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Global Perspectives on Digital Twin Smart Cities: Innovations, Challenges, and Pathways to a Sustainable Urban Future

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Abstract

The integration of Digital Twin (DT) technology into smart city frameworks is becoming increasingly vital in the digital era. As urban environments evolve into interconnected ecosystems driven by real-time data and intelligent management systems, digital twins provide a powerful and dynamic approach to urban planning and operations. This paper delivers an in-depth exploration of the role of digital twins in advancing smart city frameworks, surveying recent research, methodologies, and case studies that highlight their applicability in urban management, including sectors like mobility, healthcare, energy management, and environmental monitoring. Additionally, the paper delves into the foundational concepts of digital twins and digital twin smart cities, presenting a multilayered structure that emphasizes the role of each layer in creating a comprehensive urban digital twin platform. We also examine the ongoing global digital twin projects based on their development maturity, discuss the challenges of deploying these systems, and explore emerging tools such as synthetic sensing for areas with limited sensor infrastructure. By summarizing the state of the art, identifying research gaps, and discussing future directions, this review serves as a foundational reference for researchers and practitioners seeking to harness digital twin technology for more sustainable, efficient, and resilient smart cities.

Keywords: Digital Twin; Smart City; Urban Planning; Internet of Things (IoT); DT Applications.

List of Abbreviations

DT	Digital Twin
DTSC	Digital Twin Smart Cities
PLM	Product Lifecycle Management
HVAC	Heating, Ventilation, and Air Conditioning
MCPs	Manufacturing Cyber-physical System
CNCMT	Computer Numerical Control Machine Tools
CPS	Cyber-Physical Systems
AI	Artificial Intelligence
IoT	Internet of Things
BIM	Building Information Modeling
GIS	Geographic Information Systems
TraCI	Traffic Control Interface
DSP	Dynamic Shortest Path
RkSP	Random K-shortest Path
eCO ₂	Equivalent Carbon Dioxide
PDTs	Programmable Digital Twins
MCS	Mobile Crowd Sensing
DUET	Digital Urban European Twins
AV	Autonomous Vehicles
NLP	Natural language processing

1. Introduction

In today's digital era, urban environments are rapidly transforming into intelligent and interconnected ecosystems. A smart city is defined by the seamless integration of sensors and connected devices that continuously collect and analyze data to optimize resource allocation, enhance service delivery, and improve the management of urban infrastructure [1],[2]. The key principle behind this transformation is continuous learning and adaptation, where intelligent systems

dynamically adjust to changing conditions to maintain peak performance. This approach goes beyond mere technological integration, fostering deeper collaboration between urban services and citizens. It allows for active public participation in data collection, contributing to an ecosystem that promotes transparent governance and democratizes information flow [3]. By utilizing technology to enhance public engagement, the goal is to achieve concrete outcomes, ultimately transforming urban areas into more sustainable, efficient, and livable spaces. Smart technologies prioritize improving the quality of life as a primary objective, emphasizing the creation of a sustainable and equitable urban future. Globally, investments in smart city development are propelled by advances in AI and IoT, revolutionizing fields such as healthcare, transportation, and environmental management [4],[5],[6]. This strategic emphasis on technology underscores its role in enhancing urban adaptability and sustainability, positioning cities as global models committed to human-centric development and improvements in quality of life.

Nevertheless, there exist lots of challenges and building blocks for successful planning, implementation, and deployment of a smart city [7],[8]. The ecosystem that defines the smart city, with all the environmental variables and parameters is often non-stationary. As a result, there is a need for real-time data acquisition and on-the-fly decision-making for an effective smart city implementation [9]. Digital Twin (DT) technology, with its defining characteristics of real-time representation of physical objects; modeling and contextualizing complex behavior patterns; and on-the-go update of parameters between the physical and digital worlds, poses itself as a suitable candidate for assisting the efficient development of a smart city. Digital twin, a pivotal component of digital transformation, enables cities to achieve real-time remote monitoring and facilitate more data-driven and effective decision-making processes. There are multiple initiatives underway to develop digital twins for cities, with the goal of capturing the comprehensive complexity of their dynamics and features.

This article provides an overview of digital twin technology in the context of smart city development, as discussed in recent literature. It offers a compre-

hensive review of current research approaches and methodologies developed for digital twin technology for smart city by considering four research questions:

- What are the current trends and advancements in digital twin development for smart cities?
- What are the key challenges faced in implementing digital twin solutions at the city scale?
- What are the key stages of digital twin development, and how do they align with smart city requirements?
- How can synthetic sensing contribute to overcoming these challenges and enhancing digital twin functionalities?

This article expands upon the above established research questions and emphasizes particular smart city applications that have significantly benefited from the implementation of digital twin technology. It provides a comprehensive survey of various frameworks and case studies, summarizing key findings while identifying recent trends and persistent challenges in effectively utilizing this technology to foster a more responsive and interconnected urban environment. Before fully understanding the potential of digital twin technology in smart cities, it is crucial to grasp its fundamental concepts and principles. The following section covers the detailed history, development, and essential features of digital twin technology. Understanding this background will provide context for discussing its specialized applicability in urban environments.

Digital Twin Background: In 2003, Dr. Michael Grieves introduced the concept of digital twin during a discussion on Product Lifecycle Management (PLM) at the University of Michigan. His presentation titled “Conceptual Ideal for PLM” established the foundational concepts for the modern digital twin model. This model envisioned a seamless integration of real and virtual spaces, enabling continuous data exchange and information flow between them. This innovative approach emphasized the importance of connecting physical and virtual

systems, with each comprising two closely interconnected entities. The physical system represents tangible reality, while the virtual system encompasses all information about its physical counterpart [10]. The concept of digital twin gained further recognition in 2011 when NASA applied it to aircraft structure and lifecycle prediction, emphasizing its utility in improving and reengineering lifecycle management of physical structure. NASA described the digital twin as “the process of improving and reengineering the lifecycle prediction and management of physical structures” [11]. Later, in 2012, NASA expanded on this, describing the digital twin as “a seamless integration of maintenance records, fleet and historical data, and ultra-precise simulations with an integrated vehicle health management system. This combination provides an unmatched level of safety and dependability while faithfully mirroring the life of its aviation counterpart” [12]. In 2017, Grieves expanded the definition of digital twin, stating that “it is a complete set of virtual data structures that fully describe a physically manufactured product, from its micro atomic level to its macro geometrical level”. Table 1 provides several definitions from the literature that highlight various aspects of the digital twin concept across different fields including aerospace and healthcare, manufacturing, and smart cities. All these definitions are based on the fundamental idea of digital twin as a digital representation of the real world. Even in smart cities, digital twin is applied across various domains as a virtual model of real-world elements.

The versatility and broad applicability of digital twin technology in various sectors are evident as it leverages virtual models to optimize real-world systems. The integration of digital twin technology into urban management and smart cities represents a natural progression. As cities continue to embrace advanced technologies to become “smart”, digital twin provides a sophisticated method to manage complex urban systems by creating virtual representations that can predict, simulate, and optimize city functions. In 2017, the digital twin concept was introduced to city management, signaling a significant shift in urban planning and smart city development [40]. Unlike the earlier digital tools used in city planning, such as those developed in the 1950s for transportation, water dis-

Table 1: Digital Twin Definitions.

Author	Area	Definition	Ref.
Framling et al.	Product Mgmt.	“Agent-based architecture with each product having a virtual counterpart.”(2003)	[13]
NASA	Aviation	“Improves lifecycle prediction and management of structures.”(2011)	[14]
NASA	Aviation	“Integration of records, data, and simulations for safety and dependability.”(2012)	[12]
Hochhalter	Aerospace	“Life management paradigm using vehicle-specific history for high-fidelity modeling.”(2014)	[15]
National Instruments	HVAC	“Real-time digital replica of a physical device.”(2017)	[16]
Grieves	PLM	“Virtual data structure fully describing a product from micro to macro level.”(Basic Idea 2003, Pub. 2014 and 2017)	[17]
El Saddik	Multimedia	“Digital replica of physical entities, bridging physical and virtual worlds.”(2018)	[18]
Bruynseels et al.	Health Care	“Engineering paradigm where physical artifacts are paired with digital models.”(2018)	[19]
Leng et al.	MCPS	“Real-time cyber copy of a physical manufacturing system.”(2019)	[20]
Luo et al.	CNCMT	“Multi-domain, high fidelity digital model integrating various subjects.”(2019)	[21]
Nikolakis et al.	Factory Area	“Digital representation of real-world objects/processes, enhanced by sensor data.”(2019)	[22]
Erkoyuncu et al.	Robotics	“Digital representation of a physical asset for property, condition, and behavior analysis.”(2020)	[23]
Zheng et al.	CPS	“Provides deep integration with control systems for direct physical system control.”(2020)	[24]
Latif and Starly	Industrial	“Digital representation of physical entities/processes to optimize performance.”(2020)	[25]
Minerva et al.	IoT	“Clones physical objects into software counterparts, reflecting essential properties.”(2020)	[26]
Autodesk	IoT Services	“Living Model with dynamics/functionality, for analytics and predictive maintenance.”(2021)	[27]
Mylonas et al.	Smart Cities	“Virtual representation simulating behavior of physical things throughout lifecycle.”(2021)	[28]

Table 2: City Modeling.

Domain	Author	Year	Ref.
Transportation	Ben-Akiva, Moshe E	1973	[29]
	Boyce, David E	1984	[30]
	Echenique, M H	1985	[31]
	Warner, Stanley Leon	1962	[32]
	Wegener, Michael	1994	[33]
	Waddell, Paul	2002	[34]
Economic Development	Alonso, William	1964	[32]
	Goldner, William	1971	[35]
	Wilson, Alan	1970	[36]
Urban Growth	Lathrop, George T and Hamburg, John R	1965	[37]
	Tobler, Waldo R	1970	[38]
	White, Robert and Engelen, George	1997	[39]

tribution, and other utilities, the integration of digital twin technology brought a new dimension to these models [41]. Traditional city models were static and compartmentalized, focusing on individual infrastructure components in isolation. A few examples of these models are listed below in Table 2. However, the digital twin approach allows a holistic and dynamic representation of the city as an interconnected system. By the 2000s, 3D city models had largely replaced conventional city planning techniques used for decades, offering more dynamic and interactive tools for urban development [42]. The term “smart cities” gained popularity in the 2010s, referring to urban areas where governments and citizens collaborate to enhance efficiency, intelligence, sustainability, and safety through advanced technologies [43],[44]. The widespread deployment of sensors and data analytics in these cities allows for better planning and decision-making, demonstrating the potential of digital twin technology to

revolutionize city management [45].

The convergence of the digital twin concept with smart cities leverages its core principles, integrating physical and virtual systems for enhanced monitoring, analysis, and control. Digital twins enable city planners and managers to create accurate, real-time digital replicas of entire urban environments, allowing them to test scenarios, optimize operations, and predict the impact of changes without affecting the actual infrastructure. This capability is essential for addressing the complexities of modern urban life, from managing traffic flows and energy consumption to improving public safety and environmental sustainability [46],[47],[48],[49].The substantial benefits derived from deploying digital twins in smart cities have garnered significant interest from researchers in this domain. There are existing review and survey papers that explore the recent trends in this field.

The trends illustrated in Figure 1 signify a growing interest in research and public engagement within this field. The notable increase in the number of published articles, alongside the rising normalized search interest in "Digital Twin," according to Google trends, underscores its emerging importance as a transformative technology in urban planning and management. Concurrently, the slight decline in search interest for "Smart Cities" may indicate a strategic shift toward more specialized topics, particularly those involving the applications of digital twins. These observations align with the ongoing evolution of research priorities, highlighting the critical role of digital twins in addressing significant urban challenges and driving innovation in the development of smart cities. In this study, we employ a simple methodology to select articles based on specific keywords from an academic database. The entire article selection process is detailed in the subsequent section. This is followed by an analysis of existing literature reviews concerning the concept of Digital Twin Smart Cities (DTSC), wherein we highlight the key contributions and limitations of each survey within this context.

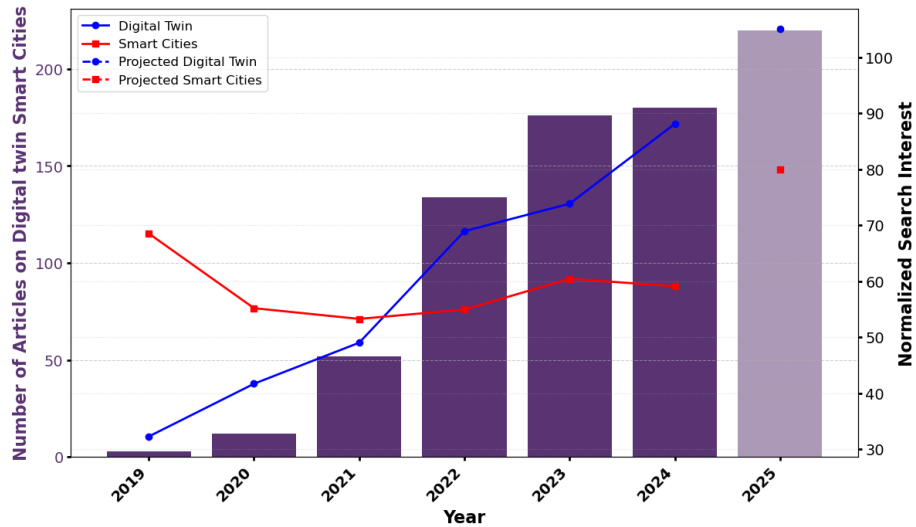


Figure 1: Research Articles and Google Search Trends (2019-2025).

2. Review Methodology

The study adopts a scoping review approach to examine and analyze the existing literature on digital twins at the city scale by following the general principle defined in [50]. The methodology comprises three key steps, as demonstrated in Figure 2. It begins with the formulation of the primary objective and research questions as defined above, followed by the establishment of the scope and boundaries of the review. Finally, the literature is organized based on the defined objective.

2.1. Paper Selection Process: Establishing Scope and Boundaries

The selection process involved searching reputable academic databases, including Google Scholar, Web of Science, and Scopus. We used carefully chosen keywords such as “digital twin,” “smart cities,” “digital twin in smart cities,” “city-scale applications,” “Digital twin smart city challenges,” and “digital twin smart cities trends.” For the initial research, the time frame was set to the last 10 years. However, to understand the basic concepts of digital twins and smart

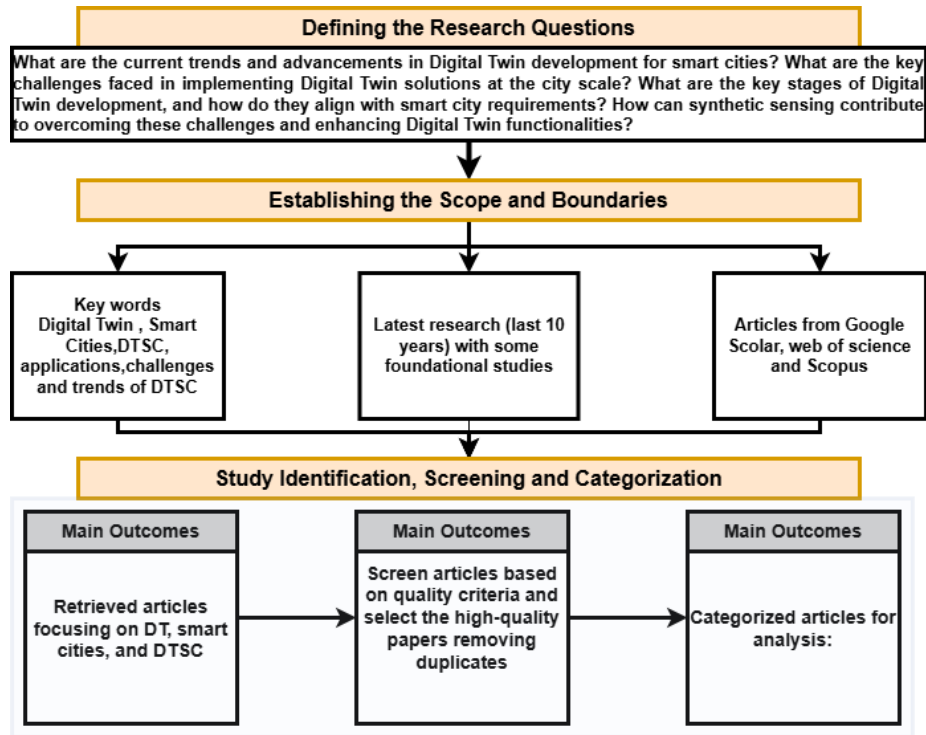


Figure 2: Review Article Methodology.

cities, some older articles from 2009 onwards were also considered. The primary focus remained on research published within the last decade to reflect the latest advancements, with a limited number of older publications included to provide essential context and trace the evolution of the digital twin concept in smart city development. After carefully gathering the data using the established filters, we then identified, tagged, and categorized the articles based on their thematic relevance, publication type, and year, as explained below.

2.2. Study Identification, Screening, Categorization

This section is a crucial part of the methodology, detailing how the selected articles were categorized into different domains for structural analysis. The goal of the categorization was to label articles according to specific fields, distinguish-

ing those that address smart city frameworks and challenges from those that focus on applications. The process also included checking for repetition among the selected papers and removing any duplicates. Additionally, we prioritized the quality of the publications by emphasizing peer-reviewed journal articles and reputable conference papers.

The selected articles were categorized into four key data sets:

- Articles focused on the concept of digital twins, exploring its evolution, foundational theories, and general principles.
- Articles centered on smart cities, covering frameworks, technologies, and urban development strategies.
- Articles combining digital twin and smart city concepts (DTSC), addressing their integration, benefits, and emerging applications.
- Articles focused on applications, challenges, and the latest advancements in the DTSC field, highlighting practical implementations, identified limitations, and proposed solutions.

The subsequent sections of this article have been organized based on the identified clustering, commencing with a comparison to existing literature on this subject.

3. Existing Literature Reviews

There are existing survey papers related to the application of Digital Twin for Smart City (DTSC). These surveys provide valuable foundational knowledge by covering the definitions of digital twin technology, its underlying technologies, and its real-world applications. Jafari et al. (2023) [51] conducted a review of energy sector applications in smart cities and briefly explained the concept of digital twin and related challenges. In 2021 Deng et al. published a survey that includes a definition of digital twin along with its application in smart cities and advanced technologies such as BIM, IoT, blockchain, and collaborative computing. The authors also explained the architecture of DT-enabled smart cities and

provided some examples of its applications [52]. Xia et al. (2022) [53] published a review article on sustainable smart city digital twin modeling. This article provides details on geographic and building modeling using Building Information Modeling (BIM) and Geographic Information Systems (GIS). The author explains the application of smart cities from the perspective of these technologies. Yang et al. [54] conducted a survey in 2021 on the use of digital twin technology in the smart city and healthcare sectors. The survey provides an overview of the concept of the digital twin and its history, along with its applications in smart city areas such as agriculture, transportation, and health management. Authors also identified the challenges associated with developing healthcare digital twin solutions in smart cities. Wang et al. (2023) [55] highlighted the challenges and research direction of digital transformation in smart cities. In the paper [56], Weil et al. (2023) review the challenges and open issues for implementing smart city digital twins. They also define future research directions based on their findings. Mylonas et al. (2021) [28] provided a brief definition of DT and presented three questions related to the key differences between digital twins in smart manufacturing and smart cities, the primary applications of digital twins in smart cities, and the existing challenges in this domain. Shahat et al. (2021) [57] presented a review on the potential of digital twins for cities. They also provided a brief explanation of the smart city concept, defined the steps for the implementation of DTSC, discussed challenges related to it, and explained a use case of Zurich. Botin et al. (2022) [58] outlined the emerging technologies and tools for developing digital twin and its applications in healthcare, highlighting the role of AI and simulation analysis tools. In 2022, Lehtola et al. [59] conducted a survey discussing the concept of a DTSC. The survey explains the needs of cities and how they can use the concept of DTSC for decision-making. The paper also provides examples of how AI and sensors can be used in the development of smart cities with DTSC.

Table 3: Digital Twin Smart City Existing Surveys Comparison.

DTSC Review	DTSC Concept	Characterization	Practical Deployment Challenges	Applications	Implementation Status	Synthetic Sensing for DTSC
Jafari et al. [51]	X	X	Challenges in Power Systems (Data, Connectivity, Security, Standardization)	Energy and Transportation	X	X
Deng et al. [52]	In-depth	X	X	Health and Transportation	X	X
Xia et al. [53]	In-depth	X	X	GIS and BIM	X	X
Yang et al. [54]	X	X	Overview of data collection and security	Health Management and Transportation	X	X
Wang et al. [55]	Overview	Overview	Data collection, modeling, and connectivity	X	X	X
Weil et al. [56]	Overview	X	Data collection, processing, visualization, and resources	X	X	X
Mylonas et al. [28]	In-depth	X	Overview	Health, transport, water management, pollution	Partial (not maturity-based)	X
Shahat et al. [57]	Overview	X	Data management, visualization, and integration	X	Zurich	X
Botin et al. [58]	In-depth	X	Data, Standardization, and integration	Healthcare	X	X
Lehtola et al. [59]	In-depth	X	Overview	X	X	X
This Survey	In-depth	Detailed	Data, connectivity, standards, integration, privacy, cost, response time	Mobility, health, climate, pollution, smart energy	In-depth with maturity levels	In-depth

3.1. Research Gaps and Key Contributions

This review paper stands out from these existing surveys on several fronts. First, this research presents a comprehensive overview and detailed analysis of DTSC projects that are implemented worldwide, which is ignored in the existing reviews mentioned above. It specifically points out the current deployment status of these DTSC implementations. It also thoroughly examines the obstacles encountered during the development of these projects and investigates how these challenges are being tackled with limited resources. Second, this paper considers the recent developments in the domain of synthetic sensing, which is an emerging tool in the context of DTSC. Third, this paper also presents a characterization and classification of DT models from the perspective of DTSC. Finally, it covers a wide range of applications in the area of smart city development and management that explore the benefits of digital twin, some of which are not explored in the existing reviews. Table 3 outlines the details of these surveys and highlights the distinctions of this work from other surveys.

Following the above discussion, we have identified **six key contributions**, which are outlined as follows:

- An overview of the concept of Smart City and its evolution to Smart City Digital Twin is presented.
- A wide range of DTSC's application in the domain of Mobility, Healthcare, Climate, Pollution, and Energy Management, is explored.
- A comprehensive discussion is provided on the classifications of the DTSC related to Passive, Predictive, Programmable, and Autonomic DTs.
- A detailed analysis of DTSC's ongoing and developed projects globally, based on their development maturity.
- A detailed overview of the challenges, faced during DTSC development and practical deployment, is provided. In addition, a discussion on synthetic sensing to achieve DTSC development in sensor-limited areas is presented.

- The paper finally points out the recent trends, challenges and open problems related to the development of DTSC.

3.2. Survey Structure

The survey is structured as follows: Section 4 provides an overview of the concept of a Smart City and its advancement towards the Digital Twin Smart City. It also delves into the various applications recommended in academic publications. In Section 5, the discussion centers on the characteristics and vital elements of the smart city digital twin. Section 6 presents a comprehensive analysis of global practices of digital twins in the realm of smart cities, followed by an evaluation of the challenges in the development of smart city digital twins in Section 7. The survey results are discussed, emphasizing the challenges encountered by the digital twin approach. Additionally, potential research avenues for limited sensor areas are suggested in Section 8. Lastly, Section 9 provides a summary of the entire article and outlines future directions.

4. Smart City to Digital Twin Smart City

In this section, we discuss the concept of a smart city, its basic characteristics, and how it progresses to a digital twin smart city.

4.1. Smart City

The term “smart city” does not have a universally accepted definition, and it is interpreted differently by scholars. Phrases like “connected city,” “digital city,” and “intelligent community” are often used interchangeably with “smart city,” showing the flexibility in defining these urban areas. However, the core idea of a smart city is about forward-thinking urban development that puts emphasis on safety, security, environmental sustainability, and efficiency.

According to Hall et al. (2000) [60], smart cities are advanced urban areas that integrate various infrastructures like power, water, and transportation using advanced materials, sensors, electronics, and network technologies.

These components are managed by sophisticated computer systems, including databases, tracking technologies, and decision-making algorithms. Giffinger et al. (2010) [61] emphasize that a smart city is built on the pillars of people, environment, mobility, governance, and economy supported by advanced infrastructure. Bakıcı et al. (2013) [62] highlight that smart cities use innovative technologies to connect people, data, and urban infrastructure, aiming to create sustainable and eco-friendly environments, foster innovative business activities, and improve the overall quality of life. All in all smart cities aim to improve citizen well-being and enhance operational efficiency. They involve the dynamic interaction between citizens, local governments, and the environment, facilitated by advanced technologies like mixed reality, augmented reality, and virtual reality. These technologies bridge the gap between citizens and their urban environment and contribute to the development of the "smart city digital twin," a digital representation of the city that enhances planning, management, and operational efficiency.

4.2. Digital Twin Smart City

Digital twins represent a groundbreaking development in creating intelligent, adaptive systems, marking a significant step toward realizing DTSC. Building a virtual twin of the city, augmented by the IoT's connection and analytical power, this digital twin gets closer to the real city with each passing update from real-time spatiotemporal data about human behavior and a city's infrastructure as shown in Figure 3. The interaction between the physical layer and the DT layer is made possible through real-time data processing. Once the data has been processed, the insights are communicated back to the physical world, allowing for informed decision-making and adaptive responses that optimize city operations and infrastructure. This intricate virtual model, fully informed of the city's infrastructure performance and human interactions, is designed to predict future behaviors and changes within the urban environment. Simulating fictitious scenarios helps to bridge the gap between an imagined smart utopia and the real-world smart reality by providing a deep understanding of how smart tech-

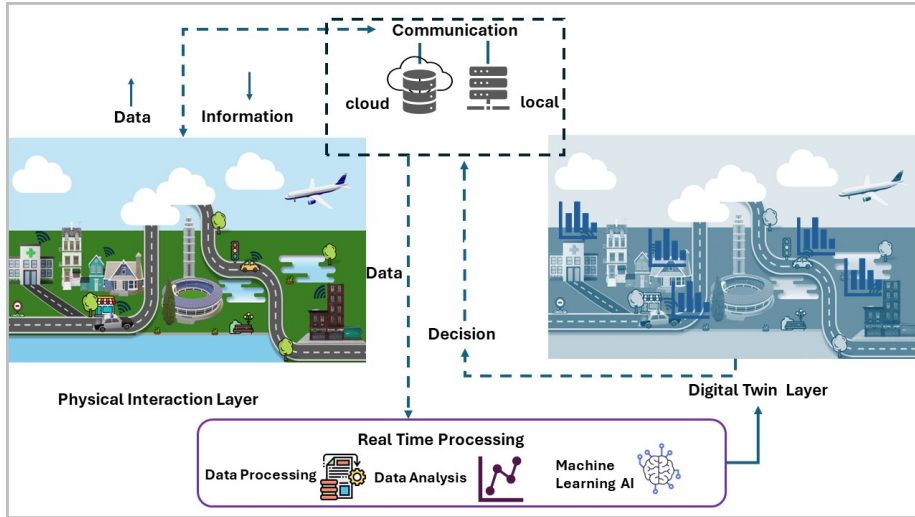


Figure 3: Digital Twin Smart City.

nology might affect city performance under various circumstances [63]. Meeting the unique needs of cities involves a wide range of activities, from sustainable development and city planning to primary education, emergency services, and healthcare. The digital twin offers comprehensive solutions to these challenges by aiding in zoning, municipal development, climate simulation, and participatory planning processes, as demonstrated in cities like Zürich [64]. It helps create a more effective and sustainable urban environment by supporting the predictive maintenance of vital infrastructure, including electricity systems, telecommunications, and roadways. Additionally, DTSC provides insights into the behavior of various urban phenomena, both expected and anomalous. Further details on the applications of DTSC are discussed in the next subsection.

4.3. Digital Twin Smart City Applications

In this section, we explore the latest research on the emerging field of digital twin applications in smart cities. This concept is rapidly gaining popularity, and numerous researchers have provided valuable insights into its potential.

Our primary focus is on critical applications essential for smart cities, such as smart grids, transportation, healthcare, and more as shown in Figure 4.

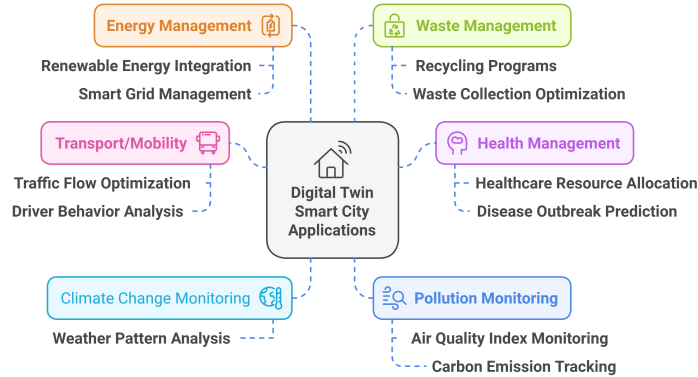


Figure 4: Digital Twin Smart City Applications.

4.3.1. Transport/Mobility

The smart city concept relies heavily on traffic management and intelligent transport systems. Digital twin technology plays a crucial role in metropolitan areas, particularly in developing mapping services like TomTom and Google Maps [65]. These services capture real-world data and create a regularly updated digital representation [55]. This technology also supports various transportation infrastructures, such as energy management, traffic prediction, transport system monitoring, energy consumption forecasting for electric vehicles, parking management, and analysis of driver and pedestrian behavior. By integrating digital twin into these infrastructures, it is possible to achieve reductions in maintenance costs and improved mobility management, prediction, and route and road network simulation [28]. Several studies show the potential of digital twin in traffic management such as in the field of traffic prediction, simulation, and real-time data integration. These studies show the importance of digital twin in making the urban transportation system more flexible and efficient, aligning with the goal of smart cities.

The research conducted by Kusic et al. in [66] presented a real-time synchronized dynamic traffic digital twin model for the Geneva Motorway in Switzerland. This model utilizes real-time data from traffic counters for each lane, as well as the speed of individual vehicles. The collected data is then integrated into SUMO’s Traffic Control Interface (TraCI) for analysis, routing, and calibration of the traffic system.

In the work by Pedro et al. [67], several solutions to traffic congestion and vehicle rerouting are proposed. They utilize continuous road traffic monitoring along with a deep learning model for predicting congestion. The study generates data through 2,400 simulations based on a traffic demand model using pseudo-random numbers. The insights gained from these simulations are then applied to optimize the rerouting process. Yang et al. in [73] presented a dig-

Table 4: Summary of Studies in Transport/Mobility in the Context of DTSC.

Author	Domain	Detail
Sharma et al.[68]	Traffic condition	V2V communication using fuzzy logic to detect local traffic condition
Guidoni et al. [69]	Traffic Congestion	Identification of the congested route by using a Re-RouTE theory.
Kumar et al. [70]	Traffic Prediction	They proposed the traffic prediction using a Kalman filter technique for the city of Vellore, India.
Yongkang et al. [71]	Driver behavior analysis	Sensor fusion technique using an image and cloud DT information to predict the lane changing behavior of the vehicle.
Rapelli et al. [72]	Traffic Simulation	Traffic simulation using a SUMO tool for Turin, Italy.

ital twin for traffic prediction and management for vehicle parking by using a recurrent neural networks (RNN) with long-short term memory (LSTM) for the area pittsburgh downtown. Wang et al. [74] propose a digital twin technology to examine and analyze real-world drivers and pedestrian behavior. They used a CARLA co-simulation platform by sumo for connected vehicles and CAVE environment for pedestrian. To detect traffic congestion, Pan et al. [75] provide a centralized system that uses real-time data from cars, including their location, speed, and direction. When congestion is detected vehicles are redirected along the shortest routes by using the method Dynamic Shortest Path(DSP). They also suggest the second approach called Random K-shortest Path (RkSP) in case the diversion causes congestion on another route. Table 4 presents a comprehensive overview of several articles that focus on mobility applications within smart cities, examining various components such as prediction, simulation, traffic conditions, and congestion analysis. For example, Sharma et al. [68] conduct an in-depth analysis of traffic conditions and their effects on vehicle-to-vehicle communication, utilizing fuzzy logic methodologies. They categorize intelligent transportation systems into three distinct architectures: centralized, distributed, and hybrid.

Guidoni et al. [69] introduced a Re-RouTE simulation model that exploits traffic density data to enhance routing efficiency. Similarly, Kumar et al. [70] and Yongkang et al. [71] have developed predictive models for traffic forecasting and analyzing driver behavior. Furthermore, Marco et al. [72] provided a simulation model tailored for the city of Turin, Italy, employing SUMO tools and datasets from the 5T company to investigate traffic flow dynamics.

4.3.2. Smart Health Management System

There are numerous applications of digital twin technology in the healthcare field. They improve, analyze, and forecast patient, hospital, and pharmaceutical company capabilities. While this technology has shown great effectiveness in streamlining operations and machinery, creating a digital twin for the human body entails much more complex and sophisticated procedures than creating

engineering items. The process of gathering data for the digital twin of the human body is usually more intricate and resource-intensive than for other applications. It frequently involves expensive and time-consuming procedures including imaging equipment, blood tests, and health checks. Despite these difficulties, developments in the human body digital twin research have the potential to speed up the diagnosis and treatment processes, which will ultimately result in higher accuracy and successful care rates. “Digital Patient” is a term that was introduced in one of the European Commission’s projects for patient diagnosis and treatment. In [76] Yuxiao et al. implement a digital version of the human brain for the visual comparison of the working of the human brain with the virtual brain. Diego et al. [77] in 2018 implemented a “HeartModel” by Philips under the concept of Digital patient. This innovative approach explores the possibility of identifying and addressing illnesses in the human body before they manifest. The HeartModel transforms a generic heart model into a personalized representation by utilizing unique images of an individual’s heart, enabling more accurate diagnostics and tailored treatment strategies. Another term in healthcare technology is the Internet of Machine Things (IoMT) which is associated with wearable healthcare devices to monitor the patient’s health linked to smart hospitals. A use case of remote patient monitoring using IoMT and the digital twin approach is given in [78] for anomaly detection using a federated learning model with LSTM model. [79] proposed a digital twin framework specifically for managing the city’s public health emergencies, by merging urban modeling with simulation techniques. Another framework for hospital systems was introduced in [80] by Karakra et al., incorporating IoT, artificial intelligence algorithms, and cloud computing. This work configures the immediate tracking of patient condition and timely allows the healthcare center to take action on it.

4.3.3. Climate Change Monitoring

Over the past 20 years, climate change has significantly increased the frequency and severity of extreme weather events, including floods and droughts

[81]. The projected rise in sea levels over the next few decades is an urgent warning of potential future consequences and poses a major threat to coastal cities.

To manage this issue, various digital twin prototypes have been developed. For example, Denmark has established a DT for hydrology and groundwater management [82] focusing on the real-time update and feedback mechanism in case of floods and droughts, while Newcastle, UK, has a prototype that tracks the impact of heavy rainfall on water levels in a specific area [83]. The model also provides insights into wastewater leakage and blockages in sewer and drainage areas by combining land, buildings, and integrating it with water company infrastructure. The European Union is developing an ambitious project called “Destination Earth,” which will replicate Earth’s atmosphere, seas, ice, land, and human behavior with unprecedented accuracy. It will use a 1-kilometer resolution, surpassing current climate models, to provide detailed forecasts of weather events, floods, droughts, and fires from days to years in advance. Its objective is to improve climate predictions, gather real-time data at a finer scale, and provide insights into the societal effects of climate change and various climate policies [84].

4.3.4. Pollution Monitoring

The World Health Organisation (WHO) has identified air pollution as a major cause of disease and death, making it a serious global public health concern [85]. In response, scientists have developed several modeling systems that simulate pollution emission, advection, and evolution in the atmosphere. Such as in [86] Arsiwala et al. present a digital twin solution for monitoring carbon dioxide levels (eCO₂). This solution integrates artificial intelligence, Building Information Modeling (BIM), and the Internet of Things (IoT) into a cohesive framework. Their approach features a machine learning-based prediction model and employs sensors to monitor temperature and humidity, alongside a micro-controller board that facilitates efficient data collection and processing for the use case of Belfast, Northern Ireland. A use case of Jakarta, Indonesia is pre-

sented by Dedy et al. in [87] in which they integrate air quality, meteorological, and traffic data for a better understanding of air pollution dynamics. Another study on the city of Vienna described in [88] and for the city of Zurich discussed in [64] for the representation of the city in terms of a 3D model for noise and air pollution. These models simulate urban climate scenarios, integrating data with the 3D representation to provide a comprehensive analysis of environmental factors.

Digital twin applications for environmental monitoring and pollution in smart cities mostly focus on air and noise pollution. These digital twin applications use a technique to get the data from the sensors and then apply the algorithm for the analysis and visualization.

4.3.5. Smart Energy Management

Energy, a crucial resource for urban areas, powers transportation, services, and building operations. The energy sector, particularly in smart cities, was quick to adopt the concept of digital twins, focusing on enhancing energy management. Innovations continue to evolve with the integration of smart energy meters and microgrids, which are self-sufficient energy systems that boost sustainability, security, and efficiency. Ongoing research explores the use of digital twins for planning, scheduling, and optimizing distributed power supplies within these systems. In [89], Ruohomaki et al. recreate the smart grid for analysis by converting the energy systems into the digital twin model for the city of Helsinki, Finland. Ejaz et al. in [90] monitored the building performance and renewable energy output and worked on the improvement of the overall energy management of the building through optimal scheduling. They classify the household appliances into three groups based on how flexible they are: weather-based (e.g., HVAC), interruptible (e.g., hot water), and shiftable (e.g., dryer). In [91] Austin et al. developed a digital twin for the city of Chicago using AI and machine learning techniques. In this model, the city is divided based on energy consumption levels. The resulting digital twin model can efficiently map the city into blocks related to energy consumption, identify criteria that indicate

buildings within particular areas, and classify buildings based on usage using data from energy benchmarking. This information improves situational awareness and supports decision-making for the management of urban infrastructure among city stakeholders. Many other city users such as Nottingham, UK, are also getting a benefit from the city platform of the digital twin, where they can visualize city-wide energy consumption. This improves decision making and increases the awareness of citizens about energy management, as demonstrated by the SCENE project, which integrated innovative tools such as a community energy center and interactive energy models to support sustainable energy practices [28],[92].

4.4. Waste Management

Waste management is one of the significant challenges associated with urbanization. According to [93], solid waste generation is projected to reach 2.01 billion tons annually by 2050. Therefore, cities, alongside other advancements, are also focusing on improving their waste management systems. Traditional landfills contribute to greenhouse gas emissions, pollution, and health risks due to methane and toxic compounds, exacerbating climate change and global warming. This highlights the importance of an effective waste management system for both residential and commercial waste [94]. Many cities are now adopting the concept of a digital twin in the realm of waste management. Lunard et al. [95] presented a waste management digital twin for a Swiss municipality. Data was collected in collaboration with industry partners and through field visits, which included information about smart bin locations, vehicle counts, and routing information. They proposed an optimal algorithm to analyze bin levels, enabling better decision-making. Another digital twin prototype was introduced by Ivan et al. [96] for the city of Tshwane, South Africa. Their study focused on integrating real-time monitoring, encouraging citizen participation, simulating waste generation, optimizing collection routes, and incorporating a control dashboard. Data was collected by the National Geo-Spatial Information Centre of South Africa, and optimal collection routes were calculated using the ArcPy

routing module. This resulted in a platform that facilitates better analysis of urban waste management. The industrial aspect of the waste management system for electrical and electronic equipment (WEEE) is described in [97]. This innovative digital twin is designed for the remanufacturing WEEE industry and aims to support manufacturing and remanufacturing operations throughout the entire product lifecycle, from design to recovery. This application of digital twins, whether for residential or industrial waste, holds transformative potential to optimize collection processes, reduce environmental impacts, and enhance resource efficiency.

5. Smart City Digital Twin Classifications

Smart city digital twins are advanced technological models that simulate urban environments accurately and interactively. They are a type of cyber-physical system designed to be highly accurate and responsive. These digital twins can be classified into four categories based on their interaction and capability in the physical world: Passive, Predictive, Programmable, and Autonomic digital twin. Figure 5 provides an overview of these four categories. Each classification represents a different level of functionality and capability, which is determined by the integration of data, analytics, and automation [98], [99],[63].

5.1. *Passive Digital Twins*

Passive digital twins are the most fundamental types, which focus on accurate mapping to create complete digital models of city infrastructure, including buildings, bridges, and streets. They are essential for understanding the current state of urban environments. This level of the digital twin is crucial for baseline urban analysis and planning. It provides a static but detailed view of the city's physical assets.

5.2. *Predictive Digital Twins*

Predictive digital twins enable dynamic interaction between virtual and real environments. These digital twins not only map the city but also track and

analyze real-time data from sensors throughout various city domains to make projections. This allows decision-makers to anticipate and plan for future urban scenarios, from individual behaviors to larger logistics and traffic flows. With this technology, urban future exploration becomes possible, providing insights into future urban normalcies.

5.3. Programmable Digital Twins (PDTs) with a Software-Driven Definition

The utility of digital twins is hereby taken to the next level. PDTs incorporate a Software-Driven definition, i.e. virtual representations that produce high-fidelity simulations of a city’s population, activities, and infrastructure. This allows urban planners and decision-makers to program and test different urban What-IF scenarios within a fully controlled virtual environment, to better optimize urban operations, and strategically deploy city resources.

5.4. Autonomic Digital Twins with Intelligent Feedback

Autonomic digital twins with intelligent feedback are the final stage in the development of digital twins. They possess a higher level of intelligence compared to the earlier stages. They make strategic decisions at each step and use planning, design, and simulation tools to provide solutions to any problems or challenges a city might face. These digital twins help the system become self-optimized, thus enabling it to give warnings, automatically adjust, prevent unintended consequences, and resolve future conflicts.

Considering these classifications, we have analyzed the maturity levels of globally implemented projects within the framework of digital twin smart cities, as discussed in the following section.

6. Global Practices in Urban Digital Twin Implementation

Recent advancements in digital twin technology have sparked global efforts to integrate this technology into smart cities. Singapore’s pioneering work in utilizing a digital twin to monitor urban landscapes has been well-regarded for quite some time [100],[101]. Other recent examples have also highlighted the growing

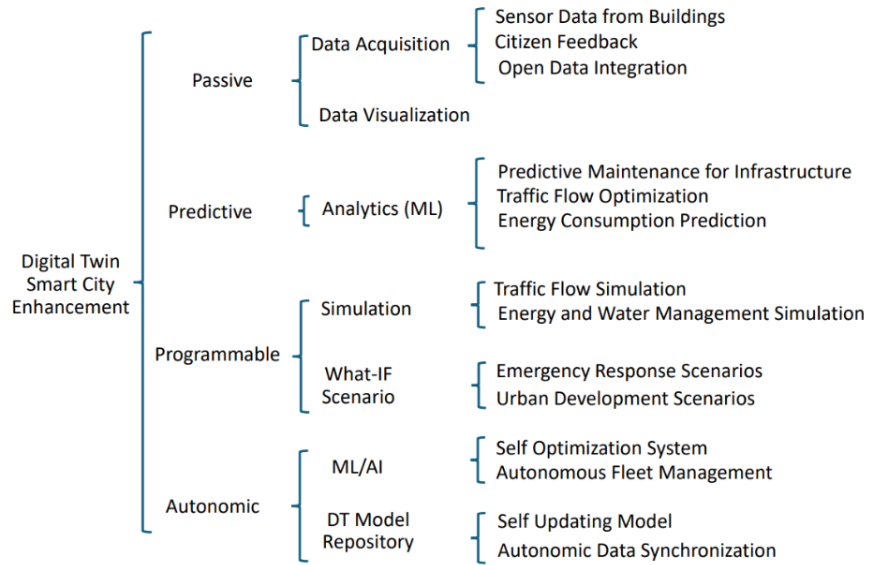


Figure 5: Digital Twin Smart City Classifications.

diversity and development of digital twin applications [102]. By comparing these international projects, we can observe differences in areas such as virtual model management, the extent of trial simulations, project objectives, the technology utilized, and the classification and implementation levels of digital twin types as depicted in Figure 6. These variances emphasize the customized approaches of cities within the digital twin framework in addressing their unique needs and goals.

This section and Table 5 present a variety of smart city digital twin use cases, showcasing the extensive range of applications and the innovative potential of digital twins in urban planning. These case studies demonstrate the dynamic and revolutionary impact of digital twins on the future of urban living, from enhancing environmental initiatives to streamlining city processes.

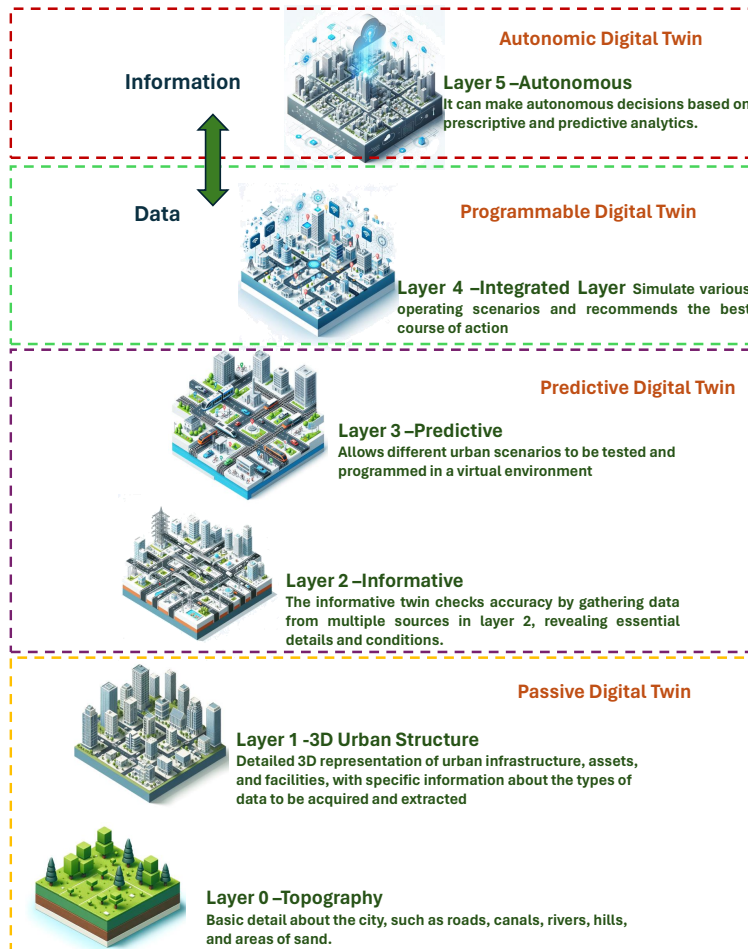


Figure 6: Essential Components of the Digital Twin Smart City Layers.

6.1. *Virtual Singapore*

In the digital twin field, Virtual Singapore is a trailblazing project that uses sophisticated digital simulation and analysis to redefine urban planning and administration. It combines enormous amounts of data about the landmass, structures, infrastructure, and social demographics of Singapore to create an all-encompassing digital reflection of the city that makes precise urban simulations possible. The need for new measures in Singapore began when the city-state faced unexpected flash floods. In 2011, heavy rains caused nine major floods, making it clear that Singapore needed to find ways to deal with this problem. Additionally, being a compact island and the world's densest country with over a million people, the use of land in Singapore requires meticulous planning. In 2012, the GPS Lands and Singapore Land Authority (SLA) began working together to create a 3D map of Singapore to better manage space and identify flood-prone areas [103]. To create this map, they used software created by Bentley Systems and planes equipped with laser scanners to capture detailed information about the ground and surfaces, also known as the topography layer [104]. This work was completed in 2016. In 2017, a second phase of the project was completed using vehicles with lasers to gather street-level data, including details like roads, street furniture, bridges, and tunnels. This information was added to the images taken from the air to create a descriptive model that follows international CityGML standards for 3D modeling of a city [105]. After all the data was gathered, GPS Land created a passive twin by putting all the information together in one system. This system is shared with the authorities, who can use it to improve city planning and design by predicting and simulating the effects of different scenarios. This model is known as the first Digital Twin in the country [106]. Virtual Singapore begins by utilizing initial land information, followed by gathering data through various methods. It then conducts diverse analyses to assist in the country's planning, facilitating interactive planning and scenario testing. Due to these capabilities, it is best described as a Programmable digital twin as shown in Figure 6. This programmable feature enables planners and policymakers to simulate various urban development

strategies, assess their impacts, and make informed decisions. One example of a PDT is Singapore’s intelligent traffic management system. In this project, real-time data from on-road sensors and weather data from local database is utilized to enhance traffic management. An AI model used to predicts traffic flow, while a simulation model was developed for various road scenarios [107]. A notable advancement in Virtual Singapore is its work in climate and energy estimation, which led to the development of a simulation platform called BESCAM, based on the Virtual Singapore database. This platform incorporates CityGML data from Virtual Singapore, including converted Building Information Modeling (BIM) structures. An Urban Canopy Model was then developed to assess microclimate conditions. Following this, energy simulations were performed using EnergyPlus, integrating microclimate data with building information [108].

While the system includes some automation in data processing and scenario simulations, its primary focus is to facilitate programmable interactions rather than operate autonomously. As a result, it requires human intervention for decision-making, distinguishing it from Autonomic digital twins, which operate independently and make decisions without human input [109].

6.2. Zurich Switzerland

Zurich, a prominent city in Switzerland, has been facing significant challenges due to its growing population. The increase in residents and employment opportunities has led to higher population density and greater demands for land use, complicating urban governance. Traditional planning tools and methods, which historically involved only a limited number of citizens and stakeholders, may no longer be sufficient to meet the needs of the expanding population. However, digital transformation, particularly through the implementation of a digital twin of Zurich, offers a promising solution to make planning and decision-making more visual, comprehensible, and accessible. This innovative approach can help overcome the challenges posed by population growth, ensuring the city continues to function smoothly and efficiently. During the 1990s, ETH Zurich started experimenting with spatial data, which eventually led to the creation of Zurich’s

Table 5: Digital Twin Smart City Use Case Examples.

Area	Applications	Implementation Status	DT level	Ref.
Virtual Singapore	City Development, Ecosystem Monitoring, Transportation	large scale developed project	PDT	[110]
Digital Urban European Twin	Urban Planning	Research Project	PDT	[111]
Dublin, Ireland	Energy Consumption, Urban Planning, climate, and city infrastructure management	DT Prototype	PDT	[112]
Rotterdam, Netherland	smart grid, smart parking, port management	DT Prototype	PDT	[113]
Helsinki, Finland	Detailed 3D model for urban planning and citizen engagement	Developed Project	Informative Twin	[114]
Wellington, New Zealand	climate monitoring	Developed project	PDT	[115]
Xiong'an China	Urban planning and management	Developed project	PDT	[116]
Shenzhen, China	Port Management system	Developed project	Automatic DT	[117]
Boston, Massachusetts	Urban development	Prototype	PDT	[118]
Wuhan, China	Urban Planning, e-services, Public services, Transportation	prototype	PDT	[119]
Hangzhou, china	Traffic Management	Developed	Autonomic DT	[120]
Copenhagen, Denmark	Traffic and Environmental management	Developed Project	Autonomic DT	[82]

comprehensive 3D city model in 2011. The model was developed collaboratively with contributions from ETH Zurich, Fachhochschule Nordwestschweiz, and TU Munich [121],[122]. The model consists of three levels of detail: the Digital Terrain Model, the Block Model, and the Roof Model, all built upon the CH1903 reference system (LV95/EPSS 2056) [123]. The Digital Terrain Model, derived from 2014 LIDAR imagery with a resolution of 50 cm, includes additional break

lines in bridge areas and manual adjustments around lake Zurich and the Limmat river. Additionally, road geometries from cadastral surveys were integrated into the model. The triangular mesh was generated using FME with tolerances of 1 m and 0.1 m, resulting in a mean height error of 30–40 cm. The Block Model is based on both existing and planned building floor plans sourced from official cadastral surveys, enhanced with photogrammetrically determined eave and gable heights. Distinct buildings of varying heights are divided into prisms, and the model also incorporates notable bridges, achieving positional accuracy within 10–15 cm and a mean height error of 50 cm. The Roof Model adds detailed structures for roofs and walls, which were evaluated using semi-automatic stereo aerial photogrammetry. This model also features prominent architectural elements such as bridges. Overall, the 3D city model captures more than 50,000 buildings with high precision and is continuously updated to reflect new developments. For Zurich, the digital twin represents a significant enhancement of its 3D spatial data collection. It involves not only modeling and detailing the data but also managing the lifecycle of both individual elements and the entire dataset. These 3D spatial datasets lay the groundwork for integrating additional spatial or diverse data types. Where feasible, real-world elements are connected to the digital realm in real time, and the digitization processes now incorporate a third dimension. Zurich's GIS City department oversees this initiative, working in collaboration with various partners, including 25 city service departments.

Zurich has been working on its digital twin model for more than a decade. The focus has been on applying it in the environmental sector, including modeling noise, air pollution, and mobile phone radiation. It has also been used in the energy sector to analyze solar potential and in urban planning to visualize construction projects and conduct shadow and visibility analyses [124] [64]. The Zurich digital twin can be classified as a passive digital twin, as it focuses primarily on the visualization of the 3D city model without incorporating predictive, autonomic features, or simulation capabilities for scenario analysis as per process describe in Figure 6. This digital twin is limited to advance

functionalities that make its utility for dynamic decision making and proactive urban planning.

6.3. Georgetown, Malaysia

Georgetown, the capital of Malaysia’s Penang province, is heavily reliant on tourism, its second-largest source of income. The city’s economy has been severely impacted by the COVID-19 pandemic. To spur economic recovery, Georgetown has adopted a digital twin city platform that helps evaluate the feasibility of new projects, infrastructure capacity requirements, and sustainability.

Moreover, Georgetown uses an urban data platform to enhance urban resilience by anticipating and mitigating different threats to city infrastructure. They collect a broad range of information from both public and commercial sources, such as energy usage, ecological statistics, and planning schemes. This data is then used to simulate and visualize the effects of new urban projects to address problems like hazards, traffic, and unemployment. Additionally, the platform provides interactive services to citizens, improving the overall livability of the city [125]. According to the data presented in Figure 6, it appears that the project’s level of maturity is currently constrained by a Programmable digital twin. It is important to note that this digital twin should be considered solely for simulation and analysis in support of decision-making processes.

6.4. New South Wales Australia

New South Wales, Australia, in collaboration with Data61 and the Commonwealth Scientific and Industrial Research Organisation (CSIRO), has developed a digital twin 4D model that utilizes real-time data to create a virtual representation of the physical environment [126]. The project aims to cover a vast area of 3,392 square kilometers and generate a 3D grid map of Sydney’s western region with a pixel resolution of less than 6 cm. To capture images of vast regions with high precision, the project employs sensor-equipped fixed-wing platforms. The platform leverages data from water, energy, and telecom utilities to modify

its images of buildings and natural resources above and below ground. Furthermore, it collects data from various sources and visualizes historical data from government, industry, and communities [127]. Another pilot project focused on three key aspects of the city. First, it conducted a sunlight exposure analysis during specific events to determine optimal locations for shade structures throughout the city. Second, it analyzed the green areas within the city. Third, it indicated the placement of sensors on the city model [128]. The aforementioned digital tools are largely passive, as they focus solely on gathering data related to city modeling and presenting it on a map, without any further analysis or programmable features.

6.5. Rennes France

Rennes, the second-largest city in northwest France and a popular tourist destination is undergoing a transformation with the help of Dassault Systèmes [129]. Together, they are creating Virtual Rennes, a digital twin of the city designed to improve urban planning, decision-making, management, and services to citizens and visitors. This is a collaborative 3D digital platform, developed by Metropolis Rennes and Dassault Systèmes, that enables various stakeholders to work together on innovative urban projects [130]. It showcases the potential for both programmable and autonomic features in a digital twin.

The digital twin technology has also been applied to the construction of the Maurepas district’s metro passenger railway, illustrating the utility of the technology in integrating and analyzing city-wide data. A detailed 3D model was developed that serves multiple purposes, from presenting broad landscape features to detailed aspects such as rooftop installations and evacuation plans. The model can also simulate the broader impact of metro construction on urban elements like traffic flow and community structures [131]. Virtual Rennes is a great example of a Programmable digital twin that uses input and collaborative design to visualize urban development scenarios and their effects. Additionally, it can simulate the impact of changes in infrastructure on urban dynamics. This blend facilitates a more nuanced approach to urban planning, where decision-

makers can pivot from traditional, experience-based strategies to more robust, data-driven ones.

Virtual Rennes has significantly reduced construction timelines, cutting down metro station development by 70% and finishing three months ahead of schedule [132]. This demonstrates the efficiency gains made possible by digital twin technology. Beyond streamlining project timelines, it fosters multi-governance frameworks, opens stakeholder communication, and encourages public and professional involvement in the urban design process. This collaborative approach not only strengthens the relationship between the government, citizens, and other stakeholders but also builds consensus on the digital twin’s utility from the project’s onset. In summary, Virtual Rennes showcases the capabilities of a Programmable digital twin by simulating "what-if" scenarios before events occur. However, these simulations rely on hypothetical situations rather than integrating real-time data from the physical world, which limits its functionality compared to an Autonomic digital twin. While Virtual Rennes is valuable for pre-implementation project analysis, it lacks the dynamic responsiveness and real-time decision-making abilities that characterize more advanced digital twin systems.

6.6. Kunming China

Kunming, a major city in western China, faced serious traffic issues during rush hours. To tackle this problem, the city created an urban traffic database using digital twins. This system enables traffic managers to effectively monitor and control traffic flow across the city, helping to alleviate congestion and improve overall traffic conditions. The 3D model of the city includes the road network, vehicles on the road, and roadside elements such as street lights. This model is highly accurate and precise. The platform combines data from different sources, including radar, video, the internet, and the road network. This integration enables a detailed analysis of urban traffic operations at macro, meso, and micro levels. On a broad scale, the platform offers a comprehensive view of Kunming city. It highlights aspects like congestion delay indices and traffic

speeds across different regions. At a mid-level, the platform digitizes vehicles and reconstructs their paths, accurately representing vehicle movements. On a detailed scale, it examines traffic flow efficiency at intersections, providing metrics such as queue lengths, flow rates, speeds, and delays at the lane level. The platform also assesses road safety by identifying emergencies or traffic rule infractions [125].

This digital twin platform appears to be a Programmable digital twin rather than an autonomic one. It relies on specific data inputs to simulate and analyze traffic scenarios, supporting human decision-making processes. Unlike an Autonomic digital twin, which would independently make decisions and adapt based on incoming data, this platform focuses on data integration and visualization to inform decisions rather than implementing them autonomously.

7. Challenges

Building upon the foundational exploration of classification in DT and globally implemented projects as outlined in previous sections, this segment aims to transition into the open issues and challenges faced by DTSC implementation.

7.1. Data Collection and Sources

One of the biggest challenges in creating a DTSC is the availability of high-quality data. The latest technological developments that enable digital twins, like as Big Data, Deep Learning, and Machine Learning, depend heavily on the quantity and quality of data. The ownership of urban datasets adds still another level of complexity. Urban data may belong to the city, commercial groups, academic institutions, or other parties, unlike industrial environments where data ownership is rarely contested [55]. Furthermore, urban data digital twins have different needs and requirement, including adaptive sampling rates for data collection to balance between performance and computation-communication resource management. To create and maintain digital models within a DT system, various sensors gather data from objects or contextual components, like GPS,

soil sensors, temperature sensors, light sensors, wearable sensors, and many others. However, reliable data is crucial for building a full image in city-scale digital twins, since data in cities can originate from multiple sources dispersed over huge areas. Other factors like imputation and sensor calibration are also important for data quality.

7.2. Connectivity and the Missing Data

After data collection, a critical step is preprocessing to assess its quality and suitability for analysis. Ensuring high-quality data is essential for the successful implementation of a digital twin for the city. It is important to assess whether the data is suitable for its intended purpose, as the accuracy and reliability of the digital twin's simulations and predictions largely rely on the quality of the input data. Issues such as hardware malfunctions and power outages can result in data loss or inaccuracies, which can consequently have a detrimental effect on the performance and efficiency of the DTSC model. It is crucial to resolve these issues in order to preserve the integrity and usefulness of the digital twin. For example, in the Virtual Singapore use case, data anomalies delayed the achievement of seamless interoperability. This problem affected the accuracy of simulations and the dependability of outcomes. To address this, standardised frameworks like CityGML were implemented, facilitating data integration and enhancing stakeholder data sharing.

7.3. Data Standards and Integration

Researchers involved with the development of digital twin agree on the fact that it's important to create common rules and ways for digital twin systems to work well together, making it easier to use them faster with things like smart city projects. This issue was also addressed by [28],[133],[56] and organizations such as the Industrial Digital Twin Association [134] the Digital Twin Consortium [135] were also established. There is a significant global effort, with organizations like ISO developing standards to assist everyone. One major advancement is the creation of a set of sample digital twin projects that others can

use as a guide to avoid issues when digital twin systems need to connect or work together. An example of this in action is the Centre for Digital Built Britain (CDBB), a government project that aims to establish guidelines for using digital twins in large-scale projects across the country, especially in city-scale digital twin projects. The CDBB is a public initiative focused on standardization at a national level, which is crucial for large city digital twin projects as it facilitates collaboration among different groups to ensure the success of these projects.

7.4. Privacy and Security

One of the main challenges in the field of DTSC is ensuring privacy and security. Each digital twin processes a vast amount of data, which creates a risk of cyberattacks. As a result, developing a secure platform has become an essential requirement. For instance, in traffic management like Rennes, France use case, if location-sensitive data generated by vehicles is deanonymized, it could enable the tracking of specific individuals, posing a serious risk of abuse. Moreover, smart cities face significant privacy challenges due to the sharing and analysis of extensive datasets among various stakeholders, which increases the risk of data breaches and re-identification. Disparities in privacy standards between the public and private sectors further aggravate these risks, particularly when employing data mashup and integration techniques that can expose sensitive information. Traditional privacy-preserving methods, such as K-anonymity, often struggle to protect high-dimensional data, rendering it vulnerable to advanced attacks [136]. Additionally, smart utility data, including electricity usage, can be intercepted during transmission, potentially revealing personal habits. Also, the trend of autonomous vehicles (AV) in smart cities aims to enhance traffic safety and make life easier. However, they pose a significant security risk, as hacking of the system can compromise both life safety and data privacy. Hackers can exploit vulnerabilities to remotely control vehicle functions like brakes, engines, and steering. Additionally, the vast personal data collected by AV systems raises serious privacy concerns [137].

7.5. Implementation Cost

The deployment of city-scale digital twins can lead to unintended consequences, such as the need for new sensing infrastructure and challenges in adapting existing systems. While many use cases have been proposed for city-scale digital twins, it is crucial to explore their practical applications across different domains. For example, it is important to consider the interrelation of factors like traffic, air quality, and noise to avoid the need for detailed new sensing infrastructure, which is discussed in section 8. Furthermore, initiatives such as Digital Urban European Twins (DUET) [138] and LEAD [139] in this context are also essential for developing "blueprints" for implementing city-scale digital twins.

7.6. Response Time

Response time is extremely important, especially in healthcare, disaster response, and traffic management. Quick and reliable data transmission is crucial in these areas. Currently, smart city sensors, which typically update every few seconds or minutes, use low-bandwidth wireless networks that are not optimized for fast response times. This situation is also common in smart manufacturing. While 5G and similar technologies show promise for improvement, it will likely be necessary to upgrade the existing infrastructure that supports digital twins in order to accommodate or transition to technologies with better response time capabilities.

In parallel with the technical issues mentioned above, some social challenges are also under consideration in the development process of DTSC, including public involvement and feedback.

7.7. Potential Biases in AI-Driven DTs and Marginalization of Underserved Populations

AI-driven DTs represent fully functional smart city systems that possess advanced capabilities such as predictive analytics and autonomous operations. However, these systems often inherit biases from their underlying algorithms,

data sources, and societal structures. Such biases can lead to unfair or discriminatory outcomes, disproportionately affecting historically marginalized populations based on factors such as race, gender, or income.

Cases like Amazon’s hiring platform and Apple’s credit card discrimination highlight the potential dangers of these biases when applied to urban services, including smart governance, transportation, and housing [140]. In the context of smart cities, the training datasets used in AI-driven systems can introduce significant algorithmic biases due to issues like sample inadequacy, selection bias, or misrepresentation of urban populations. For instance, if certain demographics or regions are underrepresented in the training data, AI systems may allocate resources or services unfairly. Another challenge in the development of smart cities is the marginalization of underserved populations. The fundamental goal of a smart city is to ensure accessibility and ease of use for everyone, including the elderly, youth, and individuals with disabilities. For each smart city development solution, it is essential to consider the needs of every resident. For example, if a city attempts to engage with its citizens through a smartphone application, those who are elderly or do not have access to such technology may be excluded from providing input or benefiting from these initiatives.

7.8. Citizen Engagement Role in the DTSC

Smart cities will operate more efficiently with active citizen involvement as discussed above. One fundamental challenge is engaging the large population in the data collection and feedback process, which is crucial for government bodies to make informed decisions regarding city development. Many cities lack awareness of how citizen participation can enhance both the development process and digital literacy. To address this challenge, co-creation, interactive workshops, and various tools are essential.

In their study, Ibrahim et al. [141] emphasized that citizen engagement is a key factor in development. They analyzed data from ten different Saudi cities using structural equation modeling. Their analysis focused on five key norms: information availability, perceived benefits, social norms, behavior management,

and social responsibility and engagement behavior. They found a direct relationship between information availability and citizen engagement. The same kind of analysis was also performed for other cities to understand the importance of citizen feedback and how to engage them, as seen in Tehran [142] and Mexico [143]. This challenge demonstrates that not only technical issues matter, but social issues also require attention for the development of digital smart cities. This approach ensures that smart cities are not only technologically advanced but also equitable and citizen-centric.

The challenges defined above for the development of the DTSC are the initial phase challenges that cities face during implementation. The major challenge is the availability of resources; if the data is available, the city can move forward in its smart city journey, and further challenges can be addressed accordingly. Another important point is the involvement of citizens, and how they can contribute, either in data collection, management or as feedback providers as we discussed earlier. One solution we have identified for the major data availability issue is synthetic sensing explained in the next section.

8. DT Development with Synthetic Sensing

The development of smart cities and their digital twins heavily relies on data collection, where sensors are the most dependable source. However, many cities aspiring to be a part of the DTSC movement, face significant challenges due to limited resources, excluding them from the race. Alvi et al. (2024) [144] propose an alternative approach to traffic management for the city of Issy-les-Moulineaux. They utilize Google data, local bus schedules, and open weather data to avoid the necessity of installing new sensors. By utilizing existing infrastructure for traffic prediction and simulation, this strategy demonstrates an effective means of managing traffic. The results also highlight significant improvements when additional factors are integrated alongside traffic data in the analysis. To improve traffic forecasting, Awan et al. (2020) [145] investigated a

novel method by using atmospheric data (wind speed, wind direction, temperature, and pressure) and air pollution data (O₃, NO₂, NO_x, CO₂, NO). They collected the hourly data from January 2019 to December 2019 for Madrid, Spain, and used the LSTM for the prediction of traffic. Their analysis focused on the correlation between various factors and traffic parameters to enhance the accuracy of the predictions. Then, in 2021, Awan et al. used noise pollution data to estimate traffic flow as vehicles per hour in the city of Madrid by considering the same approach defined before [146]. On the other hand, Lana et al. (2016) examined the relationship between traffic and pollution levels, estimating the concentrations of pollutants including O₃, NO₂, CO, NO, and PM₁₀ using data on road traffic by using regression model for the city of Madrid [147]. Zappatore et al. (2016) utilized Mobile Crowd Sensing (MCS) to estimate urban noise levels at a low cost. They presented the findings through color-coded noise maps, and they received a positive feedback from both citizens and city management in Southern Italy [148]. The table below (Table 6) summarizes further studies using various data sources for smart city planning. For instance, You Jin et al. in [149] utilized city maps to identify heat islands and examined the relationship between sensible heat and green areas. They employed K-means clustering and discovered that expanding green space by 1% could reduce sensible heat by 4.9 W/m². Additionally, a study by Stefania et al. [150] focused on land temperature in the central town of Terni, Italy. They used Landsat 7 satellite data to assess albedo and compared images from 2005 and 2015 to investigate the heat island effect. Rosser et al. in [151] and Wang et al. in [152] analyzed social media data for flood density estimation in Colorado and the UK, applying a Bayesian statistical model and Gaussian estimation.

Similar traffic estimation and analysis studies were conducted in Pennsylvania, the UAE, and Chicago using Twitter data. These studies accounted for rush hour and weather conditions in their analyses, forming clusters based on peak travel times [153] [154] [155]. Furthermore, in [156], Iani et al. analyzed weather data to predict future electricity impacts up to 2030, using data collected from 2005 to 2015.

Table 6: Summary of Research on Smart City Development Using Alternative Data Sources.

Focus Area	Data Source Used	Ref.
Thermal Areas, Seoul	City map(green area and buildings)	[149]
Land Surface Temperature (LST), Terni, Italy	Landsat 7 satellite	[150]
Flood events,UK	Social media and topographic data	[151]
Flood density estimation,Boulder Colorado	Fusion of remote sensing and social media data	[152]
Next day traffic prediction, Pennsylvania	Twitter messages to understand previous day people’s routine and events	[153]
Road traffic analysis,UAE	Twitter and Instagram data (English and Arabic language)	[154]
Traffic congestion, Chicago	Social media data(government and management tweets)	[155]
Electricity supply and demand,Britain	Weather data	[156]

However, such methods, while innovative, often fall short in accuracy compared to sensor-based data, illustrating the trade-offs between utilizing readily available data sources and the precision of dedicated sensor networks. Replicating a digital twin model from one city to another is theoretically possible with the available data. However, scalability presents a significant challenge because each city has its own unique infrastructure, demographics, and specific urban issues, making every digital twin distinct in its specifications. While cities facing similar challenges can adapt existing digital twin models, the lack of scalable and standardized infrastructure in the discussed models limits their broader applicability. To overcome this issue, it is essential to develop standardized, modular, and flexible digital twin architectures, as we mentioned in the future directions.

9. Discussion and Future Direction

In this article, we investigated the recent advancements in the application of digital twin to smart cities and how they affect the urban context. We explored various city-scale digital twin prototypes and experiments and emphasized the potential of DT-based solutions to improve smart city operations across different application domains. We also addressed the cogent challenges that are currently hindering the actual implementation, deployment, and operation of digital twin in crucial areas of smart city activities, paving the way for future research and development in this evolving field. Among these challenges, the basic need for all cities is a fully autonomic digital twin that provides effective solutions, even with limited resources, to support city development and planning systems. Recent articles emphasize the importance of these advancements. For instance, [157] highlights the role of quantum and AI-based digital twin systems, which are essential as most of the projects discussed above lack autonomy and AI capabilities. This creates a significant opportunity for advancements in cognitive and quantum digital twin concepts, as also explored in [158]. Another critical direction is the standardization of scalable digital twin architectures, which would enable other cities to follow the path toward DTSC, as emphasized in [159]. Furthermore, the challenge of limited resources or insufficient data for development and analysis remains a key issue. A promising approach to address this is data fusion combined with modeling techniques, as discussed in [160]. This method enables the creation of process-based digital twins that focus on modeling processes with minimal data resources to support city infrastructure planning. Details of these directions and their significance are discussed below.

Cognitive and Autonomic Digital Twin: A promising direction is Cognitive digital twin. Cognitive digital twins use advanced technologies like AI, ML, and NLP to create self-learning digital models. They predict infrastructure maintenance, adjust urban plans based on real-time data, and improve public service delivery by anticipating citizen needs. Cognitive digital twin could be

considered as Programmable and Predictive digital twins capable of providing decision-making support to humans. A step is the creation of autonomic digital twins. They represent another important advancement in terms of the ability to autonomously act and continuously optimize the city processes according to the goals and targets stated by humans. Autonomic digital twins are designed to autonomously manage themselves by continuously monitoring, diagnosing, and optimizing their operations. They are capable of using real-time data to understand the “situation” and to act upon it. They are an intelligent combination of sensing and actuation capabilities operating in the urban context. Additionally, in the field of security management, autonomic digital twins can independently detect and mitigate security threats, thereby enhancing the overall security of urban systems. Until now, very few projects have come close to this level. However, this level of autonomic behavior is still to be fully understood and put into practice. Many issues related to Human intervention and awareness are to be considered before fully adopting this approach.

Process-Based Digital Twin: Process-based digital twins offer significant potential for optimizing urban planning processes. By leveraging historical data, these twins can simulate and improve urban processes. For example, in the case of waste management, analyzing historical data about waste generation and recycling patterns allows cities to determine the resources needed to efficiently and effectively recycle specific amounts of waste just on-time. Through material flow analysis and process simulation supported by a digital twin, cities can estimate waste generation and required resources, such as facilities, personnel, and equipment. Optimization algorithms can then allocate these resources effectively, ensuring cost-effective and sustainable waste management. Similarly, in infrastructure development, process-based digital twins can simulate various scenarios to understand and meet infrastructure needs, ensuring balanced and efficient development. This could be the case of road circulation and studies related to the incremental closure of roads to cars and vehicles in favor of pedestrian and public transportation.

Real-Time Data Integration: Enhancing real-time data integration is cru-

cial for the future of DTSC. The smart cities needs to find out a balance between the needed sensing and actuation infrastructure (expensive and in need of management) and the possibility to act and decide with well-form and accurate data. By integrating more comprehensive and diverse data sources, cities can improve the real-time capabilities of decision-making by means of digital twins. Deploying advanced IoT sensors, utilizing 5G connectivity for faster data transmission, and employing edge computing for real-time data processing can significantly enhance the accuracy and responsiveness of urban models. On the other side, having access to synthetic data, without the need to deploy a related infrastructure could be an advantage for many small and medium-sized towns. An intelligent approach to general-purpose sensing and synthetic sensing can provide real-time data to the city by deploying a more general sensing infrastructure capable of exploiting AI for data transformation and generation [161].

Interoperability and Standardization: Increasing interoperability and standardization is another important factor for the success of DTSC. Developing standardized protocols and frameworks ensures that different systems and platforms can work together seamlessly. Implementing open data standards, using APIs for seamless communication between systems, and employing blockchain technology for secure data sharing and integrity can facilitate more cohesive and efficient digital twin ecosystems. Cities are intertwined structures that need to be represented in their complexity but also in their interdependence. A smart city will not “confine” itself to the city limits, but it will represent phenomena, processes, and activities that span beyond its borders but that are essential for the city’s behavioral description. A shared and standardized set of data models as well as behavioral ones is needed to promote interoperability between different urban areas and to interrelate them.

Scalable Digital Twin Architecture: Finally, creating modular and scalable software digital twin architectures will be essential as urban environments grow and technologies evolve. Developing microservices-based architectures, using containerization for scalable deployments, and leveraging cloud-native technologies can ensure that digital twin solutions remain flexible and scalable, able

to adapt to changing urban needs and technological advancements and at the same time capable of exploiting Edge functionalities whenever it is possible. Vehicular infrastructure could be an example of the continuum in the software architecture and for the correct development of effective digital twins.

Quantum Digital Twin: Based on the challenges and analysis discussed above, the development of DTSC in the future could be greatly improved by integrating Quantum Digital Twins (QDT) [162] in smart cities [163]. Quantum computing provides unparalleled computational power, enabling the optimization of complex urban systems in real time. For example, QDT can revolutionize urban traffic management by offering real-time solutions to optimize traffic flow, thus reducing congestion and improving overall transportation efficiency.

By exploring these advanced methodologies and directions, cities can significantly enhance their planning, management, and operational capabilities, resulting in more efficient, sustainable, and resilient urban environments. As a next step of this research, the cognitive and processes-related aspects of the digital twin facets will be firstly tackled in conjunction with the work done for reducing and optimizing the complexity of the sensor and actuation framework (general purpose sensing). These goals will be reached by research activities in collaboration with major cities of the world.

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