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Navigating urban complexity: The transformative role of digital twins in smart city development

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ABSTRACT

This research systematically explores the burgeoning field of Digital Twins (DTs) within smart cities' framework and urban development. Anchored by three research questions, the study delineates the theoretical underpinnings and practical implications of DTs at a city scale. It delves into the structure, operational dynamics, and diverse applications in various urban domains supported by case studies. Through a structured methodology employing the PRISMA framework, it includes an analysis of 64 pertinent studies from an initial pool of 519. The research synthesis highlights the dynamic nature of DTs, their multifaceted technological layers, and their instrumental role in shaping sustainable urban futures. Despite the promising outlook, the study also highlights several technological and real-world hurdles that need to be addressed to fully unlock the capabilities of DTs within urban environments.

1. Introduction

The dawn of the 21st century has witnessed an unprecedented surge in urbanization, ushering in many challenges and opportunities for cities worldwide (Avezbaev et al., 2023; Major et al., 2021; Mohammadi & Taylor, 2019). As highlighted by Deng et al. (2021), this urban expansion is not merely a demographic shift but a complex interplay of socioeconomic, technological, and environmental factors. As urban areas burgeon, accommodating and sustaining their growth becomes paramount while ensuring sustainability, resilience, and quality of life for urban dwellers (Banihashemi & Zarepour Sohi, 2022; Mohammadi & Taylor, 2019).

Central to addressing these challenges is integrating technology into urban planning and development (Barresi, 2023; Derrible, 2019; Mendula et al., 2022). Moreover, 'smart cities' concept has gained popularity, emphasizing digital tools utilization and data-driven approaches to enhance urban living (Mylonas et al., 2021). Within this digital landscape, Digital Twin (DT) is progressively being recognized and utilized in areas of urban planning and infrastructure management (Depretre et al., 2022; Deren et al., 2021; Elsehrawy et al., 2021). As described by Elsehrawy et al. (2021), DTs are virtual counterparts of real-world entities, bridging the digital and physical realms of urban landscapes. This technology, while nascent, holds much promise in urban planning through its ability to provide engaging, real-time visualizations and simulations of urban environments (Caprari et al., 2022).

The potential applications of DT in urban development are vast (Dembski et al., 2019). From infrastructure planning to environmental sustainability, DTs offer a holistic, data-driven approach to addressing urban challenges (Caprari et al., 2022). For instance, by simulating urban scenarios, city planners can anticipate and mitigate potential issues, ranging from traffic congestion to environmental degradation (Erol et al., 2020; Mylonas et al., 2021). Furthermore, DTs amalgamation with Internet of Things (IoT) and Artificial Intelligence (AI), can improve predictive analytics, optimize resource allocation, and foster citizen engagement (Fattahi Tabasi et al., 2023).

However, the journey of integrating DT into urban planning is not without challenges. As noted by Charitonidou (2022), cities face hurdles ranging from data privacy concerns to the need for robust technological infrastructure. Moreover, the multidisciplinary nature of urban planning necessitates collaboration across sectors, requiring a paradigm shift in traditional planning approaches (Charitonidou, 2022). Despite these challenges, DT's transformative impact in urban development is undeniable. While urban regions face dual challenges of growth and sustainability, DTs offer a beacon of hope. They equip cities with the

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capabilities to envision the future and make well-informed choices, and ensure a sustainable, resilient, and inclusive urban future (Deng et al., 2021).

While the possibilities of DT in urban planning are extensive, its application, especially concerning sustainability, remains in its infancy (Mylonas et al., 2021). Furthermore, the integration of social community dynamics within urban DT remains an emergent field of research. How DT can encapsulate the rich tapestry of urban social interactions, is still developing. Whereas, recognizing this dimension is crucial for creating more holistic and responsive urban management tools that truly reflect the complexity of human environments within cities. The existing literature offers fragmented insights, with some knowledge gaps in understanding the comprehensive impact and potential of DT in an urban context. Hence, this comprehensive literature review seeks to consolidate existing knowledge, identify gaps, and outline directions for upcoming studies on DT within the scope of urban planning and smart cities.

2. Review methodology

This study has adopted a systematic review approach to explore and analyse existing literature on DT at the city scale. The methodology structure consists of four primary steps as shown in Fig. 1. The first step includes defining a clear purpose of this study through three research questions. Subsequently, it includes the paper selection process where a PRISMA flowchart and guidelines are utilized to record the step-by-step approach of identification, screening, eligibility assessment and selecting the definitive papers for analysis. Following this, it includes the analysis part which consists of descriptive analysis and content analysis. The final step includes gap identification and recommendations for future research.

2.1. Research questions

This systematic review primarily aimed in establishing the theoretical base and acquiring a detailed comprehension of the principles, core technological aspects, potential applications, and limitations of DT at a city level within the fields of smart cities and urban planning. Consequently, this led to the formulation of the following three research questions:

- RQ1. How has the concept and implementation of DT evolved and pervaded within the areas of smart cities and urban planning?
- RQ2. What are the potential and current applications of DT?
- RQ3. What challenges and limitations are associated with deploying DT at a city scale?

2.2. Paper selection

A PRISMA flow diagram was utilized to record the step-by-step review process for the paper selection stage (Fig. 2). The following sections delineate the methodical steps undertaken to sort through, evaluate, and select the most relevant studies that align with the research objectives and questions.

2.2.1. Identification

The primary database utilized for this search was Scopus. Additional papers were obtained from Google Scholar for more comprehensive analysis. The search strategy incorporated the following keywords: “Digital Twin”, “Urban Planning”, “Smart Cities”, and “Infrastructure planning”. Multiple combinations of these keywords were utilized using Boolean operators “AND” and “OR”. The initial search yielded a total of 519 records, comprising 493 from Scopus and 26 from Google Scholar, without a time range.

2.2.2. Screening

Following the preliminary identification, a rigorous screening process was undertaken to verify the studies’ relevance and quality. The initial stage entailed eliminating duplicate records, resulting in the exclusion of 125 duplicates. This left 394 unique records that were then subjected to a title and abstract screening. Based on the relevance to the research topic and predefined inclusion and exclusion criteria, 279 records were excluded at this stage. Studies were included if they

- Addressed the utilization of DT in urban planning or smart city contexts.
- provided insights into the challenges or potentials of DT in urban contexts.
- consisted of articles reviewed by experts, conference papers, or credible industry reports.

Studies were excluded if:

- the language was not in English.
- a record did not focus on the application of DT in urban contexts.

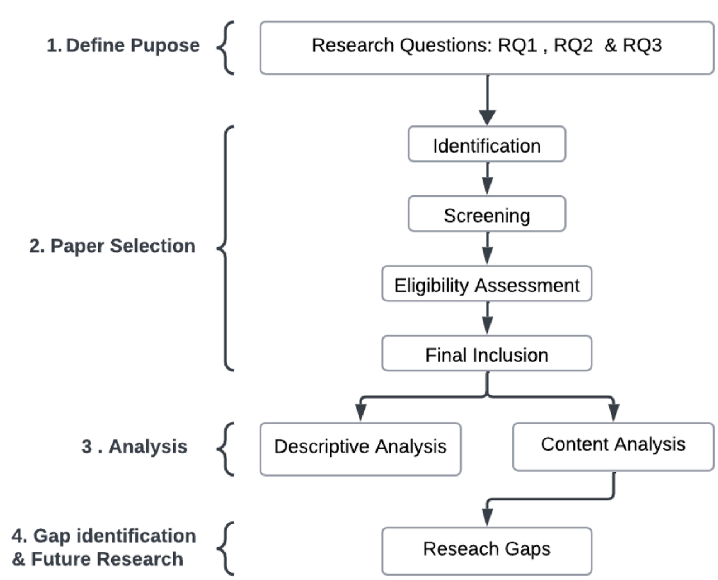

Fig. 1. Review methodology structure.

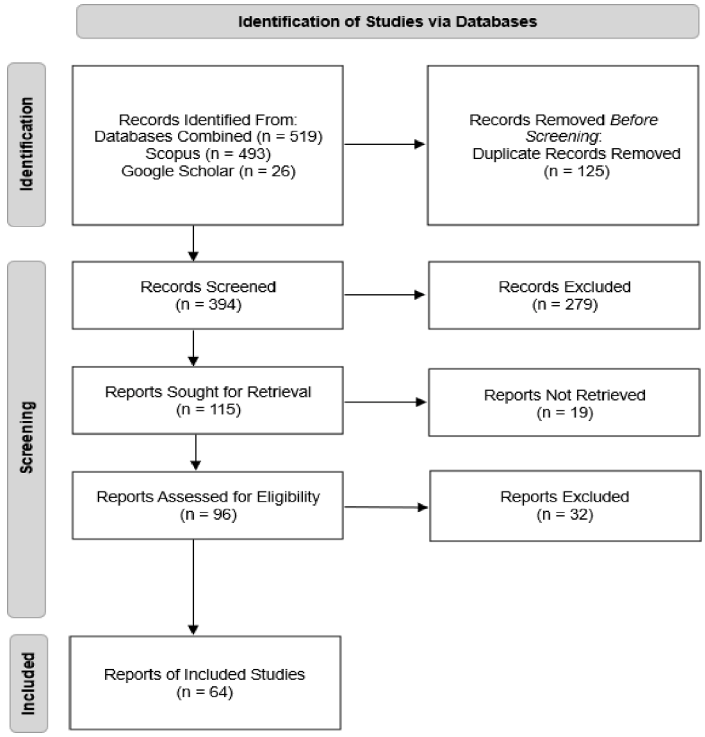

Fig. 2. PRISMA flow diagram of the study.

- a record was purely technical without any relevance to urban planning or sustainability.

2.2.3. Eligibility assessment

The remaining 115 records were then sought for a more detailed retrieval and assessment. However, 19 of these records could not be retrieved for various reasons (e.g., access restrictions, unavailability, and broken links). The full texts of the successfully retrieved 96 records were thoroughly assessed for their eligibility. Criteria for this assessment included the study's relevance to the research questions, methodological rigour, and the quality of data presented. Following this detailed assessment, 32 reports were excluded.

2.2.4. Final inclusion

After the comprehensive screening and eligibility assessment, 64 studies were found suitable for the final systematic review. These studies provide valuable insights, data, and findings that were synthesized and analyzed to address the research questions.

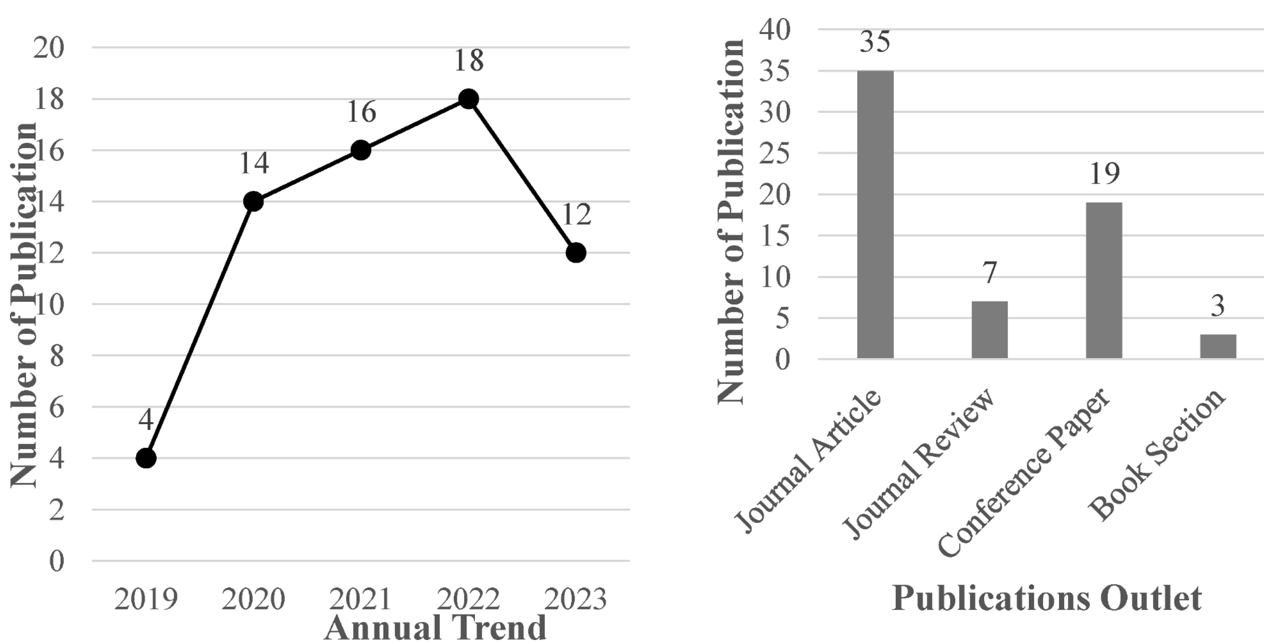

Fig. 3. a) Annual publications trend, b) Publications outlet.

3. Analysis and results

3.1. Descriptive analysis

3.1.1. The trend of publishing articles

Fig. 3.a indicates the trend of publication distribution of the selected papers over the years. With a modest number of 4 publications in the year 2019, it indicates that DT was relatively nascent or less explored. From 2019 to 2022, a notable increase in publications volume was observed. The number more than tripled from 2019 to 2022, highlighting a growing interest and recognition of the importance of the research area. In 2023, there is a slight decrease to 12 publications in 2023. While this is a reduction from the previous year, it is still three times more than the number of publications in 2019, indicating that the topic remains of significant interest. Fig. 3.b also shows the distribution of publications by type, providing an overview of the literature composition.

3.2. Thematic and content analysis

The thematic and content analysis forms the fourth step of the review methodology structure. The content of each paper was thoroughly reviewed and the key findings were analysed and outlined in six categories corresponding to the research questions. First, it includes an understanding of the historical evolution, diverse definitions and fundamental distinctions from other digital representations. Secondly, it analyses the technological aspects of DT including its system architecture, layers, underlying technologies and existing tools and products. Thirdly, it encapsulates the operational aspects of DT in a smart city context and is followed by their potential uses across different fields, encompassing urban planning and its sustainability aspects. This is then followed by an overview of the selected case studies for a comprehensive understanding of practical implementations in the real world. Lastly, limitations of DT implementation form the seventh category of content analysis. This analysis is outlined in the Section 4 below.

4. Discussion

4.1. Historical context and evolution of digital twin

The idea of DT was initially introduced by Michael Grieve in 2003 to describe product lifecycle management, a concept that has since undergone significant evolution (Ketzler et al., 2020; Mylonas et al., 2021; Wang et al., 2023). Grieves initially termed his model the “Mirrored Spaces Model,” which set the foundation for the future development of DTs (Masoumi et al., 2023). This model was pivotal in transitioning the concept into smart manufacturing, aligning it closely with the Industry 4.0 movement (Mylonas et al., 2021).

By 2010, the concept had evolved, and NASA adopted the term “digital twins” to describe a sophisticated simulation that accurately reflects the real-time status of its physical counterpart across various scales, utilizing both historical and real-time data (Wang et al., 2023). NASA’s early adoption of DTs, notably in their Apollo program, demonstrated the technology’s significance in the aerospace sector as a sophisticated model for mirroring information (Mohammadi & Taylor, 2019; Mylonas et al., 2021). NASA’s implementation of DTs was aimed at continuously forecasting the health, lifespan, and likelihood of missions’ successes involving vehicles or systems (Deng et al., 2021).

While the initial applications of DTs were predominantly in aeronautics, their use has since broadened to encompass a variety of sectors and use cases, such as product design, structural health monitoring, waste recycling, and agriculture (Ferré-Bigorra et al., 2022). The construction industry saw a notable uptake in DT development only recently, particularly focusing on city administration (Ferré-Bigorra et al., 2022). Additionally, the smart cities initiative has started to utilize this concept, thereby broadening the impact and scope of DTs (Deren et al., 2021; Mylonas et al., 2021). This evolution from NASA’s early use of digital twins to their current role as comprehensive models for more intricate processes and systems underscores their evolving definition and application, meeting the demands of various industries and technological progress.

4.1.1. Diverse definitions of digital twin

A digital twin (DT) fundamentally comprises three key elements: the physical entity, its digital representation, and the data links (Deng et al., 2021) that enable a bidirectional data exchange between them (Wang et al., 2023). Considering the novelty of the DT concept, it requires refining and clarifying the definitions and concepts, their present stage of progress and identifying future challenges (Ferré-Bigorra et al., 2022). However, despite DT’s growing recognition in research fields and practical applications, there’s yet to be a universally agreed-upon definition (Lu et al., 2020). As per Mylonas et al. (2021), DT’s understanding is complicated by the involvement of various sectors that apply them across different domains, each viewing DT through their unique perspective. As DT continues to develop, this has resulted in a broadening of the definition, which, in certain instances, extends beyond just a technological viewpoint.

Table 1 provides an overview of different DT definitions. While the core concept of a DT as a digital mirror to a physical counterpart remains consistent, the specific application and functionality of a DT can vary significantly depending on the industry. Each definition captures the essence of DTs in its context, highlighting the technology’s adaptability and the importance of real-time data and connectivity in creating a responsive and accurate digital counterpart.

4.1.2. Differentiating digital twins from other digital representation

Despite the increasing study of DTs in the industrial and manufacturing sectors, there remains ambiguity in distinguishing a fully

Table 1
Diverse DT Definitions.

Source	Application Area	Definition
(Austin et al., 2020, p. 2)	Smart Cities	"A smart city digital twin is defined here as a cyber component that mirrors the physical urban system through real-time monitoring and synchronization of urban activities."
(Mylonas et al., 2021, p. 3)	Built Environment/ Infrastructure	"a digital twin is a realistic digital representation of assets, processes or systems in the built or natural environment."
(Spiridonov & Shabiev, 2020, p. 3)	Urban Planning	"Digital twin is an interactive digital model of a city-planning object, implemented in the planning and management system based on a complex analytical urban information computer platform;"
(GE Digital, 2017, as cited in Lu et al., 2020, p. 2)	Manufacturing/ Product Design	"A dynamic digital representation of an industrial asset that enables companies to better understand and predict the performance of their machines, find new revenue streams, and change the way their business operates."
(Glaessgen & Stargel, 2012, as cited in Caprari et al., 2022. P. 5)	Aerospace	"Is an integrated multi-physics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin."

replicated DT from other digital models and shadows (Shahat et al., 2021). This confusion arises partly due to digital twins being intertwined with various technologies, leading to a mix-up in their definitions, potential, and obstacles (Raes et al., 2021). It is important to elucidate these distinctions to advance their evolution (Quek et al., 2023). A summarized overview from different authors in Table 2 illustrates the unique features of DTs in comparison to other digital models, aiming to clarify these differences (Austin et al., 2020; Hämäläinen, 2021; Quek et al., 2023; Sepasgozar, 2021; Shahat et al., 2021).

4.2. Technological aspects

4.2.1. Urban digital twin

The urban digital twin (UDT) is a realistic digital depiction of urban environments, encompassing their components, operations, and systems (Nochta et al., 2021. It supports decision-making processes aimed at achieving outcomes at the city scale, such as urban planning and management, as well as related services, offering enhanced perspectives for informed decisions (Nochta et al., 2021). An Urban DT is comprises of interconnected sub-DTs, representing certain aspects of the functioning and development of the urban environment (Lu et al., 2020; Papyshev & Yarime, 2021). These are integrated with intelligent functions including AI, machine learning, and data analytics, can enable precise adjustment and alignment with the actual condition of the city's infrastructure by integrating data from diverse sources in real time (Ivanov et al., 2020). These models are crafted to precisely mirror and forecast the present and prospective conditions of their physical equivalent, both accurately and swiftly. (Lu et al., 2020).

4.2.2. Urban digital twin architecture

The architecture of DT is a multi-layered framework, starting from the physical reality and extending into the cyber domain through various layers of data handling, modelling, integration, and service delivery (Fig. 4). While there is a common consensus among researchers that the DT architecture is fundamentally layered, the number and function of these layers vary. A summary of these varying layers according to different authors is provided in Table 3.

Lv et al. (2022) propose a four-layer architecture comprising physical, data, model, and functional layers, emphasizing the progression from tangible and intangible physical elements to the functionalities that deliver DT's value. However, Alva et al. (2022) streamline the structure into three layers physical, cyber, and cognitive layer, focusing on the flow from physical components to a cognitive layer that supports decision-making, emphasizing the user experience and the interpretative processing of data. Jiang et al. (2022) offer a component-based view, identifying five essential parts of a DT: physical, virtual, connections, data, and service. This perspective encapsulates the functionalities of the layered architectures but focuses on the interconnectivity and the operational aspects of DTs.

In contrast, Lu et al. (2020) describe a hierarchical five-layer system that separates data acquisition and transmission into distinct layers, highlighting the complexity of data handling and the importance of robust communication technologies for DTs. It includes a data acquisition, transmission, digital modelling, data/model integration, and service layers. The data acquisition layer is the foundational layer that deals with the gathering of heterogeneous data from multiple sources while the transmission layer is responsible for transferring data to the other upper layers. The digital modelling layer encompasses a digital depiction of physical structures such as BIM and CIM models. The data/model integration layer serves as the central component of DT architectural framework, integrating all the data and models and providing functionalities for manipulation, storage, analysis, and processing. The service layer, positioned at the uppermost level, delivers services to the community, and facilitates interaction between individuals and the integrated models.

Ferré-Bigorra et al. (2022), on the other hand, provide a unique perspective by situating a 3D digital urban model at the foundation of UDTs. They advocate for a four-layer architecture with an additional physical layer, emphasizing the interactive capabilities through sensors and actuators and the importance of direct actuation and user data provision in the service layer. The four layers include the data acquisition layer, data modelling layer, simulation layer and service/actuation layer. The data acquisition layer plays a pivotal role in autonomous gathering and conveying data to the digital modelling layer, which is tasked with maintaining an up-to-date digital counterpart of the actual system. Following this, the simulation layer takes over, analyzing the data within the model and forwarding the outcomes to the service/actuation layer. It is at this juncture that DT engages with the physical system, both by directly influencing it and by supplying information to the users, thereby completing the cycle between virtual and real-world entities.

4.2.3. Advanced technologies for DT development

The development of a DT relies on a variety of advanced technologies. This section highlights the key technologies for developing DT, especially within the realms of urban management and planning.

- *5G-enabled IoT*

In the context of Urban DT development, DT requires collecting data from physical objects or processes to create their digital virtual models, a process greatly enhanced by 5G-enabled IoT technologies. As highlighted by Wang et al. (2023), 5 G technologies significantly improve data connectivity and the effectiveness of information dissemination in DT-supported Smart Cities. The 5G-enabled IoT, identified as the backbone for dynamic data collection and feedback mechanisms, serves a vital function in data acquisition and transmission layer (Lu et al., 2020). This technology is pivotal in enabling

Table 2
Distinction between digital twin and other digital representations (adapted from Austin et al. (2020); Hämäläinen, (2020); Quek et al. (2023); Sepasgozar, (2021); Shahat et al. (2021)).

Feature	Traditional 3D Models	BIM Model	Digital Shadow	Digital Twin
Static or Dynamic Representation	Static digital representation	Static digital representation with physical information for management	Static with dynamic updates	Dynamic digital representation
Data Flow	None	Manual interaction with physical data	Unidirectional data transfer from physical to virtual	Bi-directional and continuous data flow
Update Mechanism	Do not update over time	Require manual data entry	Automatic, but only one way physical to digital	Automatic and integrated in both directions
Synchronisation	Static, no synchronization	Static, manual synchronization	Updates from physical to digital, no reverse influence	High-level, real-time synchronization
Control	None	None or limited to the design phase	No control over the physical system	Sends control information to the physical system
Integration	Visual representation only	Design and construction information	Partial, with updates from the physical system only	Full cycle of data exchange and management between physical and virtual system

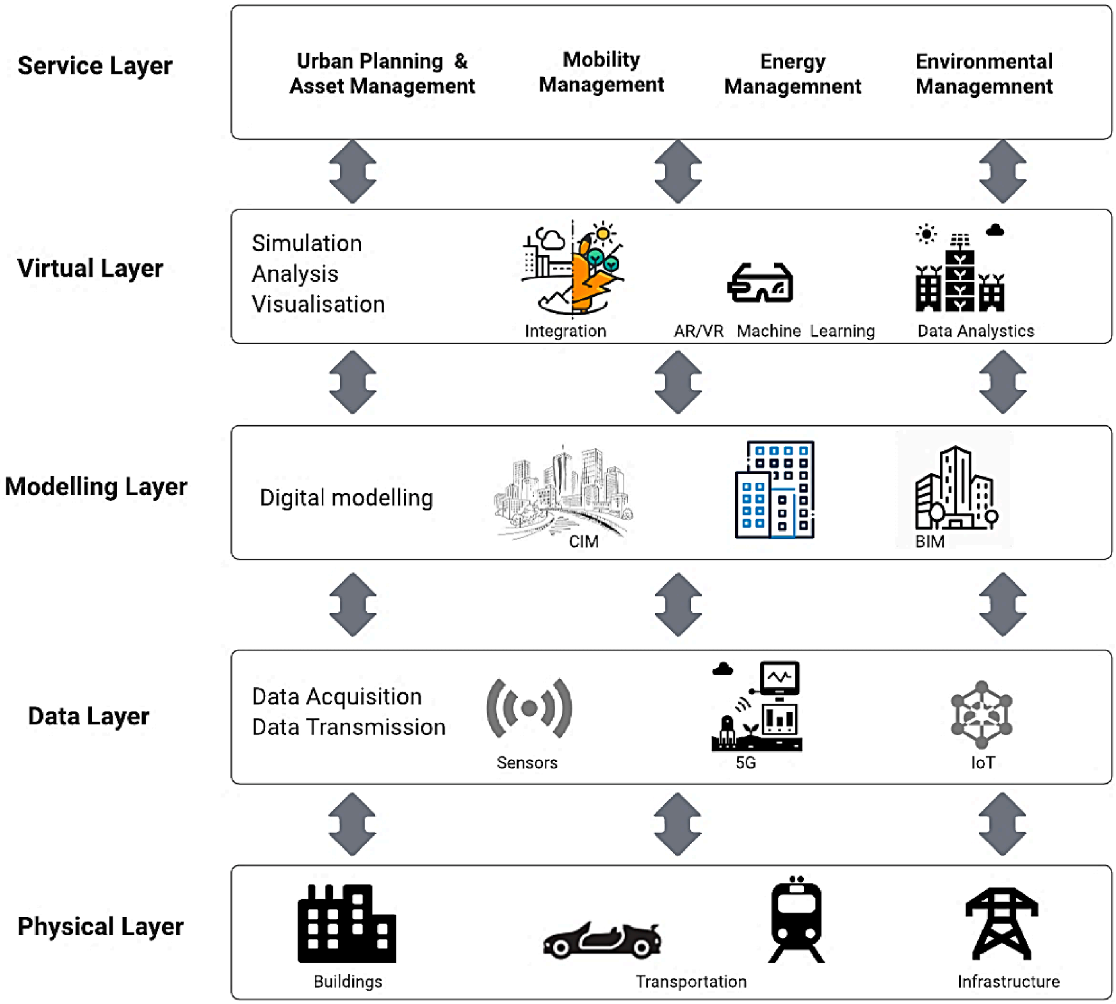

Fig. 4. Urban DT architecture (Adapted from Ferré-Bigorra et al. (2022); Lu et al. (2020); Lv et al. (2022)).

massive IoT connectivity, essential for the real-time data processing and management of urban services (Deng et al., 2021). This innovative concept, evolving from embedded computing, sensor networks, and ubiquitous systems, enables various objects in our surroundings to interact and collaborate towards fulfilling the collective objectives of the city (Mylonas et al., 2021).

- *GIS and BIM Integration*

The integration of GIS with BIM marks a significant advancement in the representation and management of urban environments. As outlined by Deng et al. (2021), DT in the city context creates a virtual mirror of the physical city, facilitating various operations such as disassembly, duplication, transfer, modification, deletion, and repeated manipulation of its digital equivalent. The combination of GIS and BIM brings together the strengths of both systems: GIS's geospatial analysis capabilities and BIM's detailed architectural and structural data. This integration offers a more holistic and multidimensional view of urban landscapes, allowing for enhanced real-time visualization and analysis of urban spaces. However, Shirowzhan et al. (2020) note that while this combination enables real-time visualization and analysis, it also faces challenges with interoperability, geospatial big data computation, and maintaining data integrity across multi-cloud environments.

- *Surveying and Mapping Technology*

Deng et al. (2021) highlight that the technology of surveying and mapping in urban environments encompasses two main areas: first, the assessment of a city's topography, environmental features, and spatial layout; and second, the integration of this data into a cohesive system using GIS. The surveying phase involves four key technologies: tilt photography, the use of Unmanned Aerial Vehicles (UAVs), 3D laser scanning, and GPS. For the mapping phase, the focus is on two technologies: the reconstruction of real-world three-dimensional models and the processing of geographic data from multiple sources. Tilt photography and UAV technology enable immediate and precise collection of orthographic, tilted, or LiDAR point cloud data in urban areas, considerably decreasing the amount of field mapping required. They facilitate detailed measurements of urban features from various perspectives, encompassing land, air, waterways, and subterranean areas. 3D laser scanning employs high-speed laser scanning and distance measurement to gather extensive dense point cloud data, including 3D coordinates, reflectivity, and surface detail. It is instrumental in creating detailed 3D models and various map data such as lines, areas, and volumes rapidly. GPS technology acquires global coordinate point cloud data with high positional accuracy, enhancing the precision and reliability of surveying data.

These technologies collectively form the technological foundation of DTs, facilitating the collection, integration, processing, and secure management of urban data (Deng et al., 2021). The amalgamation of the above technologies is crucial for the successful implementation and operation of DTs in urban management and planning.

Table 3
Urban Digital Twin Layers.

Source	Digital Twin Layers	Description
Lv et al. (2022)	Physical layer	Tangible elements and objects within the actual environment.
	Data layer	Physical layer's data collection and storage.
	Model layer	Creating of models which depict the physical entities
	Functional layer	Applications and services that use the models to deliver value.
Alva et al. (2022)	Physical layer	The real-world physical components.
	Cyber layer	The digital representation and processing of the physical layer.
	Cognitive layer	The decision-making and intelligence layer interprets data and supports user experience.
Jiang et al. (2022)	Physical	The actual physical entities.
	Virtual	The digital counterparts of the physical entities.
	Connection	The links between physical and virtual entities.
	Data	The data generated and used by the DT.
	Service	The services provided by the DT to users.
Lu et al. (2020)	Data acquisition layer	Collection of data from various sources.
	Transmission layer	Transfer of data to other layers.
	Digital modelling layer	Creation of digital representations like BIM and CIM.
	Data/model integration layer	Integration and manipulation of data and models.
	Service layer	Delivery of services to society and interaction with integrated data/ models.
Ferré-Bigorra et al. (2022)	Data acquisition Layer	Autonomous data gathering from the physical world.
	Data modelling layer	Maintenance of an up-to-date digital counterpart.
	Simulation layer	Analysis within the model to predict and analyze outcomes.
	Service/actuation layer	Interaction with the physical system and provision of information to users.

4.2.4. Existing DT tools and products

The literature analysis further provides an overview of various software solutions and platforms that are currently available for creating and managing DT, especially within smart cities' framework. Table 4 summarizes the tools and products, along with their key features, applications and use case examples adapted from Mylonas et al. (2021).

4.3. Smart city and urban digital twin

The idea of a smart city has been a major driving force in the digital transition initiatives of urban areas (Hämäläinen, 2020, 2021). This concept is fundamentally composed of technological, human, and institutional elements which collectively enhance the management of various urban sectors including transport, environmental concerns, energy, waste, public safety, and education (Mohammadi et al., 2020; Ricciardi & Callegari, 2023). In this context, the integration of advanced technologies, particularly the implementation of urban DTs, is poised to amplify the effectiveness of smart cities in governing these built environments (Ricciardi & Callegari, 2023). These virtual models encapsulate the core aspects of smart cities—technological infrastructure, human capital, and governance structures and extend their application to critical areas such as urban planning, physical and ICT infrastructure, and intelligent solutions. By incorporating additional domains like disaster management, tourism, and economic activities, the smart city framework not only fosters environmental and economic sustainability but also supports a more resilient and adaptive urban development (Shahat et al., 2021)

Table 4
Existing DT tools and products.

Tool/Product	Company	Applications	Key Features	Use Case
3DEXPERIENCE	Dassault Systemes	City-scale DTs, 3D modeling, simulation	Designing 3D models, simulating DTs, and information management	Virtual Singapore Jaipur
Azure Digital Twins	Microsoft	Knowledge graphs, environment modelling	DTDL language, integration with Azure IoT services, live graph visualization	NA
HxDR	Hexagon	3D replicas of urban environments	Subscription-based SaaS, combines heterogeneous data, 3D model focus	NA
SmartWorldPro	CityZenith	Consolidation of BIM, CAD, GIS, and IoT sensors	Unity engine, SDK for extension, scalable from buildings to cities	Amaravati
51City OS-POS	51WORLD	Virtual world integration and control	Visualization front-end, 3D model tool, urban management solutions	Jiangbei New District, Shanghai
Twin Builder	ANSYS	Simulation scenarios, IoT integration	1D model creation, ready simulation models	NA
iTwin Platform	Bentley Systems	Building DT applications, reality data management	Cloud platform, APIs for DT apps, NVIDIA Omniverse integration	Helsinki Dublin
Optimal Reality	Deloitte	Traffic and network scenarios	Real-time data ingestion, dynamic modelling, web portal access	NA
ArcGIS	ESRI	GIS, Reality Capture, BIM data integration	PaaS offering, real-time IoT and AI integration, location services	Boston Rotterdam
ICL Digital Twin	IES	Insights on energy, operations, carbon, capital	3D models, simulation engine, real-time data, AI algorithms	NTU Singapore
GE Solutions	General Electric	Asset, Network, Process DTs	Solutions for various use cases, Predix IoT platform integration	NA
Mindspere	Siemens	DT hosting, data from products/ systems	Cloud-based IoT platform, part of Xcelerator portfolio	NA
Descartes Labs Platform	Descartes Labs	Analytics geospatial platform	Data refinery, modelling environment, analytics solutions	NA

4.3.1. Operational aspects of smart city's digital twin

As per (White et al., 2021), a smart city's DT development can follow a six-layered hierarchy of data and information, ranging from the most fundamental level to the highest. This model, as depicted in Fig. 5, is composed of six distinct layers: terrain, buildings, infrastructure, mobility, digital layer/smart city, and virtual layer/digital twin. These layers can be presented as:

- Terrain Layer: This foundational layer maps the physical geography of the city and includes its topographical, geological, and hydrological elements. This layer details natural features like water bodies, gradients, and soil types, which are crucial for understanding the city's environmental context and potential challenges (White et al., 2021). This layer can be employed to model water-related risks such as flood scenarios. These models can provide valuable insights into flood dynamics, such as how water flows through urban terrains, identifying potential high-risk areas, and evaluating the effectiveness of existing water management infrastructure. This information is essential for developing proactive measures and strategies to prevent or minimize the impact of risks such as flooding, earthquakes, and extreme weather conditions (Mylonas et al., 2021).
- Buildings Layer: The Buildings Layer in a digital twin city incorporates highly detailed models of existing buildings, using BIM, 3D laser scanning and 3D data, to produce precise virtual representations of the built environment (White et al., 2021). DTs employing technologies like AI, machine learning, and semantic modelling can classify buildings according to their energy usage, thereby optimizing energy efficiency. Additionally, the real-time monitoring and benchmarking of building energy use are integrated into this layer, contributing significantly to efficient energy and carbon management in buildings (Mylonas et al., 2021). These integrations ensure that the building layer not only represents the physical structure of the urban environment but also serves as a dynamic tool for sustainable and efficient energy management, playing a vital part in reducing city's total carbon footprint.
- Infrastructure Layer: The third layer incorporates the fundamental services and infrastructures, including roads, power, telecommunications, water distribution and sewer networks sourced from comprehensive databases like OpenStreetMap and enhanced with 3D mapping for topographical accuracy. DTs monitor and maintain city infrastructure like roads and utilities, integrating data into BIM models and GIS (Wang et al., 2023). This aligns with the

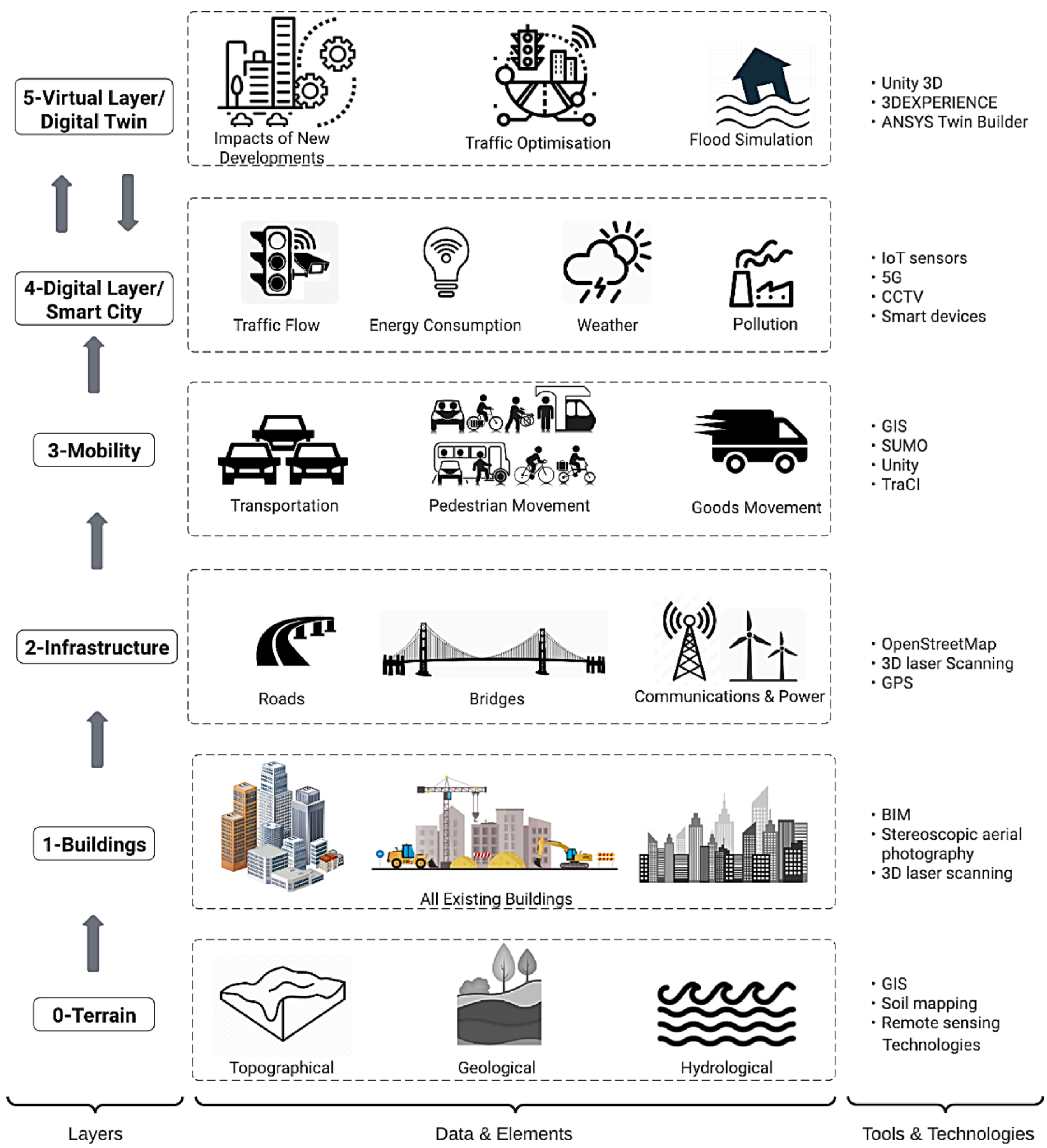

Fig. 5. Layers required to develop a smart urban DT, adapted from White et al. (2021).

infrastructure layer, focusing on the health and functionality of essential city structures. One such example can be DTs' application in real-time modelling of urban stormwater networks is relevant to this layer, helping manage infrastructure related to water distribution and quality (Elsehrawy et al., 2021).

- Mobility Layer: Here, the movement of people and goods is simulated, integrating various transportation modes and behaviours to understand traffic patterns and optimize urban mobility. Data from video surveillance, public transport databases, and sensors are used to model traffic flows and enhance transportation systems (Ferré-Bigorra et al., 2022).
- Digital Layer/Smart City: In a study by White et al. (2021), the Digital Layer/Smart City of a digital twin has become a central hub for integrating IoT sensors throughout the urban landscape. These sensors collect a vast array of data, which is crucial for the real-time monitoring and effective management of various urban services. This comprises transportation, infrastructure, waste disposal, safety, institutions, healthcare, and other community amenities. This layer collects essential data for simulations in the following Virtual Layer/Digital Twin, drawing inputs from the preceding layers. Insights acquired from simulations are then distributed throughout the city's layers as actionable intelligence. Data sources in this stratum are varied, encompassing citizens, mobile devices, and assets across the urban landscape.
- Virtual Layer/Digital Twin: As noted by White et al. (2021), this layer is an integral component that utilizes data from the Digital Layer/Smart City for advanced simulations and analyses, crucial for urban planning and management. This layer effectively interconnects with the Digital Layer, enabling a bidirectional flow of data. It is instrumental in specific use cases, such as renewable energy planning, where offshore wind data informs simulations for the optimal placement and sizing of wind turbines, considering factors like visual impact and navigation routes. Another key application is in building construction, where the layer assesses the impact of new structures on sunlight distribution and structural integrity based on wind and seismic data. Additionally, the Virtual Layer/Digital Twin actively involves citizens in urban development, allowing them to provide feedback on proposals like new buildings and park designs, thereby enhancing participatory planning. This interactive platform not only gathers public input but also informs city councils and urban planners, facilitating informed decision-making. Through this layer, the digital twin city becomes a dynamic tool for visualization, experimentation, and collaborative urban management (White et al., 2021).

4.3.2. Developmental stages of smart urban DT

The development of an Urban DT involves a sophisticated integration of the physical and virtual realms where Petrova-Antonova and Ilieva (2019) propose six interconnected stages to apply. It includes six distinct stages: create, interact, aggregate, analyse, insight and the decision stage (Fig. 6).

First, the 'Create' stage lays the groundwork by assembling a CIM (City Information Model) from diverse data sources, including sensor readings and existing municipal information systems. During the 'Interact' phase, a real-time, bidirectional communication is established between city's physical and virtual counterparts, employing cutting-edge communication and edge computing technologies. The 'Aggregate' stage then centralizes and refines this data, ensuring its readiness for analysis. In the 'Analyse' stage, AI and cognitive computing techniques are applied to extract meaningful insights. The 'Insight' stage takes these insights and renders them into visual formats, such as 3D models and dashboards, to highlight areas for potential improvement. Finally, the 'Decision' stage translates these insights into actionable strategies, aiming to enhance the physical city's operations to mirror the efficiency and optimization modelled in its DT (Petrova-Antonova & Ilieva, 2019).

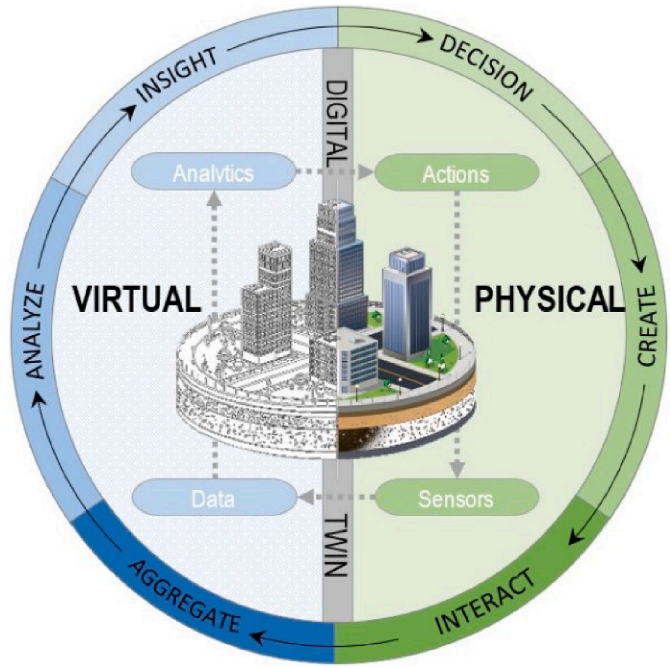

Fig. 6. Stages of DT development, adopted from Petrova-Antonova and Ilieva, (2019).

In essence, an Urban DT serves as a dynamic, interactive model that not only reflects the current state of an urban environment but also predicts future conditions and informs decisions that shape the real-world city. This iterative process ensures that DT evolves in tandem with the city it represents, furnishing a potent instrument for urban planning and administration.

4.4. DT application in urban planning and smart city domain

The Urban DT bridges the gap between smart cities' theoretical concepts and actual interventions as it helps optimize a smart city's performance (Petrova-Antonova & Ilieva, 2019). It can capture real-time data (Shirowzhan et al., 2020), allowing visualisation of all resources and interactions in the city which then helps monitoring of infrastructure, utilities, businesses and planning future developments (Mashaly, 2021). It provides insights into urban efficiency, prompting real-world measures such as modifications to city design or transportation methods (Petrova-Antonova & Ilieva, 2019).

Mylonas et al. (2021) have discussed various smart city domains for which an Urban DT can be utilized, including building surveillance, urban planning, circular economy, transport, risk alleviation and healthcare and sustainability. Similarly, (Alva et al., 2022) have listed six use cases for the Urban DT including predictions and scenario modelling, preparing for emergencies, optimizing functionalities, and formulating strategies. The applications in urban development and administration, transport, environment and energy, and disaster are also discussed in studies by Yang and Kim (2021), Wang et al. (2023), Ferré-Bigorra et al. (2022) and (Elsehrawy et al., 2021). These various application aspects are categorized into nine application areas in Table 5.

4.4.1. Mobility management

DTs in mobility management involve a comprehensive approach to optimizing urban traffic and transport systems (Elsehrawy et al., 2021). Utilizing data from video surveillance, public transport databases, and sensors, DTs model and simulate traffic patterns, including peak hour flows, across various modes of transportation like roads, private transport, and public transport (Ferré-Bigorra et al., 2022). These simulations

Table 5
Application aspects of urban DT.

Application Aspect	DT layers					Tools and Technologies
	Physical	Data acquisition	Modelling	Simulation	Service	
Mobility Management	Road infrastructure, private transport, public transport	Video surveillance, public transport database, sensors	Mobility simulation model	traffic flow and peak hour simulation	Optimization of traffic flow, fleet operations, public transport systems, road infrastructure management	GPS tracking, traffic management software
Urban Planning	Buildings, terrain, infrastructure	LiDAR point clouds, IoT device data	City information model, BIM models	Visualisation and Scenario planning for urban development proposals	New development planning, Participatory planning, policy implementation	LiDAR, cyberGIS, BIM, AI, Machine Learning, IoT, Unity3D
Public Infrastructure Management	City infrastructure (roads, bridges, utilities)	Sensors for structural health monitoring, environmental data collection	Infrastructure BIM models, Geospatial data integration	Simulations of infrastructure usage, stress testing	Infrastructure maintenance scheduling	IoT sensors, BIM, GIS, Structural analysis software, Simulation software
Risk Mitigation and disaster management	Buildings, terrain, infrastructure, transport	Sensors for environmental monitoring, structural health monitoring systems	Risk assessment models	Flood, earthquake, and extreme weather simulations	Emergency response coordination, disaster mitigation strategies	GIS, Remote sensing, Structural analysis software, Simulation platforms
Energy Management	Electrical grid (electrical power transmission and distribution network)	Electric meters, energy consumption sensors	Energy simulation model	Simulate energy distribution and consumption	Real-time energy usage monitoring and benchmarking, automated energy conservation measures	AI, machine learning
Water and resource management	Water distribution network, sewerage, and stormwater network	Water meters, water quality monitors and sensors	Hydrological models	Fluids dynamic model	Water supply and sewage treatment and stormwater management	GIS, IoT
Environmental and carbon management	Transport, buildings, factories	CO2 sensors, air quality monitors, noise detectors	Atmospheric pollution, meteorology, and climatology modelling	Pollution and carbon emission simulations	Pollution monitoring and control, carbon emission reduction strategies, waste management,	Environmental monitoring sensors

enable effective traffic flow optimization, fleet operations management, and public transport system enhancements (Mylonas et al., 2021). Tools like GPS tracking and traffic management software play a crucial role in analyzing data and implementing changes to improve overall mobility and reduce congestion (Wang et al., 2023).

4.4.2. Urban planning

In urban planning, DTs leverage innovative methods like LiDAR-generated point clouds and IoT device data to create spatial 3D city models of cities, enabling the unsupervised and detailed representation of urban environments (Mylonas et al., 2021). This approach is pivotal for addressing complex city modelling challenges, such as unknown taxonomies of city objects, thereby enriching the accuracy and utility of urban DTs. This enables visualizations and scenario planning for urban development proposals, facilitating participatory planning and informed policy implementation (Alva et al., 2022). Furthermore, the incorporation of additional advanced technologies like cyberGIS, BIM, AI, and machine learning technologies (Banihashemi & Khalili et al., 2022) form an integrated data management system, crucial for creating dynamic, responsive DTs of cities. The multilayered nature of DTs allows for comprehensive simulations, offering visual feedback on proposed urban changes and potential consequences, thus making urban planning more dynamic, inclusive, and effective (Mylonas et al., 2021).

4.4.3. Public infrastructure management

DTs in public infrastructure management focus on monitoring and maintaining critical city infrastructure like roads, bridges, and utilities (Wang et al., 2023). They employ sensors for structural health monitoring and environmental data collection, integrating this data into BIM models and geospatial information systems (Khoshamadi et al., 2023). Simulation tools are used to test infrastructure under various stress scenarios, guiding maintenance scheduling and real-time service adjustments (Mylonas et al., 2021). The integration of IoT sensors, BIM, GIS, and structural analysis software enables effective management of urban infrastructure, ensuring its longevity and optimal performance (Elsehrawy et al., 2021).

4.4.4. Resilience and disaster management

DTs are emerging as a powerful tool in risk and resilience management within urban environments, demonstrating a strong capacity to simulate and mitigate infrastructure-related risks (Elsehrawy et al., 2021). Water-related risks, particularly flooding, have been a focus for hydrological DTs, which help create safer urban spaces by linking with traffic and urban planning DTs (Mylonas et al., 2021). White et al. (2021) in their research, presents DT utilization to model flood scenarios, providing valuable insights into flood dynamics and potential preventive measures. DTs utilize sensors for environmental monitoring and structural health to model risks associated with natural disasters such as floods, earthquakes, and extreme weather events. These models are crucial for running simulations that inform emergency response strategies and disaster mitigation plans (Alva et al., 2022). Tools like GIS, remote sensing, and structural analysis software aid in simulating potential disaster scenarios, enabling cities to prepare and coordinate responses effectively, thus enhancing urban resilience.

4.5. Sustainability aspects of digital twins in urban development

The integration of DTs in smart city frameworks facilitates the enhancement of urban sustainability by enabling real-time monitoring and city infrastructures administration (Shahat et al., 2021). This is particularly evident in the application of DTs for urban planning within the Green Deal era, where they bridge global sustainability policies with local urban needs (Caprari et al., 2022). The DTs' sustainability aspects in urban planning and design include energy management, water management and resource management, and environmental and carbon management. Fig. 7 shows these sustainability aspects and their

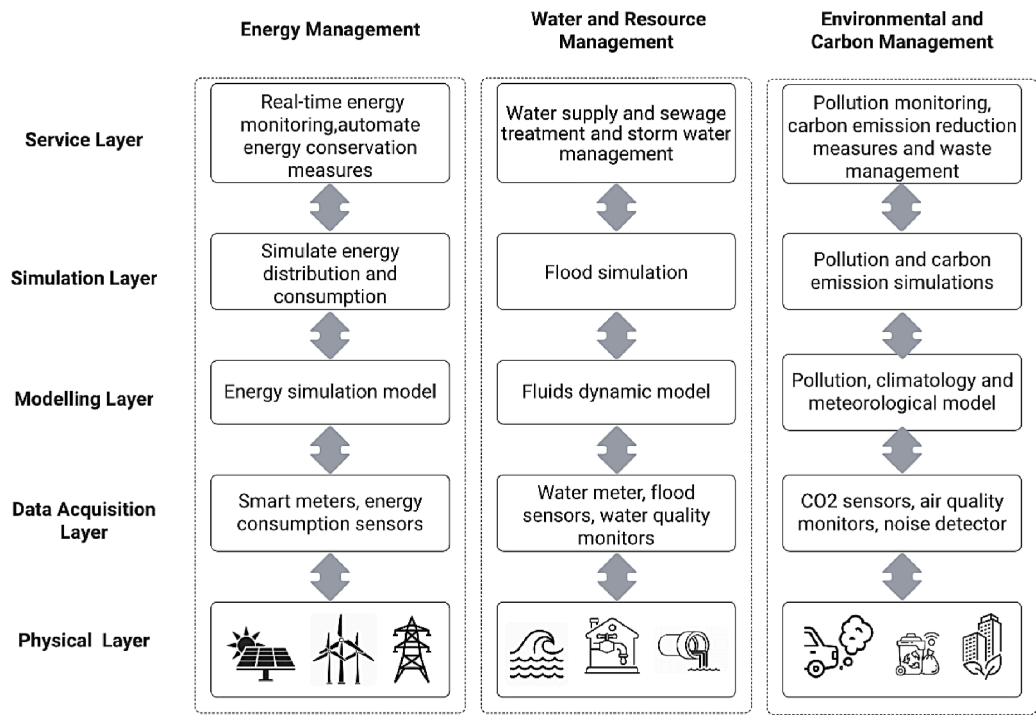

Fig. 7. DT Sustainability aspects (adapted from Ferré-Bigorra et al. (2022)).

corresponding layers and elements within a DT framework.

4.5.1. Energy management

As detailed by Mylonas et al. (2021), DTs leverage advanced technologies like AI, ML, and semantic modelling to enhance energy efficiency and decision-making processes in smart cities. Semantic modelling and data-driven rule-based reasoning are used to collect and process data, enabling the identification of patterns and automating decisions. This approach generates an intricate model, which can be utilized to classify buildings and urban areas for energy usage, aiding in the categorization of buildings and urban blocks for better energy management (Banihashemi & Golizadeh et al., 2022). Furthermore, urban scale models use city building datasets and 3D representations to simulate energy consumption, providing a basis for evaluating energy efficiency at the city level. This helps in identifying the best strategies for sustainable urban development and supports the implementation of energy and environmental policies.

Moreover, DT platforms support real-time energy benchmarking by transforming raw energy data into valuable insights, that city energy managers can use to visualize energy usage and formulate effective energy conservation strategies. Additionally, integrations of BIM and IoT technologies within DTs monitor and regulate building energy efficiency and indoor environmental quality, aligning with broader environmental protection and social well-being goals (Mylonas et al., 2021).

4.5.2. Water and resource management

DTs are increasingly pivotal in resource management as they aid in identifying optimal areas for infrastructure investment. DT technology is also applied to the real-time modelling of urban stormwater networks, offering a proactive approach to managing overflow and water quality events (Elsehrawy et al., 2021). A DT prototype in Newcastle, UK, aims to monitor water network malfunctions and manage heavy rainfall impacts, while Valencia, Spain, has implemented a DT for its water distribution network management (Mylonas et al., 2021).

4.5.3. Environmental and carbon management

DTs are proving to be instrumental in advancing environmental and carbon management efforts primarily through pollution monitoring, waste management and real-time monitoring and benchmarking of energy use within urban settings (Elsehrawy et al., 2021). They utilize a variety of data, including traffic dynamics, to predict and mitigate air pollution. This predictive capability allows for proactive measures in traffic management, potentially leading to reduced emissions (Elsehrawy et al., 2021). Furthermore, GIS-based DT applications integrate GIS, BIM, and IoT to deliver real-time pollution data, which is integrated into the model's data layer, enhancing urban monitoring, and offering technology-independent solutions (Mylonas et al., 2021). Herrenberg's city-scale DT prototype incorporates sensor data into computational models for air pollution simulation to visualize pollution levels, addressing the city's main environmental issues and promoting digital solutions for urban planning (Dembski et al., 2020).

Furthermore, the potential of DTs in revolutionizing waste management within smart cities points towards a zero-waste sustainability goal, reflecting the current research interest in sustainability and circularity (Mylonas et al., 2021). In waste management, DTs are facilitating more efficient processes through the integration of IoT and computer vision technologies (Elsehrawy et al., 2021). By monitoring the fill levels of smart bins, DTs can inform waste collection teams about the optimal times for collection and propose the most efficient collection routes. This not only streamlines waste management logistics but also contributes to the reduction of the carbon footprint associated with waste collection services. Additionally, in the realm of energy consumption, DTs enable real-time monitoring and benchmarking of building energy use, aiding in the optimization of environmental performance and supporting the achievement of carbon reduction targets (Elsehrawy et al., 2021).

These examples underscore the versatility of DTs in enhancing various aspects of urban environmental management, from improving air quality to optimizing energy usage and revolutionizing waste management practices. By leveraging DT technology, cities can take significant strides towards sustainability and more effective carbon management.

In summary, DTs offer a promising avenue for supporting sustainability in urban environments. Their ability to simulate, predict, and manage urban systems presents a forward-thinking approach to achieving resilient and sustainable urban ecosystems. As the technology matures, it is imperative to develop common metrics and computational tools to support the diverse stakeholders involved in urban development.

4.6. Integrating social-community dynamics into urban DT

As discussed in preceding sections, DTs have emerged as powerful tools for simulating and managing cities' infrastructures and environmental systems (Xu & Liu, 2024). However, to truly reflect the complexity of urban environments, DTs must also incorporate the social and community dimensions that underlie the human experience in cities (Shahat et al., 2021). This integration ensures that this technology reflects not only the physical characteristics of urban environments but also the vibrant social interactions and community behaviours fundamental to urban vitality (Dembski et al., 2020). Recognising this need also reflects a growing trend in urban systems modelling that seeks to combine technological advances with insights from social sciences (Batty, 2018).

Cities are complex ecosystems characterized by diverse social interactions and relationships (Shahat et al., 2021). By embedding these elements into DTs, planners gain deeper insights into how urban spaces are utilized and how various planning decisions impact community well-being. These elements of social dynamics can be incorporated from various sources of data and methodologies. Social data integration utilizes surveys, social media, and public forums to gather qualitative insights into community sentiments and community needs, while IoT devices and sensors can help collect data on social interactions and human activity patterns within urban spaces (Sohi et al., 2024). These data can help simulate the social behaviours of urban populations and be analyzed to improve public areas and services (Shahat et al., 2021). Additionally, agent-based modelling can be utilized in simulating individual and collective behaviours to predict social outcomes of urban planning decisions (Batty, 2013). This can further promote participatory design by actively engaging citizens directly in the urban planning process through interactive platforms and virtual reality simulations (Elsehrawy et al., 2021).

4.6.1. Social behaviours simulation

DTs can simulate social behaviours and interactions within urban spaces, which can help urban planners understand how people use public spaces, their movement patterns during different times of the day or special events, and their interactions within the community (Dembski et al., 2020). This understanding can lead to better design of public spaces that cater to the needs of the population, improve pedestrian flows, enhance safety, and increase the usability of urban areas (Weil et al., 2023b). For instance, data-driven simulations determine the optimal locations for public amenities like parks, benches, and playgrounds, or identify areas where improvements are necessary to enhance accessibility and encourage more community interaction (White et al., 2021). This is particularly beneficial in designing neighbourhoods that promote social interaction among residents, which is a key component of mental health and well-being.

Additionally, modelling crowd movements during public events or even daily commutes allows urban layouts to be optimized for improved accessibility and reduced congestion, enhancing the quality of urban life (Batty, 2013; Townsend, 2013; White et al., 2021). By modelling how these events affect traffic, pedestrian flows, and public transportation, planners can make informed decisions about event locations, timings, and the necessary infrastructure improvements to support activities (Elsehrawy et al., 2021; White et al., 2021). The use of DTs to model social dynamics can be seen in projects such as the Virtual Singapore initiative. This digital twin incorporates human activity data to simulate scenarios like public gatherings and emergency evacuations, providing valuable insights into urban management and planning.

4.6.2. Agent-based modeling and spatial behaviour

Agent-based models (ABMs) have been effectively used to not only simulate pedestrian flows but also to delve into more nuanced spatial behaviours and relationships within urban areas. These models, as described by Bonabeau (2002), represent individuals as autonomous agents, but their potential extends to capturing complex interactions within specific urban contexts—such as interactions within public spaces, responses to urban changes, and the dynamics of crowds during various urban events (Ye et al., 2023). Simulating the behaviours and interactions of individual agents based on different scenarios can help predict how changes in the urban environment might affect human behaviour and social structures (Ye et al., 2023). So, integrating ABMs into DTs allows for the simulation of social interactions and mobility patterns, thereby enhancing the predictive capabilities of digital twins (O`Sullivan & Perry, 2013).

To enhance the predictive capabilities of digital twins and their applicability to real-world scenarios, advanced ABM techniques have been implemented:

- Modelling Interactions in Varied Environments: Urban settings such as residential areas, commercial zones, and recreational spaces are modelled to understand how spatial configurations influence social interactions and community engagement (Crooks & Heppenstall, 2011).
- Simulating Scenario-based Planning: Various "what-if" scenarios are simulated using ABM to observe how changes in urban design, like new pedestrian zones or public transit routes, impact community behaviour and spatial usage (Batty, 2008).
- Integrating Real-time Data: The granularity and accuracy of simulations are enhanced by incorporating real-time data from sensors and IoT devices, allowing urban planners to observe and analyze the immediate impacts of spatial changes on community behaviour (Ye et al., 2023; Zheng et al., 2014).

Furthermore, these sophisticated simulations are integral in participatory planning processes. They provide stakeholders with visual and data-driven insights into potential urban developments and their impacts, fostering a collaborative environment for urban design. Projects like the Virtual Singapore initiative, underscore the practical benefits of this approach by enabling more informed decision-making regarding urban planning and development.

4.6.3. Participatory and collaborative planning

Beyond social behaviour simulation and ABM, DTs empower citizens and encourage their active participation in the decision-making processes that shape their future cities, promoting a more human- or citizen-centric approach to urban planning (Elsehrawy et al., 2021; Nochta et al., 2021). Engaging citizens directly in urban planning through interactive platforms and virtual reality simulations allows them to visualize changes and contribute ideas. This approach not only democratizes urban planning but also ensures that a DT's outputs align with the residents' expectations and lived experiences(Dembski et al., 2020). In Herrenberg, Germany, the city leveraged a DT to engage the community in the urban planning process. Through VR and AR technologies, residents were able to visualize and provide feedback on urban development proposals, leading to designs that closely matched community preferences (Dembski et al., 2020).

Furthermore, the integration of DTs also facilitate a collaborative environment where stakeholders from different city domains can co-create and develop the digital twin (Shahat et al., 2021). Online and open platforms enhance data sharing and stakeholder inclusion in urban planning, policy design, and evaluation. This collaborative approach ensures that DTs are not only tools for visualization but also platforms for community interaction and public decision-making (Shahat et al., 2021). By providing various levels of authorization, this technology can be made accessible to different stakeholders, allowing them to navigate and discuss urban planning issues openly. This accessibility is crucial for fostering public engagement and incorporating a wide range of perspectives in urban development (Shahat et al., 2021).

By integrating these methodologies, DTs not only simulate the physical and environmental aspects of urban life but also actively involve citizens in shaping their urban environments. This approach not only enriches the DT functionality but also ensures urban interventions are socially inclusive and aligned with the community's aspirations. This approach promotes greater public engagement and acceptance, resulting in urban environments that are not only efficient but also vibrant and inclusive.

4.7. DT in urban planning and development- case studies

The concept of an urban DT, applying DT technology to urban environments, is increasingly seen as a transformative tool for enhancing urban planning and fostering the creation of successful smart cities (Yang & Kim, 2021). As DT offers new vistas for urban planning (Schrotter & Hürzeler, 2020), this industry is increasingly intrigued by the potential of DT implementation in enhancing planning and asset management in addition to developing safe and sustainable urban spaces (Ferré-Bigorra et al., 2022).

Even though DT is an emerging field with a wide array of potential use cases (Barresi, 2023; Dembski et al., 2019), it is relatively new in the urban management field, with only a handful of cities and towns currently utilizing operational urban DTs (Dembski et al., 2020; Ferré-Bigorra et al., 2022). To understand the real-world implementation of DTs at the city level and within the urban planning context, a list of five case studies, mostly prototypes, from the existing literature is summarized in Table 6. It demonstrates their purpose, technologies used and applications along with the limitations of each case.

4.8. Limitations and barriers

Despite the benefits and various potential application aspects of DTs, there is a multitude of challenges associated with their development and implementation for smart city governance and urban planning (Zhang et al., 2022). This is evident in the preceding section outlining some of the real-world case studies. These challenges are crucial for understanding the sustainability and practicality of DTs, especially when applied to complex systems like cities and urban development. These limitations as indicated in Fig. 8, include data management and integration, data quality and synchronisation, interoperability, standards and connectivity, cybersecurity and data privacy, data modelling, utilization and visualisation, technical complexity and infrastructure, financial constraints and resource allocation, and socio-political implications and public engagement (Fig. 8).

4.8.1. Data management and integration

The city data is often large, complex, and heterogeneous, requiring high computing power and interoperability for effective acquisition and processing. There is a need for universally acknowledged standards for data models and design schemas to streamline city modelling and to reduce time, cost, and errors (Shahat et al., 2021). Lu et al. (2020) discuss the multifaceted nature of data integration, which is a foundational challenge in DT development. The disparate nature of data sources requires sophisticated Extract, Transform, and Load processes, service-oriented architectures, and data virtualization techniques. The authors stress that the heterogeneity of source data systems and the lack of standard identifiers across these systems make efficient data extraction and linkage a complex task.

4.8.2. Data quality and synchronization

Data quality which is a critical factor for the utility of DTs is another concern. The data encapsulation within each DT is necessary to maintain quality, as the responsibility for data integrity cannot be offloaded (Weil et al., 2023a). The data synchronization, especially in real-time monitoring scenarios, poses challenges where the quality of data can be compromised by the need for speed and efficiency (Lu et al., 2020).

4.8.3. Interoperability, standards, and connectivity

A significant limitation is the absence of widely accepted standards, impacting urban digital twins' capacity to exchange data with other municipalities or entities (Weil et al., 2023a). This lack of interoperability and standardization means that only a few urban DTs can exchange data effectively (Ferré-Bigorra et al., 2022). It can result in misinterpretation of data, leading to potential safety and security risks, as well as suboptimal city performance across various sectors

Table 6
Case studies and their DT use cases.

Case Studies	Purpose	Technology	Application	Limitation
Herrenberg, Germany (Dembski et al., 2020)	Urban planning, urban design, and decision support; to improve collaborative planning processes	3D model (DEM), Laser Scan, BIM, VR and AR for visualization,	Participatory and collaborative processes in urban planning, urban design, decision-making support, and visualization in VR for public participation. Traffic planning scenarios, urban mobility simulation, airflow simulation	The model does not encompass the entire information in the actual environment; the need for additional socio-economic and environmental data
Zurich, Switzerland (Schrotter & Hürzeler, 2020)	Urban planning, decision-making, public awareness, and participation	3D spatial data models, Java Script API from Esri, BIM models, mobile mapping, point cloud data, LIDAR	Urban planning, decision-making, scenario development, public participation, climate analyses, architectural competitions	Complexity in modelling urban objects, integration of real-time data, high computational requirements
Kalasatama district, Helsinki, Finland (Hämäläinen, 2021)	To monitor the entire lifecycle of the district's-built environment. To offer an avenue for smart city design and testing, application, and service development	3D modelling, IoT, data analytics, AI, ContextCapture application for 3D mesh model creation	Simulating and observing the impact of changing weather conditions on the district, evaluating solar energy potential, analyzing storm wind influence, stakeholder collaboration in urban development	High computing capacity required for generating 3D models, laborious data cleaning and preparation for 3D models
Docklands area, Dublin, Ireland (White et al., 2021)	Urban planning and policy decisions; citizen feedback on planned changes; tagging and reporting problems in the area	Unity3D Software, IoT devices, WebGL, Stereoscopy, SUMO, Online Digital Twin, 3D, and Urban Mobility Model	Designing cityscape and green spaces; flood and crowd simulations; engaging citizens in urban planning decisions	The initial approach did not include urban mobility data; the model was not publicly available initially, limiting citizen interaction and feedback
Cambridge (Nochta et al., 2021)	To support urban planning and management, improve decision-making, and contribute to urban sustainability goals	Data and modelling insights, sensory technology, 3D visualization, big data analytics	Conceptualizing, designing, and implementing data-driven solutions and digital tools for urban "smartification"	Obstacles in collating data from diverse sources, complexity in modelling, and demand for outcome-oriented strategies and policies.

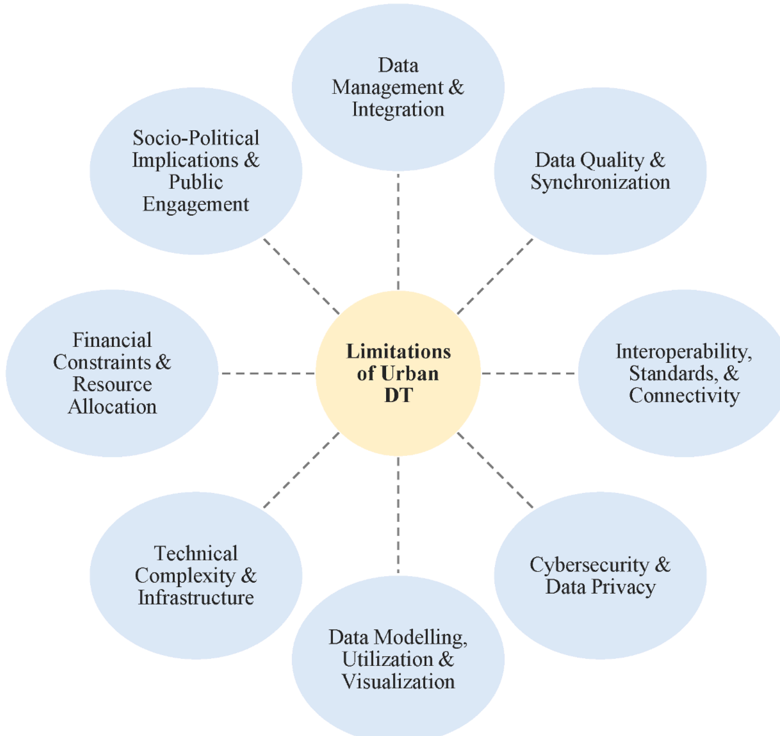

Fig. 8. Limitations of DTs for smart city governance and urban planning.

(Petrova-Antonova & Ilieva, 2019). Interoperability issues affect data connectivity, making it difficult to exchange data between Smart Cities (Wang et al., 2023). While establishing data standards is a current solution, the complexity and diversity of systems involved in smart cities make it challenging to create a unified city model standard.

4.8.4. *Cybersecurity and data privacy*

Cybersecurity is a major concern as a breach and sensitive data leaks could have far-reaching consequences, not just in terms of data privacy but also in the potential for malicious control over critical urban infrastructure. This raises questions about the legal accountability for decisions made by DT and the security of citizens' data (Ferré-Bigorra et al., 2022). Data ownership often remains ambiguous, and concerns about data privacy and security complicate the understanding of data limitations and permissions for use in various applications (Petrova-Antonova & Ilieva, 2019).

4.8.5. *Data modelling, utilization and visualization*

GIS and BIM are limited to static data management and require additional tools to handle real-time data (Wang et al., 2023). Efforts to integrate GIS and BIM with sensor data for dynamic data management have led to the development of integrated models that encompass geography, buildings, and cities. Augmented Reality (AR) and Virtual Reality (VR) can represent 3D physical entities but are not equipped to handle real-time data flows between the real and its virtual counterparts. The challenge lies in integrating BIM, GIS, AR, and VR to manage data in an unstructured environment, with data privacy and security issues being somewhat overlooked in current research (Wang et al., 2023).

According to Shahat et al. (2021), current Urban DTs may experience limited model precision, comprehensiveness, and visual depiction quality. Employing participatory sensing and crowdsourced information to overcome challenges in sensory data has resulted in localization inaccuracies and inconsistent data. Inaccuracies and errors in modelling impacts both the visual representation and city's actual condition (Shahat et al., 2021). Moreover, identifying the specific types of data required for particular tasks is a critical challenge. In DT-supported cities, there is a neglect in data utilization, primarily due to the insufficiency of computing resources to handle city-wide and unstructured data (Wang et al., 2023).

4.8.6. *Technical complexity and infrastructure*

The technical complexity of DTs necessitates a workforce that is not only skilled but also sizable enough to handle the design, installation, and ongoing maintenance (Ferré-Bigorra et al., 2022). The infrastructure required for Urban DTs is not just about the physical hardware but also encompasses the software and networking capabilities that are needed to process and manage large and complex datasets in real-time (Weil et al., 2023a).

4.8.7. *Financial constraints and resource allocation*

The budget set aside for the deployment and administration of Urban DTs is constrained, necessitating a balance between cost and functionality. This financial limitation can affect the extent to which DTs can be utilized for city management (Ferré-Bigorra et al., 2022).

4.8.8. *Socio-Political implications and public engagement*

Involving the public and various city departments while ensuring model access presents challenges due to the absence of governance frameworks, data-sharing agreements, and perception of stakeholders (Shahat et al., 2021). The socio-political implications of using Urban DTs have not been fully explored. There is a need for socio-political analysis to understand their nature and implications, and to identify problems and obstacles that could hinder their broad acceptance (Ferré-Bigorra et al., 2022)

The above limitations underscore the multifaceted nature of the challenges facing DTs and Urban DTs. Addressing these challenges requires a concerted effort to improve data management, enhance interoperability, ensure cybersecurity, manage financial resources effectively, engage the public and stakeholders, and develop comprehensive and accurate models.

5. Research gaps and future directions

The limitations in the previous section highlight the nascent stage of urban DT technology and the need for further research and development to address these challenges. To tackle these issues and gaps, upcoming studies could concentrate on the development of sophisticated data management frameworks capable of handling the complexity and heterogeneity of urban DT data, ensuring its quality, and achieving real-time synchronisation. Additionally, there is a critical need for the establishment of universal standards that promote interoperability across diverse systems and cities, thereby enhancing the scalability and transferability of DT solutions (Fig. 9).

Furthermore, future research can also investigate how emerging technologies like 5 G, edge computing, and AI can be incorporated within DT architecture to enhance data processing and real-time analytics. Additionally, the study could explore the potential of advanced machine learning techniques to enhance the forecasting accuracy of Digital Twins, enabling better prediction of city dynamics. This can include accurate prediction of environmental conditions, such as air quality and water levels, allowing cities to pre-emptively respond to potential issues and mitigate risks associated with climate change.

Another research gap that the future study should investigate is the carbon emissions and environmental impacts of DTs. The research should delve into the role of DTs in promoting urban sustainability by monitoring environmental indicators, focusing on reducing the carbon footprint and promoting environmental and infrastructure resilience. This can include creating and designing DT modules specifically for renewable energy management, waste reduction, and optimizing the use of natural resources. The DTs could also be used to simulate the impacts of various green infrastructure and low-impact development initiatives, such as widespread tree planting or the creation of green roofs, on urban heat islands and overall city temperatures (Fig. 9).

Additionally, while our review highlights the integration of social and community dynamics within DTs, it is pertinent to note that research in this area, particularly how these dynamics interact within digital simulations, is still emerging. Future research should focus on how social interactions and community behaviours can be more effectively simulated and integrated into DTs to enhance their realism and applicability in urban planning. It should emphasize the development of frameworks that not only consider the technological and environmental aspects but also deeply integrate the social community dimensions that significantly influence urban development. This approach deepens our understanding of urban complexities and improves the participatory design processes that are crucial for creating inclusive and resilient urban environments.

Fig. 10 offers a comprehensive view of the multifaceted role that DT technology plays in urban planning and development. The following presents a concise discussion of the various components of the framework and their interplays. The model begins by tracing the origin of DT in aeronautics, showing its initial use in creating and testing aircraft models, then moves to its expansion to other sectors. This leads to its application in urban development, where DTs serve as dynamic and interactive models for planning and managing cities.

Central to the DT model are key technologies including BIM, GIS and IoT. With this application lens, BIM provides detailed digital representations of buildings' physical and functional traits, where GIS offers spatial analysis and mapping, and IoT enables continuous and instantaneous data collection from a myriad of sensors across the urban landscape.

These key technologies, collectively, deliver the smart city integration and real-time applications grounded on the operational layers. DTs facilitate an interconnected urban environment where real-time data enhances decision-making and efficient utilization of resources. Through dynamic simulation and predictive analysis, DTs allow for the real-time application in urban scenarios, significantly improving urban planning and public policy support. The operational layers in DT highlight the process from data collection to analysis and application, ultimately leading to informed decisions in urban planning and governance.

Hence, DTs make key contributions by enhancing urban planning through improved design processes and by promoting stakeholder engagement. They also contribute significantly to resource management, where monitoring and control of resource distribution become more efficient. However, there are multiple challenges and limitations in this process which should be taken into account. The framework

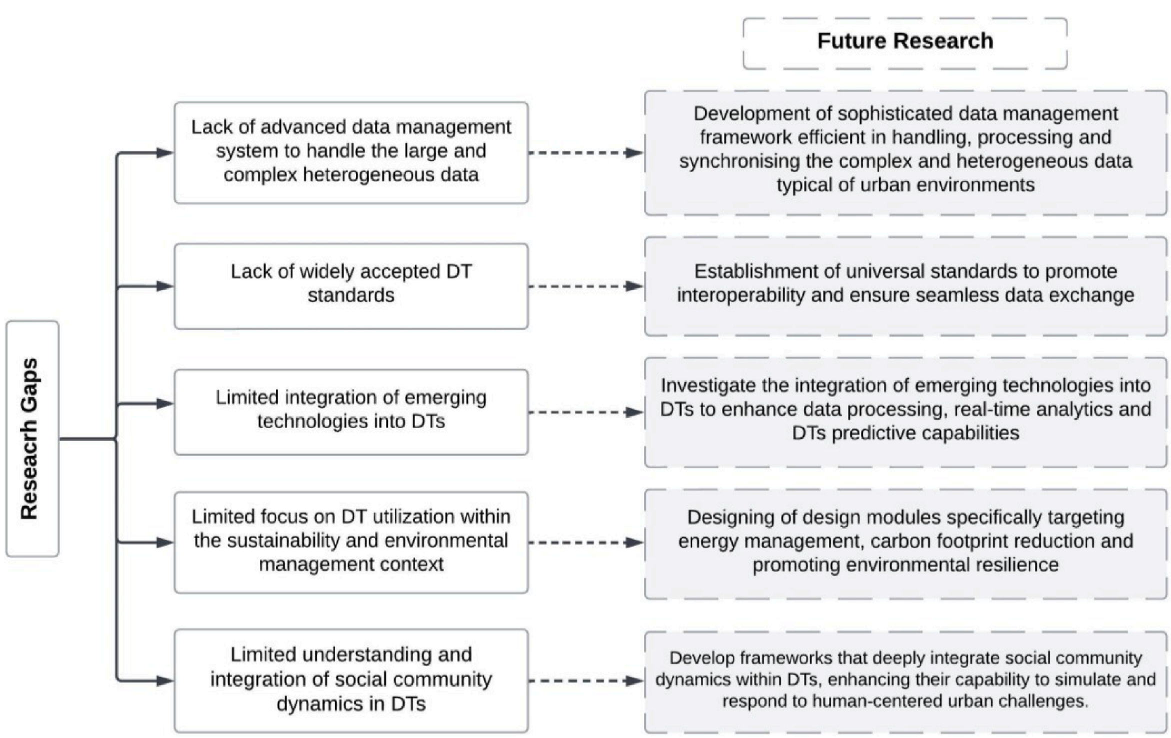

Fig. 9. Research gap identification and future research agenda.

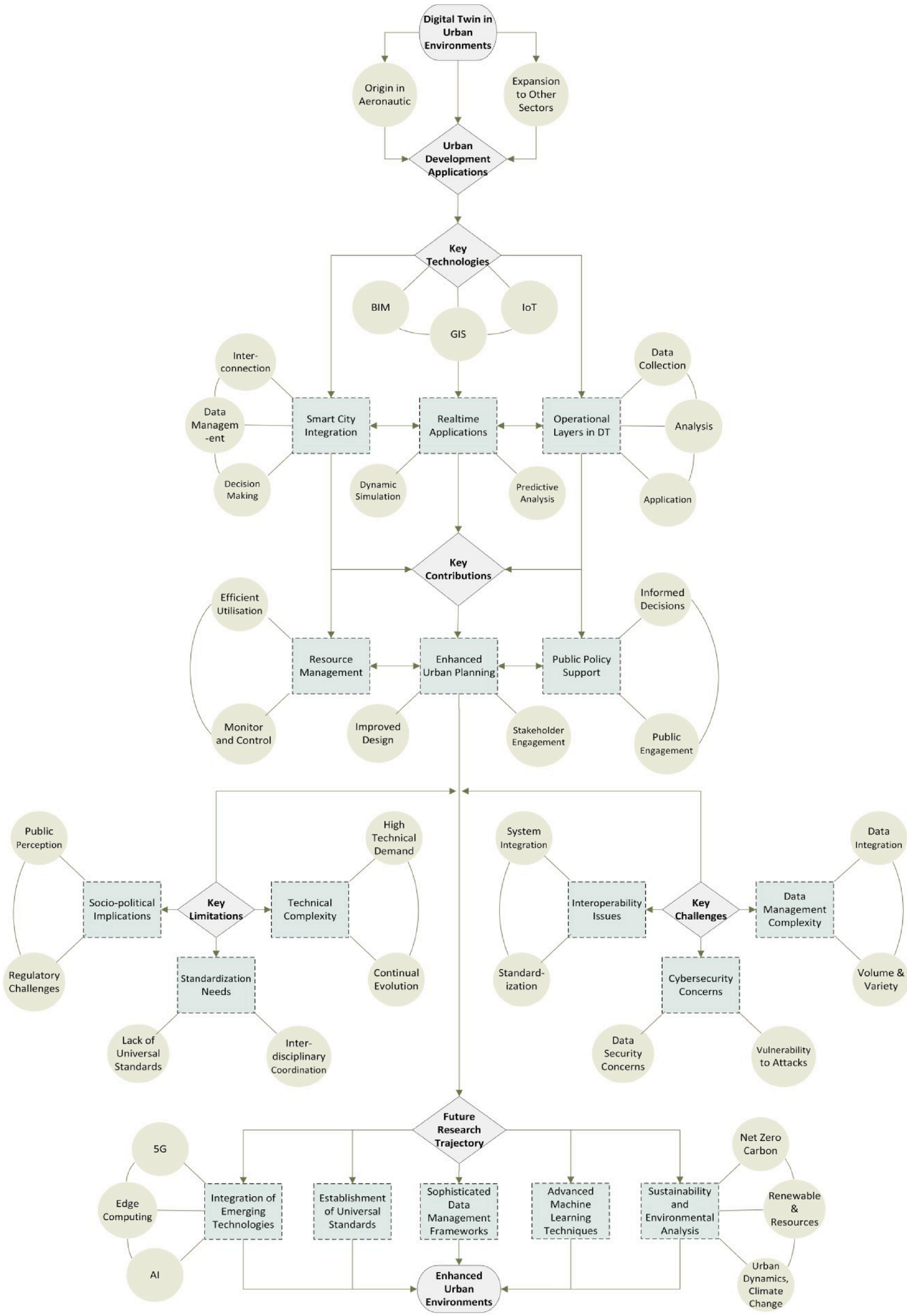

Fig. 10. DT application and implementation model in urban environments.

identifies the data management complexity arising from the volume and variety of data, interoperability issues due to system integration challenges, and cybersecurity concerns that pose risks to data security and privacy. The limitations include the technical complexity of DT systems, the socio-political implications of their adoption, and the standardization needs to ensure DT systems can work across various platforms and cities.

Therefore, looking forward, the model outlines the future research trajectory that includes:

- Developing sophisticated data management frameworks to handle the complexity of urban DT data.
- Establishing universal standards to promote interoperability and enhance scalability.
- Integrating emerging technologies such as 5G, edge computing, and AI to advance data processing and analytics.
- Applying advanced machine learning techniques for better predictive capabilities concerning environmental conditions and urban dynamics.
- Focusing on the sustainability and environmental impact of DTs, such as net-zero carbon initiatives and the optimization of renewable resources.

All these components contribute to the overall goal of enhanced urban structures, where DT technology not only improves the design and operation of urban spaces but also leads to sustainable and resilient cities equipped to tackle future challenges. This framework provides a clear path for understanding and developing DT in urban environments, highlighting the interconnectedness of technology, policy, resource management, and the challenges to be addressed through future research and innovation.

6. Conclusion

The integration of DTs in smart city frameworks presents a transformative potential for urban development. This review has systematically examined the multifaceted nature of DTs, from their operational layers to the intricate stages of their development. The applications of DTs in urban planning are vast and varied, offering innovative solutions for energy management, infrastructure monitoring, and public services, among others. Numerous cities are adopting DT idea to facilitate urban administration, development, and decision-making processes. The analysed case studies provide a glimpse into the practical application of DTs, showcasing both their capabilities and the challenges inherent in their adoption.

This study also revealed that the complete realization of a city-scale DT has not yet been achieved, but there is a discernible drive towards this goal. Despite the advancements, significant barriers such as data management complexities, interoperability issues, and cybersecurity concerns are identified that must be addressed in future developments. The limitations in scalability and technological sophistication required pose barriers to the widespread adoption of DTs in urban settings. The study underscores the necessity for a concerted effort towards the development of sophisticated data frameworks, the establishment of universal standards, and the integration of emerging technologies and DTs' sustainability and environmental impacts. Furthermore, future research should specifically address the integration of social community dynamics to enhance the realism and effectiveness of DTs in urban planning. Future research should aim to bridge these gaps, paving the way for DTs to enhance urban living and manage the intricate dynamics of smart cities effectively. As DT technology matures, it is imperative that stakeholders collaborate to ensure these systems are not only technologically robust but also socially attuned, facilitating the creation of resilient, sustainable, and truly smart urban ecosystems

Declaration of generative AI and AI-assisted technologies in the writing process

In preparing this document, the authors employed ChatGPT to enhance the language and readability of the text. Subsequently, the authors conducted a comprehensive review and revision of the content as required, taking full responsibility for the publication's accuracy and integrity.

CRediT authorship contribution statement

Dechen Peldon: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Conceptualization. **Saeed Banihashemi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Conceptualization. **Khuong LeNguyen:** Writing – review & editing, Validation. **Sybil Derrible:** Writing – review & editing, Validation.

Declaration of competing interest

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

Data availability

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

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