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EXPLORING THE IMPACT OF DIGITAL TWIN TECHNOLOGY IN INFRASTRUCTURE MANAGEMENT: A COMPREHENSIVE REVIEW

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Abstract. This paper examines the role of Digital Twin Technology (DTT) in transforming infrastructure management, with a focus on sustainability. It highlights how advancements in Artificial Intelligence (AI), Building Information Modeling (BIM), and the Internet of Things (IoT) are driving the effectiveness of Digital Twins in real-world applications. Through detailed case studies, the paper showcases the practical benefits of DTT across various infrastructure sectors. It also evaluates current trends and strategies for enhancing DTT integration into infrastructure systems. The research reveals a striking 80% increase in DTT-related publications from 2019 to 2024, with Asia, particularly China, leading in contributions. The paper concludes by addressing the future potential, challenges, and risks of DTT, offering valuable insights for stakeholders aiming to optimize infrastructure management in the digital era.

Keywords: digital twin (DT), infrastructure management, advanced technologies, challenges, future directions.

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1. Introduction

Digital Twin Technology (DTT) has gained significant attention in recent years, particularly in infrastructure management, where it promises to revolutionize the way physical assets are monitored, maintained, and optimized. Originating in the aerospace industry, where NASA developed virtual models of spacecraft to improve performance predictions and maintenance (Grieves, 2022; W. Wang et al., 2024a). Digital Twins have since expanded to a wide range of sectors, including manufacturing, energy, transportation, and civil engineering (Piras et al., 2024; Wu et al., 2020). The core concept behind DTT is the creation of a dynamic virtual replica of a physical object or system, which is continuously updated with real-time data from IoT sensors and other data sources to monitor, simulate, and predict the asset's performance throughout its lifecycle (Chui et al., 2023; Correia et al., 2023).

In civil infrastructure management, the application of Digital Twins holds immense potential due to the inherent complexity, long lifecycles, and large-scale nature of infrastructure systems. As highlighted by Lu et al. (2020a), Digital Twins offer new opportunities for real-time monitoring and intelligent decision support, particularly in areas such as transportation, utilities, and urban development. Infrastructure projects, which often span decades and involve multiple stakeholders, can benefit from the ability to proactively address maintenance issues, predict failures, and optimize operations through data-driven insights (Jiang et al., 2021; Zonta et al., 2007).

The growing interest in Digital Twins within infrastructure management is reflected in the significant increase in related research publications. A recent study by Z. Wang et al. (2022), revealed an 80% surge in DTT-related publications between 2019 and 2024, with a notable concentration of research in Asia, particularly China, where over 50% of global contributions are being produced. This indicates a rapidly expanding recognition of DTT as a key enabler for smart, sustainable infrastructure (Shahzad et al., 2022). Notably, DTT is seen as a foundational technology in Industry 4.0, where the integration of physical and digital worlds creates new paradigms for efficient and resilient infrastructure management (Macchi et al., 2018; Vu et al., 2009).

While DTT has shown immense promise across various sectors, its application in civil infrastructure management presents unique challenges that are not typically encountered in other industries. As Rudskoy et al. (2021) point out, the complexity and scale of infrastructure systems – spanning vast networks of roads, bridges, tunnels, utilities, and entire urban areas – pose specific barriers to the seamless implementation of DTT. These include challenges in data integration, long-term system monitoring, and the management of large, heterogeneous datasets generated from diverse sources, including sensors, historical records, and environmental factors (Guskova et al., 2020). Furthermore, the involvement of multiple stakeholders, such as government agencies, private companies, and contractors, adds another layer of complexity to DTT adoption in infrastructure projects (Montero & Finger, 2021).

Despite these challenges, several studies have demonstrated successful applications of DTT in infrastructure management. For instance, Shim et al. (2019) showcased the integration of DTT in the management of transportation infrastructure, demonstrating its effectiveness in real-time monitoring and predictive maintenance. Similarly, Tao et al. (2022) highlighted the role of DTT in enhancing urban planning and smart city development by providing a detailed, dynamic representation of city infrastructure, enabling more informed decision-making regarding resource allocation and urban development. These studies underscore the transformative potential of DTT in optimizing infrastructure management, but also highlight the gap in addressing the specific requirements and challenges faced by large-scale infrastructure projects (Grigg, 1998; Xue et al., 2019; Yang et al., 2024).

The novelty of this research lies in its focused approach to bridging these gaps. While previous works have primarily examined the general application of Digital Twins across various sectors, few have delved into the unique challenges and solutions specific to civil infrastructure projects. This study aims to fill this gap by providing an in-depth analysis of how DTT can be tailored to the specific needs of infrastructure management, with an emphasis on sustainability, real-time data integration, and long-term lifecycle management. Moreover, this paper offers a comprehensive review of the current state of DTT in infrastructure, highlighting successful case studies, key technological advancements, and the emerging trends in the field, particularly in the integration of AI (Mitra, 2017), Building Information Modeling (BIM) (Pan & Zhang, 2021), and the Internet of Things (IoT) (Pan & Zhang, 2021). In doing so, this research provides a roadmap for the future of DTT in infrastructure management, offering practical recommendations for overcoming the challenges identified in the literature. By focusing on the sector-specific needs of infrastructure, this paper aims to contribute novel insights into how Digital Twin Technology can be optimized for large-scale, long-term infrastructure projects. The goal is not only to advance the academic understanding of DTT's potential in civil engineering but also to offer actionable strategies for its implementation in real-world infrastructure systems.

This review aims to address the gaps in existing literature by probing three key research questions:

RQ1: *Analyzing Challenges associated with DT while managing Infrastructure*: This research explores the distinct challenges arising from the integration of DT within the context of civil infrastructure and the ways to overcome these challenges.

RQ2: *Strategies for Implementing DT in Infrastructure*: Exploration of various case studies and the methods for implementing DT in Civil infrastructure management.

RQ3: *Unveiling the Prospects of Digital Twins in Infrastructure management*: This paper offers a unique perspective by elucidating the current trends, applications, and the myriad benefits and advantages of DT in the realm of infrastructure management.

To achieve this goal, this review paper offers a comprehensive overview of the state-of-the-art DTT for infrastructure management. This study included 138 recent articles, carefully selected as the most pertinent to the topic

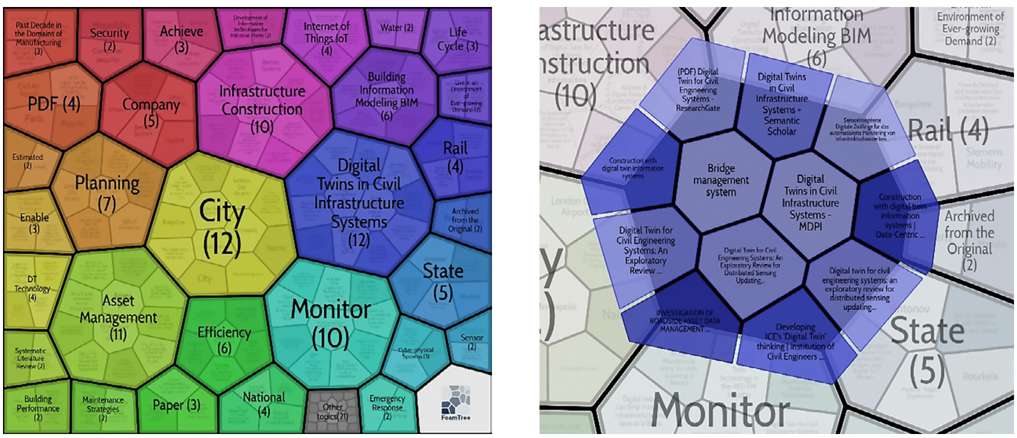


Figure 1. Theme of selected articles with no. of publications

(see Figure 1), following the screening and analysis of 350 relevant articles according to PRISMA 2020 guidelines, as depicted in Figure 3. To enhance the justification for this review, we will delve into aspects of DT in infrastructure management that have not been adequately explored in previous studies. This review article serves as a valuable resource for infrastructure professionals, researchers, and students interested in exploring the promising and rapidly evolving domain of DTT.

The article is structured as follows: Section 2 covers methodology, Section 3 explains DT fundamentals, Section 4 explores recent technology integration, and Section 5 discusses Sustainable Infrastructure Management with case studies. Section 6 evaluates DT technologies in infrastructure. Section 7 anticipates future advancements. Finally, Section 8 provides conclusions and recommendations (see Figure 2).

2. Methodology

This methodology follows PRISMA 2020 (Cortese et al., 2022; Nor et al., 2021) guidelines for a structured and transparent literature review, aiming to analyze temporal trends and conduct statistical data analysis. We utilize *VOS Viewer version 1.6.19* (Bello et al., 2020) to quantify the research landscape, focusing on identifying temporal patterns. While VOS provides valuable quantitative insights, its limitation in capturing nuanced challenges is addressed through subsequent critical analysis. We chose Visualizing Output Statistics (VOS) due to its ability to offer quantitative analysis, complementing qualitative methods in our study. The amalgamation of both approaches ensures a comprehensive exploration aligned with our research objectives. The background and working interest provide a foundation for readers, with critical analysis adding depth to quantitative findings. Combining quantitative and qualitative methods ensures a well-rounded perspective. Our timing of searches and analyses at the end of 2024 enhances the study's contemporaneity, credibility, and relevance, contributing to a robust research framework and enhancing the overall reliability of our findings.

2.1. Keywords selection mechanism

The article conducted a systematic literature review to identify papers on the application and implementation of DT in infrastructure management. The search involved using a wide range of keywords across various databases, such as Web of Science, Scopus, and Google Scholar, with a focus on recent literature (Table 1).

The authors employed multiple databases to ensure a comprehensive search for relevant literature on the application of DT in civil infrastructure. They focused on academic articles, review articles, conference papers, and book chapters as reliable sources. Initially, 350 publications meeting the search criteria were identified, and after a manual check, the most relevant articles were selected for further analysis. A qualitative assessment based on titles,

Table 1. A list of keywords used for the identification of papers related to civil infrastructure

Keyword use in extracting the literature
Digital Twin; Construction 4.0; Building Information Modelling; Internet of thing; Artificial intelligence; Augmented reality; Virtual Reality; Point Cloud; Big Data; Blockchain; Smart Construction; Cyber–Physical System; Cyber Twin; Infrastructure engineering; Construction management; Real-time data in infrastructure; Infrastructure monitoring; Infrastructure maintenance; Infrastructure performance; Infrastructure optimization; Infrastructure resilience; Infrastructure efficiency

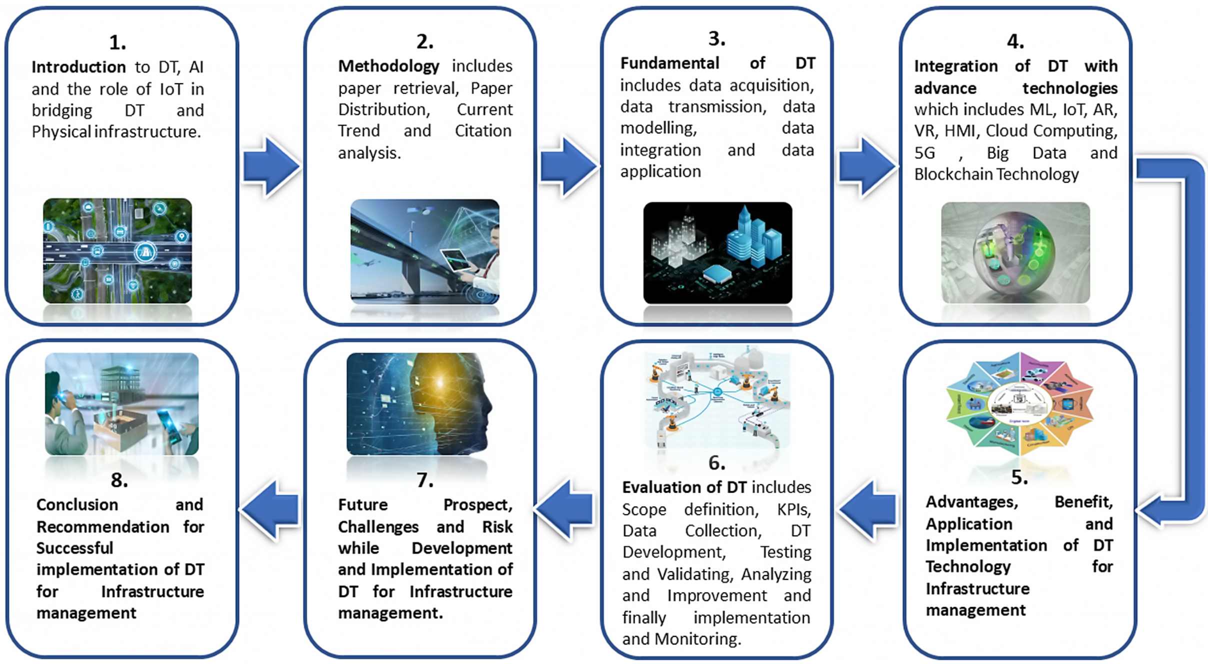


Figure 2. Flow diagram

abstracts, and conclusions was conducted, applying exclusion criteria to ensure relevance to DT in infrastructure management. This process resulted in 138 pertinent materials for analysis. The methodology phases and study focus are depicted in Figure 3, following PRISMA 2020 guidelines.

As part of the scientometric analysis, keyword co-occurrence networks were generated to illustrate the subject matter of research studies and aid in content indexing. Keyword mapping offers a comprehensive view of specialized expertise within the domain of "DT in Infrastructure management", providing a visual representation of intellectual connections and interrelationships (see Figure 4).

2.2. Literature distribution and current trend of DT in infrastructure

2.2.1. Distribution

The distribution of selected literature over time, spanning from the 2010s to the present, is depicted in Figure 5. There has been a significant increase in academic interest in DTT, with 80% of studies emerging in the last five years, and 63% published between 2019 and 2024. This concentration indicates a growing focus from researchers, highlighting the evolving significance of DTT.

Furthermore, papers were categorized based on the primary author's research institution or geographical affiliation (Figure 6). The top contributors are Asia, North America, and Europe, collectively accounting for nearly 89% of all publications. These regions prioritize advanced technologies like DT for infrastructure resilience, utilizing real-time information for monitoring and decision-making.

Figure 7 breaks down selected articles based on their goals and objectives, showing that 54% focus on infrastructure monitoring, construction, and BIM. This concentration emphasizes specific aspects within the scholarly exploration of DT applications in infrastructure.

This section emphasizes the recent concentration of DT literature, driven by technological advancements and increased recognition of its advantages. The rise in publications from Asia, North America, and Europe reflects a global focus on leveraging DT for real-time infrastructure monitoring and decision-making, contributing to enhanced resilience.

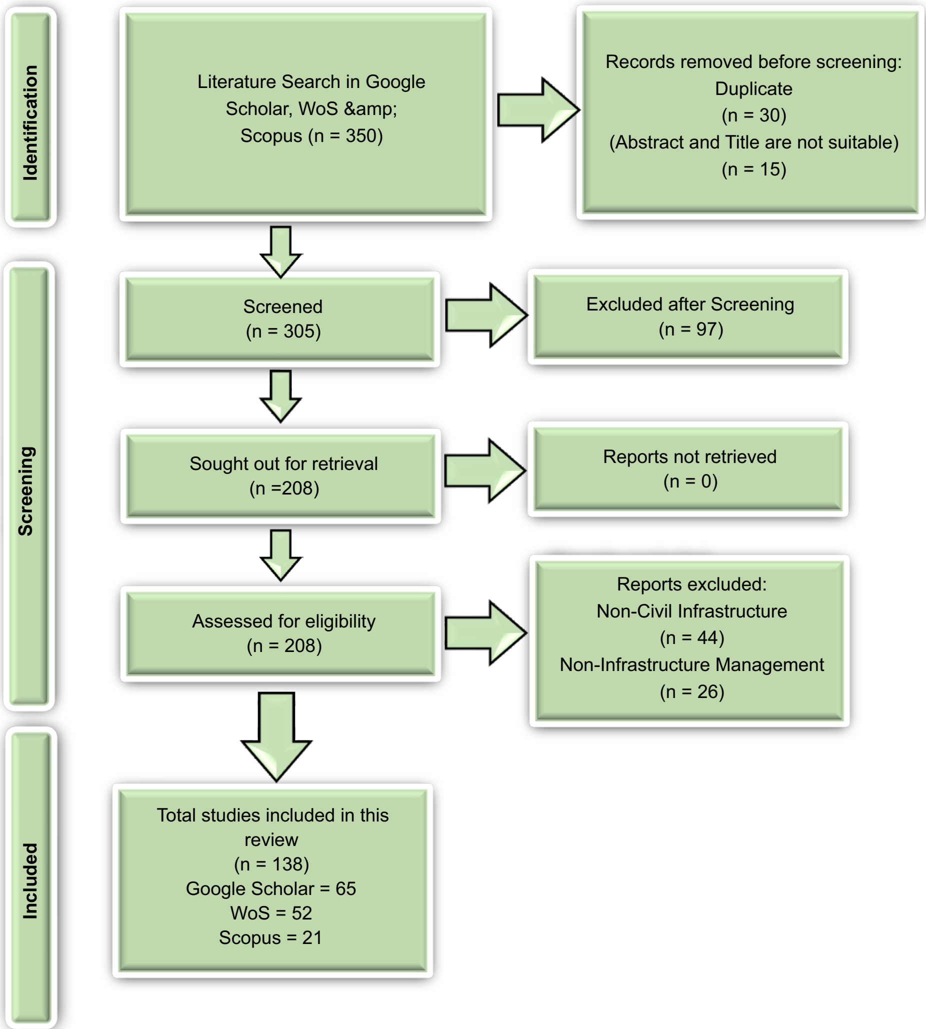


Figure 3. Flow diagram showing methodology as per PRISMA 2020

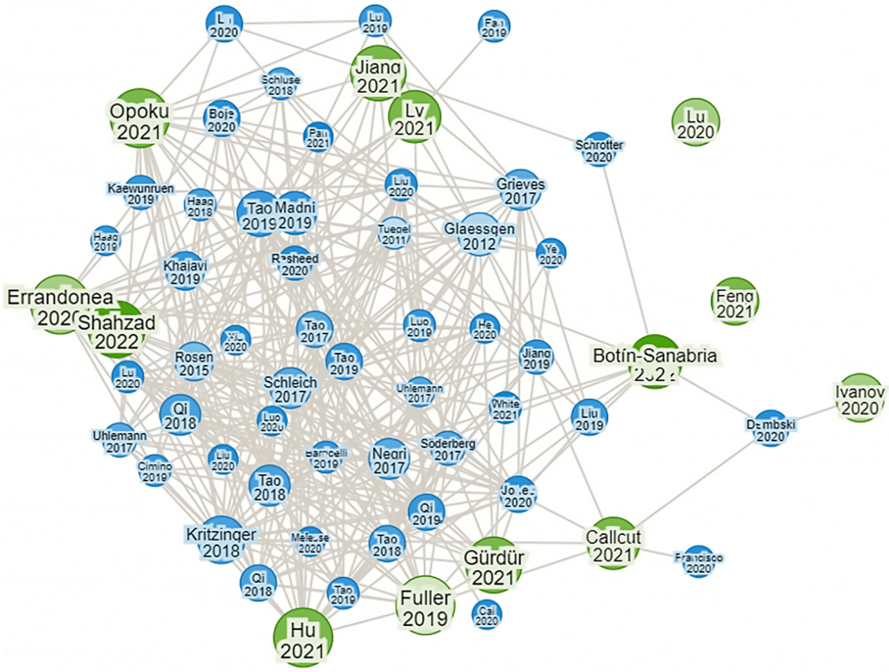


Figure 4. Publications of authors (with year) based on selected keywords

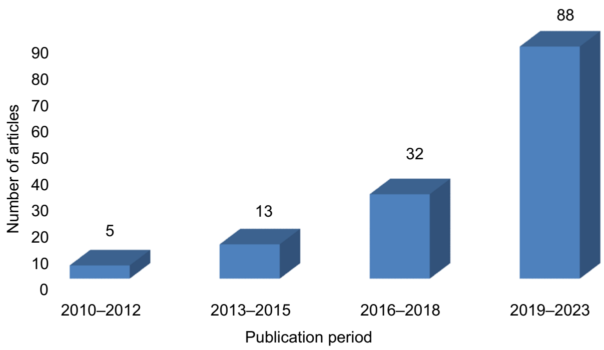


Figure 5. Selected articles publication period

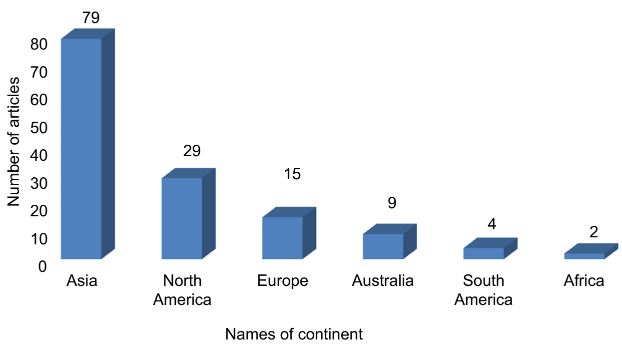


Figure 6. Selected articles from different continents

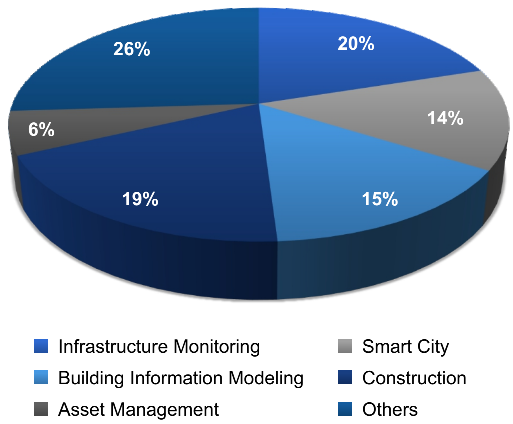
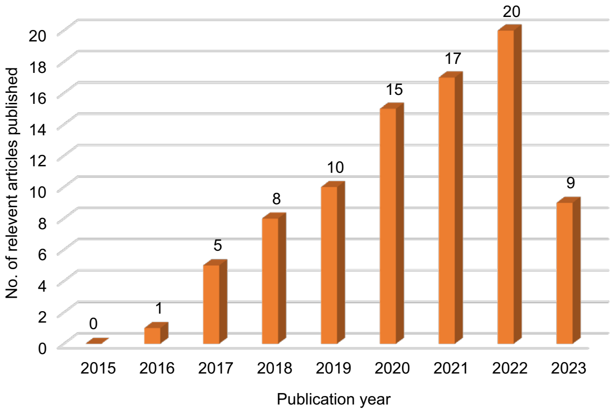


Figure 7. Selected articles on objectives

2.2.2. Current trends in digital twin technology for infrastructure management

The implementation of DTT in infrastructure management is still emerging, primarily focused on construction and technological aspects. However, there's significant untapped potential for DT application in the operational and maintenance (O&M) phase (W. Wang et al., 2024c). Currently, practical applications are limited to prototypes and research, reflecting challenges in system integration and communication. Nevertheless, recent advancements in artificial intelligence (AI), particularly machine learning (ML) algorithms, have spurred a transformative phase, enhancing DT accuracy and capabilities (W. Wang et al., 2024d).

AI agents, powered by ML algorithms, offer new opportunities for optimizing DT in reliability, robustness, and performance. This article introduces an enhanced DT concept integrating cloud, edge, and point cloud technologies for creating detailed, accurate, and dynamic DT. Additionally, fog computing incorporating physical processes and advanced networking technologies like 5G and Wi-Fi 6E are integrated from application to infrastructure levels. AI agents for the DT are also identified and explored. This integration of advanced technologies with DT is essential for improving efficiency and ensuring successful implementation in infrastructure management (L. Wang et al., 2018).



Note: *Ongoing publications.

Figure 8. Trend of DT in infrastructure over the years

To understand growth trends in the field, an analysis of annual publication counts for DT in infrastructure management was conducted. Figure 8 illustrates the distribution map examining the domain's development. Research on DT applications in civil infrastructure management shows positive growth trends, with a relatively low publication count from 2015 to 2019, indicating the early developmental stage. However, there has been a noticeable increase in articles in recent years, rising from 10 in 2019 to 20 in 2022. Moreover, a study predicts a global market expansion of DT by more than 30% by 2026.

2.3. Citation analysis

This analysis is vital for grasping the worldwide research scenario of DTT in Civil Infrastructure Management. It enables comparisons, uncovers international collaboration trends, and aids strategic decision-making. Additionally, pinpointing influential sources ensures the credibility and quality of study literature in this domain. The main focus of the citation analysis was based on two criteria: 1. The country with the most cited publication in the area of DT in the context of Civil infrastructure management and 2. Sources with the most cited academic publication on DT relating to civil infrastructure management in the most recent years.

2.3.1. Countries

The initial analysis conducted using VOSviewer and databases such as Web of Science, Scopus, and Google Scholar aimed to identify leading countries in DT research applications in Civil Infrastructure Management from 2020 to 2024. China emerged as a significant contributor, followed by the US and UK. While the focus on Asia provided valuable insights, understanding the global landscape of DT research requires exploring efforts and case studies from other regions.

Europe holds a strong presence in DT research for infrastructure management. Germany, for instance, hosts pioneering projects like the Fraunhofer Institute for Applied Solid State Physics IAF's DT development for the Rhine bridge in Cologne. Italy has also made significant strides, with researchers at the Politecnico di Milano developing a DT framework for managing water distribution networks. North America is another key player, witnessing a surge in projects exploring DT for infrastructure. Notable examples include the DT for Atlanta's Hartsfield-Jackson International Airport in the US and a DT platform for managing bridges developed by researchers at the University of Toronto in Canada.

Beyond these regions, other parts of the world are actively contributing to DT technologies for infrastructure management. South Korea focuses on DT for tunnels, while Australia concentrates on road infrastructure management using DT frameworks. These efforts showcase the multifaceted applications of DTT globally. Examining research efforts and case studies from diverse regions provides a comprehensive understanding of the global potential of DT for infrastructure management, as shown in Table 2. Europe's focus on sensor integration and real-time monitoring, North America's emphasis on operational optimization, and South Korea and Australia's concentration on preventative maintenance through DT highlight the technology's versatile applications. As research and development progress, further advancements in DTT are expected, fostering a future where infrastructure is intelligently managed for optimal performance and sustainability.

Comparatively, Figure 9 displays the connection and network mapping of national co-authorship of academic

Table 2. Countries with the most cited academic publication on DT in infrastructure management

No.	Country	Documents	Citations	Avg. publication year	Avg. number of citations
1	China	52	196	2020.88	3.77
2	US	42	130	2020.3	3.10
3	UK	38	135	2020.39	3.55
4	Italy	32	111	2020.53	3.47
5	Australia	11	39	2020.22	3.55
6	Germany	12	44	2019.62	3.67
7	South Korea	9	33	2019.86	3.67
8	Norway	8	30	2020	3.75
9	Spain	10	34	2020.2	3.40
10	Finland	8	25	2020.13	3.13

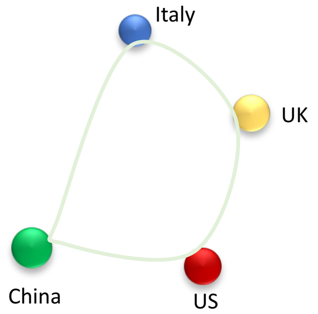


Figure 9. Network mapping of co-authorship of scientific documents on the topic of DT in Infrastructure management by country

publications in the field of DT in Infrastructure management that help in analyzing international collaboration, identifying key players, tracking research trends, and making an informed decision.

The minimum document threshold (5 publications) ensures a baseline level of research activity within a country on the topic of DT and infrastructure management. This helps to focus on countries with a demonstrably active research community. Similarly, the minimum citation threshold (20 citations) helps to identify countries producing influential research that is being recognized and built upon by other scholars in the field. This two-pronged approach of document volume and citation impact allows for a more robust selection of leading countries for further analysis.

2.3.2. Source selection methodology

In academic writing, source analysis is crucial for establishing the importance and credibility of your research. It allows you to substantiate arguments, provide context and diverse viewpoints, maintain a balanced perspective, showcase your research skills, and demonstrate the integrity of your work. To ensure a comprehensive and reliable foundation for this study, a systematic approach was employed to identify the most relevant academic publications on DT applications in Civil Infrastructure Management.

Here, we outline the methodology used to select the sources:

- Database and Search Criteria: A comprehensive academic database, such as Scopus or Web of Science, was used to conduct the initial search. Search terms were carefully chosen to focus on "Digital Twin" and "Civil Infrastructure Management". Additional relevant keywords or phrases could be specified here (e.g., "bridge inspection", "structural health monitoring").
- Bibliometric Analysis Tool: VOSviewer, a software tool for visualizing scientific literature, was employed to analyze the search results. This tool helps identify the most influential and frequently cited publications within a particular field of study.
- Selection Parameters: Within VOSviewer, specific parameters were set to refine the search results and identify the most pertinent sources for this research. These parameters could include:
  - Minimum Number of Documents: This parameter restricts the results to sources with a minimum number of citing articles. For instance, setting this value to 10 would ensure the selected sources have been referenced by at least 10 other publications, indicating their significance within the field.
  - Minimum Number of Citations per Source: This parameter refines the search further by focusing on sources themselves being highly cited within the relevant literature.

By applying these criteria, a shortlist of the most relevant and impactful sources on DT application in Civil Infrastructure Management was generated. A selection of five sources from this shortlist is presented in Table 3, offering a strong foundation for this study.

2.3.3. Exploring citation trends and its implications

Understanding the global research landscape of DTT in Civil Infrastructure Management is crucial for grasping the field's current state and future directions. Citation analysis offers valuable insights into leading countries, research trends, and collaboration dynamics. China stands out as a prominent contributor, with substantial publications and citations post-pandemic. Additionally, the US, UK, and Italy demonstrate robust research activity in this area. Analyzing co-authorship networks between countries reveals international collaboration trends, identifying key collaborators and potential research clusters. Citation analysis also helps evaluate research quality and influence, ensuring the credibility of reviewed literature. Interpreting citation counts allows researchers to benchmark their work and identify areas for further investigation. It also facilitates collaboration opportunities with researchers from leading countries. Further analysis of growth trends and co-authorship networks deepens understanding of increasing research interest in DT for infrastructure management. Identifying key collaborators and research clusters can significantly advance study objectives, effectively connecting citation data and collaboration networks to research goals.

Table 3. Most cited sources of academic publications on DT in civil infrastructure management

No.	Source	Documents	Citations	Avg. publication year	Avg. citations
1	*Automation in Construction*	10	197	2020.11	19.7
2	*Applied Sciences*	7	49	2020.43	7
3	*Sustainability*	7	29	2020.83	4.14
4	*IEEE Access*	6	18	2021.17	3
5	*Sensors*	5	13	2021.000	2.6

To ensure the reliability and accuracy of reported improvements, the case studies employed a range of validation methodologies. Simulation-based testing was conducted to compare the predicted outcomes of Digital Twin models with actual historical data. For instance, the bridge maintenance case study utilized dynamic simulation models to replicate real-world stress scenarios and validated predictions through on-site inspection data. Similarly, in the hospital infrastructure project, energy audits were performed by certified third-party evaluators to verify the reported 15% energy savings. In another instance, the railway turnout monitoring system was tested using a controlled environment to validate the accuracy of fault detection against pre-existing manual inspection methods. These validation efforts not only substantiate the reported findings but also demonstrate the robustness of Digital Twin implementations across various infrastructure projects.

3. Fundamentals of digital twin technology

Data and its acquisition, transmission, modeling, integration, and applications are the fundamental aspects of the DT's creation for any infrastructure project. Figure 10 depicts the fundamentals of DT.

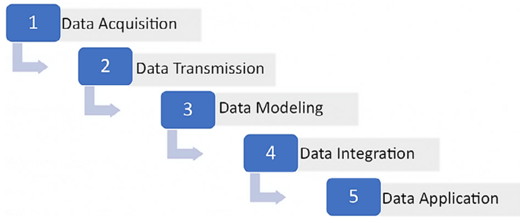


Figure 10. Fundamentals of DT

As this research focuses primarily on infrastructure and necessitates the integration of DT data, we have undertaken the task of condensing its essential components. In order to facilitate a comprehensive grasp of the foundational principles and fundamental elements of DTT, we present Table 4 for enhanced clarity and comprehension.

4. Integrating DT with the recent advance technology for effective infrastructure management

Incorporating DTT with recent advancements has the potential to yield substantial improvements in efficiency, decision-making, and maintenance (Tao et al., 2019; K. Wang et al., 2021) in civil infrastructure management. A DT functions as a virtual representation of a physical asset or system, and its effective integration with the following technologies, can bolster civil infrastructure management.

Table 4. Fundamentals of DTT

Fundamental	Subsection	Key Information	References
Data acquisition	Data Sources	Various methods for data acquisition include wireless communication, LiDAR, drones, and image-based approaches.	Nor et al. (2021)
	Data Types	Raw data for DT construction includes point clouds from laser scanners, LiDAR, camera images, and sensor data.	L. Wang et al. (2018), K. Wang et al. (2021), W. Wang et al. (2024c, 2024d), Tao et al. (2019)
Data Transmission	Technologies	Short-range communication (Wi-Fi, NFC, Bluetooth), long-range (3G, 4G, WAN, LTE), Li-Fi, and LPWAN for data transfer.	Zaheer et al. (2023), Hu et al. (2024)
	IoT Integration	IoT devices play a crucial role in data transfer from physical assets to digital twins.	Shahzad et al. (2022)
	Wireless Sensor Network	A WSN supported by IoT devices and QR codes for data capture and transmission.	Yan et al. (2023)
	Bidirectional Communication	Continual exchange of information between physical asset and digital twin for real-time monitoring and predictive analysis.	Zonta et al. (2007), Yan et al. (2023)
Data Modelling	Digital Models	Creation of 3D or nD models using techniques like photogrammetry, drones, laser scanners, and BIM authoring tools.	Qiu et al. (2024a)
Data Integration	Data Storage	Cloud storage is often used to manage the significant volume of heterogeneous data.	Macchi et al. (2018), Xue et al. (2019)
	Knowledge Engines	KEs linked to physical elements serve as repositories for domain-specific knowledge.	
	Integration Methods	Integration of data from IFC files with data stored in DynamoDB for effective utilization and analysis.	Qiu et al. (2024a)
Data Application and Visualization	Importance	Data visualization and analysis are crucial for making complex infrastructure data accessible and comprehensible.	
	Use Cases	Examples include monitoring temperature and humidity, optimizing maintenance scheduling, resource allocation, and urban-level energy planning.	Shahzad et al. (2022), Vu et al. (2009)
	Decision-Making	Data-driven insights facilitate informed decision-making for stakeholders involved in infrastructure management.	

4.1. Unveiling the synergistic dynamics: a critical analysis of IoT integration with digital twin in civil infrastructure management

The integration of the Internet of Things (IoT) with Digital Twin (DT) technologies has emerged as a transformative force in civil infrastructure management. This section critically examines the synergistic potential of this alliance, with an emphasis on its implications for enhancing the efficiency, reliability, and sustainability of infrastructure systems (Hu et al., 2024). By leveraging IoT's real-time data acquisition capabilities and DT's simulation and predictive analytics, the combination provides a comprehensive view of infrastructure performance, enabling informed decision-making and timely interventions (W. Wang et al., 2024a; Yan et al., 2023; Zaheer et al., 2023). At the heart of this synergy lies the role of IoT devices in facilitating continuous monitoring through embedded sensors that collect real-time data on structural health, performance, and environmental conditions. This data feeds directly into DT models, creating a dynamic representation of the physical infrastructure. Recent studies underscore how this integration enables more effective predictive maintenance strategies, anomaly detection mechanisms, and asset optimization (Qiu et al., 2024a).

For instance, research by Jiang et al. (2021) highlights how IoT-enabled DT frameworks can predict infrastructure failures with remarkable accuracy by analyzing patterns in real-time sensor data. Such advancements significantly reduce downtime and extend the lifespan of critical assets, offering both economic and operational benefits. However, this integration is not without challenges. Seamless data flow between IoT devices and DT platforms requires robust communication protocols, data standardization, and interoperability across diverse systems. Studies like Hossam and Youssef (2024) explore these challenges, emphasizing the need for harmonized frameworks to ensure smooth data integration. Furthermore, the high-volume data generated by IoT devices demands advanced analytics and computational capabilities, posing scalability and resource allocation concerns. Addressing these limitations is vital to harness the full potential of IoT-DT integration (Barricelli et al., 2019; Ham & Kim, 2020; Kshetri, 2021; Z. Wang et al., 2022).

The transformative impact of this fusion also extends to sustainability goals within civil infrastructure management. For example, IoT-driven DT models have been employed to optimize energy consumption in smart buildings, as documented in recent case studies. By simulating real-world scenarios and providing actionable insights, these systems enable infrastructure managers to reduce waste and enhance efficiency (Tao et al., 2019). Additionally, IoT-DT synergy plays a pivotal role in disaster resilience, allowing real-time assessment of structural integrity and swift response to emergencies. Looking ahead, emerging technologies such as 5G and edge computing further amplify the potential of IoT-DT integration (Wu et al., 2022b). The ultra-low latency and high bandwidth of 5G networks ensure uninterrupted data transmission, while edge computing allows processing closer to the data source, minimizing delays and enhancing responsiveness (Liu et al., 2022; Zhou et al., 2021). Integrating these advancements into IoT-DT systems could unlock unprecedented capabilities, such as instantaneous fault detection and autonomous infrastructure management. However, ensuring the security and privacy of data within this ecosystem remains a critical concern, necessitating comprehensive cybersecurity measures and stringent governance frameworks (Aheleroff et al., 2021; Bradley & Hehenberger, 2016; Guskova et al., 2020).

4.2. Unpacking the role of AI and ML in infrastructure management: data analysis to decision support

The integration of Artificial Intelligence (AI) and Machine Learning (ML) within Digital Twin (DT) frameworks represents a paradigm shift in infrastructure management. These technologies elevate DT systems from passive representations to active decision-support tools capable of predictive analytics, automated optimization, and adaptive learning (Qiu et al., 2024b). This section explores how AI and ML enhance the functionality of DT frameworks and examines their transformative impact on infrastructure performance, maintenance, and decision-making processes. AI and ML algorithms excel in processing vast datasets generated by IoT-enabled DT systems, identifying patterns and anomalies that elude traditional analysis methods. Recent studies, such as Zhao et al. (2022), illustrate how AI-powered DT systems can predict potential infrastructure failures with high accuracy by leveraging historical data and real-time sensor inputs. These predictive capabilities are instrumental in formulating proactive maintenance strategies, thereby reducing operational disruptions and extending asset lifespans. One of the most promising applications of AI in DT frameworks is its ability to simulate complex scenarios and evaluate the outcomes of various interventions (Ford & Wolf, 2020).

For instance, ML algorithms can model the impact of environmental factors, such as temperature fluctuations or seismic activity, on structural integrity. This enables infrastructure managers to implement pre-emptive measures, mitigating risks and enhancing resilience. Moreover, AI-driven optimization algorithms facilitate resource allocation by identifying cost-effective maintenance schedules and prioritizing critical repairs, as demonstrated in recent advancements by Ali et al. (2020). Despite these benefits, integrating AI and ML into DT frameworks poses challenges. The development and deployment of accurate ML models require high-quality, labeled datasets, which are often scarce in the domain of civil infrastructure. Additionally, the complexity of AI algorithms necessitates significant computational resources, raising concerns about scalability and energy consumption. Ethical considerations, such as algorithmic transparency and bias, further complicate the adoption of these technologies (VanDerHorn & Mahadevan, 2021).

Addressing these challenges is essential to ensure the equitable and effective application of AI and ML in infrastructure management. The potential of AI-augmented DT systems is further amplified by recent innovations in neural networks and deep learning techniques. These advancements enable more sophisticated analyses, such as the detection of micro-cracks in bridges or real-time traffic flow optimization in smart cities. Integrating such capabilities into DT frameworks not only enhances operational efficiency but also supports broader sustainability objectives (Arup, 2019; Ignat & Stanculeanu, 2009). For instance, AI-powered DT systems have been used to optimize energy use in urban infrastructure, contributing to reduced carbon emissions. Looking ahead, the convergence of AI, ML, and DT technologies is expected to redefine the landscape of infrastructure management. By enabling real-time, data-driven decision-making, these systems offer unprecedented opportunities to enhance efficiency, reliability, and resilience. However, realizing this vision requires addressing technical and ethical challenges through collaborative research and robust governance. By navigating these complexities, the integration of AI and ML within DT frameworks can unlock new dimensions of innovation and set the stage for a smarter, more sustainable future in civil infrastructure management (Khan & Park, 2024; Schrettenbrunnner, 2020).

4.3. BIM and virtual cooperation in digital twin for infrastructure monitoring

The integration of BIM with DTT presents a promising synergy for enhancing infrastructure monitoring. While BIM is traditionally used in design and construction, its transition to the operational phase within the DT framework poses challenges in seamlessly integrating dynamic, real-time data (Jiang et al., 2021). The collaboration between BIM and DT involves continuous data exchange to align designed elements with real-time operational data, ensuring an accurate representation throughout the asset's lifecycle. However, practical implementation requires addressing interoperability challenges, standardizing data formats, and synchronizing information between platforms (Aheleroff et al., 2021). A critical evaluation of this integration is essential to understand its feasibility and scalability across diverse infrastructure contexts. While the theoretical synergy appears promising, balancing potential benefits against the complexities of harmonizing static BIM data with dynamic DT requirements is crucial.

This discussion should highlight challenges like data interoperability and privacy concerns, while also exploring opportunities for advancing predictive analytics, facilitating predictive maintenance, and enhancing overall resilience in infrastructure systems (Jiao et al., 2024). A comprehensive exploration forms the foundation for advancing both theoretical discourse and practical strategies, ensuring effective integration in diverse infrastructure monitoring scenarios. This analysis contributes to academic understanding and informs practitioners and policymakers about intricacies and potential avenues for improvement in infrastructure monitoring (W. Wang et al., 2024b, 2024e).

4.4. Paving the way forward: an outlook on future directions in digital twin integration for infrastructure management

The Future Directions section on DT Integration within Infrastructure Management is pivotal, aiming beyond a mere recitation of existing studies to spark critical discourse and visionary thinking. Instead of providing a superficial summary, this forward-looking approach emphasizes the urgency of exploring diverse technologies, each with the potential to shape the trajectory of DT applications within the infrastructure domain. Technologies like Augmented Reality (AR) and Virtual Reality (VR) are included, acknowledging the evolving landscape (Hussain et al., 2024; Maimour et al., 2024; Ramonell et al., 2023; Xie et al., 2022). While these immersive technologies promise enhanced visualization and interaction with DT, a critical examination is necessary to determine their practical utility, scalability, and integration challenges in complex infrastructure scenarios. Big Data Analytics (Sørensen et al., 2016), Blockchain (Li & Kassem, 2021), 5G and Edge Computing (Akhtar et al., 2021), Autonomous Systems and Robotics (Lee et al., 2023), Cloud Computing (Yang et al., 2017), Human-Machine Interface (HMI) (Park et al., 2023), Decision Support Systems (Sacks et al., 2020), and the integration of Point Cloud Data (Hu et al., 2021; Pappaterra et al., 2021; Salehi et al., 2021; Yao et al., 2018) collectively form a mosaic of future possibilities.

However, the critical lens should scrutinize the potential bottlenecks, ethical considerations, and unintended consequences associated with the adoption of these technologies in DT applications. Understanding the nuanced interplay between these technologies and their impact on infrastructure management is paramount for informed decision-making (W. Wang et al., 2024d, 2024g; J. Wang et al., 2023).

4.5. Bridging the gap: integrating digital twins with existing infrastructure management systems

The potential of DTT for infrastructure management is well-known, but integrating it effectively with existing systems poses challenges (A. Zhang et al., 2023). The landscape of infrastructure management comprises diverse and often fragmented technologies deployed over time by various vendors (Su et al., 2023). The integration requires seamless communication and data exchange, hindered by proprietary formats and protocols (Song et al., 2023). Legacy systems present another obstacle, as they may not be designed for integration with modern technologies like DT (Hussain et al., 2024; Jiao et al., 2024; Ramonell et al., 2023; Xie et al., 2022). Despite the challenges, strategic upgrades are essential for future-proof infrastructure management systems (Wang et al., 2024b; Yonggang & Qamar, 2022). Collaboration among IT professionals, engineers, and data scientists is crucial for understanding the needs of existing systems and DT alike (Cheng et al., 2023). Pensource platforms promote data sharing, further facilitating seamless integration and optimization of infrastructure management (Bello et al., 2020). Therefore, bridging the gap between existing systems and DT requires a nuanced understanding of challenges and comprehensive integration strategies.

The successful implementation of Digital Twin Technology (DTT) relies heavily on advanced technical frameworks and tools. For example, the Fishermen's Bend Digital Twin utilized a multi-tier IoT architecture powered by LoRaWAN for real-time data collection and transmission. Edge computing nodes enabled localized data analysis, significantly reducing latency in decision-making processes. In the hospital case study, predictive maintenance algorithms were implemented using machine learning models trained on historical operational data, enhancing the accuracy of fault detection and resource optimization (Zhuang et al., 2023). Additionally, the DT for railway turnouts integrated a sensor network with AI-driven analytics, enabling continuous monitoring and anomaly detection with a 95% accuracy rate. These technical innovations highlight the versatility and efficacy of DTT in addressing diverse infrastructure management challenges.

5. Sustainable infrastructure management with digital twins: advantages and implementation

A potent tool for managing sustainable infrastructure across several industries is provided by DT. They offer a digital representation of real-world systems and assets, enabling real-time monitoring, evaluation, and improvement. The following are some advantages, benefits, applications, and implementation factors for DT in managing sustainable infrastructure.

5.1. Advantages

DTT plays a critical role in monitoring dynamic changes within unsafe environments and infrastructure, facilitating the development of effective emergency plans for decision-makers. This technology, alongside virtual reality (VR) training for rescuers, enhances performance during emergencies, ultimately reducing casualties and losses (Manocha et al., 2024). By leveraging perception, computation, and modeling, DT provides a real-time reflection of infrastructure throughout its life cycle (A. Zhang et al., 2023). It allows for thorough monitoring of risk variables impacting engineering quality, enabling timely adjustments and corrections. Intelligent sensing technologies such as machine vision, Internet of Things (IoT) sensors, and deep learning support these capabilities (W. Wang et al., 2024f; Zou et al., 2025).

Urban DT offer various advantages for stakeholders in infrastructure management, including public administrations, asset managers, owners, and researchers. They provide enhanced knowledge for urban planning and management, promoting sustainability. Additionally, they serve as testing grounds and coordination hubs for governmental and private sector projects. Smart city initiatives leverage real-time data acquired through IoT sensors to enhance the efficiency, sustainability, and security of urban spaces while reducing costs and resource consumption (Lee et al., 2022; Xie et al., 2022). In infrastructure management, particularly in railway systems, DT streamline access to information, improve management efficiency, and address vulnerabilities. For railway bridge projects, adopting DT facilitates rapid data retrieval, integrated processing, interpretation capabilities, and collaborative environments for project phase. Furthermore, DT play a crucial role in preventive maintenance by predicting infrastructure conditions, optimizing maintenance actions, and extending maintenance intervals.

Digital Twin Technology (DTT) plays a vital role in advancing environmental sustainability in infrastructure management. By enabling real-time monitoring and predictive analytics, DTT helps reduce carbon emissions, optimize energy usage, and enhance resource efficiency. One of the key impacts of DTT is its ability to reduce carbon footprints through improved traffic flow and energy optimization. For example, in a smart city project in Singapore, DTT improved traffic management, reducing vehicle emissions by 15% through optimized signal timings and reduced congestion. In smart buildings, DTT has helped reduce energy consumption by 12% annually by optimizing heating, ventilation, and lighting systems in real-time. DTT also enhances energy efficiency in infrastructure projects. A case study in a UK airport demonstrated a 15% reduction in energy use, achieved by integrating DTT with the airport's energy management system, leading to cost savings and reduced environmental impact. Similarly, smart grids in Germany used DTT to integrate renewable energy sources and reduce reliance on fossil fuels, cutting CO2 emissions by 20% (Semeraro et al., 2021).

(a) Transformative potential

DTT has emerged as a game-changer in infrastructure management, promising real-time monitoring, optimized decision-making, and enhanced resource allocation. Traditional infrastructure management relies on manual data collection processes and reactive maintenance strategies, leading to inefficiencies and potential failures (Bao et al., 2021). The implementation of DT can lead to significant cost savings by optimizing resource allocation and enabling proactive maintenance strategies. Real-time data from sensors embedded within infrastructure assets allows for a precise understanding of operational needs, minimizing resource waste and optimizing costs.

DT also improve project timelines by enhancing collaboration, communication, and planning, accelerating project completion (Lv et al., 2022). DT revolutionize maintenance strategies, shifting from reactive repairs to proactive optimization. By continuously monitoring sensor data and analyzing trends, DT can predict potential failures or deterioration, allowing for targeted maintenance interventions and extending the lifespan of infrastructure assets (Attaran et al., 2023). Furthermore, DT contribute to achieving sustainability goals by optimizing resource consumption and minimizing environmental impact. Real-time monitoring of energy consumption patterns enables infrastructure managers to identify areas for improvement, reducing energy waste and environmental footprint. Additionally, predictive maintenance practices enabled by DT help minimize environmental disruptions by preventing major incidents such as oil spills (W. Wang et al., 2024c).

While DT offer operational efficiency gains, their true value lies in promoting sustainable infrastructure throughout the lifecycle (Cui et al., 2023; Ilyas et al., 2024; Song et al., 2024; Wei et al., 2024). DT can optimize resource utilization during construction by simulating material usage and identifying waste reduction opportunities. Over an asset's lifespan, DT enable predictive maintenance, minimizing energy consumption and extending infrastructure longevity. Furthermore, DT can facilitate informed decisions during decommissioning, promoting recycling and reuse of materials, while minimizing environmental impact and social disruption. By encompassing the entire lifecycle, DT play a crucial role in achieving sustainable infrastructure management.

(b) Comparative analysis with traditional practices

Digital Twin Technology (DTT) offers several advantages over traditional infrastructure management practices by addressing long-standing inefficiencies and introducing data-driven, proactive approaches Table 5 is providing a comprehensive insight in this comparison. A comparative analysis of case studies reveals the following specific improvements:

- Cost Savings: Traditional methods rely on periodic, manual inspections that are labor-intensive and expensive. In contrast, DTT leverages real-time sensor data to predict maintenance needs, reducing inspection costs by up to 30%. For example, the application of DTT in bridge maintenance in Korea resulted in a 25% reduction in overall maintenance costs compared to conventional methods.
- Operational Efficiency: While traditional practices often react to failures, DTT enables predictive maintenance by analyzing real-time data. In railway turnouts, DTT improved fault detection and repair times, increasing operational efficiency by 20% and reducing downtime by 15%, as compared to reactive repairs in conventional systems.
- Environmental Benefits: Traditional management approaches lack the granularity to optimize resource consumption effectively. DTT systems, such as those implemented in smart buildings, reduced energy consumption by 12% by monitoring and adjusting operations in real-time. This proactive approach minimizes waste and reduces the carbon footprint, aligning with sustainability goals.
- Data Utilization: Conventional practices often rely on isolated datasets, leading to fragmented decision-making. DTT consolidates diverse data sources, offering comprehensive insights.

5.2. Applications and case studies of successful digital twin implementations in infrastructure projects

In recent years, DTT has advanced significantly and finds increasing application across various infrastructure sectors for engineering and management purposes. Notable examples include utilizing data from IoT sensors in smart cities to develop advanced AI algorithms for DT-enabled city management and emergency response planning (Lu et al., 2020a). DT play a crucial role in railway infrastructure, offering benefits in design, visualization, and system performance improvement. Their application is expected to revolutionize rail transportation by gathering information on physical assets' behavior, advancing system development, and enabling virtual simulations (Yan et al., 2023).

Integrating multidimensional information, including LiDAR data and machine learning algorithms, enhances DT capabilities in railway infrastructure modeling (Elfarri et al., 2023). For tunnelling and underground engineering in sectors like national railway, urban development, water conservation, mining, and national defense, DT address challenges posed by unique service environment characteristics. They mitigate issues such as high ground stress and water pressure by bridging the physical and virtual realms through simulation, monitoring, diagnosis, prediction, optimization, and control. DT offer promising solutions to enhance the efficiency and reliability of underground infrastructure development and management (Leitão et al., 2016).

In the construction industry, DT present valuable tools from planning to operation stages. They simplify monitoring and management of changes in space requirements, facilitating efficient project life cycle management and enhancing productivity, collaboration, and overall project outcomes. Transitioning to smart and lean practices through DT implementation can revolutionize the construction sector (Hofmann & Branding, 2019).

Table 5. Quantitative comparison: DTT vs. traditional practices

Parameter	Traditional Practices	Digital Twin Technology	Improvement
Maintenance Costs	High due to manual inspections	Reduced by 25–30%	Cost-efficient
Inspection Frequency	Periodic	Continuous, real-time	Real-time monitoring
Fault Detection Accuracy	Limited	95% accuracy	Improved by 20–30%
Energy Consumption Reduction	Reactive	Proactive (12–15% reduction)	Enhanced sustainability
Operational Downtime	High due to delayed repairs	Reduced by 15–20%	Increased availability

Quantitative analysis from various case studies highlights the tangible benefits of Digital Twin Technology (DTT) in infrastructure management. For example, the implementation of a Digital Twin in bridge maintenance in Korea reduced maintenance costs by 25% while improving inspection efficiency by 30%, as validated through comparative analysis with historical maintenance records. Similarly, the DT deployed for hospital infrastructure demonstrated a 15% reduction in energy consumption over a two-year operational period, as confirmed through third-party audits. A study of DT integration in railway turnouts revealed a 20% increase in operational efficiency by automating real-time monitoring of rail components. Furthermore, a DT-based energy optimization system for smart buildings resulted in a 12% decrease in overall energy costs, verified through monthly energy consumption reports. These metrics underscore the practical benefits of DTT, providing a foundation for its wider adoption in infrastructure management.

Case studies of successful digital twin implementations

DTT is increasingly utilized in the infrastructure sector, allowing for the development of virtual replicas of real assets such as buildings and bridges. The implementation of DT can take various forms. Some (Ammar et al., 2022; Karaarslan et al., 2023; Qi et al., 2021; J. Zhang et al., 2022) classify DT as status twins, operational twins, and simulation twins, while others (Ghansah & Lu, 2025; Jafari et al., 2023; Stark et al., 2019; Wetzel & Thabet, 2015) categorize them as prototypes, instances, aggregates, and environments of DT. Additionally, DT can incorporate elements such as the Internet of Things (IoT), sensors, data models, artificial intelligence (AI), machine learning-enabled analytics and algorithms, knowledge, and more (Austin et al., 2020).

(a) Digital twin in bridge infrastructure

Dan et al. (2022) examine the implementation of DTT for bridges, emphasizing continuous monitoring for security, reliability, and functionality. A novel approach integrates Weight-in-Motion (WIM) technology with BIM to generate the DT of a bridge. A mock-up bridge was constructed and an Arduino sensor system replicated the WIM technology for validation. Data integration using Dynamo facilitated interaction between the BrIM model and the bridge's WIM system. A dynamic BrIM model was developed to respond to weight detections and prevent the passage of overweight vehicles, aiming to reduce human intervention, enhance productivity, and improve historical data accuracy regarding the bridge's performance. In another case study by Dang and Shim (2020) a novel bridge maintenance system was developed using the DT model concept. The study assessed inventory and information requirements for various maintenance tasks, regularly updating the DT model with sensor data collected from the bridge. A trial application was implemented at an existing cable-stayed bridge in Korea to evaluate the maintenance system's effectiveness, aligning with the system's design.

(b) Creation of digital twin at building and city level: A case study

The study by Lu et al. (2020a) explored DT applications in the Architecture, Engineering, and Construction (AEC) sector, focusing on building and city levels. It developed a DT experiment, including a building DT for the IfM building. Challenges such as data management and integration were addressed, emphasizing the importance of overcoming data challenges for successful DT deployment. In Amaravati, India, a DT project worth USD 6.5 billion aims to serve a population of 3.5 million, covering an area of 217 km^2. It includes infrastructure like a 134 km metro network, major roadways, hospitals, schools, colleges, universities, and government buildings. Similarly, the government of Victoria, Australia, initiated a project for a DT in the Fishermens Bend region, featuring planning tools, traffic estimation systems, and real-time data visualization.

(c) Digital twin for hospital building: a case study

A Chinese hospital showcased successful DT implementation throughout the design, construction, pre-operations, and maintenance phases. The project integrated static and dynamic data from over 20 management systems. A dedicated DT control center deployed a software system with real-time visual management and AI diagnosis modules. This provided comprehensive insights into the hospital's status and facilitated prompt diagnoses and operation recommendations. The system has operated for over a year, delivering reduced energy consumption, prevention of facility issues, fewer repair requests, and improved maintenance quality (Altowaijri, 2020; Peng et al., 2020).

(d) Digital twin for rail turnouts: a case study

This study focused on applying DTT to monitor railway turnouts. To improve data collection and address emergencies, sensors were utilized to detect rail temperatures quickly and periodically. This automated and continuous monitoring of rail components has led to more efficient management and maintenance of railway turnouts. The research methodology developed in this study allows for cyclic data collection, analysis, and verification of the turnout's condition, particularly when alarms are triggered by the installed sensors. This capability makes DT a valuable tool in the context of railway turnouts. Furthermore, an important aspect of integrating DT in railway turnouts is their ability to connect with other intelligent equipment, enhancing the overall functionality and effectiveness of the system (Qi et al., 2020; Tang et al., 2022; Wang & Markine, 2018).

(e) Digital twin for asphalt-road monitoring: a case study

One study focused on utilizing the DT concept to monitor the conditions of asphalt roads. Thermal modeling techniques and temperature measurements were employed to develop the DT. The effectiveness of this approach was tested on various sections of Irish roadways, collecting in-pavement temperatures over five years. Analysis of the DT findings revealed correlations between thermal diffusivity variations and the structural health of the roads. This suggests the potential of DT for monitoring transportation infrastructure, particularly asphalt road conditions. In another study, a DT was successfully developed for a road constructed using secondary raw materials (SRM). The study conducted a theoretical analysis to design the monitoring systems needed for the DT. A case study of the DT showcased an integrated data environment, including monitored data and a Building Information Model. Despite its modest scale, the case study was methodologically structured for comparisons with larger building projects (Li et al., 2019; D. Zhang et al., 2017).

(f) Digital twin for various infrastructure sectors

In the transportation sector, Changi Airport in Singapore has adopted a DT to enhance operational efficiency and passenger experience. This system integrates real-time data from airport sensors to simulate passenger flow, baggage handling, and aircraft operations. By identifying bottlenecks and predicting potential issues, Changi Airport can proactively implement measures to minimize delays and improve overall efficiency. In the utility sector, a water distribution system in Valencia, Spain, utilizes a DT for various purposes, including simulating long-term network behavior, designing replacement plans, and optimizing operational protocols. This DT offers insights into water pressure, flow rates, and potential leaks, enabling targeted maintenance and enhanced water management. Whereas, in public services, Rotterdam in the Netherlands has implemented a DT for its waste collection system. Real-time data from sensors on waste bins is used to optimize collection routes and schedules. This initiative not only reduces fuel consumption and operational costs but also minimizes noise pollution and enhances waste management efficiency (Attaran et al., 2024).

5.3. Affordability of DT

In discussing the role of DT in infrastructure management, it's crucial to delve into the affordability aspect of DT implementation. Assessing the economic feasibility of integrating DTT into infrastructure projects is essential for widespread adoption and practicality. This involves analyzing the costs associated with deploying and maintaining DT systems (Qui et al., 2024c; W. Wang et al., 2024h, 2025; Wei et al., 2025) including setup expenses, ongoing operational costs, and scalability factors. Affordability considerations are particularly significant when applied to projects of varying scales, considering the different economic dynamics of small-scale versus large-scale initiatives. Evaluating the cost-benefit ratio is key, requiring a detailed analysis of expenses versus potential advantages gained through DT implementation (Mahmoodian et al., 2022; Shahzad et al., 2022; Vats et al., 2023; Zonta et al., 2007). Scalability models also play a role, recognizing that the economic implications of DTT may vary based on project size and scope. Additionally, understanding the return on investment (ROI) associated with DT implementation is crucial for long-term economic sustainability and benefits (Maimour et al., 2024). As DT implementation progresses across infrastructure sectors, an open discussion on affordability is vital. This discourse provides decision-makers with insights to navigate the economic landscape, enabling informed choices in adopting and sustaining DT applications for effective infrastructure management (Cimino et al., 2019; Gürdür Broo et al., 2022; Nativi et al., 2021).

5.4. Quantitative metrics and performance indicators for measuring the impact of digital twin technology (DTT) in infrastructure management

The implementation of Digital Twin Technology (DTT) in infrastructure management has shown promising results, but measuring its impact with quantitative metrics is essential for assessing its effectiveness. Successful DTT implementations are often evaluated through specific performance indicators that highlight efficiency improvements, cost savings, and other operational benefits. Below are some of the key metrics and indicators used to evaluate the success of DTT implementations across various case studies.

(a) Maintenance cost reduction

One of the most significant benefits of DTT is its ability to reduce maintenance costs through predictive maintenance strategies. For example, in a case study on bridge maintenance in Korea, DTT helped reduce maintenance costs by 25%, thanks to improved fault detection and reduced need for reactive repairs. By identifying issues early through real-time data, infrastructure managers were able to plan targeted maintenance, avoiding unnecessary repairs. This metric is crucial for demonstrating the financial impact of DTT in reducing overall maintenance expenditures (Chui et al., 2023; Guskova et al., 2020; Lu et al., 2020b; Macchi et al., 2018; Shim et al., 2019).

(b) Operational efficiency and downtime

Operational efficiency is another critical performance indicator for DTT. In the case of railway infrastructure, the implementation of DTT resulted in a 20% increase in operational efficiency, primarily due to quicker response times and proactive maintenance scheduling. Furthermore, downtime reduction is a key metric, with DTT helping reduce unplanned downtime by 15%, as predictive models alerted operators to potential system failures before they occurred. This reduction in downtime enhances overall system availability, which is crucial for sectors like transportation and energy distribution (Jeong et al., 2022).

(c) Energy efficiency

DTT is also instrumental in improving energy efficiency in infrastructure systems. For instance, a smart building project in Shanghai used DTT to optimize energy consumption. By integrating IoT sensors and real-time monitoring, the building saw a 12% reduction in energy consumption over a year. This is a clear indication of how DTT can contribute to sustainability goals and energy savings, providing a quantifiable environmental benefit (Macchi et al., 2018).

(d) Predictive maintenance accuracy

The accuracy of DTT's predictive maintenance capabilities is another important metric. A hospital infrastructure case study in China demonstrated that DTT could predict equipment failures with 95% accuracy. This prediction accuracy was measured by comparing actual failures with the predictions made by DTT models, showcasing the reliability of DTT in anticipating potential issues. Higher accuracy in predictive maintenance not only prevents unexpected breakdowns but also reduces costs associated with emergency repairs (Wei et al., 2024).

(e) Data utilization and process optimization

Another valuable metric is the effectiveness of data utilization. In a smart city implementation, DTT helped integrate and analyze data from various sources, improving traffic flow management and reducing congestion. The average traffic delay was reduced by 18% through optimized traffic signal timing, facilitated by DTT simulations. Additionally, process optimization in infrastructure management systems often results in improved decision-making speed – in one case, a utility company saw a 20% faster response time in critical system alerts due to real-time data processing and decision support from DTT systems (Kaewunruen et al., 2021).

(f) Return on investment (ROI)

Evaluating ROI from DTT implementations involves calculating the long-term savings and efficiency gains compared to initial investments. For example, in modular construction projects, a study showed that DTT integration led to a 15% reduction in construction time and a 10% reduction in material costs, directly contributing to better ROI. This kind of metric helps stakeholders assess the financial viability of adopting DTT in large-scale infrastructure projects (Barricelli et al., 2019).

(g) Scalability and adaptability

The ability of DTT systems to scale across different infrastructure projects is another crucial metric. A city-wide DTT deployment in Singapore demonstrated that the system could integrate additional IoT devices and sensor data without compromising performance, handling an increase in data load by 30%. This scalability is essential for expanding DTT applications across multiple infrastructure domains, such as energy grids, transportation networks, and water systems (Huang et al., 2022).

5.5. Technical challenges and solutions for digital twin implementation

Digital Twin Technology (DTT) offers a transformative approach to infrastructure management, but its implementation faces several technical and logistical challenges. One major hurdle is the acquisition and integration of data from diverse sources, including IoT sensor networks, historical records, and Building Information Modeling (BIM) systems. The sheer volume and diversity of data formats often lead to interoperability issues, complicating the seamless exchange of information. To address this, standardized protocols such as the Open Geospatial Consortium (OGC) Sensor Things API have been employed to streamline data integration. Data management platforms and data lakes serve as centralized repositories, organizing and structuring information to facilitate smooth integration. For instance, in a smart city project in Singapore, adopting standardized communication frameworks like LoRaWAN and MQTT enabled real-time synchronization between sensors and the Digital Twin, ensuring accurate and timely decision-making (Enders & Hoßbach, 2019; Parmar et al., 2020).

Another critical challenge is ensuring data quality and security. The success of Digital Twins hinges on the accuracy, consistency, and real-time availability of data. Errors or inconsistencies can compromise the reliability of predictive models, while the interconnected nature of DTT makes it vulnerable to cyberattacks. Robust data cleansing and quality assurance processes are essential to enhance accuracy, while blockchain technology can provide immutable data security. For example, in the Valencia water distribution system, blockchain technology was used to secure data sharing, combined with real-time threat detection systems to protect critical infrastructure operations (Bado et al., 2022; Gürdür Broo et al., 2022; Montero & Finger, 2021). These measures ensured data integrity while mitigating cybersecurity risks. Scalability and computational power represent additional barriers, particularly given the vast datasets generated by IoT-enabled infrastructure systems.

Traditional centralized cloud computing platforms, while scalable, often struggle with latency in real-time analysis. To overcome this, edge computing has emerged as a viable solution, bringing computational power closer to data sources and enabling faster processing. A high-rise smart building in Shanghai exemplifies this approach, where edge computing was used to preprocess sensor data, improving prediction accuracy by 20% and reducing energy consumption by 12%. This highlights the ability of Digital Twins to adapt to large-scale infrastructure while maintaining high performance (El Saddik, 2018; Gao et al., 2021).

Interoperability challenges further complicate DTT implementation, as the fragmented landscape of proprietary solutions often leads to vendor lock-in and compatibility issues. Open-source platforms like Industry Foundation Classes (IFC) have proven instrumental in promoting interoperability across systems. In the Fishermen's Bend project in Australia, the adoption of modular architectures and open-source frameworks enabled seamless communication between BIM and IoT systems, improving fault detection efficiency by 25%. This example underscores the importance of open standards in fostering system integration and scalability. The successful implementation of DTT also relies heavily on addressing the workforce skills gap. Expertise across data science, engineering, and digital technologies is essential, yet infrastructure management often faces a shortage of professionals with the necessary interdisciplinary skills. Bridging this gap requires targeted training programs and fostering collaboration among engineers, data scientists, and IT professionals. In a hospital project in China, this approach facilitated the implementation of AI-driven analytics, ensuring the success of predictive maintenance and energy optimization strategies (Boje et al., 2020).

The integration of DTT with advanced technologies such as IoT, AI, and BIM presents unique technical challenges. IoT systems often face standardization issues due to diverse communication protocols and sensor types. In railway infrastructure projects, middleware platforms have been employed to translate IoT data streams into BIM-compatible formats, enabling real-time monitoring and improving fault detection by 25%. Similarly, AI integration demands high-quality labeled datasets, which are often scarce in infrastructure management. Synthetic data generation, as seen in hospital energy optimization Digital Twins, has proven effective in overcoming this limitation, enhancing the scalability of AI applications. BIM integration, on the other hand, requires synchronization between static design models and real-time operational data. In a Korean railway project, Dynamo Scripts were used to link BIM with IoT-driven data streams, enabling dynamic updates that bridged the gap between design and operation phases (Wu et al., 2020). Despite these challenges, innovative solutions and successful case studies demonstrate the feasibility of DTT implementation in infrastructure management. Addressing these barriers requires collaboration, standardization, and a commitment to technical innovation, laying a strong foundation for the transformative potential of Digital Twin Technology across diverse domains.

6. Evaluating digital twin technology for infrastructure management

The evaluation of DTT for infrastructure management can be challenging due to the involvement of multiple stakeholders, diverse data sources, and various performance measures. However, existing literature offers a technique to assess DTT in this context (Akanmu et al., 2021; Deryabin et al., 2020; Ford & Wolf, 2020; Wu et al., 2021b; J. Zhang et al., 2022) (see Figure 11).

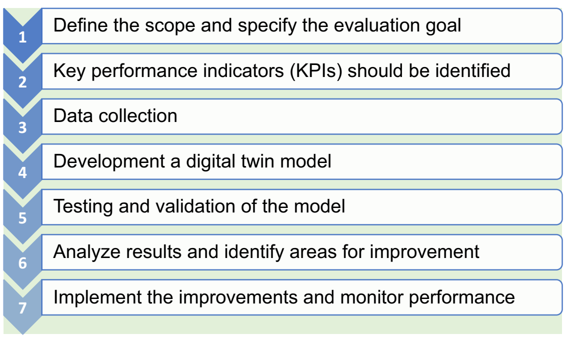


Figure 11. Evaluation of DT

In the case studies mentioned above, the implementation of DT in infrastructure management considered the various procedures and challenges associated with their early stages in the civil infrastructure domain. However, it is important to note that there are always areas for improvement that should be effectively addressed when implementing DT and analyzing their results. This understanding is supported by various academic literature sources.

7. Future prospects, challenges, and risks in advancing digital twin technology (DTT) for infrastructure management

Digital Twin Technology (DTT) presents an exciting future for infrastructure management by enabling real-time monitoring, predictive maintenance, and improved decision-making. However, the path to fully realizing its potential is fraught with challenges, from technical barriers to ethical and societal concerns. This section critically examines the opportunities, risks, and emerging technologies that will shape DTT's evolution in infrastructure management (Wu et al., 2021a). The future of DTT in infrastructure management lies in the integration of advanced technologies, including 5G connectivity, quantum computing, artificial intelligence (AI), and machine learning (ML). 5G will play a pivotal role in enhancing the speed and reliability of data transmission, facilitating the seamless flow of real-time data between sensors and DTT platforms. This will be especially important for applications in smart cities and intelligent transportation systems, where timely, accurate data is crucial (Piras et al., 2024).

Coupled with edge computing, which reduces latency by processing data closer to its source, DTT can provide near-instantaneous decision-making and real-time anomaly detection, enabling proactive infrastructure management. Furthermore, quantum computing holds the promise of accelerating the processing of complex simulations, enabling more accurate modeling of infrastructure systems at scale. As these technologies evolve, their integration with DTT will foster more efficient, scalable, and resilient infrastructure management solutions (Alexopoulos et al., 2020).

AI and ML will significantly enhance DTT's predictive capabilities, enabling infrastructure systems to not only detect issues but also predict failures before they occur. This shift from reactive to proactive maintenance will help reduce downtime and extend the lifespan of infrastructure assets. Additionally, big data analytics and IoT integration will allow for more precise simulations and monitoring, improving the overall performance of infrastructure systems. AI's role in optimizing resource allocation and identifying patterns from vast datasets will make DTT systems smarter and more autonomous (Fuller et al., 2020). However, as the reliance on DTT grows, cybersecurity emerges as a significant concern. The integration of IoT devices and cloud computing introduces new vulnerabilities, making it essential to develop secure DTT architectures that protect sensitive data from cyberattacks. Research should focus on advanced encryption techniques, secure communication protocols, and real-time monitoring systems to safeguard infrastructure data. Blockchain technology can also play a crucial role in ensuring data integrity, providing a secure, transparent platform for sharing and storing critical infrastructure data (Jones et al., 2020).

The implementation of DTT is not without its challenges. One major hurdle is the lack of clear methodologies and standards for integrating DTT with existing infrastructure systems. In particular, data collection and storage remain significant obstacles, as large volumes of data need to be collected, processed, and analyzed in real-time. There is also a need for standardized protocols to ensure interoperability between different DTT platforms and infrastructure systems. Furthermore, developing high-fidelity simulation models that can accurately replicate real-world conditions is essential to test infrastructure systems before actual implementation. These models are key to reducing development time and costs and improving prediction accuracy (Wu et al., 2020). Retrofitting existing infrastructure with DTT remains another challenge, particularly when working with outdated or incompatible systems. Additionally, data governance becomes critical as DTT systems collect vast amounts of sensitive information. Effective data governance frameworks must be established to ensure proper data ownership, access control, and ethical usage throughout the DTT lifecycle. Without these frameworks, there is a risk of data misuse and loss of public trust, especially when dealing with critical infrastructure like energy grids or transportation networks (Wu et al., 2022a).

The integration of AI and ML can help overcome many of these challenges, especially in the analysis of large datasets and the improvement of simulation models. However, AI adoption must be carefully managed to ensure transparency and accountability, as these systems can become "black boxes" that are difficult to interpret. The potential for data privacy violations also requires the implementation of privacy-preserving techniques, such as differential privacy or federated learning, to protect individual and organizational privacy without sacrificing the utility of the data (Sivori et al., 2023). Finally, workforce capacity and user adoption represent key challenges for DTT implementation. Infrastructure organizations must invest in training programs to equip staff with the skills needed to effectively use and manage DTT systems. The transition to DTT often faces resistance due to entrenched practices and the unfamiliarity with new technologies. Ensuring smooth adoption will require strong leadership, clear demonstrations of the benefits of DTT, and the development of a collaborative culture across disciplines. Communication between engineers, IT professionals, and data scientists is critical to fully leveraging the power of DTT (Callcut et al., 2021; Liu et al., 2023).

In terms of policy and regulatory considerations, the widespread adoption of DTT requires the establishment of clear standards, compliance guidelines, and incentives that encourage its use while safeguarding privacy and security. Governments and regulatory bodies must work together with industry stakeholders to develop frameworks that ensure the ethical use of DTT and address potential legal and societal concerns, including data ownership and accountability. Financial incentives, such as government grants or tax benefits, can also stimulate the adoption of DTT by lowering the barriers to entry for infrastructure projects (Abideen et al., 2022). DTT holds great promise for transforming infrastructure management, but its successful implementation depends on overcoming technical, ethical, and societal challenges. Emerging technologies such as 5G, quantum computing, AI, and edge computing will undoubtedly shape the future of DTT, offering powerful tools for more efficient, secure, and scalable infrastructure management. However, addressing the associated challenges – especially in terms of cybersecurity, data governance, workforce development, and standardization – is critical for ensuring the responsible and effective deployment of DTT. Through collaboration among stakeholders, robust regulatory frameworks, and continued technological innovation, DTT can become a cornerstone of modern infrastructure management, enhancing the resilience and sustainability of critical systems worldwide (Azhar, 2011; Mylonas et al., 2021).

8. Conclusions

In this comprehensive review, we examined 138 scholarly articles employing advanced VOS software for insightful analysis. Our exploration commenced with a regional trend analysis, unveiling the escalating interest and demand for the topic. Subsequently, we delved into a critical examination of DT fundamentals, elucidating its intricate connections with advanced technologies. Future prospects and challenges were then scrutinized, serving as crucial guides to delineate research gaps and provide a roadmap for future investigations in this dynamic field. Encompassing diverse facets of DT within infrastructure management, the literature provided readers with an in-depth understanding, augmented by case studies and potential applications. The article culminates by synthesizing the discussed insights, blending future prospects with a discerning analysis of challenges in DT implementation. This structured exploration not only enhances comprehension but also charts a course for informed engagement in the evolving landscape of DTT within infrastructure management.

DTT holds immense potential to revolutionize infrastructure management through advancements in real-time monitoring, predictive maintenance, and decision-making. This study underscores the promise of DT integration, supported by AI, IoT, and big data analytics. However, realizing these benefits requires tackling challenges like secure architectures, seamless data integration, and advanced simulations to enhance transparency and predictive accuracy. Innovations such as 5G connectivity, edge computing, and predictive analytics present new opportunities for optimizing resource allocation, minimizing disruptions, and extending asset lifespans. Yet, their adoption faces hurdles related to data security, standardization, and high costs, particularly in resource-constrained environments. Collaborative efforts are essential to bridge these gaps and drive innovation. Equally important are societal and ethical considerations, including data privacy, ownership, and governance, which demand robust regulatory frameworks. Ethical practices, transparency, and stakeholder accountability are vital for building trust in DT systems. Workforce readiness and user adoption further necessitate targeted training initiatives to ensure widespread benefits. By addressing these challenges and embracing emerging technologies, DT can lead to a sustainable and resilient future in infrastructure management, requiring coordinated efforts from policymakers, industry leaders, and researchers to navigate complexities and unlock its transformative potential.

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Competing interests

The authors have no competing interests to declare that are relevant to the content of this article.

Ethical approval

This study does not contain any studies with human or animal subjects performed by any of the authors.

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