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Review

Digital Twin-Enabled Internet of Vehicles Applications

Junting Gao [1], Chunrong Peng [2], Tsutomu Yoshinaga [1], Guorong Han [3], Siri Guleng [4] and Celimuge Wu [1,*]

[1] Department of Computer and Network Engineering, The University of Electro-Communications, Tokyo 182-8585, Japan; k2141014@edu.cc.uec.ac.jp (J.G.); yosinaga@is.uec.ac.jp (T.Y.)
[2] Inner Mongolia University of Finance and Economics Library, Inner Mongolia University of Finance and Economics, Hohhot 010051, China; pengchunrong1978@gmail.com
[3] B & S Tech Co., Ltd., Arakawa-ku, Tokyo 116-0014, Japan; bstechtokyo@gmail.com
[4] School of Computer Science and Information Engineering, Hohhot Minzu College, Hohhot 010051, China; siriguleng.imnc@gmail.com
* Correspondence: celimuge@uec.ac.jp

Abstract: The digital twin (DT) paradigm represents a groundbreaking shift in the Internet of Vehicles (IoV) landscape, acting as an instantaneous digital replica of physical entities. This synthesis not only refines vehicular design but also substantially augments driver support systems and streamlines traffic governance. Diverging from the prevalent research which predominantly examines DT's technical assimilation within IoV infrastructures, this review focuses on the specific deployments and goals of DT within the IoV sphere. Through an extensive review of scholarly works from the past 5 years, this paper provides a fresh and detailed perspective on the significance of DT in the realm of IoV. The applications are methodically categorized across four pivotal sectors: industrial manufacturing, driver assistance technology, intelligent transportation networks, and resource administration. This classification sheds light on DT's diverse capabilities to confront and adapt to the intricate challenges in contemporary vehicular networks. The intent of this comprehensive overview is to catalyze innovation within IoV by providing an essential reference for researchers who aspire to swiftly grasp the complex dynamics of this evolving domain.

Keywords: intelligent traffic system; internet of vehicles; digital twin; intelligent transportation; assisted driving

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1. Introduction

Digital twin (DT) is a technology used to create virtual models for entities in the real world and realize real-time synchronization between virtual and real space so that digital representation and physical entities can interact. Michael Grieves first put forward the concept of DT at the Society of Manufacturing Engineers meeting held in Troy, Michigan, in 2003 and regarded it as a management mode to product life cycle [1]. Initially, DT was used in the Apollo program of the National Aeronautics and Space Administration (NASA) [2]. NASA has created two identical spacecraft, one of which stays on the earth and is called the "twin" responsible for reflecting the status of the spacecraft. DT helps spacecraft make decisions through simulation and simulation experiments. With the development of DT, it is now possible to collect data through sensors and other devices to create virtual models. Advancements in sensor technology have since enriched DT's capabilities. It continuously updates virtual models based on real-time data collected from physical entities. These capabilities have endowed DT with distinct advantages such as real-time responsiveness, interoperability, scalability, and autonomy [3].

With the continuous development of Internet of Things (IoT) technology, the Internet of Vehicles (IoV) has received more and more attention. IoV is a concept rooted in IoT technology, aimed at integrating vehicles, roads, drivers, and infrastructure into a unified network for communication and information exchange [4]. Utilizing wireless communication, sensor technology, and data analysis, IoV enables vehicles to communicate with each other, interact with traffic infrastructure, and connect to drivers and cloud-based servers [5]. IoV fosters intelligent connections between vehicles, roadways, and infrastructure, offering a safer, more efficient, and environmentally friendly transportation system. IoV promises enhanced safety, efficiency, and environmental sustainability, revolutionizing traffic management and travel experiences.

Although IoV has been widely used, challenges persist in the IoV. Firstly, from the vehicle's perspective, failures or accidents may occur after it leaves the factory. Nevertheless, imperfect monitoring during the vehicle production process and inconsistent standards among manufacturers make it challenging to maintain and interoperate parts in the later stages [6]. Recording and monitoring the entire vehicle life cycle can facilitate quickly identifying and resolving problems. Secondly, IoV cannot fully obtain the behavioral data of all drivers, hindering its ability to accurately predict the following actions of the vehicle [7]. Current traffic condition predictions typically cover only local road sections. That necessitates re-prediction when switching routes, increases calculation costs, and limits the efficiency of path planning. Lastly, regarding the entire transportation system, the central control system cannot acquire real-time information from all vehicles. This results in a lag in vehicle information acquisition and an inability to provide accurate guidance promptly [8]. However, when the central control system issues instructions to the vehicle, the short duration of these instructions poses a risk. If the vehicle fails to receive the instructions in time, it may become invalid, potentially leading to traffic accidents.

In view of the above problems of IoV, researchers propose to use DT to solve these challenges [9]. By creating a digital copy of the vehicle in the virtual space, DT can monitor the status and behavior of the vehicle in real-time and make accurate predictions and simulations. With DT, the maintenance efficiency of vehicles and the accuracy of driving behavior prediction can be improved, and more timely guidance and traffic control can be achieved, thus promoting the optimization and improvement of the IoV system [10].

Firstly, real-time monitoring of the entire production process can be achieved by creating a DT to monitor the production cycle of vehicles [11]. The data generated in the vehicle production process will be transmitted to the digital model of the DT in real-time, which enables us to simulate and predict the vehicle performance and possible faults efficiently. Through effective health monitoring and early warning, vehicle problems can be solved promptly, thus reducing maintenance costs. Additionally, assuming that the vehicle maintenance unit and manufacturer are located in different places, the data in DT can be used to quickly check the status of the vehicle and save maintenance time [12]. At the same time, in the process of vehicle operation, the data is transmitted to the digital model in DT in real-time. By comparing with the model of a healthy vehicle, the time when the vehicle may fail can be predicted, thus improving driving safety [13]. In addition, DT's digital model can also simulate the performance and fuel efficiency of vehicle parts. It can also detect and adjust the running status of vehicles in real-time to achieve the energy conservation goal. By constantly monitoring and optimizing the operation of vehicles, the fuel efficiency of vehicles can be maximized and energy consumption reduced.

Secondly, according to the driver's driving behavior, the vehicle will upload the driver's habits, experiences, data, and surrounding environment to the digital model of the DT in real-time [14]. In twin, these data will be analyzed and evaluated in real-time to provide helpful feedback for drivers, help them improve their driving behavior, and improve driving safety. Furthermore, the digital model of DT can also provide real-time optimal route planning for drivers according to different drivers' driving habits and current road conditions [15]. Such personalized navigation services can help drivers reach their destinations faster, reducing congestion and unnecessary delays. Additionally, by providing driving safety and navigation services, DT can also meet users' needs for higher-level services. For example, through an in-depth understanding of driver preferences, DT can provide users with personalized driving settings to meet the specific needs of different drivers [16]. Furthermore, DT can also provide personalized experiences, such as entertainment while driving, making driving more pleasant and comfortable.

Finally, the application of DT in IoV can achieve a high degree of interaction with the physical world and simulate the operation of the entire transportation system by building a digital model [17]. By applying DT to the IoV, the driving conditions of all vehicles are acquired in real-time, and through interoperability with physical vehicles, the vehicles can upload information in real-time and receive real-time guidance from the twin to effectively avoid traffic risks. Additionally, the application of DT can provide optimal path planning for vehicles and predict traffic conditions by simulating the driving plans of different vehicles [18]. Such intelligent path planning can effectively avoid congestion, control traffic flow, and realize space management. Through DT's accurate prediction and real-time feedback, vehicles can choose faster and safer routes to improve the efficiency and safety of the entire transportation system.

Given the burgeoning interest in the application of DT within the IoV, our review aims to fill the gap in the existing literature on this application. Despite a considerable number of publications from 2020 to 2023 that discuss the integration of DT in IoV, there is a dearth of structured reviews in this specific area [19]. Most existing reviews either focus on the broader applications of DT or barely scratch the surface of its potential roles within IoV. Hence, our paper aims to provide a comprehensive summary and classification of existing research while placing emphasis on the unique contributions and goals of integrating DT and IoV. This paper summarizes the research results from the past 3 to 5 years and summarizes these results in four main directions according to the application direction: industrial production, assisted driving, intelligent transportation, and resource management. The research contributions of this paper are as follows:

1. This paper provides foundational aspects of IoV and DT, demystifying prevalent misconceptions and positing a stratified four-layer architecture—Physical, Connection, Twin, and Visualization Layers.
2. IoV's challenges in industrial production, assisted driving, intelligent transportation, and resource management are identified and explored, proposing how DT can address these issues due to its inherent capabilities.
3. This review adopts a unique classification of DT's recent IoV applications over the past 3–5 years into four categories according to the application direction, presenting a fresh perspective and comprehensive analysis that offers clear insights and research directions.
4. Open questions regarding DT's incorporation into IoV are discussed. It proffers prospective trajectories for constructing a DT-infused IoV landscape, thereby expanding the theoretical and practical horizons for academicians. In addition to the technical issues, we also discussed the opening issues in the implementation process and future research directions to accelerate the innovative development of DT-based IoV.

Paper Organization: In Section 2, this review first briefly introduces the fundamentals of IoV and then discusses the fundamentals and related technologies of DT in depth to help researchers fully understand the field of DT. In Section 3, this review will focus on the current challenges faced by IoV, as well as the motivation and advantages of applying DT technology to IoV. In Section 4, this review will review the research achievements of DT in IoV in recent years and comprehensively summarize these applications and progress. In Section 5, this review will put forward some open questions that stimulate thinking and explore the possible research directions of DT in IoV in the future, leaving room for researchers to explore further. The structure diagram of this paper is presented in Figure 1. The abbreviations used in this manuscript are listed in Table 1.

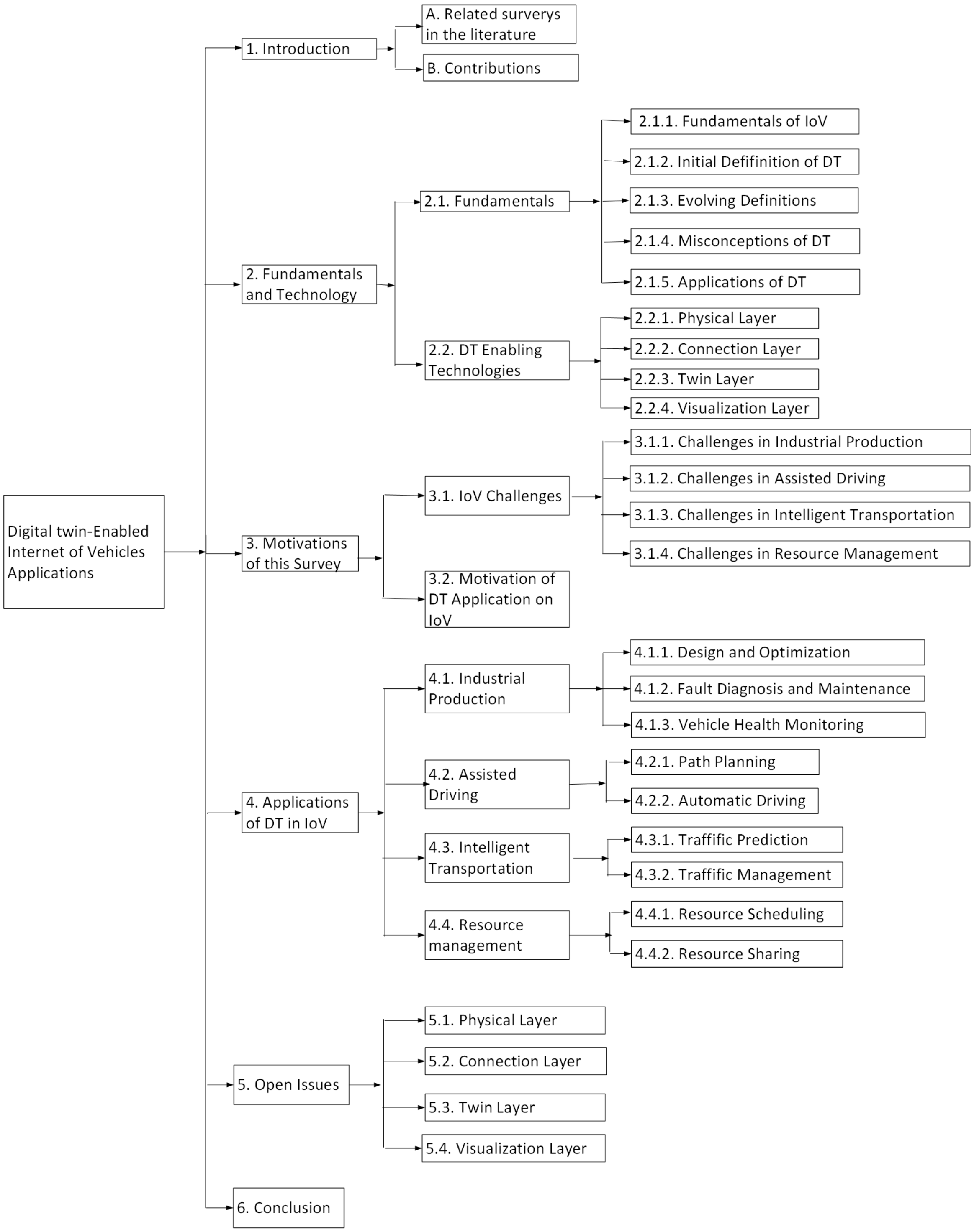

Figure 1. Structure of this paper.

Table 1. Abbreviations.

Full Name	Abbreviations
Digital Twin	DT
Internet of Things	IoT
Internet of Vehicles	IoV
National Aeronautics and Space Administration	NASA
Augmented Reality	AR
Virtual Reality	VR
Cyber Physical Systems	CPS
Three-Dimensional	3D
Data Distribution Service	DDS
HyperText Transfer Protocol	HTTP
JavaScript Object Notation	JSON
eXtensible Markup Language	XML
Extended Reality	XR
Intelligent Transportation System	ITS
Car as a Service	CaaS
Convolutional Neural Network	CNN
Vehicular Ad hoc Networks	VANET
Artificial Intelligence	AI

2. Fundamentals and Technology

This section provides a comprehensive introduction to IoV and DT. This review first elaborates on the fundamental principles of the IoV and then segues into the core aspects of DT, including its definitions, common misconceptions, and applications. Finally, it discusses the basic and essential technologies that support the Internet of Vehicles and underpin DT.

2.1. Fundamentals

2.1.1. Fundamentals of IoV

The IoT is a network that connects various physical devices through the internet to realize data sharing and exchange [20]. With the development of IoT technology, the connection between vehicles, between vehicles and pedestrians, and between vehicles and infrastructures has gradually become a reality, which is IoV. IoV uses technologies such as sensors, wireless communication, and big data to connect vehicles to the internet, realize data exchange and other operations, and provide multiple services for vehicles [21]. However, with the continuous growth of people's travel demand, simple IoV technology has been unable to meet the requirements. Therefore, assisted driving has become a new research hotspot. On the basis of IoV, assisted driving carries out path planning, automatic parking, lane keeping, and other actions according to the current traffic conditions, providing auxiliary guidance for vehicle driving behavior, thus improving the efficiency of traffic travel and ensuring the safety of vehicles [22].

IoV has many applications in daily life. For example, in terms of communication and navigation [23], the vehicle can obtain the surrounding environment information through sensors and upload it to the IoV system. The central controller can integrate road section information and provide integrated navigation suggestions for vehicles to reduce road congestion and improve the efficiency of the traffic system. Complementarily, if an abnormal situation occurs on a particular road (such as a traffic accident, jam, or obstacle), the central controller can quickly obtain the information sent by the vehicle ahead, change the navigation scheme, and transmit the information to subsequent vehicles as a reminder. At the same time, it can also quickly notify rescuers to request a rescue, thus improving traffic safety.

In addition, IoV can also help identify dangerous driving behaviors such as fatigue driving [24]. The central controller can obtain the vehicle driving data. Once the driver is found to have abnormal behavior, it can remind the driver to pay attention to safety, keep the vehicle running on the regular lane, and even assist in braking in an emergency. IoV also takes into account the emotions of drivers and passengers [25]. It can provide vehicles with personalized entertainment activities, such as video, music, and radio, to improve the driving experience.

In general, the application of IoV has brought many benefits in terms of vehicle navigation, traffic safety, and ride comfort. It has brought convenience and safety improvement to daily traffic life.

2.1.2. Initial Definition of DT

DT is a twin virtual digital world for the physical world, connecting the physical objects in the physical world with the corresponding objects in the virtual world [26]. The virtual world is a digital model of the physical world, which completely presents the state of objects. Through communication technology, the physical and virtual worlds can interact, give feedback, and operate with each other in real-time. However, the exact definition of DT has yet to be unified in the industry.

The term DT first appeared at the Society of Manufacturing Engineers conference in 2003, proposed by Michael Grieves [27]. The primary purpose of the DT proposed at this meeting is to digitize product life-cycle management and transform product data from manual writing to a digital model for better management. Michael Grieves divided DT into three parts: real entities in the physical world, virtual representations of real entities in the twin, and the connection between the physical world and the twin, which laid the foundation for the future development of DT. In 2012, NASA defined DT in "The Digital Twin Paradigm for Future NASA and U.S. Air Force Vehicles" [28]. However, as DT has aroused intense interest in various industries, it has led to the emergence of diversification in the definition of DT [29].

2.1.3. Evolving Definitions

2010: Shafto et al. defined DT as that through the integration of multi-physicals, multi-scale, and probabilistic simulations of vehicles or systems, the life cycle of its twin was reflected by the best physical model, sensor updates, fleet history, and other information [30].

2012: Tuegel believed that DT was a model that could meet the task requirements in the whole life cycle from product design to terminal operation [31]. In the same year, Glaessgen and Stargel thought similarly to Shafto that DT was a surreal technology that could combine multiple interdependent systems [32].

2013: Lee et al. defined DT as a coupling model of real entities and simulated the state of entities through data-driven analysis algorithms and other knowledge [33]. Reifsnider and Majumdar identified DT as a high-fidelity physical model [34]. Majumdar et al. believed that DT was a highly sensitive structural model [35]. USAF believed that DT was a virtual representation of a system integrating data, model, and analysis [36].

2014: Grieves also divided DT into physical products, virtual products, and the connection of data and information between the real world and the virtual world [37].

2015: Rios et al. defined DT as an interaction model between the real world and the world that reflects the current process of the real world [38]. Rios et al. considered DT as the corresponding digital product of physical products [39]. For the aircraft industry, Bielefeldt et al. argued that DT was an ultra-realistic multi-physics computational model associated with each unique aircraft [40]. Bazilevs et al. defined DT as a complete digital correspondence structure model in the physical world [41].

2016: Schluse and Rossman thought DT was a virtual substitute for the physical world [42]. Gabor et al. considered that DT was the simulation of physical objects, which could be used for prediction [43]. Schroeder et al. thoroughly considered the network system in DT [44]. Kraft realized that DT mirrored physical entities and made predictions through digital implementation [45].

2017: Abramovici et al. proposed that DT was an interdisciplinary technology [46]. Stark et al. said that DT was a digital representation of assets, simulated asset status, attributed through models [47]. Schleich et al. believed that DT was a two-way relationship between physical entities and virtual models, which runs through the entire life cycle [48].

2018: Tao et al. defined DT in five parts: physical world, virtual world, two-way connection, data, and services [49]. Authiosalo identified DT as the network part of the cyber–physical system [50]. Demkovich et al. believed that DT was a digital layout, which contained multiple layers and simulated real-world developments by acquiring data in real-time [51].

2019: Madni et al. believed that DT was a virtual instance of the physical world and managed all data in the life cycle of physical entities [52]. ISO/ISOAWI 23247 considered that DT synchronized changes in physical entities [53].

2020: Jones et al. argued that the connection between physical entities and virtual worlds was more important than features in DT [3]. Cheng et al. believed that DT provided end-to-end integration in the product life cycle [54].

2021: Ma et al. believed that DT created a synchronous virtual model of the physical world [55].

2022: R Geng applied DT to engineering and manufacturing, mainly to provide virtual representation and workflow of physical entities [56]. In the medical field, De Benedict used DT to simulate the characteristics of patients, monitor the health of patients in real-time, and give treatment [57]. Xiong defined DT in the field of aerospace, especially the feature simulation of aircraft [28].

2.1.4. Misconceptions of DT

Although the definition of DT constantly evolves, several misconceptions still exist in the industry. These misconceptions include confusing DT with Augmented Reality (AR) or Virtual Reality (VR), with the concept of Cyber Physical Systems (CPS), or treating DT only as three-dimensional (3D) modeling. Next, this review will introduce these misconceptions about DT in detail.

1. DT and AR/VR: Some people confuse DT with virtualization technologies such as AR/VR [58]. Although AR and VR can be used in combination with DT, DT is much more than these technologies. DT involves a broader range of concepts, including modeling and analysis of simulation, mirroring, and prediction of the integrity of physical entities. AR/VR is just a tool for DT to realize visualization.
2. DT and 3D Modeling: Some people simply understand DT as 3D modeling [59]. DT not only includes the geometry of objects but also involves the simulation and analysis of object behavior, performance, sensor data, and other aspects in addition to simple 3D modeling. On the other hand, building DT does not necessarily mean that 3D modeling is necessary. The scope of modeling and analysis of DT is more extensive, which can cover multiple aspects, not limited to the representation of 3D shapes.
3. DT and CPS: CPS is a system of physical and computing resources. It mainly realizes functions through the interaction of physical and virtual components. The main goal of CPS is to achieve the integration of the physical world and computing, so as to achieve the purpose of real-time monitoring, control, and decision-making. DT simulates, twins, and predicts physical entities through digital models and real-time data. The main goal of DT is to build virtual digital representations for physical entities to achieve optimal design and maintenance. Additionally, CPS is primarily used in automation, intelligent manufacturing, and other fields, while DT is mostly used in industries with physical entities for performance simulation [60].
4. DT's Own Misconception: In addition to the inherent misconceptions about DT mentioned above, there are internal misconceptions about what DT is or should be:
    - Static Digital Models: Some assume that once a DT model is created, it remains static and does not update according to changes in the physical entity [61].
    - Digital Shadows: This concept implies a one-way data flow from the physical world to its DT. Changes in the digital world do not affect the physical entity and thus lack predictive and control capabilities [62].

- True DT: A true DT involves a bidirectional data flow, allowing both the physical and virtual realms to influence each other. Only with this two-way communication can DT offer robust support for real-time monitoring, optimization, and maintenance.

Figure 2 provides a schematic representation of a DT framework applied to vehicular systems. In the diagram, the physical world contains real vehicle information, including the rearview mirror, wheel, car door, headlight, and windshield. The virtual world can realize functions such as AI, data analysis, simulation, 3D modeling, and machine learning. The virtual world can accept changes in the physical world and make corresponding changes. At the same time, the physical world can also accept instructions from the virtual world and perform corresponding actions. DT involves continuously updating and interacting with physical entities and virtual models to achieve more accurate and reliable simulation, prediction, and control effects. Only a true DT can realize the two-way information transmission between the physical world and the virtual world, thus providing more robust support for real-time monitoring, optimal design, maintenance, and other fields.

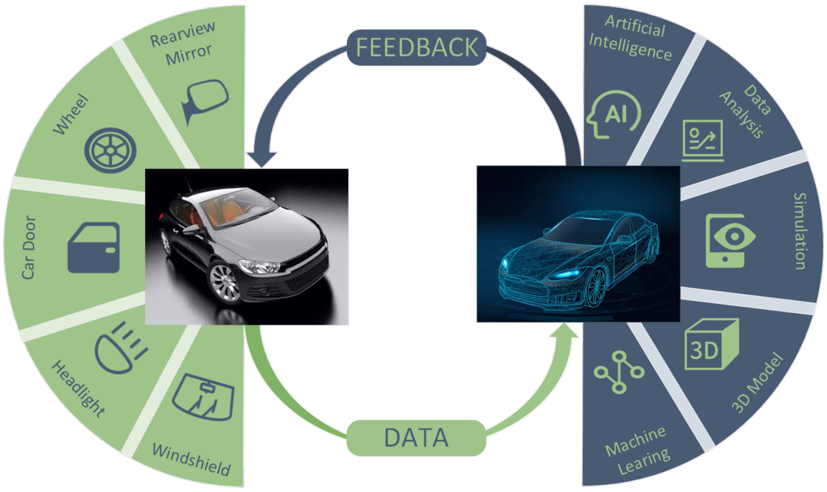

Figure 2. Diagram of DT.

2.1.5. Applications of DT

DT has garnered widespread adoption across a range of industries. In this section, this review provides a concise introduction to various applications of DT technology. A detailed list of these applications is shown in Figure 3.

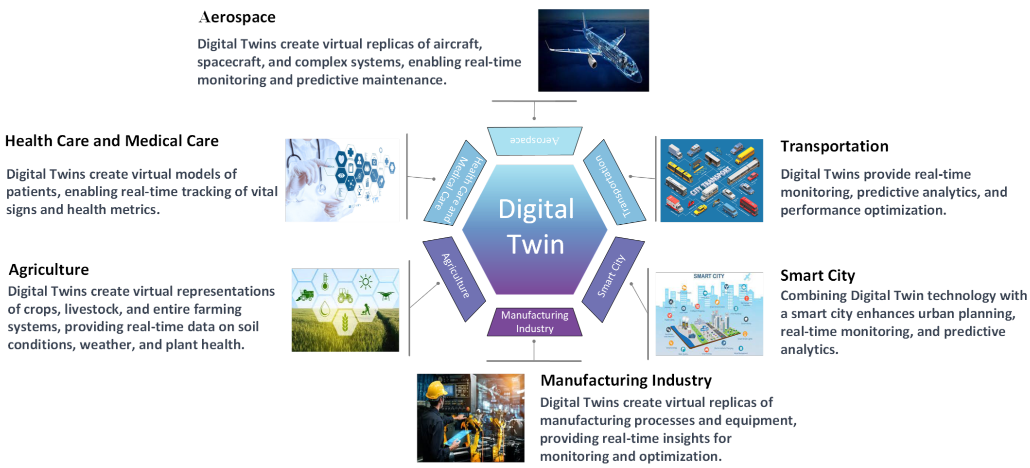

Figure 3. Applications of DT.

1. Aerospace: In aerospace, DT technologies are leveraged for predicting component failures, thereby reducing maintenance costs. For instance, the U.S. Air Force Research Laboratory (AFRL) developed a comprehensive DT of an aircraft to monitor its real-time data and foresee potential failures. This results in cost-effective and timely preventive maintenance, enhancing the longevity and reliability of the aircraft [63]. Other studies develop reusable DT tools that simulate and optimize the manufacturing process of aircraft components [64] and high-precision monitoring of spacecraft components [65].
2. Health Care and Medical Care: DT has extensive applications in the healthcare sector, enhancing the quality, efficiency, and personalization of medical services, including medical diagnosis, surgical planning, equipment design, and process optimization. There is research that focuses on using machine learning techniques to analyze cancer-related data and construct a precise breast cancer DT model [66]. Medical professionals can use this model to simulate and predict patients' cancer progression, treatment response, and prognosis. This modeling approach facilitates personalized diagnosis and treatment decisions and can provide more accurate disease assessment and treatment options. To simulate and optimize various aspects of the healthcare system, including healthcare processes, resource management, patient care, and equipment utilization by creating DT models, Mohamed et al. model and simulate the system to identify potential bottlenecks and improvement opportunities and provide practical solutions [67]. Lv et al. focus on using DT to assist in the diagnostic process of healthcare [68]. Disease-related data, including patient symptoms, physiological parameters, and medical records, are collected through a client application. Subsequently, these data are utilized to create DT models for a better understanding of disease progression trends and potential patterns.
3. Agriculture: Alves et al. comprehensively consider soil, crop, and weather data and design a DT model to calculate the most suitable irrigation water amount. This intelligent irrigation system can provide precise irrigation recommendations based on real-time environmental conditions and crop requirements, reducing waste and enhancing the efficiency of water resource utilization [69]. Fatima et al. spread knowledge widely to farmers by creating DT models of agricultural knowledge [70]. Farmers can use these models to understand agricultural practices such as optimal seed selection, soil management, and irrigation strategies under specific conditions. Chen et al. focus on creating a DT model for transplant machines of plant factories, which is capable of five-dimensional modeling. By collecting and integrating the sensor data of the machine, the working status of the transplanted machine can be monitored in real-time [71].
4. Manufacturing Industry: Considering the quality problems that may occur in the process of manufacturing new products, DT is created for manufacturing tasks through heterogeneous information networks driven by digital threads to accurately simulate and monitor the manufacturing process of products, including design, raw material selection, production process, and other aspects, so as to achieve the control of the overall product production process [10]. To meet the needs of discrete workshops, Chao et al. propose a DT unit, then a multidimensional and multi-scale DT model and modeling method are developed based on this unit [72]. This approach can comprehensively simulate all aspects of the discrete workshop and provide detailed multi-scale analysis to help optimize the production process and improve efficiency and quality. In order to solve the problems of low precision and late response of discrete production lines, a thought fusion modeling method is proposed by Xie to optimize the DT system architecture of discrete production lines [73]. In this way, knowledge and technology from multiple fields are integrated, and information and data from all links are integrated to achieve comprehensive modeling and optimization of discrete production lines to improve the accuracy, efficiency, and responsiveness of production lines.

5. Smart City: In order to create an intelligent and sustainable smart city, Nica et al. use predictive modeling algorithms to create a DT for the city and combine it with deep learning and other technologies to achieve efficient smart city management [74]. City managers can better understand the needs and challenges of the city, formulate corresponding planning and decision-making, optimize resource utilization, and provide better urban services. Wang et al. create a five-dimensional DT model of the city [75]. Based on that, edge computing is introduced to expand the data processing and decision-making ability from the central server to the edge device close to the data source. The model can provide real-time data analysis and responses, which enable DT to perceive and predict traffic conditions in real time and support intelligent traffic management and decision-making. Kuru et al. construct a high-fidelity metaverse interactive virtual world, implant it into the urban management system, and propose an ecological framework for the urban metaverse [76]. In this city meta-universe ecological framework, they connect the virtual world with the actual urban management system and realize real-time data transmission and sharing through data exchange and integration with the city management system.
6. Transportation: Aiming at micro expressway simulation and real-time data integration during system operation, a DT modeling method for traffic data flow on expressway traffic is proposed by Kuvsic [77]. This DT can provide more precise and accurate traffic simulation results. Through the simulation and analysis of key indicators such as traffic flow, speed, and congestion, it can evaluate the performance of the traffic system, predict traffic congestion, and propose optimization measures. Nie et al. utilize the advantages of DT in network management in the transportation system, and a network traffic prediction algorithm is proposed [78]. Through the construction of DT, the traffic flow in the traffic network can be accurately simulated and analyzed, and the operation status of the network can be monitored in real-time. In order to solve the problem of COVID-19 medical waste transportation, a DT driven framework model is proposed by Cao to optimize waste collection and transportation routes and improve the efficiency and reliability of transportation by real-time monitoring and forecasting the generation and distribution of medical waste [79].

2.2. DT Enabling Technologies

After a comprehensive review of the existing literature, we find that a majority of research predominantly categorizes DT into a three-layered architectural framework. To extend this conventional model and to better align with user-centric requirements, particularly those concerning visualization, this review introduces an additional layer in our conceptualization. This refined architecture, depicted in Figure 4, consists of four principal layers: the Physical Layer, the Connection Layer, the Twin Layer, and the Visualization Layer. Below, this review offers an analytical discussion of the technological underpinnings associated with each of these layers.

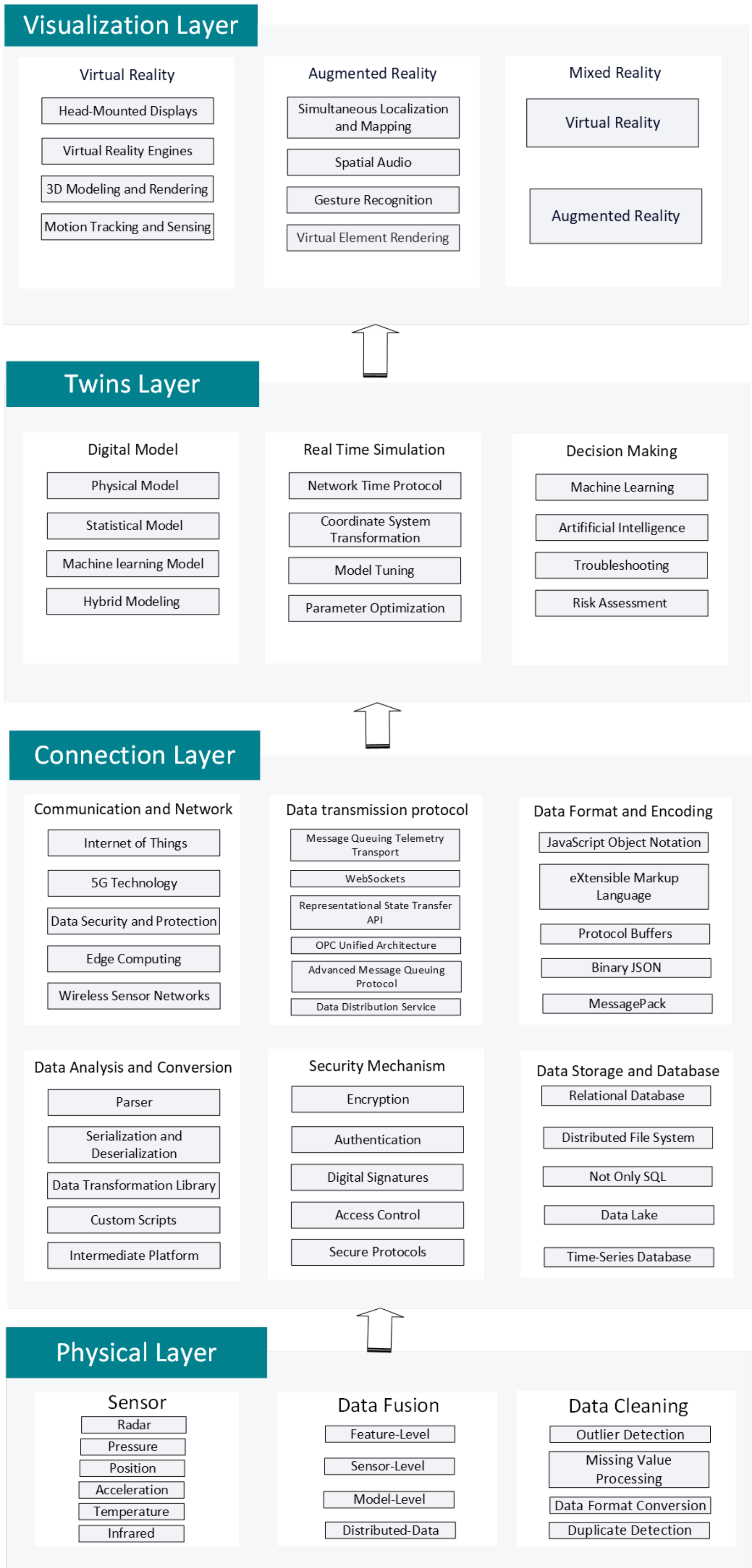

Figure 4. Layered diagram of DT technology.

2.2.1. Physical Layer

The physical layer refers to entities existing in the real world, which are responsible for sending their characteristics and other states to the twin layer so that the twin layer can be accurately simulated. The key technologies involved in this layer are as follows:

1. Sensor Technology: Physical entities rely on sensor technology to collect and detect data and upload them in real-time [80]. According to different DT applications and needs, different types of sensors are used to meet specific detection and acquisition requirements. Current sensors mainly include temperature sensors, pressure sensors, acceleration sensors, radar, infrared sensors, and position sensors.
2. Data Fusion Technology: The construction of DT requires comprehensive data from multiple directions and angles, but a single sensor cannot obtain such data. Therefore, in the face of heterogeneous data generated by multiple sensors, how to integrate these data is a challenge [81]. Current data-fusion technologies include sensor-level fusion, which can fuse the same type of sensor data to obtain more reliable data in this dimension; feature-level data fusion, which achieves the purpose of data fusion by extracting and integrating different data features and attributes, mainly for data such as image, text, voice and other data; model-level data fusion, which integrates outputs from different models through integrated learning, model integration, model fusion and other methods; and distributed-data fusion, which requires the use of distributed computing and collaborative algorithms to fuse data from different locations.
3. Data Cleaning Technology: There may be a lot of noise, missing, or errors in the fused data. Unprocessed data may impact the construction of the virtual world at the twin level, leading to errors or failures in model construction [82]. Therefore, data cleaning technology is needed to detect and correct data errors and provide accurate, complete, and reliable data for the system. Current data cleaning technologies include missing value processing, outlier detection, duplicate detection, and data format conversion.

2.2.2. Connection Layer

The Connection Layer serves as the conduit for bi-directional data transfer between the physical and twin layer. This layer employs several technologies to ensure effective and secure communication.

1. Communication and Network Technology: Communication and network technologies play a vital role in implementing DT. Here are some common communication and network technologies. First, the IoT technology connects physical objects to the Internet through wireless sensor devices so that data can be shared between various devices [83]. The second is 5G technology, which creates transmission conditions for DT because of faster transmission speed, lower latency, and greater network capacity [84]. Then there is data security and protection technology [85]. The communication between the physical world and the twin needs to protect the security of both parties and the privacy of data. Therefore, some security mechanisms, such as encryption technology, access control, and authentication, are required to ensure the security of data storage and transmission. In addition, technologies such as edge computing can also be used to build a two-way bridge between the physical world and the twin, which can reduce network latency and improve real-time interaction efficiency [86]. Finally, wireless sensor networks are often used in the IoT, where sensor nodes can communicate directly with the twin to provide real-time data [87].
2. Data transmission protocol: In DT, data transmission technology is widely used in the interaction and communication between physical entities and the twin. The following are some common data transmission protocols to ensure the real-time communication of DT.
    - Message Queuing Telemetry Transport (MQTT) [88]: MQTT is a lightweight message transmission protocol that supports the publish–subscribe model and can provide good real-time communication between devices with low energy consumption and DT.

- WebSockets [89]: WebSockets is a duplex communication technology, generally used between the web browser and server, which can provide long-term connection and support two-way communication between DT.
- Representational State Transfer API (RESTful API) [90]: This protocol is a web service architecture based on the HyperText Transfer Protocol (HTTP) protocol. It defines a good API interface and can request and respond to real-time communication between DTs.
- OPC Unified Architecture (OPC UA) [91]: OPC UA is a communication protocol and data model with security, reliability, and interoperability, which is now primarily used to provide real-time connection for automated plants.
- Advanced Message Queuing Protocol (AMQP) [88]: This protocol is message-oriented and can realize real-time communication and data transmission in a distributed environment. It is characterized by high performance and low latency.
- Data Distribution Service (DDS) [92]: DDS is a data distribution and communication protocol that supports the publication and subscription of real-time data and is used to realize real-time high-performance communication between systems. It has the characteristics of reliability, real-time, and scalability.

3. Data Format and Encoding Technology: In DT, the physical entities are diversified, and the data is highly heterogeneous. If the data format and encoding are not unified, it will bring great trouble to the creation of DT. Here are some data formats and coding technologies.
    - JavaScript Object Notation (JSON) [93]: It is a lightweight data exchange format that uses key-value pairs to represent data. It can simply express data objects and nested structures. Also, it is very friendly for writing and reading.
    - eXtensible Markup Language (XML) [94]: XML is a pervasive markup language used to describe data structures. It is extensible and readable and can represent complex data structures.
    - Protocol Buffers [95]: Protocol Buffer is more suitable for large-scale data transmission, can define structured data as a message format, and provides an efficient encoding method. It is a lightweight data serialization protocol.
    - Binary JSON (BSON) [96]: BSON is extended based on JSON for efficient storage and transmission. It not only has the flexibility of JSON but also improves efficiency through binary encoding, which can reduce data transmission consumption.
    - MessagePack [97]: It is a binary data serialization format, mainly used for data exchange in different programming languages, and can be quickly encoded and decoded. Also, it can provide high-performance data transmission.
4. Data Analysis and Conversion Technology: Generally, there may be differences in the structure and format between the data of the digital model and the data of the physical entity in the twin. At this time, data analysis and conversion technologies are required to convert the data of both sides into acceptable data. Here are some methods.
    - Parser [98]: It is a convertible data format. Different parsers have different functions. For example, JSON parsers can parse JSON data into internal data or XML data into operable data objects.
    - Serialization and deserialization [99]: Serialization is the process of converting different data objects into specific formats (JSON, XML, binary.). The process of deserialization, on the contrary, is the process of reversing formatted data into data objects. Through serialization and deserialization, data transmission between DT will become easier.
    - Data transformation library [100]: It provides a lot of data transformation and mapping, such as Extensible Stylesheet Language Transformations, which provides methods for transforming XML into other formats.

Additionally, data can be converted into special formats by writing programs and custom scripts. Furthermore, data can also be converted through the intermediate platform. All data is collected in the intermediate platform, which judges and converts by itself, and then allocates data in the corresponding format under different requirements.

5. Security Mechanism: In DT, not only the communication quality should be considered, but communication security is also essential. Regardless of data leakage or corruption, DT will be hit. Therefore, a certain security mechanism is required to ensure the data security.
    - Encryption [101]: Encryption is a common data protection mechanism. The encryption mechanism converts data into ciphertext for transmission, which can effectively prevent unauthorized terminals from accessing data. Encryption mechanisms are generally divided into one-way, two-way, symmetric, asymmetric, digital signature, and other encryption methods.
    - Authentication [102]: Authentication can ensure that the objects accessing the database are authenticated and can effectively reduce the access of malicious nodes to the database through digital certificates and other methods.
    - Digital Signatures [103]: Digital Signatures ensure the integrity and authenticity of data. Digital Signatures can ensure that the data has not been tampered with by verifying the signature and can also trace the identity of the data sender, which can ensure the security of data reception.
    - Access Control [104]: When sensitive resources or system resources are accessed, Access Control can be used to manage access permissions according to different access requirements through operations such as access control and permissions management.
    - Secure Protocols [105]: Secure Protocols are required to ensure data security during data transmission.
6. Data Storage and Database: In the process of DT creation and operation, a large amount of data transmission will occur. However, how to store these data is also a problem that needs to be considered. Some data storage methods are introduced below.
    - Relational Database [106]: It stores data through table structure, support queries, and applies to structured data.
    - Not Only SQL [107]: Contrary to Relational Database, it is a non-relational database suitable for storing unstructured or semi-structured data, such as documents and graphs. The database has high flexibility and scalability.
    - Data Lake [108]: Data lake can store a large amount of raw data that has yet to be processed. It can store structured, semi-structured, and unstructured data. It is suitable for storing underlying data in DT and can be analyzed by DT.
    - Time Series Database [109]: Time Series Database can store data related to time, such as real-time sensor detection data.
    - Distributed File System [110]: This storage mode has high reliability and scalability. It is usually used to manage large amounts of data.

    In addition, blockchain [111], as a distributed ledger structure, is often used to store data. Since blockchain has characteristics such as tamper-proof and transparency, the application of blockchain technology in DT is a more secure storage method.

2.2.3. Twin Layer

The Twin Layer serves as the central core of the DT architecture, housing the digital representations of all corresponding physical entities. Functionally, this layer acts as the “brain” of the DT system, overseeing critical tasks such as monitoring, simulation, management, optimization, and control. In the following subsections, this review will explore the essential technologies and features that various Twin Layers must incorporate.

1. Digital Model: The digital model is the digital representation of physical entities, which is used to describe the characteristics and behaviors of physical entities. It is the core component of DT. The digital model describes and predicts physical entities through algorithms. Common digital models are as follows.
    - Physical model [112]: The physical model is created based on the physical characteristics of the entity through mathematical formulas, physical equations,

and parameters and is used to describe the modeling method of the physical characteristics of the entity.

- Statistical model [113]: Statistical model refers to statistics and probability theory and is usually used for statistics and to predict the behavior of entities. The statistical model can analyze the historical data using statistical methods to analyze the trend and probability distribution of the system and then predict and optimize the system. Classical statistical models include regression models, time series models, and stochastic processes.
- Machine learning model [114]: The development of machine learning makes DT automation possible. Machine learning is a data and algorithm-driven model that is good at learning from data and extrapolating the development of transactions. The original machine learning model can be used for classification, prediction, and clustering. With the increasing interest of researchers in machine learning, machine learning has been able to handle more complex tasks.
- Hybrid model [115]: It creates a multi-dimensional and comprehensive digital model of physical entities by mixing different models. Physical models can be used to create physical properties of entities, and machine learning models can be used to predict and simulate the behavior of the system. This approach can integrate the advantages of the above models.

2. Real-Time Simulation: Since DT is a process that requires real-time communication and real-time decision-making, real-time simulation technology is required to update the digital model that has been built according to the changes of physical entities over time [116]. Real-time simulation can provide the simulation results and feedback of physical entities and digital models at any time so that the two worlds of DT can be interoperable. It should be noted here that real-time simulation requires real-time data input: that is, it needs to receive the data of physical entities such as sensors in real-time and then upload it to the digital model in time. The digital model updates the status and parameters through input and simulates the changes in physical entities. After the twin gets the simulation results, it also needs to transmit them to the physical entity in real-time to control the operation of the physical entity. In this process, real-time simulation needs to provide interaction and feedback between the twin and the physical world.
3. Decision Making: DDT is different from digital models and digital shadows. DT can receive changes in the physical world. Then, it predicts and simulates the twin corresponding to the entity according to the requirements. In this process, the twin needs to analyze the data of the physical entity, make decisions, and then issue orders to the entity, which is the central control part. With the development of machine learning and artificial intelligence, many learning methods can support decision-making, and different machine learning methods can be used according to different needs. For example, suppose a user wants to know about road congestion when leaving work, the system can predict the traffic situation according to the historical data and the current accident data of the road section. At this time, the learning model that is good at prediction can be used. If the user needs assisted driving, the twin needs multiple functions such as finding routes, optimizing routes, and avoiding obstacles. Decision-making can provide accurate simulation results for physical entities, help users make correct choices, and improve system operation efficiency.

2.2.4. Visualization Layer

The Visualization Layer serves as the user interface of the DT ecosystem, presenting system data, computational models, and analytical outcomes for user engagement. This layer enables real-time visual monitoring of the system's operational status, thus serving as a critical touchpoint for users. The Visualization Layer also incorporates advanced immersive technologies like VR, AR, and Hybrid Reality, collectively known as Extended Reality (XR) [117,118]. XR technologies offer a seamless integration between the physical and virtual worlds, creating a visually compelling, immersive, interactive experience for users. Interactions within this layer are typically facilitated through wearable devices, enriching the user's engagement with the digital models.

3. Motivations of This Survey

In this section, this review highlights some challenges currently existing in IoV and then introduces the motivation for applying DT to IoV.

3.1. IoV Challenges

Although IoV technology is constantly developing in many aspects, it also faces many problems. Firstly, there may be some things that could be improved in the production process of vehicles. With the promotion of automated factories, the current production of vehicles and parts tends to be automated. However, this automated factory only monitors the production process. It no longer tracks after the completion of vehicle production, which leads to short maintenance cycles of vehicles and parts and complicated maintenance. Secondly, with the continuous research on assisted driving technology, safety has become the focus of attention. Assisted driving involves the life safety and property safety of drivers and passengers. Once a small error or system failure occurs in path planning, serious accidents may occur. Intelligent Transportation Systems (ITS) require a large amount of complex data for control and prediction. However, it is challenging to process these data manually, especially to quickly extract target-related information from data with different structures and forms and conduct accurate analysis. Finally, in terms of resource allocation, IoV involves a large number of data resources and network resources. However, at present, many resource allocations only consider the local scope and lack a global perspective, which may lead to resource waste and local optimization. Here are some current challenges of IoV.

3.1.1. Challenges in Industrial Production

There are indeed many challenges in the vehicle production process, especially in terms of modular management and full life-cycle tracking. Most of the current production workshops are modular. Each workshop is only responsible for its own module and will no longer track the status after the end of the production process. This kind of production mode without full life-cycle tracking will lead to the inability to integrate data of all modules of the vehicle, low interoperability, and the lack of full life-cycle tracking, which will make it impossible to accurately predict the use of the vehicle module.

Furthermore, after the vehicle leaves the factory, due to the different technologies and standards of different manufacturers, these data are usually sensitive. They cannot be easily shared with other factories or users, which will lead to the problem of data islands. When the vehicle uses parts from different manufacturers, the relevant information on all parts cannot be obtained during maintenance, thus increasing the difficulty and complexity of maintenance.

3.1.2. Challenges in Assisted Driving

With the maturity of IoV technology, user demand for services provided by IoV is also increasing. The user hopes that the vehicle can give certain opinions and support during driving, such as path planning and emergency obstacle avoidance. However, IoV faces some technical challenges and limitations when implementing these functions.

Firstly, in terms of route planning, vehicles need to master a large amount of traffic information. However, the current data transmission and processing capabilities of IoV cannot handle such a massive amount of data. Therefore, IoV can only analyze the traffic congestion of the current road section and the road section to be driven to carry out simple path planning.

Secondly, vehicles must possess the capability to promptly respond to emergencies. In case of an emergency on the road, such as a traffic accident or mudslide, the vehicle needs to quickly obtain relevant information and make timely judgments to take corresponding measures to avoid accidents. This puts higher requirements on the response speed and data acquisition capability of the IoV.

Lastly, another critical concern is the vehicle's proficiency in executing emergency avoidance maneuvers. Indeed, drivers need to respond quickly when encountering emergencies, and sometimes, inexperienced drivers may face difficulties. In this case, the vehicle needs to judge whether to automatically avoid obstacles according to the driver's experience and driving habits. This puts high demands on the autonomous judgment ability of the vehicle because once the judgment is wrong, serious accidents may be caused. In this regard, the development of automatic driving technology and the improvement of intelligent auxiliary systems is the key to solving the problem.

3.1.3. Challenges in Intelligent Transportation

With the development of smart cities, intelligent transportation, as an essential part of it, has become a research focus. Intelligent transportation mainly includes traffic prediction and traffic management. For traffic prediction, IoV needs to predict the traffic situation by analyzing the real-time data and historical data of the current road section and many surrounding road sections. However, this prediction process requires a large amount of data storage, transmission, and analysis, which is indeed a massive challenge to the current IoV technology.

Because the data on all road traffic conditions in a city is enormous, traffic management pays more attention to data storage than traffic prediction. Therefore, how to store these data efficiently is an important issue. In addition, traffic data is closely related to time and space, so the system needs to quickly capture the dynamic changes in traffic so that it can quickly make adjustments when needed, such as when fire engines or ambulances need to quickly arrive at the scene, emergency evacuations, and other tasks.

3.1.4. Challenges in Resource Management

Resource management is an important issue that needs to be considered in any industry, especially in complex and resource-limited IoV networks. The resources here include data resources, network resources, channel resources, and computing resources. Rational allocation and utilization of these resources are critical to improving the efficiency and performance of IoV networks. By optimizing resource allocation, vehicle driving and traffic management can be improved, and users can be provided with better service and experience.

Data resources collect, transmit, and store data reasonably, which can improve the efficiency and accuracy of traffic forecasting, path planning, and other systems. Network resources are the basis for supporting IoV communication. It is necessary to plan network topology and bandwidth reasonably to ensure real-time data transmission and interaction. Channel resource refers to the channel of wireless communication, which needs reasonable scheduling between vehicles and between vehicles and infrastructure to avoid interference and collision and improve communication efficiency. Computing resources refer to the internal computing power of vehicles. It is necessary to reasonably allocate computing tasks according to the actual needs of vehicles to avoid waste of resources.

In addition, IoV can also improve efficiency by making full use of idle resources of vehicles. For example, when a vehicle is idle, its idle bandwidth, storage, and computing power can be shared with other vehicles or systems to achieve resource sharing and optimization.

In order to realize the rational allocation and utilization of resources, it is necessary to design intelligent resource management algorithms and mechanisms to dynamically adjust according to real-time data and needs. At the same time, it is also necessary to strengthen the monitoring and management of the IoV network, discover and solve resource bottlenecks in time, and ensure the stability and reliability of the system.

3.2. Motivation of DT Application on IoV

In light of the challenges facing the IoV, the capabilities of DT in efficient simulation, fault diagnosis, real-time monitoring, and knowledge sharing present a compelling case for their integration into IoV systems. Researchers are increasingly focusing on leveraging DT to offer innovative solutions to the complexities inherent in IoV. Below, this review outlines critical motivations for the application of DT within the IoV landscape.

Firstly, DT can provide comprehensive simulation and optimization capabilities in the design and development phase of IoV. By simulating and testing the functions and systems of different vehicles in a virtual environment, automobile manufacturers can optimize design and configuration parameters, thereby reducing development cycles and costs. DT can also provide real-time fault diagnosis and prediction through vehicle data comparison to help vehicle manufacturers and service providers find and solve problems in a timely manner, thus reducing vehicle maintenance time and costs. Simultaneously, DT can protect the privacy of sensitive data by setting access rights, authentication, and other ways to improve the life and maintainability of vehicles.

Secondly, DT can interact with vehicle sensors and real-time data, evaluate the safety and efficiency of driving behavior, and provide personalized driving suggestions to help drivers improve driving skills and safety to optimize driving behavior. In addition, DT can also be used for analysis and prediction of vehicle and network security. By supporting the simulation of vehicle systems and network environments and providing security improvement measures, DT helps prevent malicious attacks and improve the security of vehicle networks.

Thirdly, DT plays an essential role in the optimization and congestion mitigation of ITS. By simulating and optimizing traffic flow, signal control, and road network planning, DT can provide accurate traffic prediction and optimization strategies, thus helping to reduce traffic congestion and improve road traffic efficiency. In addition, DT can also identify potential accident risks through actual traffic data, predict and prevent traffic accidents, and improve road traffic safety.

Finally, DT provides an efficient resource management solution for IoV. By fully understanding the resource availability of each vehicle, DT can realize the reasonable allocation, sharing, and collaboration of resources, thus improving the efficiency of resource utilization. In addition, DT can also customize services and allocate resources reasonably according to the different needs of vehicles to avoid waste of resources. In the process of resource management, the security of resources is equally important. DT can ensure the security of resources and vehicles through access control, authorization, and identity authentication.

4. Applications of DT in IoV

This section categorizes the applications of DT technology in the IoV into four key areas: industrial production, assisted driving, intelligent transportation, and resource management.

4.1. Industrial Production

In traditional manufacturing sectors, interoperability poses a significant challenge due to varying data standards across different manufacturers, leading to isolated data silos. Additionally, concerns over the sensitivity of production data often prevent manufacturers from sharing information. This lack of data exchange can result in component mismatches and complicate subsequent maintenance efforts. To address these issues, this review surveys recent research results focusing on industrial production and then categorizes these studies into three key areas: design and optimization, fault diagnosis and maintenance, and vehicle health monitoring.

4.1.1. Design and Optimization

The breakthrough of DT technology lies in overcoming the limitations of traditional simulation technology in design and local application, realizing the coupling of multiple physical fields and data linkage between virtual and physical entities, thus significantly improving the simulation accuracy. In the face of complex systems and multivariable environments, DT can reflect the information of the entity system comprehensively, accurately, and in real time. Bai et al. use DT technology to significantly simulate the energy consumption and operation of various components of solar-powered vehicles and establish a mature vehicle energy consumption architecture [119]. To this end, they propose a novel DT framework, which combines the hybrid modeling method and SVM technology to improve the accuracy of the DT system. By applying both mechanical and data-driven modeling approaches, they can more effectively simulate the behavior and performance of solar-powered vehicles so as to more accurately predict energy consumption and operation. The frame diagram of this paper is shown in Figure 5. Firstly, in the physical world, sensors collect vehicle, weather, and road information and send it to the data management part. The data management is responsible for sorting, simple analysis, and uploading to the server. Then, the physical world sends the organized data to the cloud, and the cloud creates a virtual world to simulate, monitor, analyze, store, and report the physical world. Finally, the virtual world feeds back the analysis results to the physical world to assist with vehicle driving.

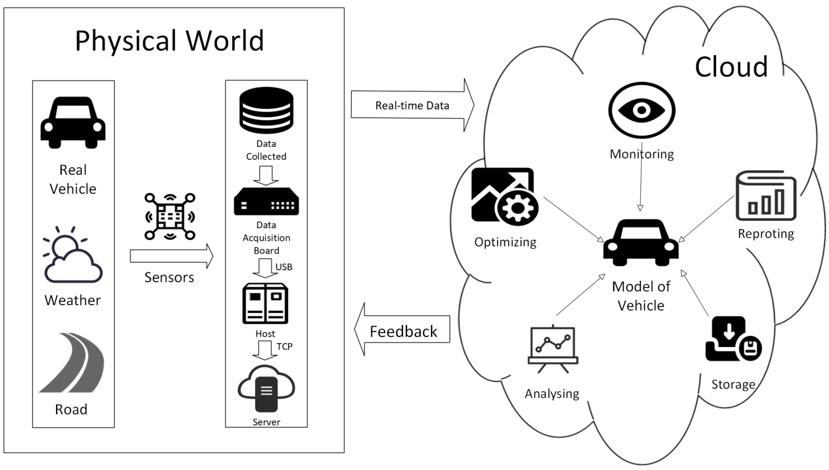

Figure 5. Solar-based hybrid modeling DT framework.

Zheng et al. focus on the combination of intelligent manufacturing system and DT technology, aiming to realize the online detection of body-in-white geometric features [120]. They propose an element-behavior-rule three-layer virtual modeling method for digital modeling of the physical environment. Through this method, they can map the actual physical environment and the virtual environment in real time to achieve high synchronization between the physical space and the virtual space. In order to achieve this real-time mapping, they design a three-layer communication architecture of the DT system to ensure that the data of the physical environment can be transmitted to the virtual model in time. In this research, they also develop an online detection system, which proves that the virtual model can drive the detection data of the physical environment in real time.

With the continuous advancement of digital technology, traditional products have gradually evolved into a service-centered model. In order to successfully integrate individual components of systems such as Car as a Service (CaaS) and smart cities, especially at different granularity levels, clear standards need to be established to model the system and define the architecture. Steinmetz et al. mainly focus on CaaS and propose the main components needed to build a system based on DT technology and arrange them in order to clarify the importance of each part of the system [121]. Through case studies, they demonstrate the application and deployment of DT technology in CaaS, highlighting its key role in promoting the development of CaaS.

4.1.2. Fault Diagnosis and Maintenance

In the realm of intelligent manufacturing, DT technology plays a pivotal role, particularly in fault diagnosis. Xu et al. put forth an innovative approach that utilizes deep transfer learning for two-stage auxiliary fault diagnosis [122]. Initially, a high-fidelity model operates within a virtual environment to pre-emptively detect issues overlooked during the design phase. This allows for the training of a deep neural network-based diagnostic model. Subsequently, the trained model is transferred from the virtual to the physical realm via deep transfer learning, facilitating real-time monitoring and predictive maintenance. This technique offers a robust solution for both developmental and maintenance phases.

In addition, electric vehicles have always been the focus of research in the field of new energy vehicles. However, as the main energy storage device of electric vehicles, the internal reaction of lithium batteries is quite complex, which leads to rapid aging of batteries and specific potential safety problems. Wang et al. apply DT technology to overcome the challenge of current battery research without full life-cycle management [123]. This paper sorts out the development history, basic concepts, and key technologies of DT. Then, they summarize the current research methods and challenges in battery modeling, state estimation, residual life prediction, battery safety, and control. After that, they focus on the design of digital battery modeling, real-time state estimation, dynamic charging control, dynamic thermal management, and dynamic equilibrium control in the intelligent battery management system. These designs provide valuable development opportunities for DT research in the battery field.

4.1.3. Vehicle Health Monitoring

Integrated vehicle health management is a method to ensure the excellent operation and maintenance of vehicles by monitoring, diagnosing, and predicting the health status of main vehicle systems. Ezhilarasu et al. discuss the important role of DT technology in integrated vehicle health management, the extensive application of DT technology in different industries, and the continuous development of academia [124]. In addition, the study also discusses how to combine DT technology with integrated vehicle health management technology to assess the health status of complex systems (such as aircraft) and provide more accurate and reliable methods for vehicle health maintenance and operation.

Venkatesan et al. develop health monitoring and prediction of electric vehicle permanent magnet synchronous motor (PMSM) in traffic of the system by creating intelligent DT in MATLAB/Simulink [125]. The remaining lifetime of PMSM is calculated by mapping the form time and input distance of EV into the artificial neural network and fuzzy logic, output temperature.

A unique study focuses on using DT for monitoring the status of railway bifurcations, taking into account factors like environmental temperature [126]. This application highlights the flexibility and range of DT technology, proving its utility in various transport-related scenarios.

4.2. Assisted Driving

Assisted driving is becoming increasingly integrated into the framework of smart cities, and DT technology offers significant advancements in this area. Within the IoV, DT plays a crucial role in developing and refining auxiliary driving systems. DT creates a real-time virtual model of the vehicle that enables predictive simulations of vehicle status and behaviors, facilitating inform decision-making in varying driving conditions and road environments.

Resource Management: Next, we will introduce the progress of papers in these two application areas in the past 3–5 years, respectively.

4.2.1. Path Planning

Path planning has always been one of the essential topics in assisted driving. DT can simulate more accurate environmental models for path planning, simulate the results of different path choices, support real-time and dynamic path planning, and combine other technologies to improve the intelligence and personalization of path planning. DT provides a powerful tool and support for the optimization and decision-making of path planning algorithms, significantly improving traffic efficiency, reducing congestion, and optimizing travel experience.

In order to solve the security problem of Cooperative Intelligent Transportation System (CITS) DTs, Lv et al. combine Convolutional Neural Network (CNN) with Support Vector Regression (SVR) and introduce DT technology [127]. The CITS DTs model based on CNN-

SVR is constructed, and its security performance is verified through simulation experiments. Compared with other algorithms, the safety prediction accuracy of this model reaches 90.43%. At the same time, the algorithm is superior to other algorithms in precision, recall, F1, and data transmission performance. It can adapt to different road environments and provide high-speed data transmission and reasonable path planning so vehicles can reach their destinations faster.

A DT-aided decision-making framework is also designed by Fu et al. for vehicle transportation safety [128]. They realize DT in edge, plan sub-goals for the vehicle, and enhance communication and cooperation of the vehicle. Simultaneously, they design a hierarchical multi-agent reinforcement learning method to achieve end-to-end training. However, this paper does not consider the impact of various obstacles that may appear during the driving process.

In order to solve the problem of obstacle avoidance in vehicle driving, Du et al. design a vehicle obstacle avoidance framework based on a platoon. In this framework, they deploy DT in the head vehicle for trajectory planning to reduce communication overhead and decision delay [18]. On this basis, a trajectory planning algorithm is designed according to the urgency. At the same time, the DT auxiliary system is designed and deployed in auxiliary vehicles to detect vehicles outside the sensing range of the head vehicle. They also design a variable resource reservation interval to ensure the synchronization of DT and auxiliary DT. They carry out a simulation experiment in MATLAB. Compared with the existing scheme, the system reduces the collision by 95% and increases the obstacle avoidance speed by 10%.

In addition to the timely response of the auxiliary vehicle to various obstacles during driving, the trajectory tracking error caused by inaccurate model, data noise, environmental changes, and other reasons in the DT system cannot be ignored. A multi-vehicle track tracking framework for crossroads is proposed by Ji et al. to solve this problem [129]. The framework first unifies the coordinate system, then uses LSTM and GAT to extract spatial features to predict the state, finally calculates the proposed tracking loss, feeds back the error to DT, and connects the last marked coordinate with the trajectory in DT through iteration. As Figure 6 shows, the real world first transmits data to the edge server for simple calculations, and then the edge server transmits the data to the cloud. The cloud generates a twin world based on the data to achieve the purpose of vehicle path tracking.

Current research on cooperative driving intersections without signal control mainly focuses on motion planning and control algorithms. However, little attention is paid to the driver's human–machine interface design, communication delay, and data loss. In order to solve these problems, Wang et al. develop a cooperative driving system using DT, which can help vehicles to achieve effective cooperative driving at non-signalized intersections without stopping [130]. The system includes the First-In-First-Out (FIFO) slot reservation algorithm, the consistent motion control algorithm, and the model-based motion estimation algorithm to address the challenges of vehicle sequence, longitudinal motion, and communication.

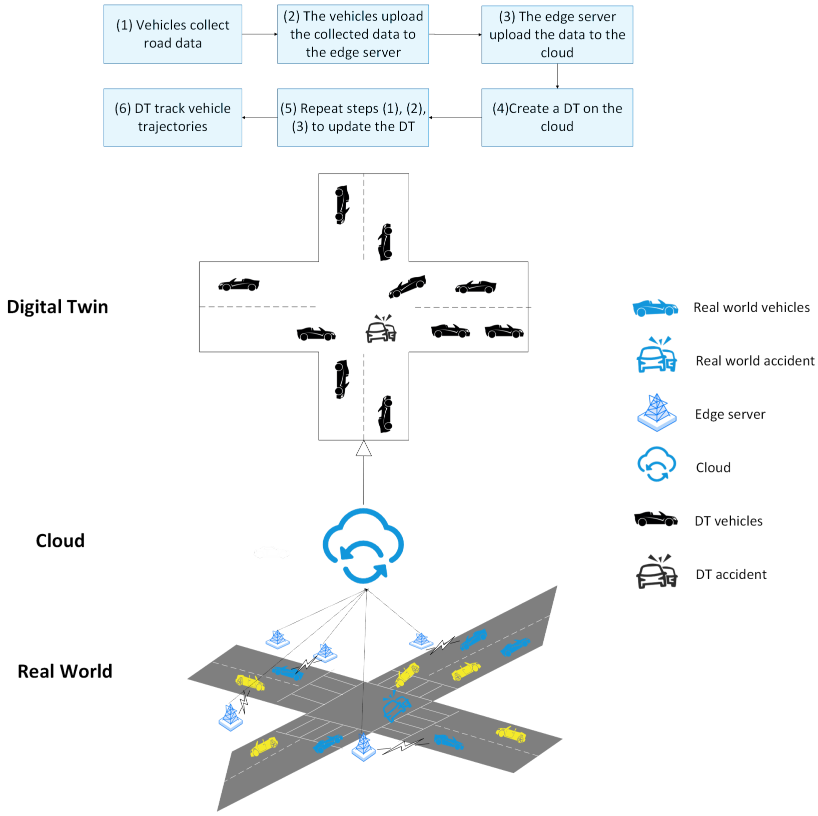

Figure 6. Multi-vehicle track tracking framework for crossroads.

4.2.2. Automatic Driving

As an essential part of digital transformation, autonomous vehicles are becoming increasingly intelligent and autonomous. In the design of autonomous vehicles, DT is closely related to the transformation of data-driven vehicles. DT can not only speed up the development and testing process, improve the efficiency of monitoring operation and maintenance, but also support path selection and decision-making, as well as update and upgrade vehicles. With the continuous development and application of DT technology, autonomous vehicles will be more intelligent, safe, and reliable.

In order to achieve a safe, intelligent manufacturing and transportation system to reduce accidents and ensure the safety of drivers and pedestrians, Almeaibed et al. propose a solution to the safety problem of autonomous vehicles [131]. By determining the standard framework of vehicle DT, data collection, processing, and analysis are promoted to achieve an end-to-end security autonomous system. By analyzing the case study of collision caused by manipulating radar sensors, the effectiveness of the proposed method is being verified. Although this paper provides guidance for future research on the application of DT in the autonomous driving industry, there is no in-depth discussion on the calculation load and cost of autonomous vehicles.

Collaborative driving can reduce communication costs by offloading computing tasks to edge computing devices. However, frequent information exchange also consumes time and resources. The computing power and cost differences of different AVs, as well as the type of cooperation and distribution of vehicles, have a direct impact on the performance of collaborative driving. In order to solve this challenge, Hui et al. propose a DT-based cooperative automatic driving scheme. By designing DT for each AV and building a DT-enabled architecture, its collaborative driving decision-making in a virtual network is facilitated. They use the Auction Game-based Collaborative Driving Mechanism (AG-CDM) to select the head DT and tail DT within the group and use the Coordination Game-based Distributed Driving Mechanism (CG-DDM) to determine the optimal distribution to minimize driving costs [132]. This scheme can efficiently realize cooperative automatic driving and reduce communication costs.

In the future, Connected Autonomous Vehicles (CAVs) will share roads with Human Driven Vehicles (HDVs), so it is necessary to consider a mixed traffic environment. To ensure safety, CAVs need to understand the behavior of HDVs and take appropriate measures. Liao et al. develop driver DT to predict the behavior of surrounding vehicles, especially personalized lane change behavior, using DT technology [133]. Driver DT is deployed on the vehicle-edge-cloud architecture. The cloud server models the driver behavior of each HDV based on historical driving data, while the edge server processes real-time data through DT to predict lane change operations. In the simulation platform, the system can identify the lane-changing intention on average 6 s before the vehicle crosses the lane separation line, and the average Euclidean distance difference between the prediction window and the actual track within 4 s is only 1.03 m.

In the simulation of autonomous driving, DDT is always complex. In addition to simulating various vehicle motion states, it also considers the presence of pedestrians and RSUs. Yun et al. realize a DT-based autonomous vehicle simulation method from a new perspective [134]. To reduce costs and complexity, they use the online game 'Grand Theft Auto 5' as the simulation foundation, leveraging its rich objects, characters, and road resources to simulate the traffic environment. They capture the game screen using OpenCV and utilize Python-based YOLO and TensorFlow for image analysis, creating a precise object recognition system. This method effectively achieves a simulation resembling real-world scenarios, providing a valuable tool for designing and testing autonomous vehicles while significantly simplifying simulation costs.

Different from the starting point of the above article, A Rassõlkin et al. pointed out that currently few scholars have optimized Electric Propulsion Drive Systems (EPDS) by using autonomous and monitoring sensors [135]. They set the target vehicle as an energy vehicle, hoping to improve the performance of new energy systems. Estimate the tasks required to specify a specialized unsupervised prediction and control platform. To accomplish this goal, the authors analyze the DT drive response of EPDS to help measure steady-state and transient EPDS quality and, on this basis, recommend methods for drive regulator tuning, control looping, sensor allocation, and feedback arrangements. And unlike most methods that divide DT into three layers, the author introduces two additional components (digital twin data and service system) as part of DT to reduce the constraints of DT on the virtual environment. On this basis, the author designed the ISEAUTO platform minibus to demonstrate the above goals in a campus environment.

4.3. Intelligent Transportation

The ITS leverages advanced information and communication technologies to optimize and manage transportation networks. IoV can realize the real-time information exchange between vehicles and interaction with transportation infrastructure, providing a broader development space for intelligent transportation. With the in-depth application of DT in IoV, more ITS also integrate DT technology to simulate data and the environment. DT technology and intelligent transportation also promote and support each other and jointly promote the development of ITS. DT improves the decision-making ability and efficiency of ITS utilizing data analysis, simulation, and optimization. At the same time, ITS provides real-time data and scenarios required by DT and verifies and applies DT technology to achieve a more intelligent, efficient, and safe transportation system. Figure 7 shows the hierarchical application structure of DT in the field of intelligent transportation. At the infrastructure layer, elements such as vehicles, signposts, and traffic lights are covered. The data layer includes data from the IoV as well as traffic-related data. The platform layer is responsible for the construction and simulation of DT. Ultimately, the completed twin can be used in application layers such as virtual display, industrial application, emergency rescue, and traffic simulation.

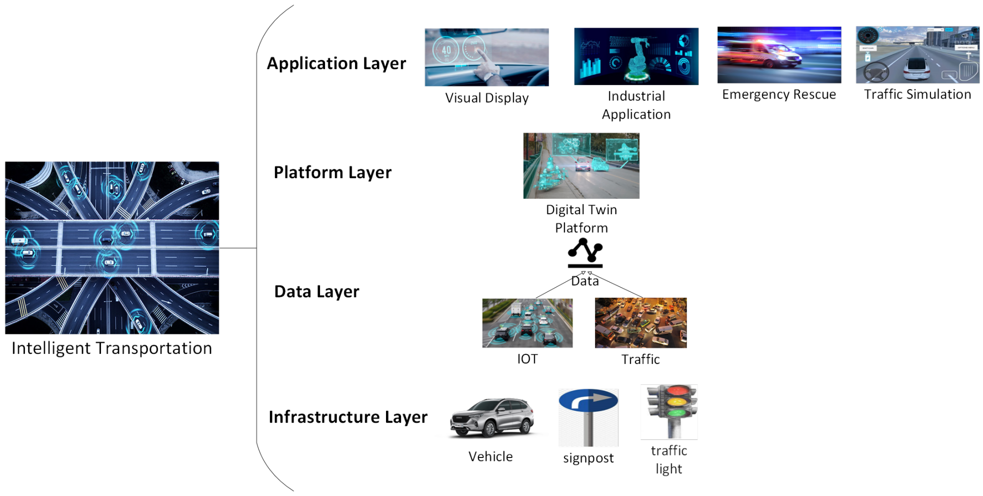

Figure 7. ITS diagram.

This section will elaborate on the application of DT in intelligent transportation from two aspects: traffic prediction and traffic management.

4.3.1. Traffic Prediction

In the ITS, an important topic is how to predict future traffic flow, congestion, travel time, and road section conditions by analyzing historical traffic data, real-time traffic information, and other relevant factors. This predictive information can help drivers avoid congested road sections in advance and provide decision support for urban traffic management. The addition of DT can help the traffic forecasting system establish a perfect traffic model and predict future traffic conditions through the analysis and modeling of traffic data.

Uncertain events in the transportation system, such as weather and accidents, will put forward requirements for the adaptability of the urban transportation system. Considering the impact of these uncertain events on traffic conditions, Feng et al. firstly analyze the impact of travelers' travel habits on the traffic network and construct a travel behavior model of travelers to predict travel habits [136]. Then, they build a DT system on the RSU, share, and trade data through the blockchain. Finally, the system returns the calculation results to the physical vehicle. They select the data of Xi'an railway station for one year, and the system predicts the road section and time of traffic congestion and accidents through the analysis and modeling of historical data. At the same time, the twin in each region implements a local consensus and broadcasts the results to other RSUs for a secondary consensus, which reduces the communication overhead of each twin. Eventually, they compare the predicted results with the actual traffic situation, and the predicted results are consistent with the actual trend.

In addition to the uncertain events in the transportation system that will affect the traffic conditions, IoV data are usually collected by sensors distributed on different roads and inevitably face availability issues such as failures, weather, environment, and battery damage. Therefore, the recorded and transmitted traffic data lack key IoV data, resulting in sparse and incomplete data sets, which poses challenges to traffic resource scheduling and condition prediction. In order to solve the problem of data loss or sparse and incomplete data sets due to the failure of data acquisition and recording equipment, Hu et al. introduce the Local Sensitive Hash (LSH) and DT-assisted 5G IoV real-time traffic data prediction method to improve traffic resource scheduling and alleviate congestion during peak hours [137]. At the same time, they also introduce temporal a context to improve the prediction performance and prove the feasibility of the algorithm in requiring rapid response and high-precision intelligent traffic flow and speed prediction.

Traffic congestion in large and medium-sized cities is another stubborn problem in the transportation system. In order to solve this problem, the Long Short-Term Memory

(LSTM) neural network model and DT technology are used to establish a traffic flow prediction model and traffic infrastructure evaluation model, and the data envelopment analysis method is used for verification [138]. Taking the data of Jiangsu Province as an example, Tu et al. prove that these two models provide a powerful reference for investment and planning of transportation infrastructure and provide new ideas for the analysis of transportation infrastructure.

In recent years, the rapid development of Vehicular Ad hoc Networks (VANET) has generated a wealth of traffic data that can be used for planning and safe driving. However, the diversity of VANET is the main challenge in applying DT in transportation big data. A network traffic prediction algorithm is proposed, which combines deep reinforcement learning and the generation of confrontation networks to extract network traffic characteristics [78]. Deep reinforcement learning is used to predict network traffic, and the generation of the countermeasures network is used to increase the number of samples to improve the prediction accuracy, which is of great significance for VANET network management and anomaly detection.

4.3.2. Traffic Management

Traffic management system is an important part of intelligent transportation. Using DT to control traffic data can help the traffic management system to monitor, control, and optimize traffic flow. It provides new ideas for solving traffic signal control, traffic monitoring, congestion management, and traffic incident response.

The modernization of DT and AI provides a new way to solve urban traffic management problems. A reference model of ITS is proposed to realize the functions of traffic flow organization, allocation optimization, emergency management, information sharing, and infrastructure development [139]. The model meets the core requirements of ITS and provides an effective solution for improving the urban transportation network. However, this paper is ideal for emergencies and does not take into account the unexpected situations that often occur in the transportation system.

Feng et al. discuss the applicability of DT to the transportation system and its response to emergencies [136]. Firstly, the application of DT in ITS is analyzed, and how traveler behavior pattern is affected by uncertain events is studied. Secondly, they propose an IoV system based on DT and blockchain, which is used to solve the problem of redundancy and large amounts of computation in in-vehicle data sharing. Then, the local-aware multi-agent algorithm is used to optimize the performance of the twin system. Finally, they effectively solve the problem of data sharing between vehicles and infrastructure by using DT blockchain.

In addition, the security performance of VANET in the smart city has important practical significance for reducing traffic congestion and accidents. Feng et al. introduce DT technology and blockchain to construct a DT model of VANET [140]. By mapping the traffic conditions of the real road network to the virtual space, complex situations such as vehicle congestion and pedestrian crossing are solved. Simulation results show that the model algorithm has low delay time, stable data delivery and leakage rates, and low communication overhead. Therefore, the model provides an experimental basis for intelligent development and safety performance improvement in the field of smart city transportation while ensuring low delay and high safety performance.

The traffic management system should not only consider the safety of vehicles, pedestrians, and roads but also pay attention to improving the communication security of IoV nodes in intelligent transportation. By studying the ITS based on blockchain, Liu et al. integrate big data and DT to construct the IoVDTs model [10]. Aiming at the security problem of IoV communication, a secure architecture based on immutable and traceable blockchain data is proposed. The risk prediction of the IoV node is carried out using the Wasserstein distance-based generated countermeasure network (WaGAN) model. The research also solves the problem of network channel congestion, proposes a group authentication and privacy protection (GAP) scheme, and improves intelligent traffic management.

The DT-based traffic management system can not only macro-control the overall traffic situation but also improve the driver's driving experience. Dasgupta et al. introduce a DT method for Adaptive Traffic Signal Control (ATSC), which improves the driving experience of travelers by reducing and redistributing the waiting time at intersections [141]. This method considers the waiting time of vehicles approaching the target intersection and the upstream intersection and realizes DT-based ATSC (DT-ATSC) through real-time data exchange between physical devices and DT. They conduct a case study using SUMO to establish a digital replica of the urban road network and collect real-time vehicle and traffic signal data to remedy the shortcomings of traditional ATCS.

4.4. Resource Management

In IoV, the application of DT involves the efficient management of a large number of resources to support vehicle monitoring, driving guidance, and traffic system optimization. Firstly, we need to focus on the management of data resources. Since DT needs a large amount of data to establish and update models, resource management must effectively deal with data collection, storage, processing, and transmission. A reasonable data acquisition strategy and storage scheme ensure the accuracy and completeness of data. In contrast, efficient data processing and transmission technology ensures that real-time updates and transmission meet the real-time requirements of DT. Secondly, computing resource management is crucial. DT requires extensive calculation and simulation work, including tasks such as modeling, analysis, and prediction. Resource management must allocate and schedule computing resources reasonably to ensure the efficient operation of models and the timely completion of computing tasks. Finally, network resource management also plays an important role. DT needs to obtain real-time data on vehicles and traffic conditions and transmit models and instructions to vehicles and traffic systems. Therefore, efficient utilization of network resources is crucial to the real-time and reliability of DT. In addition, the management of storage and energy resources cannot be ignored. Effective storage management ensures data security and fast access, while energy resource management is related to the long-term stable operation of the system. To sum up, resource management can be divided into two aspects: resource scheduling and resource sharing. This review will discuss these two aspects.

4.4.1. Resource Scheduling

The combination of edge computing and DT has brought IoV a strong, intelligent transportation capability. However, the vehicle computing resources in IoV are limited, which may lead to overloading and affect the quality of service. To solve this problem, an innovative service offloading method is proposed by Xu et al. based on deep reinforcement learning to improve the service quality through a multi-user diversion system [142]. This service offloading method uses the deep Q-network as a tool to optimize the offloading decision. It combines the value function approximation technology of deep learning and reinforcement learning to optimize the service offloading, thus improving the performance of the ITS.

Li et al. propose a DT Vascular Edge Network (DTVEN) based on blockchain. Firstly, DT is used to monitor and manage network computing, communication, and cache resources in real time, and blockchain is used to ensure DT offloading transactions. Then, a collaboration scheme between DT and edge servers is designed, and a smart contract based on DT is designed. Finally, for task offloading and resource allocation, they improve the cuckoo algorithm and the allocation scheme based on the greedy strategy. They compare the network cost under six offloading schemes and finally prove that the cost of the method proposed in the paper is the lowest among the offloading time, offloading cost, and network cost [143].

Currently, the research on computing task offloading in IoV mainly focuses on low latency and high reliability to ensure timely data processing and transmission. However, the existing works often ignore factors such as the mobility of vehicles and changes in data traffic. Also, these works fail to consider the possible existence of light UAVs as auxiliary devices in IoV. In the air-assisted IoV scenario, in order to better meet the resource requirements of vehicles and improve the overall energy efficiency, Sun et al. introduce Dynamic Decision-Making Technology (Dynamic DT) [144]. This dynamic DT can reflect the demands and supply of resources by vehicles in real time so that resource allocation can be performed more accurately. In order to achieve effective resource allocation and incentive mechanism, a two-stage resource allocation incentive mechanism based on the Stackelberg game is designed. This mechanism allows the vehicle to optimize its resource allocation strategy according to its needs and capabilities while considering the overall system efficiency. To reduce the computing burden and delay, the Alternative Direction Method of Multipliers (ADMM) is adopted to run the incentive mechanism on multiple edge computing nodes in parallel.

For network resources, Zheng et al. propose a DT data synchronization network based on game theory, which allows vehicles in IoV to choose to connect to different networks (WIFI, cellular network, and the TV white space) [145]. Due to the uneven distribution of vehicles and the dynamic nature of heterogeneous networks, a network selection algorithm based on game theory is proposed. They identify vehicle behaviors as the competition for wireless resources. At the same time, a prediction model based on deep learning is designed in DT to predict the waiting and transmission time, and the results are sent to the vehicle. In the waiting time prediction, the method proposed in this paper can achieve an accuracy of 98.3%. At the same time, they compare the three baselines: Optimal, Random Selection, and Policy Gradient-based Network Selection. The results show that the algorithm proposed in this paper performs best in QoS, especially when the number of vehicles increases.

4.4.2. Resource Sharing

In order to ensure the safe sharing of data among all parties in the life cycle of DT, new solutions need to be adopted. Decentralized applications are ideal for addressing these shared challenges. These applications rely on distributed ledger and decentralized databases to ensure data availability, integrity, and confidentiality. Putz et al. propose a decentralized sharing model with the data owner as the core and adopt a formal access control model to solve the integrity and confidentiality problems [146]. They design a model named EtherTwin, which successfully meets the challenges of fully decentralized data sharing and effectively manages DT components and their related information.

With the development of IoV, the computing and communication resources of vehicles are growing rapidly. There are some schemes for short-distance resource sharing between adjacent vehicles, but the problem of resource sharing between remote vehicles is still unsolved. Tan et al. propose a city-wide vehicle data-sharing platform based on DT and combine federal learning and transfer learning frameworks on this basis to achieve personalized data sharing on the basis of not revealing vehicle privacy [147]. Simultaneously, to increase the trust of vehicles and encourage vehicles to share data, they design an incentive mechanism based on game theory.

Similarly, for all vehicle resource sharing, Tan et al. propose a DT fair trading platform based on the consortium blockchain to achieve vehicle resource sharing in the city [148]. They develop a vehicle platform based on DT and track and protect resource sharing through the consortium chain. Smart contracts and efficient Proof of Service (PoS) consensus algorithm are used to ensure the operation of the consortium chain. Simultaneously, they innovate the incentive mechanism to promote the sharing of vehicle resources in the city and achieve the maximum profit for task publishers.

In addition, Zheng et al. pay more attention to the data synchronization between vehicle DT and Vehicle User Equipment (VUE) [145]. The uneven distribution of VUE and the dynamics of heterogeneous vehicle networks increase the complexity of the environment. Therefore, they propose a network selection algorithm to achieve data synchronization between VUEs and DTs, where the behavior between VUEs is regarded as the competition for wireless resources. They develop a learning-based prediction model, which resides in DT and is used to predict the waiting time of the relay and transmit the prediction results to VUE for decision-making. They model the network selection problem as a potential game and consider the transmission and waiting times comprehensively.

5. Open Issues

This section delineates the unresolved challenges and prospective avenues for research in the IoV landscape. Going beyond the scope of the discussions in Section 4, we intend to shed light on both immediate challenges and longer-term research directions, particularly focusing on advancing the IoV system in key aspects such as intelligent traffic management and vehicle monitoring. By delving into these crucial issues, this section aims to serve as a comprehensive guide for future scholarly pursuits and technological innovations in the IoV domain.

5.1. Physical Layer

When establishing DT, physical entities need to collect and transmit a large amount of data, then simulate and reflect the state of entities through physical layer devices such as sensors. However, since DT may involve many types of entities, such as vehicles, roadside units, and smartphones, these entities may come from different manufacturers, and there may be differences in the data format. Although there are some data fusion and format unification methods, it is still necessary to focus on the uniqueness of DT and special data processing methods. In addition, DT has high requirements for real-time data and spatiotemporal correlation. That means the sensors of physical entities need to accurately collect data related to time and space and quickly upload it to the DT system. There is a serious challenge to the physical layer equipment. Therefore, in the future, more research needs to be devoted to data acquisition and data fusion technology for DT to ensure that the system can reflect the state of the physical world in real time and accurately so as to provide more reliable and efficient intelligent traffic and vehicle monitoring services.

5.2. Connection Layer

At the connection layer, IoV faces the challenges of real-time and latency sensitivity. Latency can have a serious impact on IoV applications that require an immediate response. In order to deal with this problem, DT can establish historical data models and prediction models and predict data in the future period by analyzing historical data and current vehicle status, traffic conditions, and other information so as to reduce the impact of delays on the system. That is a solution worth considering. In addition, network coverage and reliability are also important challenges. In the real world, vehicles may enter areas with poor or no network coverage, such as tunnels, remote areas, or underground parking lots. When the vehicle loses connection, how to minimize data loss and realize fast reconnection becomes a problem that needs to be solved. Another challenge is the network pressure caused by large-scale network connections. How to effectively reduce network pressure, deal with protocol and standard differences between different vehicles, and ensure security and privacy during data transmission are also directions worthy of research.

5.3. Twin Layer

In the process of creating DT, the twin layer is the core part, responsible for key tasks such as modeling, analysis, simulation, and prediction. However, the twin layer faces some challenges: Firstly, the precision and accuracy of physical entity modeling are problems. In reality, the behavior of vehicles is affected by many interference factors, such as road conditions and weather. How to avoid the influence of these interference factors in the process of model establishment to ensure the accuracy and reliability of the modeling results is a problem worthy of attention. At the same time, the state of the vehicle changes over time, so it is also a challenge to update and calibrate the model in a timely manner and accurately. Secondly, the establishment of twin models requires a large amount of real data to support model training. Different entities produce different data formats, and data quality and accuracy are also different. How to deal with different data uploaded from heterogeneous entities, ensure data quality, and effectively integrate them for model training is a problem that needs to be solved. In addition, due to the limitations of physical layer devices, the data collected by entities may contain noise. The twin needs to filter the noise without losing the correct data to establish an accurate model, which is also a challenging task. Finally, the safety of the transportation system is crucial. The twin must correctly simulate, analyze, and predict the current traffic conditions to ensure that the generated instructions are timely and accurate to avoid possible irretrievable losses. How to ensure the timeliness and correctness of the instructions and to establish a safe and reliable traffic management model are issues worthy of in-depth discussion.

5.4. Visualization Layer

In DT, data visualization is a method that is easier to understand and use. It can make abstract data intuitive and easy to analyze. However, when visualizing data, we are faced with some challenges. Firstly, DT involves multi-dimensional and multi-angle data. How to present these complex data in a clear, concise, and intuitive way so that users can quickly understand and analyze information is one of the issues that needs to be considered. Secondly, the IoV system covers multi-dimensional data such as vehicles, pedestrians, and infrastructure. For the visual display, the challenge of data integration and display needs to be solved. In addition, different drivers may have different needs and preferences for visual data. How to customize the visual interface according to the individual needs and habits and provide information display that meets their needs is an important consideration. Finally, interactive design is also a key challenge. The DT system should have interoperability, provide an interactive friendly interface, and enable users to interact and explore effectively with the system. However, to design a simple, intuitive, and easy-to-operate user interface to meet user needs and operation modes, it needs to consider the complexity of user experience and interaction design fully. In order to meet these challenges, we need to explore innovative data visualization methods and technologies and use visualization tools and graphical representation to make the information of DT more expressive and insightful. At the same time, we also need to pay attention to user participation and feedback, continuously improve the design of the interface, and put user needs and experience at the core of the design so as to provide a more intelligent, intuitive, and easy-to-use DT system.

5.5. Implementation Issues

In addition to the above-mentioned opening issues on the technical layer, practical implementation issues of DT-enabled IoV applications also deserve careful consideration. During implementation, user privacy and data security should be the most important concerns, and strict compliance with policy and regulations needs to be ensured. Moreover, recognizing the limitations of a single organization, collaboration among multiple organizations becomes a tool to achieve DT-enabled IoV.

Consumer privacy and data security can be protected with strong strategies: A. Conduct a comprehensive privacy impact assessment to identify potential risks and develop effective response strategies. B. Implement strong encryption measures to ensure the security of data during transmission and storage, supplemented by a strong authentication mechanism to restrict access to only authorized users. C. Ensure strict compliance with relevant data protection regulations through regular policy reviews and updates to keep pace with the changing regulatory environment, such as General Data Protection Regulation (GDPR) or California Consumer Privacy Act (CCPA). D. Conduct routine security audits and vulnerability assessments to proactively identify and mitigate potential threats to prevent exploitation by malicious actors. Additionally, the design and implementation of DT-enabled IoV applications must be consistent with local policies and regulations. Therefore, DT implementers should establish partnerships with policymakers, regulators such as transportation authorities, data protection authorities, legislators, etc., to promote a comprehensive dialogue on the potential impact of DT-enabled IoV applications and related legal issues. The professional team should also provide innovative policy and regulation development solutions, support data sharing and interoperability, then accelerate DT's innovation and development in the field of DT-enabled IoV applications. This proactive approach ensures that applications maintain the highest standards of privacy and security. In addition, multi-organization cooperation can make it easier to create DT-enabled IoV applications. For example, educational institutions provide technical support and design for DT and IoV. Intelligent transportation system developers are responsible for implementing systems. Automakers provide real vehicles that can be used for testing. Relevant government departments provide corresponding road environmental protection support. This multi-organization cooperation model enables pilot testing of proposed applications in real-world settings or field trials to assess their effectiveness and scalability.

5.6. Further Research

In future research work on DT enabled-IoV, it is imperative to delve deeper into specific areas while also considering data privacy and security, as well as engaging with policy and regulations in IoV applications, such as advanced data analysis technology for real-time vehicle monitoring, novel methods for enhancing vehicle-to-vehicle communication protocols, adaptive control systems for self-driving vehicles, and cyber-security measures to protect the security of the IoV ecosystem.

- Data privacy and security: For DT-enabled IoV applications, data privacy and security must be fully considered to ensure system robustness and user trust. In future work, further research and development of data privacy protection technology for DT-enabled IoV applications is needed. For example, strengthen research privacy-protecting data sharing models to promote data sharing and collaboration. In addition, the security of DT-enabled IoV applications should be strengthened, secure software update and maintenance mechanisms should be developed, and vulnerability repair strategies should be implemented to ensure that the system is always in the latest security state to prevent malicious attacks and data leaks. By placing data privacy and security in a more prominent position, it will help promote the sustainable development of DT-enabled IoV applications and provide users with more secure and reliable services.
- Advanced data analysis technology for real-time vehicle monitoring: High-speed moving vehicles quickly generate large amounts of data, and how to analyze the data in real time requires in-depth exploration, for example, using predictive machine learning methods, using historical data for prediction and real-time data for verification and correction; developing anomaly detection systems to detect abnormal vehicle behavior or performance deviations for timely intervention and maintenance; and exploring rapid data fusion solutions from multiple sources can also speed up data analysis.
- Novel methods for enhancing vehicle-to-vehicle communication protocols: Current research focuses on how to enhance the connection between vehicles and edge servers or cloud servers, but communication between vehicles may have problems such as delays and disconnections. To address this problem, secure and decentralized communication can be achieved between vehicles by introducing blockchain to achieve secure data exchange. In addition, collaborative sensing technology can enhance traffic environment perception by sharing vehicle sensor data and perception information. Adaptive communication protocols can automatically adjust communication parameters based on factors such as network congestion, communication distance, and vehicle density. This method can optimize communication performance and ensure that vehicles maintain communication stability and reliability under different environmental conditions. Artificial intelligence technologies such as deep learning and reinforcement learning can help optimize the design and parameter settings of communication protocols and improve communication efficiency and performance by analyzing fused data and interactive information.

- Adaptive control system for autonomous vehicles: Reinforcement learning algorithms can enable autonomous vehicles to learn and optimize control strategies through interaction with the environment, so that the vehicle can gradually learn and improve driving strategies through continuous trial and error to cope with various complex driving scenarios. The model predictive control algorithm can predict the dynamic behavior and environmental response of the vehicle and adjust the control input in real time to achieve optimized driving performance, thereby achieving adaptive adjustment of the control strategy to achieve stable vehicle motion and safe driving. Swarm intelligence algorithms can search and optimize complex control parameter spaces to find optimal control strategies and achieve efficient adaptive control. Model recognition technology models and identifies the dynamic behavior of the vehicle and environment and adjusts the control strategy in real time to adapt to changing driving conditions to achieve precise autonomous driving control.
- Cyber-security measures used to secure the IoV ecosystem: In addition to the above issues, it is crucial to protect the security of the IoV ecosystem, prevent cyber attacks and threats, ensure the stable operation of the IoV ecosystem, and protect user data and privacy. By strengthening the identity authentication and access control mechanisms, we ensure that only authorized users can access the resources of the IoV ecosystem, perform specific operations, and access sensitive data, thereby increasing the data security of the IoV ecosystem. Further research on data encryption and decryption mechanisms can ensure the authenticity of the data by ensuring that the data is not eavesdropped or tampered with. In addition, strengthening network monitoring and intrusion detection can promptly detect and respond to network attacks, malicious behaviors, and abnormal activities.
- Engaging with policy and regulations in IoV applications: The aforementioned specific areas all require development within policy and regulations. However, the existing specialized policy and regulations governing DT and the IoV warrant further exploration. Developers and institutions can leverage their practical development experiences to offer valuable innovative suggestions and insights for refining policy and regulations. This collaborative effort aims to foster the evolution of policy and regulations, making them more adept at accommodating the rapid advancements in DT and IoV technologies.

6. Conclusions

This paper focuses on the potential and complexities of integrating DT into the IoV ecosystem. Initially, this review provides a rigorous introduction to the DT paradigm, dispelling prevalent misconceptions and summarizing its successful implementations across various sectors. Building on this foundational understanding, this review delves into the unique challenges that the IoV faces across four critical dimensions: industrial production, assisted driving, intelligent transportation, and resource management. Moreover, this review articulates the rationale behind the assimilation of DT technologies into IoV systems. This comprehensive investigation serves as a catalyst for future research, aiming to accelerate advancements in IoV through the integration of DT technologies.

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