions and predicting lifespan enables transportation officials to implement preventive measures before infrastructure deteriorates, significantly reducing the safety hazards associated with aging infrastructure.

Evaluating and diagnosing facilities involves simulation diagnostic algorithms, performance metrics, anomaly detection techniques, and data model evaluations that support the structural service state diagnosis of urban transportation infrastructure. For instance, using metrics like wind speed, direction, vehicle loads on bridges and roads, and settlement figures for tunnels, roads, and hubs, along with data on key bridge deformations and vibrations, can establish critical performance model diagnostic indicators. These indicators generate risk levels, early warnings, and deformation forecasts for transportation infrastructure. Facility evaluation and diagnostics incorporate diverse metrics and algorithms for an exhaustive performance evaluation and anomaly diagnosis. Based on the characteristics of the chosen indicators, suitable visual representations, such as tables, bar charts, scatter plots, heat maps, line charts, and pie charts, are used to display the results. These analyses clarify various issues related to model analysis, including data quality, congestion, traffic bottlenecks, flow and travel time, signal strategy, and model errors, performance, and stability.

5.5. Decommissioning and Replacement Phase

A decommissioning plan entails the systematic dismantling, replacement, or repurposing of transportation infrastructure like bridges, roads, and tunnels, upon reaching the end of their service life, presenting safety risks, or becoming obsolete. This process generally considers multiple aspects, such as structural health, impact on urban traffic, replacement options, and resource recycling or reuse. At this stage, DT technology not only provides precise assessments of conditions but also enhances the management of decommissioning and resource utilization.

DT systems during the decommissioning and replacement stage offer services that include assessments for decommissioning, resource reuse, environmental impacts, and the design and testing of new facilities.

As mentioned in previous sections, the continuous gathering and analysis of data, even up to the point of decommissioning, permit very accurate verification of the structural and usage conditions of the facility. This process helps to find the right timing and strategy for decommissioning. For example, in the deconstruction of the bridge [98], the application of DT simulation of different decommissioning schemes can yield the best dismantling method, which would provide the least interference to surrounding traffic and minimize safety risks. Precise evaluation and planning ensure the safety of the decommissioning process and create more favorable conditions for the subsequent construction of replacement facilities. Noise Barrier Tunnels (NBT) are composed of prefabricated members that are readily replaceable, reusable, and can offer better performance when used as replacement members. Reusing NBT members is far more cost-competitive and environmentally friendly compared to producing new members. However, one of the key challenges involves determining the remaining lifetime of existing NBT members before dismantling. To this end, [99] adopted a prototype of the NBT DT to perform condition and lifespan predictions through numerical behavior analysis for tunnel components.

It can also be applied in the decommissioning process, in which DT technology supports the planning and optimization of resource reuse in decommissioned facilities [100]. For instance, through the detailed model and data incorporated, DTs are able to analyze and assess which of the building materials can be recycled or reused, and which have to undergo safe treatments. Resource reuse planning reduces [101] not only the waste generated during decommissioning but also minimizes negative environmental impacts, thereby achieving sustainability goals. A DT can simulate the environmental impacts of infrastructure decommissioning by combining sensor-based environmental data with material properties. Regarding the decommissioning process in the context of a tunnel, for example, DTs can be adopted to simulate dust and noise propagation produced during demolition, again proposing measures to reduce environmental impact while guaranteeing that decommissioning work follows the requirements related to environmental protection.

After decommissioning, new facilities are often built instead. DTs also play an important role in this regard. Through virtual simulation and comparative analysis of multiple scenarios, DTs are able to help managers choose the best replacement plan and conduct ample testing in advance before construction starts. For example, in the redesign of a road or even in the replacement of a bridge, using DTs allows for the simulation of the operation of new facilities, the analysis of their impact on traffic flow, and the assessment of effects on the environment and infrastructure in general, while at the same time supporting the managers in making informed decisions prior to actually building the new facility. Together with the aforementioned factors, a significant reduction in uncertainties and risks can be achieved during the construction process by means of virtual testing with a DT. Thus, the new facility can better respond to the needs of urban development when it is in use, thereby increasing the efficiency and sustainability of the transportation system in general.

As summarized in Table 2, digital twin technology provides comprehensive support across all phases of urban transportation infrastructure, from planning and design to decommissioning and replacement. This table consolidates the key focus areas, benefits, and references discussed in Sections 5.1–5.5.

Table 2. Digital twin (DT) technology across the transportation infrastructure lifecycle.

Lifecycle Phase	Key Focus and Activities	Key Benefits	Selected References
Planning and Design	- Multi-dimensional modeling and high-fidelity simulation - Integrated data (traffic flow, weather, environment) for design decisions - Scenario evaluation, multi-objective optimization, and collaborative design	- Multi-dimensional modeling and high-fidelity simulation - Integrated data (traffic flow, weather, environment) for design decisions - Scenario evaluation, multi-objective optimization, and collaborative design	[34,62,64–70]
Construction and Implementation	- Real-time construction monitoring (progress, resource usage) - Risk prediction and on-site safety management - Quality control with BIM and sensor data	- Reduced human errors and delays - Improved resource allocation and safety - Proactive risk mitigation and continuous quality assurance	[68,71–77]
Operation and Management	- Real-time traffic monitoring, dispatch optimization, and incident management - Equipment status monitoring (structural health, loads, etc.) - Data-driven decision-making for improved resilience and emergency response	- Decreased congestion and improved traffic flow - Lower downtime and enhanced safety - Quick response to incidents and dynamic changes in urban environments	[24,78–87]
Maintenance and Upgrade	- High-fidelity simulations (e.g., AC and wheel wear) - Socio-technical rail DT - Integration of advanced SHM and NDT methods to identify potential structural defects	- Reduced unexpected failures and costs - Extended service life of assets - Improved safety through timely upkeep - Real-time condition assessment and targeted interventions	[3,42,88,90,95,96]
Decommissioning and Replacement	- 3D dynamic displacement measurement (no targets) - Deep learning for damage detection	- Minimal impact on surrounding traffic - Lower environmental footprint via material reuse - Optimized design of replacement assets	[97–100]

5.6. Chapter Summary

This chapter systematically develops the application of DT technology throughout the full lifecycle of urban transportation infrastructure, from planning and design to construction, operation, maintenance, and finally decommissioning and replacement. The DT offers a comprehensive and dynamic perspective that has significant potential to optimize design efficiency, improve construction quality, enhance operational management, and extend the life of infrastructure assets. This highly precise virtual simulation, integrated with real-time data, helps urban transport managers make better decisions at each step, particularly regarding efficiency, cost savings, and sustainability.

However, despite the pervasiveness of DT technology in the transportation infrastructure sector, there are still problems regarding the data quality instability, data security, high costs, and a lack of professionals. The direction of future studies should focus on model accuracy and enhancing data processing capabilities to meet the increasing and varied demands currently occurring in urban transport infrastructure. It is also worth mentioning that research on how to deeply integrate DTs with AI and big data technologies should be indispensable to advance more efficient lifecycle management. This will not only contribute to the sustainability of infrastructure but also considerably reduce resource waste, further promoting the development of smart cities.

6. Current Applications of DTs in Transportation Infrastructure

DT technology has found applications in several fields within transportation infrastructure and has greatly enhanced the approach through which cities plan, manage, and maintain their networks. The architecture of a digital twin platform for urban transportation, as illustrated in Figure 4, integrates industry applications, platform services, visualization, simulation-based deduction, IoT devices, and supporting platforms to enable efficient operations and maintenance management. DTs in areas regarding urban planning, traffic management, and infrastructure maintenance are currently being implemented. In this section, the applications will be explored through case studies that show the impact of transport systems.

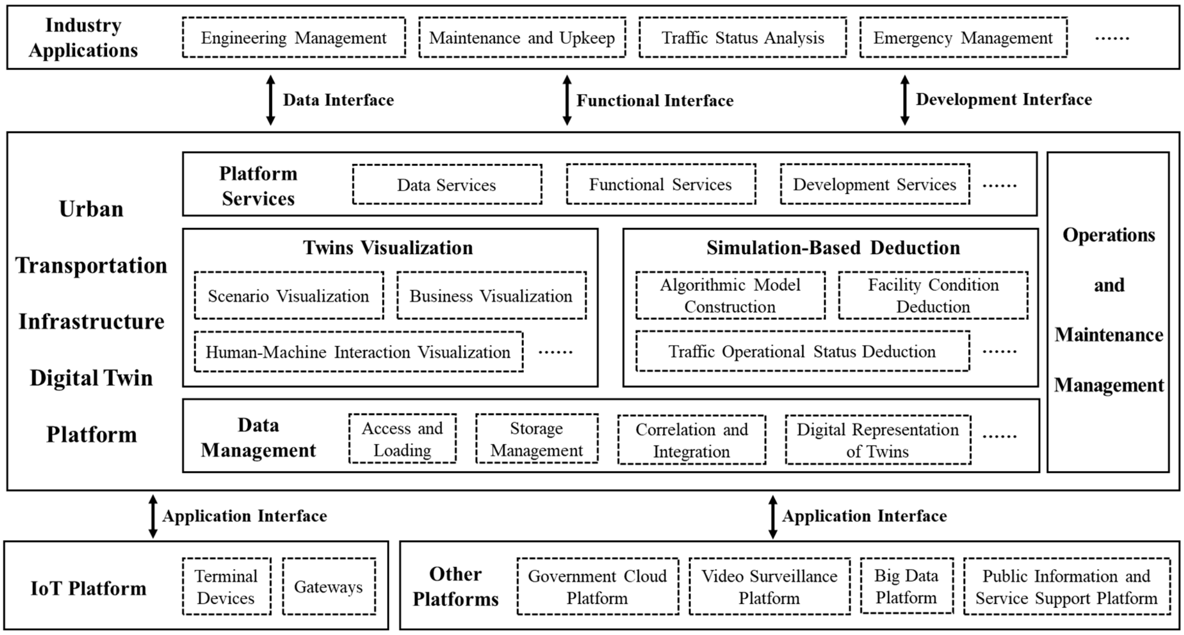

Figure 4. Architecture of the urban transportation infrastructure digital twin platform.

6.1. Urban Planning

It is among the most transformative uses of DTs in transportation, in which the simulations of various infrastructure layouts are conducted to assess their potential effects on traffic flow, air quality, and noise pollution. DTs help urban planners make informed decisions based on evidence. For instance, Singapore has developed a city-wide DT necessary for simulating different urban development scenarios, with projected factors such as population growth, vehicle ownership, and demand for public transport [102]. It helps the planners to simulate and estimate the impact that could be initiated by policy changes, such as road expansions or the introduction of new public transport routes, before these changes are actually implemented. Certain scholars have presented decisions on the intelligent development of transportation infrastructure and made forecasts with regard to functional design and intelligent development, effectively integrating new media, aiming at providing references for smart development and construction with regard to subsequent transportation infrastructure in the smart city [103].

Digital twins (DTs) in urban planning extend beyond conventional traffic flow simulations by enabling high-fidelity evaluations of environmental and socio-economic impacts. For instance, DTs simulate how new road configurations affect air quality across diverse urban zones, integrating multisource datasets, including real-time traffic patterns, meteorological conditions, and pollutant dispersion models. These simulations assist planners in designing sustainable urban layouts that prioritize public health [62]. High-fidelity simulations require granular datasets, such as high-resolution geographic information system (GIS) layers, demographic statistics, and transportation logs, selected based on their ability to capture spatial heterogeneity and dynamic interactions within urban ecosystems. To ensure accuracy, raw data undergo rigorous preprocessing: GIS data are georeferenced and normalized, traffic logs are cleaned to remove outliers, and demographic data are disaggregated to neighborhood-level resolution. Advanced analytical tools, such as computational fluid dynamics (CFD) for air quality modeling and machine learning algorithms (e.g., random forests for traffic pattern prediction), process these datasets. These tools are selected for their ability to manage non-linear relationships and adapt to urban complexity. However, the absence of standardized data formats and theoretical frameworks for DT modeling poses significant challenges. For example, merging physical sensor data (e.g., IoT-based air quality monitors) with socio-economic information requires novel data fusion techniques that are still underdeveloped [104]. Additionally, the computational intensity of high-fidelity simulations necessitates scalable cloud infrastructure and adaptive algorithms to optimize precision and processing efficiency. Addressing these gaps through unified data standards and interdisciplinary methodologies is critical for improving predictive accuracy and enabling holistic urban planning models [105].

6.2. Traffic Management

Through the integration of technologies such as the IoT, big data, BIM, AI, and augmented reality, DTs enable devices to transmit data states from the bottom up and facilitate remote automatic control, transforming them from being ”blind, deaf, and mute” into responsive entities.

The second most important area in which the role of DTs is significantly enhancing is traffic management. Since large sections of road transportation can be built piece by piece with the help of GIS technology, DTs provide real-time data on integrations and simulation capabilities to optimize the flow of traffic without congestion and improve safety. Advanced traffic management systems using DTs capture data from a wide range of sources, including sensors in the road, traffic cameras, and GPS from vehicles. It then takes that information and monitors current conditions to make dynamic adjustments to traffic signals, lane usage, and speed limits. The DT model works as a data-driven simulation platform, eliciting information on, for instance, the impact of new technology deployments, such as intelligent signal control or perhaps traveler information systems, in a real-time environment. These systems monitor impacts and provide insights into how ITS technologies impact road traffic and environmental performance [106]. Related research highlights the use of model-based systems engineering (MBSE) technology systems and tools, designed based on DT technology, to help simplify the complexity of command operating systems and make them more manageable [107].

This is being practically applied in London through Transport for London (TfL) DT, which is used for the monitoring of various traffic conditions and the management of the road network. The DT integrates data from thousands of sensors and cameras, enabling it to make real-time adjustments in traffic signals and route guidance for public transportation. Therefore, it significantly reduces congestion during rush hour traffic and offers quick responses in the case of road incidents. However, deploying such systems is not without challenges. Real-time traffic management involves processing huge amounts of data in the shortest time possible with high accuracy, leading to computationally intensive and data handling challenges. Further, reaping the benefits of data integration from heterogeneous sources, which come in a variety of formats and standards, involves sophisticated data processing techniques along with strong communication protocols [59].

Another critical application of DTs in traffic management involves the application of DTs in predictive analytics. These DTs analyze historical data on traffic conditions against real-time input to predict future traffic conditions and, consequently, mount preventive measures against building congestion. For example, a DT inspects and analyzes the development of traffic congestion resulting from either an event scheduled to take place or weather conditions, thereby prompting authorities to take preemptive traffic control measures, such as the diversion of traffic or adjustment of traffic signal timings [32]. This proactive management of roadways improves not only the flow of traffic but also enhances the safety of the roads by minimizing the chances of accidents associated with congestion.

While designing a simulation environment that exactly replicates on-road conditions can prove to be very expensive and ineffective, the online game GTA5 features a range of well-executed objects, pedestrians, and roads; it can always be used as a foundation for simulating self-driving cars. Through OpenCV's capture of the GTA5 game screen and image analysis using YOLO and Python-based TensorFlow to design algorithms for target collision avoidance and lane recognition, highly precise target recognition can be achieved [108].

6.3. Infrastructure Maintenance

Apart from planning and traffic management, the use of DTs is also finding increasing application in infrastructure maintenance. Traditional maintenance—usually based on periodic inspection with reactive repairs—causes sudden failures and expensive downtime. DTs, in this view, will enable a shift toward predictive maintenance since the continuous monitoring of the health of infrastructure assets allows for the early detection of potential issues that could become critical. DTs are based on real-time sensor data, providing very high accuracy in simulations and data analytics, so as to allow improvements to be made in the facility's interaction with both the environment and users [109].

In this respect, a highly relevant case study is the application of DTs in the maintenance of bridges in China. A host of sensors integrated into the bridge structure monitor factors such as stress, vibration, and temperature. These data feed into the DT, which processes the data using machine learning algorithms to identify anomalies and predict potential structural failures [110]. By examining these trends, proactive scheduling of repairs and rehabilitation by maintenance teams limits the possibility of surprise closures of these bridges and helps provide a longer life to the asset. This chapter describes the application of DTs in intelligent construction and their relative advantages and disadvantages. It then analyzes the research theme through a case study approach to explain the importance of DTs in smart construction. Some researchers have designed a methodology for constructing full lifecycle energy consumption detection based on DT technology to try to reduce errors caused by traditional full lifecycle building energy consumption detection methods [51]. In this case, the whole-lifecycle building energy consumption detection data fit well with the holographic mirroring capability of DT technology. This study presents two cases involving the use of UAVs with visible cameras in creating DTs for better monitoring and management of assets, which allows for possible preventive maintenance and cost savings for transportation agencies [111].

Tunnels and roadways have also found uses in this technology. For example, a DT of a tunnel can integrate data on humidity, air quality, and structural stress for real-time condition monitoring. An alert is sent to maintenance teams when the DT detects conditions that could bring about structural damage so that interventions can be carried out much earlier. This approach will not only improve safety but also help maintain the road at a lower cost through reductions in emergency repairs accompanied by unplanned disruptions.

Even with several advantages of using DTs in infrastructure maintenance, several barriers still remain. Of these, the foremost is highly accurate and reliable sensor data; faulty or incomplete data leads to erroneous predictions and thus wrong maintenance decisions. A full-scale predictive maintenance system requires a significant investment in sensors, processing infrastructure, and human resources that can understand outputs from the DT and take necessary actions [112]. In light of the aforementioned factors, the solution to these challenges will require the further development of sensor technology, different methods of data processing, and elaboration on standard protocols for predictive maintenance in transport systems.

In recent years, rapidly evolving non-destructive testing (NDT) techniques—such as UAV-based inspections, robotic crawlers, and advanced sensing—have significantly enhanced Structural Health Monitoring (SHM) practices for bridges and other critical infrastructure [39,113]. Unlike traditional SHM, which relies primarily on fixed sensors and periodic manual inspections, these methods facilitate targeted, high-resolution data collection to detect surface cracks, corrosion, spalling, and other localized defects in real time. By integrating detailed inspection datasets into building information modeling (BIM) and digital twin (DT) platforms, engineers can continuously update virtual models with geometric, material, and environmental data. This synergy enhances the fidelity of structural condition assessments by enabling both local (defect-level) and global (system-level) performance analyses. Furthermore, incorporating NDT-derived data—such as crack width progression and steel reinforcement corrosion—into finite element or machine learning models within DT environments enables more accurate predictions of load-bearing capacity and structural risk [114]. Consequently, maintenance plans can be adjusted based on the actual state of deterioration rather than fixed schedules, thereby reducing costs and minimizing unexpected downtime. Dynamically updated NDT data not only enhance predictive maintenance strategies but also prevent catastrophic failures through proactive interventions, extending service life and ensuring bridge infrastructure safety.

6.4. Smart Mobility and Autonomous Vehicles

In real life, self-driving technology promises to decrease traffic incidents, optimize the use of time and space, and significantly ease the driving process for individuals with disabilities. However, autonomous vehicles must undergo extensive simulation testing to confirm their safety before deployment. Traditional virtual simulation environments, where only the controller is real while elements like the driver, transmission, power, and road environment are virtually simulated, often suffer from limited computational capabilities. This restricts the complexity of the simulation environment, thus affecting the accuracy of vehicle performance under test and introducing deviations in test accuracy. Conducting tests in actual settings is frequently impractical due to various physical constraints and the challenge of replicating the same test conditions consistently. Therefore, leveraging DT technology is essential for developing autonomous driving systems. The variety of potentially safety-critical scenarios in urban traffic is too extensive to be fully evaluated through natural driving or controlled laboratory experiments alone. Virtual testing, facilitated by DT technology, generates extensive databases and provides the statistical capacity required for safety assessments and stress tests in the vast traffic scenario space [115]. Utilizing PanoSim, which merges real autonomous vehicles, their actuators, and controllers with accurate positioning data, allows for seamless digital-to-physical mapping and a high degree of integration between virtual and real environments. This enables the efficient and safe conduction of various simulation tests, including automatic and acceleration tests, offering crucial validation support for the commercialization of autonomous driving technologies [116].

6.5. Case Studies

Several cities and regions have begun adopting DT technology to address specific transportation challenges, demonstrating the versatility and efficacy of DTs in this domain.

1. Singapore: Singapore's comprehensive DT incorporates real-time data from its road networks, public transit systems, and environmental sensors. This system facilitates the simulation of various urban development scenarios, aiding decision-making

in road network configuration, public transit enhancements, and traffic congestion mitigation [103]. The successful implementation of this technology showcases its potential to foster more efficient, sustainable, and responsive urban environments.

2. London: In the UK, national-level DT strategies are supported by initiatives such as the National Digital Twin Programme [112], which aims to enable connected digital twins across different sectors, including transportation. DT technology is employed primarily in three areas: alleviating road congestion, managing motorway projects, and enhancing real-time traffic and travel information systems. As a leading city-level example, Transport for London (TfL) utilizes a DT to oversee traffic and public transport in real time. By integrating data from numerous sensors, cameras, and public transport networks, the DT facilitates dynamic traffic signal adjustments, congestion tracking, and incident management. This integrated approach has significantly decreased traffic delays and enhanced public transport reliability. London's case demonstrates how a city can pilot and refine DT solutions within a broader national policy context.
3. China: In China, DTs monitor the health of essential infrastructure such as bridges and tunnels. By employing sensor data and predictive analytics, these DTs detect structural issues early, enabling prompt maintenance and extending the assets' service life [117]. This proactive strategy has proven to be more cost-effective and safer than conventional maintenance methods. Leveraging technologies such as BIM, GIS, IoT, AI, and cloud computing, the East China Survey and Design Institute of CECC has developed a next-generation integrated management system for the entire lifecycle of BIM in rail transit engineering. This system enhances visibility and ensures the seamless flow of information across the design, construction, operation, and maintenance phases, alongside intelligent perception, analysis, and decision-making. The system's capabilities were demonstrated on Chengdu Metro Line 18, facilitating enhanced design, construction, operation, and maintenance coordination.
4. Germany: Germany's DT technology achieves exceptionally detailed simulation accuracy, extending to the real-time perception of car air conditioning and wheel wear. The German railway department has begun implementing a new DT train set. Rail transport logistics systems have developed a GIS for DTs, using a qualitative-explorative design to establish a validated strategy. This strategy emphasizes a socio-technical system focus, enabling user-oriented development and accounting for complex conditions [118]. The GIS and derived recommendations aim to facilitate the operational optimization and intelligent management of rail transport assets.
5. Australia: Curtin University in Australia has introduced a three-dimensional dynamic displacement measurement technique using a binocular camera system without targets, allowing for the full-field measurement of civil engineering structures' dynamic displacements. Additionally, the university has developed a deep-learning-based method for structural dynamic response noise reduction, deletion recovery, and reconstruction, achieving high-intensity signal denoising. It has also formulated several deep-learning-based structural damage identification methods, enhancing identification accuracy [119]. These innovations have been successfully applied in the dynamic testing, modal identification, condition assessment, and comfort evaluation of significant projects like the large-scale pedestrian bridge in Matagarup and the long-term monitoring and performance evaluation of the Rockingham Freeway Bridge, among other landmark structures.
6. In the United States, state Departments of Transportation (DOTs) are piloting digital twin (DT) projects to enhance real-time traffic management and asset maintenance. For example, California's I-210 Pilot integrates sensor data, connected vehicle inputs, and

traffic signals to reduce congestion through adaptive control. These DT-driven insights also improve safety, incident response, and operational efficiency [120]. Colorado's I-70 corridor project combines continuous sensor data with AI-based traffic predictions and cloud analytics to optimize real-time traffic flow [121]. These initiatives aim to streamline congestion management and enable predictive maintenance for highway infrastructure, contributing to cost-effective and resilient transportation networks. The U.S. Federal Highway Administration collaborates with research institutions on DT studies, reflecting a growing interest in leveraging DTs for nationwide infrastructure modernization.

7. The Netherlands, renowned for its advanced logistics and water management, has deployed a digital twin at the Port of Rotterdam to optimize maritime traffic and multimodal coordination. Real-time data from ships, road transport, and rail systems are integrated into a unified DT platform for route optimization and congestion reduction. Additionally, Dutch authorities are exploring national-level, cross-sector DT strategies that integrate water management, energy, and transportation infrastructure to enable holistic planning and operational efficiency [122,123].

To illustrate how various cities and regions have leveraged DT technologies to address specific transportation challenges, Table 3 presents concise case studies highlighting their primary focus, key technologies, and notable achievements. These case studies illustrate the diverse applications of DTs in transportation infrastructure and underscore the need to address challenges such as data integration, model accuracy, and system interoperability to fully capitalize on the benefits of DT technology.

Table 3. Representative case studies of DT applications in transportation.

Region/City	Focus	Tech	Achievements
Singapore [103]	- Real-time data on roads, transit, environment - Urban scenario simulation	IoT, simulation frameworks	- Enhanced road and transit planning - Reduced congestion
United Kingdom (e.g., London TfL) [112]	- Managing congestion and motorway projects - Real-time traffic info	Sensors, cameras, dynamic control	- Lowered traffic delays - Improved public transport reliability
China [117]	- Bridge/tunnel health monitoring - BIM-based lifecycle management for rail	BIM, GIS, IoT, AI, cloud	- Early fault detection - Extended asset lifespan (e.g., Chengdu Metro Line 18)
Germany [118]	- High-fidelity simulations (e.g., AC and wheel wear) - Socio-technical rail DT	GIS, user-oriented design	- Detailed simulation accuracy - Optimized rail operations and asset management
Australia [119]	- 3D dynamic displacement measurement (no targets) - Deep learning for damage detection	Computer vision, deep learning	- Successful in large-scale bridge monitoring (Matagarup, Rockingham Freeway) - Improved modal identification
United States [120,121]	- Highway DT pilot projects (e.g., real-time sensor data, connected vehicles) - Integration with state DOTs	IoT, AI, cloud computing, sensors	- Reduced congestion via adaptive signal control - Enhanced safety and incident response (e.g., I-210 Pilot, Colorado I-70) - Data-driven asset management
Netherlands [122,123]	- Port of Rotterdam DT for traffic and logistics - National-level DT infrastructure initiatives	IoT, big data analytics	- Enhanced port traffic prediction and multimodal coordination - Exploration of integrated, cross-sector DTs for water, energy, and transport

6.6. Chapter Summary

DT technology has emerged as a strong enabler in the field of transport infrastructure, with applications spilling over into strategic urban planning, real-time traffic management, asset maintenance, and even smart mobility and autonomous vehicle development. Case studies from Singapore, London, China, Germany, and Australia show how DT technology can help improve decision-making, actuate traffic flow optimization, predict the maintenance of structures, and safely deploy autonomous driving systems. DTs have a significant effect on every aspect of transportation infrastructure, and their gradual infiltration into this industry is underway.

There are clearly many hurdles that must be overcome to achieve the full potential of this technology. Issues of data accuracy, model complexity, multiple sources of data, and assurance of sensor data's reliability remain very real hurdles. Finally, standardized protocols and further research in data processing techniques are quite indispensable. Nevertheless, the promises of development and improvement in advanced DT technologies can further transform transportation infrastructures into more efficient, sustainable, and safer systems in the future.

7. Discussion

7.1. System and Technical Challenges

The implementation of digital twins (DTs) in transportation infrastructure faces several system and technical challenges, including issues related to data quality and integration, real-time processing requirements, sustaining model accuracy, and ensuring system interoperability. Addressing these challenges is critical to unlocking the full potential of DTs throughout the entire lifecycle of transportation infrastructure, from planning and design to operation, maintenance, and decommissioning.

7.1.1. Data Quality and Integration

The success of DT systems in transportation heavily relies on high-quality data and seamless integration throughout the infrastructure's lifecycle. DTs depend on vast amounts of data from diverse sources, such as infrastructure-embedded sensors, IoT devices, traffic cameras, and GPS systems. However, integrating this data poses significant challenges due to differences in formats, protocols, and update frequencies across various systems. These discrepancies can hinder the creation of a unified and coherent DT model [37].

Ensuring data quality is equally critical across all lifecycle stages. During the planning and design phase, data quality issues can lead to flawed simulations and suboptimal designs. In the construction phase, poor data integration can result in delays and cost overruns. During the operation and maintenance phase, noisy or inconsistent data can degrade the performance of predictive models, leading to inefficient maintenance schedules and increased risks. Advanced data processing techniques, such as machine learning algorithms, are increasingly being used to filter noise and detect errors in real-time data streams. Additionally, the development of standardized data formats and communication protocols can streamline data integration [27]. Despite these advancements, maintaining consistently high-quality data inputs remains a persistent challenge, particularly in large and dynamic urban environments.

7.1.2. Real-Time Processing Requirements

Real-time processing is essential for DTs to support applications such as traffic management and incident detection, which require immediate responses to dynamic conditions. The ability to process large volumes of incoming data, identify patterns, and make rapid decisions is crucial for ensuring that the DT accurately reflects the state of the physical system throughout its lifecycle.

During the operation phase, real-time processing enables dynamic adjustments to traffic signals, lane usage, and other operational parameters, thereby improving efficiency and safety. In the maintenance phase, real-time data processing supports predictive maintenance by identifying potential issues before they escalate. However, achieving low latency in data transfer and processing presents a significant challenge. For example, a DT designed for traffic congestion management must process data from thousands of sensors during peak hours, dynamically adjusting signal timings and lane usage in real time. This requires high-throughput data processing with minimal delays, placing significant demands on computational resources and network infrastructure.

Edge computing has emerged as a potential solution to this challenge. By processing data locally at the source, edge computing reduces the need for continuous data transmission to central servers, thereby lowering latency and improving system responsiveness. However, this approach introduces its own set of challenges, including the need for robust hardware for local processing, ensuring data security in decentralized systems, and maintaining consistency between local and central data repositories [124].

7.1.3. Model Accuracy and Updating

Model accuracy is a cornerstone of the predictive capabilities of DTs across the entire lifecycle of transportation infrastructure. The simulation and prediction models within a DT—whether for forecasting traffic patterns or assessing infrastructure health—are highly sensitive to the quality and completeness of input data. Inaccurate or incomplete data can lead to flawed predictions, resulting in poor decision-making [125].

During the planning and design phase, accurate models are essential for simulating different scenarios and optimizing designs. In the construction phase, models must be updated in real time to reflect progress and ensure quality control. During the operation and maintenance phase, accurate models enable predictive maintenance and optimize system performance. Building accurate models requires extensive and diverse datasets that capture the complexities of transportation systems. For instance, a DT for an urban road network may need years of historical traffic data, detailed weather records, and vehicle usage patterns to reliably predict future traffic conditions. However, collecting such comprehensive datasets can be challenging, especially in regions with limited data collection infrastructure [50].

Maintaining model accuracy over time is another significant challenge. Transportation systems are dynamic, and DTs must continuously update their models to reflect current conditions. For example, a DT used for bridge health monitoring must constantly process data from sensors measuring structural stress and vibrations. This requires advanced machine learning algorithms capable of adapting to new data and evolving conditions [47]. However, frequent updates can introduce errors or inconsistencies, underscoring the need for rigorous validation and quality assurance processes.

An increasingly vital factor in ensuring accurate updates for structural components is the integration of advanced Structural Health Monitoring (SHM) and non-destructive testing (NDT) data—particularly from UAV-based inspections, robotic crawlers, and emerging sensor technologies. These high-resolution data streams enable the precise identification of localized defects (e.g., cracks, corrosion) in real time, providing granular updates to the DT model. By integrating NDT-derived insights with geometric information from BIM and sensor data within the DT framework, engineers obtain a robust foundation for structural performance analysis, including assessments of load-bearing capacity and fatigue predictions. This dynamic incorporation of NDT data enhances the fidelity of digital replicas and facilitates proactive, precision-targeted interventions, thereby mitigating catastrophic failure risks and optimizing maintenance schedules.

7.1.4. System Interoperability

Achieving seamless interoperability across various DT systems and transportation infrastructure components is essential for realizing a truly integrated and efficient transportation network throughout its entire lifecycle. Currently, many DTs operate in isolation, focusing on specific aspects of transportation, such as road traffic management or bridge health monitoring [28]. These standalone systems limit the overall effectiveness of DTs, as they often fail to account for the interdependencies and interactions between different infrastructure components across the planning, construction, operation, and decommissioning phases.

To address this challenge, future research must focus on developing interoperability frameworks that enable communication and data sharing across diverse DT systems. Establishing common standards for data exchange and developing APIs that allow different systems to interact seamlessly are critical steps in this direction [27]. For example, an interoperable urban transportation DT could integrate real-time data from roads, railways, public transit systems, and pedestrian pathways, providing a comprehensive view of the entire network [96].

A centralized transportation infrastructure data repository could further enhance interoperability by serving as a shared resource for various DT systems. However, achieving true interoperability requires overcoming technical challenges related to data integration, as well as addressing regulatory issues concerning data privacy and security [126]. By fostering collaboration among stakeholders and promoting the adoption of universal standards, the transportation sector can move closer to a fully interconnected DT ecosystem that supports infrastructure management throughout its entire lifecycle.

7.1.5. Data Privacy and Security

DT systems rely on vast amounts of data, ranging from real-time sensor data to GPS and camera feeds, throughout the lifecycle of transportation infrastructure. While this data is critical for the functionality of DTs, it also raises significant concerns about privacy and security. The potential misuse or breach of sensitive data poses a serious risk, making data privacy and security essential for gaining public trust and support for DT technologies [61].

Future policies must establish clear guidelines on data privacy, usage, and security for DT applications across all lifecycle stages. For instance, during the planning and design phase, regulations could define the types of data that can be collected, their intended uses, and the duration for which they can be stored [112]. In the construction phase, robust measures such as encryption, access controls, and regular audits should be implemented to prevent unauthorized access and data breaches [126]. During the operation and maintenance phase, continuous monitoring of data security is essential to ensure the integrity of real-time data streams.

Beyond technical safeguards, ethical considerations must also be addressed. Policymakers and researchers must ensure that DT systems are designed and deployed in ways that promote equitable access to transportation services and avoid exacerbating existing inequalities in urban mobility. By embedding ethical guidelines into the development and use of DTs, stakeholders can create a framework that balances innovation with social responsibility [127].

The effective application of DT concepts to transportation infrastructure faces several technical and systemic challenges, including data quality and integration, real-time processing, model accuracy, system interoperability, and data privacy. Addressing these issues is critical to unlocking the full potential of DTs in creating smarter, more efficient, and sustainable transportation systems throughout their entire lifecycle.

Future efforts must prioritize collaboration among researchers, industry experts, and policymakers to develop solutions that overcome these challenges. By fostering innovation while ensuring ethical and secure practices, the transportation sector can harness the transformative power of DTs to improve urban mobility and infrastructure management, from planning and construction to operation, maintenance, and decommissioning [46]. This holistic approach ensures that transportation infrastructure remains adaptive, resilient, and responsive to evolving demands, ultimately contributing to long-term sustainability and societal well-being.

7.2. Future Directions and Research Opportunities

Digital twin (DT) technology holds immense potential for transforming transportation infrastructure throughout its entire lifecycle, from planning and design to construction, operation, maintenance, and decommissioning. However, realizing this potential requires addressing several critical challenges and exploring new research opportunities. These challenges include standardization, advanced analytics, interoperability, policy development, and privacy considerations. This section highlights these future directions and identifies key areas where researchers, policymakers, and industry experts must focus their efforts to advance the field.

7.2.1. Standardization

Standardization is a critical enabler for the widespread adoption of DTs throughout the lifecycle of transportation infrastructure. Currently, the lack of standardized frameworks for data exchange, modeling methods, and communication protocols poses significant challenges. Different DT systems use varying data formats and standards, making integration and interoperability difficult [119]. Developing universal standards is essential to enable seamless data exchange across DT platforms and transportation management systems [27].

During the planning and design phase, standardized data models and protocols would facilitate the integration of diverse datasets, such as geographic, environmental, and traffic data, enabling more accurate simulations and optimized designs. In the construction phase, standardized communication protocols would ensure real-time data sharing between DT systems and construction management tools, improving quality control and progress monitoring. As infrastructure moves into the operation and maintenance phase, standardized sensor data formats would allow consistent data integration across different systems, enhancing real-time monitoring and predictive maintenance capabilities. Finally, during the decommissioning phase, standardized frameworks would support the efficient transfer of data and models to new systems, ensuring continuity and minimizing disruptions during infrastructure upgrades or replacements.

Future research should focus on creating standardized data models and protocols tailored to the needs of transportation infrastructure. For example, standardized sensor data formats would allow for consistent data integration across different DT systems, regardless of the data source or system developer. Similarly, standardized communication protocols would enable DT systems to share results effortlessly with external applications, such as urban planning databases, Intelligent Transportation Systems (ITS), and public transit networks.

While some progress has been made in developing data exchange standards—particularly in niche areas like building information modeling (BIM) and geographic information systems (GIS)—much work remains to establish a widely accepted framework for DTs in transportation [102]. Achieving this goal will require collaboration among stakeholders to address the diversity of technologies involved, including IoT devices, machine learning models, and 3D visualization tools.

7.2.2. Advanced Analytics and AI

The integration of advanced analytics, particularly artificial intelligence (AI) and machine learning (ML), represents a promising direction for the future of DTs in transportation. While current DT frameworks primarily focus on real-time monitoring and basic predictive modeling, future systems could leverage advanced analytics to provide deeper insights and optimize transportation networks throughout their entire lifecycle.

In the planning and design phase, AI algorithms can analyze complex datasets, such as historical traffic patterns and environmental conditions, to optimize infrastructure designs and simulate future scenarios. During the construction phase, advanced analytics can enhance real-time monitoring of construction progress, identifying potential issues early and improving efficiency. As infrastructure enters the operation and maintenance phase, machine learning models can predict infrastructure wear and tear, optimize maintenance schedules, and improve traffic management. For example, AI can analyze complex traffic patterns to reduce congestion and enhance safety. Finally, in the decommissioning phase, predictive analytics can assess the environmental and operational impacts of decommissioning activities, ensuring sustainable and efficient processes.

By training machine learning models on large datasets, DTs can enhance their predictive capabilities, enabling more accurate forecasts of congestion, accidents, and maintenance needs [128]. This would allow transportation management to become more proactive, thereby reducing downtime and improving safety.

Moreover, integrating big data analytics into DTs can support long-term decision-making for urban planners and policymakers. By analyzing data from diverse sources—such as historical traffic patterns, socio-economic factors, and environmental conditions—DTs can simulate future scenarios and assess the impacts of various policy measures. However, implementing advanced analytics in DT systems requires significant computational resources and sophisticated data processing techniques. Continued research is needed to optimize these technologies for real-time applications, ensuring they can deliver actionable insights efficiently.

7.2.3. Interoperability

The seamless integration of digital twin (DT) systems across transportation infrastructure remains a critical yet underdeveloped challenge. While DTs have demonstrated value in isolated applications—such as bridge health monitoring—their standalone deployment limits their potential to enable integrated networks. For example, in bridge health monitoring, DTs utilize embedded sensors (e.g., strain gauges, accelerometers, and temperature sensors) to collect real-time stress, vibration, and thermal fluctuation data. These parameters are selected for their capacity to capture dynamic structural responses and environmental interactions, which are critical for predicting fatigue, corrosion, and failure mechanisms. To enhance predictive accuracy, raw sensor data undergo preprocessing steps such as noise filtering, normalization, and feature extraction (e.g., identifying resonant frequencies or stress thresholds), followed by analysis with machine learning algorithms like convolutional neural networks (CNNs) and anomaly detection models. These algorithms are chosen for their ability to process high-dimensional time-series data and detect early-stage degradation patterns. However, despite their technical sophistication, existing bridge health monitoring DTs often operate independently of broader infrastructure systems, such as traffic management or weather forecasting platforms [28]. This fragmentation impedes the integration of contextual data (e.g., traffic load variations or extreme weather events), which could improve predictive models and decision-making processes. Additionally, reliance on localized sensor networks risks creating data silos, limiting the assessment of interdependencies between infrastructure components (e.g., correlations between bridge stress and adjacent roadway conditions). Resolving these interoperability gaps is essential for advancing from reactive, component-specific maintenance to proactive, system-level resilience strategies.

Future research should focus on establishing DT systems that can share data seamlessly across all lifecycle stages. This will require the adoption of common data exchange standards and the creation of APIs to enable communication between diverse systems [8]. For instance, an interoperable DT for urban transportation could aggregate real-time data from roads, railways, public transit, and pedestrian pathways, providing a holistic view of the entire network [102].

Moreover, creating a centralized data repository for transportation infrastructure, accessible to different DT systems throughout the lifecycle, could significantly improve data sharing and analysis. Achieving true interoperability, however, will require addressing technical challenges related to data integration, as well as regulatory issues concerning data privacy and security [126].

7.2.4. Policy and Privacy Considerations

Consolidating transportation infrastructure data into a single repository, accessible by multiple DT systems throughout the lifecycle, can enhance data sharing and analytics. However, achieving complete interoperability is a multi-faceted challenge that involves not only technical issues but also regulatory concerns related to data privacy and security [61].

The broad use of DT technology raises critical policy and privacy issues, particularly as it relies on the collection of vast amounts of data—from real-time sensors to GPS devices and cameras [112]. This opens the door to risks of sensitive data being compromised or misused. Addressing these concerns is fundamental for gaining public confidence and ensuring the acceptance of DT projects throughout their lifecycle [126].

Another key policy consideration is the ethical use of DT technology. Scholars and policymakers must ensure that DT systems are designed and implemented in ways that promote equitable access to transportation services and avoid exacerbating existing inequalities in urban mobility. Ethical guidelines should guide the development and use of DTs, balancing innovation with societal values throughout all lifecycle stages [128].

7.2.5. Integration with Emerging Technologies

To fully realize the potential of DTs, they must be integrated with other emerging technologies, such as blockchain, the Internet of Things (IoT), and 5G communication networks. Blockchain technology can provide secure and transparent data management for DTs, enhancing traceability and integrity throughout the lifecycle. This is particularly important for applications like smart mobility, where real-time data from autonomous vehicles and smart infrastructure must be shared and processed securely.

Similarly, IoT devices can enhance DT systems by enabling detailed real-time data collection from various sources, such as traffic sensors, environmental monitoring stations, and vehicle telematics. The integration of 5G networks can further support this by providing high-speed, low-latency communication channels, making DT applications more responsive and reliable throughout the infrastructure lifecycle.

7.2.6. Expansion to Broader Urban Systems

The future of DT technology extends beyond transportation management and infrastructure maintenance. There is growing interest in applying DTs to larger urban systems, including smart energy grids, environmental monitoring, and logistics [129]. By connecting DTs of different urban subsystems, cities can optimize resource use, reduce environmental impacts, and improve the quality of life for their residents throughout the entire lifecycle of urban infrastructure.

In summary, DT technology has immense potential to transform transportation infrastructure from a lifecycle perspective. However, its future development will depend on addressing key challenges and exploring new research opportunities. Standardization, advanced analytics, interoperability, policy and privacy considerations, and integration with emerging technologies are critical areas that require further research [26]. Addressing these areas will enable the transportation industry to leverage DTs in building more efficient, resilient, and adaptive infrastructure systems for the future, ensuring value creation at every stage of the lifecycle.

8. Conclusions

Digital Twin technology holds transformative potential for the management of transportation infrastructure, yet its current implementation remains in the early stages, particularly in large-scale urban systems. To date, most research and applications have focused on specific components of transportation networks, such as traffic management or infrastructure health monitoring. These efforts are largely isolated and have yet to provide a comprehensive, integrated solution for managing the entire lifecycle of transportation infrastructure. This review delves into the existing gaps in current research and explores a DT system for transportation infrastructure from a full lifecycle perspective, spanning all stages from planning and construction to ongoing operation and maintenance.

Through an extensive review of the relevant literature, the key concepts and infrastructure of DT for transportation infrastructure were reviewed and summarized. Subsequently, from a full lifecycle perspective, a taxonomy was analyzed that categorizes DT systems based on functional scope, data integration methods, and application stages. This classification unifies fragmented research efforts by providing a structured approach to DT deployment, enabling stakeholders to identify domain-specific solutions while maintaining interoperability across lifecycle phases.

Furthermore, a foundational framework for DT in transportation infrastructure is explored from a full lifecycle perspective, focusing on the "4 Horizontal + 4 Vertical + N" framework for urban transportation infrastructure. The four horizontal layers include the data layer, model layer, service layer, and application layer. The data layer is responsible for data collection and integration throughout the lifecycle, providing real-time updates to virtual models. The model layer creates dynamic virtual models to support prediction and simulation. The service layer translates model outputs into actionable decision support, while the application layer directly interacts with users, enabling simulation, monitoring, and optimization. The four vertical phases encompass Planning and Design, Construction Implementation, Operations Management, and Summary Optimization, covering all stages of the infrastructure lifecycle. Additionally, the "Form-Condition-Mechanism-Tendency" concept is investigated, which further refines the understanding of infrastructure performance through digital reconstruction, precise mapping, mechanistic deduction, and trend prediction. This framework provides a robust tool for the full lifecycle management of urban transportation infrastructure, supporting its efficient operation and sustainable development.

Moreover, from the perspective of application stages, the current applications of DT technology in transportation infrastructure are summarized and analyzed. The analysis reveals that to achieve the full lifecycle application of DT technology, several challenges must be addressed, including data quality and integration, real-time processing requirements, model accuracy and updating, system interoperability, and data privacy and security. Future research priorities will focus on areas such as standardization, advanced analytics and ai, interoperability, policy and privacy considerations, and integration with emerging technologies. For instance, advanced analytical tools, including artificial intelligence and machine learning, can significantly enhance the capabilities of DT systems, enabling more accurate predictions of traffic patterns and infrastructure conditions. Addressing policy and privacy concerns is also crucial for the ethical use of DT and for gaining public trust in these technologies. The integration of emerging technologies such as blockchain and 5G networks can further enhance the functionality of DTs. Blockchain technology can provide robust data management, improving data reliability and transparency, while 5G technology can facilitate real-time communication, enhancing the responsiveness and reliability of DT systems. Extending the application of DTs to other urban infrastructure systems, such as energy grids and environmental monitoring, will contribute to the development of more resilient, flexible, and sustainable cities, ultimately improving the quality of life for residents. Additionally, integrating advanced structural health monitoring (SHM) and non-destructive testing (NDT) methods, such as drone-based inspections and robotic crawlers, into the DT framework holds great promise for infrastructure maintenance and safety. By collecting high-resolution defect data and integrating it with building information modeling (BIM) or finite element models, DTs can enable precise assessments of load-bearing capacity and facilitate proactive preventive maintenance before structural degradation occurs. This approach not only extends the operational lifespan of critical infrastructure assets, such as bridges, but also reduces the risk of unexpected failures, advancing the overall goal of developing safer and more efficient transportation systems.

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