buildings

Article

Data Fusion for Smart Civil Infrastructure Management: A Conceptual Digital Twin Framework

Obaidullah Hakimi [1], Hexu Liu [1,*], Osama Abudayyeh [1], Azim Houshyar [2], Manea Almatared [1] and Ali Alhawiti [1,3]

1 Department of Civil and Construction Engineering, Western Michigan University, Kalamazoo, MI 49008, USA; obaidullah.hakimi@wmich.edu (O.H.); osama.abudayyeh@wmich.edu (O.A.); maneamohammeds.almatared@wmich.edu (M.A.); aliatallahe.alhawiti@wmich.edu (A.A.)
2 Department of Industrial and Entrepreneurial Engineering and Engineering Management, Western Michigan University, Kalamazoo, MI 49008, USA; azim.houshyar@wmich.edu
3 Civil Engineering Department, Faculty of Engineering, University of Tabuk, Tabuk 71491, Saudi Arabia
* Correspondence: hexu.liu@wmich.edu

Abstract: Effective civil infrastructure management necessitates the utilization of timely data across the entire asset lifecycle for condition assessment and predictive maintenance. A notable gap in current predictive maintenance practices is the reliance on single-source data instead of heterogeneous data, decreasing data accuracy, reliability, adaptability, and further effectiveness of engineering decision-making. Data fusion is thus demanded to transform low-dimensional decisions from individual sensors into high-dimensional ones for decision optimization. In this context, digital twin (DT) technology is set to revolutionize the civil infrastructure industry by facilitating real-time data processing and informed decision-making. However, data-driven smart civil infrastructure management using DT is not yet achieved, especially in terms of data fusion. This paper aims to establish a conceptual framework for harnessing DT technology with data fusion to ensure the efficiency of civil infrastructures throughout their lifecycle. To achieve this objective, a systematic review of 105 papers was conducted to thematically analyze data fusion approaches and DT frameworks for civil infrastructure management, including their applications, core DT technologies, and challenges. Several gaps are identified, such as the difficulty in data integration due to data heterogeneity, seamless interoperability, difficulties associated with data quality, maintaining the semantic features of big data, technological limitations, and complexities with algorithm selection. Given these challenges, this research proposed a framework emphasizing multilayer data fusion, the integration of open building information modeling (openBIM) and geographic information system (GIS) for immersive visualization and stakeholder engagement, and the adoption of extended industry foundation classes (IFC) for data integration throughout the asset lifecycle.

Keywords: digital twin; smart infrastructure management; O&M; data fusion; openBIM; GIS; IFC

check for updates

Citation: Hakimi, O.; Liu, H.; Abudayyeh, O.; Houshyar, A.; Almatared, M.; Alhawiti, A. Data Fusion for Smart Civil Infrastructure Management: A Conceptual Digital Twin Framework. *Buildings* **2023**, *13*, 2725. https://doi.org/10.3390/buildings13112725

Academic Editors: Pedro F. Pereira and Nuno M. M. Ramos

Received: 3 October 2023
Revised: 26 October 2023
Accepted: 27 October 2023
Published: 29 October 2023

1. Introduction

Civil infrastructure systems are the backbone of modern societies and provide shelter, transportation, clean water, communication, energy and keep the economy functioning [1,2]. However, infrastructure owners and managers are struggling with the inefficiency and financial burden associated with aging infrastructure, which is deteriorating at an extensive rate and impacting the serviceability of the assets and quality of life for societies [1,3,4]. Infrastructure networks encompass a large number of interdependent infrastructure facilities, and their fragmented management complicates smart decision-making [5]. Civil infrastructure asset management has been the focus of cities and municipalities due to its significant strategic, operational, and financial benefits for transparently funding infrastructure lifecycle costs [6–8].

Currently, civil infrastructure is mainly managed by computerized maintenance management systems (CMMS) to record and plan routine maintenance activities, and decision support systems (DSS) are used for mid to long-term budget planning [8]. These currently used asset management processes rely on historical data and manual inputs from site visits, maintenance activities, and asset inspections and are financially unviable and prone to human errors [9]. In addition, current asset management systems use highly variable asset inventory systems in terms of asset location and hierarchy referencing [9,10]. Moreover, traditional asset management systems use standard classifications for managing assets and do not integrate information from all asset lifecycle phases [9,11]. Assumptions are often made to predict the remaining useful life of the assets [8]. Asset management through the lifecycle requires digital continuity of the data along separate phases of the facility for predicting asset performance and smart maintenance decision-making [12]. Thus, there is an eminent need for modernization and digital transformation in infrastructure asset management to achieve smart and resilient cities.

The emergence of Industry 4.0 necessitated real-time data acquisition and integration, resulting in a broader research focus on digital twins (DT). Figure 1 depicts the milestones of DT development summarized by Madubuike et al. [13] and further enriched by this study. Essentially, digitalization and real-time monitoring of physical assets require seamless integration of physical assets and their virtual counterparts. With the advancement of information technology such as the internet of things (IoT), cloud computing, artificial intelligence (AI) tools like deep learning (DL) and machine learning (ML), simulation, virtual reality (VR), and augmented reality (AR), the process of digitalization is gaining momentum [14]. Smart infrastructure management as a data-driven approach necessitates the integration of systems, facilities, and components [15]. DT is claimed to resolve the integration issue and provide real-time monitoring and data-driven intelligent decision-making [13,16]. In particular, DT is a prominent technology that enables instant two-way integration between virtual and physical systems, facilitating intelligent decision-making. According to Deng et al. [17], DT has evolved from BIM through four stages of development and integration with other technologies, including simulation, sensors, and AI at various levels. DT leverages IoT technology, smart sensors, lasers, photogrammetric tools, and measuring machines to gather real-time information about assets. Moreover, DT employs AI tools like ML and DL to organize and analyze data in real-time, allowing for condition monitoring, environmental learning, system-failure prediction, real-time feedback, and bi-directional information integration throughout the asset lifecycle [18,19].

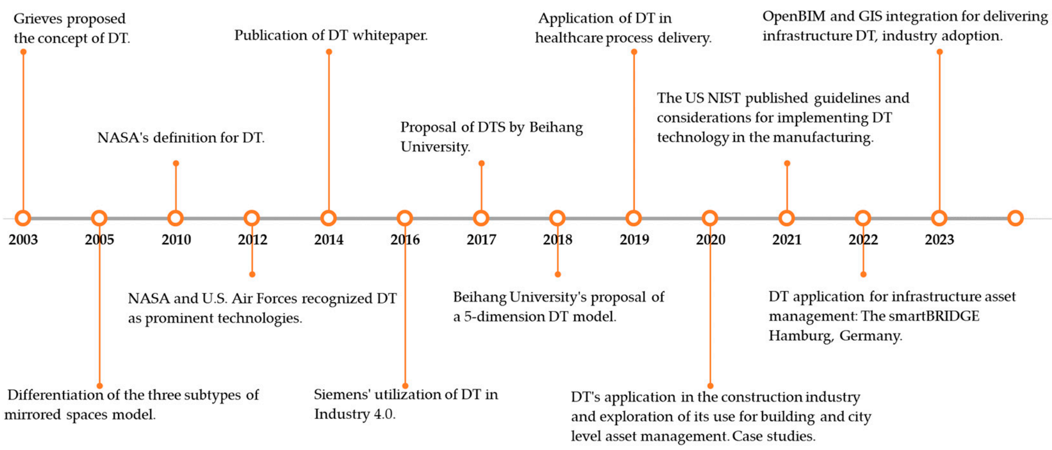

Figure 1. DT development and adoption millstones.

The literature about DT has been gaining momentum, and various systematic reviews have been conducted on the DT application and its enabling technologies. For example, Cheng et al. [20] conducted a systematic literature review of 174 papers on DT in civil infrastructure emergency management, discussing its development, technologies, and resilience.

The authors proposed a framework for civil infrastructure emergency management that outlines how DT aids in lifecycle reinforcement during mitigation, virtue planning and training in preparation, real-time assessment and optimization in response, and collaboration and learning during recovery. The authors also outlined that semantic-rich digital modeling, knowledge management, cybersecurity, and data quality in DT models are challenges associated with full DT deployment. Later, Jiménez Rios et al. [21] systematically reviewed 76 papers on bridge management through DT-based anomaly detection. The findings of the review were within the following themes: bridge DTs, bridge information modeling (BrIM), finite element modeling (FEM), bridge health monitoring (BHM), AI, unmanned aerial vehicles (UAVs), satellite monitoring, and other DT-related technologies. The authors revealed that there is a complete consensus towards DT adoption for bridge management and that a successful DT framework needs to be based on as-is information, data-driven finite element models, interoperability, and geometry. The study also found that the main challenges for DT deployment are software interoperability, anomaly-detection algorithms, DT integration at a macro scale, data quality, cost, institutional barriers, and resistance to change. Naderi and Shojaei [22] systematically reviewed 85 articles on infrastructure digital twins (IDTs) to investigate twinning technologies and interoperability solutions. The authors highlighted the versatility of BIM and IoT for IDTs, the need for complex architectures, edge-based solutions for simple IDTs, and standardization for interoperability. Through evaluating potential IDT frameworks, the authors found that data security, a lack of DT standards, data latency, and user interface issues are some challenges hindering DT adoption in the civil infrastructure sector. Wei et al. [23] highlight that traditional data analytics methods support decision-making from a single data source, while data fusion enhances accuracy by integrating multiple sources. Data fusion from heterogeneous sources and multiple sensors offers a more comprehensive representation of measurements and improves prediction performance [24,25].

Many studies focused on DT for civil infrastructure management and discussed twinning technologies, interoperability, and DT applications. Some studies [5,15,26] proposed integrated infrastructure system architectures that were concerned with infrastructure systems of systems and infrastructure interdependency. However, they lack focus on data-driven civil infrastructure management through seamless data integration throughout the whole lifecycle, data fusion, geospatial integration of infrastructure systems, multi-stakeholder involvement, security, and privacy. The implementation of DT for data-driven civil infrastructure management and predictive maintenance is associated with big data fusion from heterogeneous sources, realizing the gaps in the prominent DT frameworks, underscoring the core DT technologies for seamless big data management, and understanding the needs for DT application during the O&M phase including lifecycle data integration, federated digital modeling, interoperable open data standards, stakeholder involvement and human-in-the-loop. Another notable gap in current predictive maintenance practices is the reliance on single-source data instead of heterogeneous data, decreasing data accuracy, reliability, adaptability, and further effectiveness of engineering decision-making. Data fusion is demanded to transform low-dimensional decisions from individual sensors into high-dimensional ones for decision optimization. Given this, this study attempts to address this gap by answering the following research questions (RQs):

- RQ1: what are core data fusion approaches, applications, and challenges in the DT domain?
- RQ2: what are the capabilities of the current DT frameworks for data-driven civil infrastructure asset management? Considering applications, technologies utilized, and challenges.
- RQ3: what are the core DT-enabling technologies for data-driven civil infrastructure asset management?
- RQ4: what are the needs of DT applications during the O&M phase for data-driven infrastructure asset management? Including as-is digital modeling, data standards for interoperability, systems integration, stakeholder involvement, and human-in-the-loop.

Toward the objectives, this study systematically analyzed 105 academic publications. A content and qualitative thematic analysis approach was utilized, which is a widely recognized technique for theme identification and analysis. To address RQ1, 13 academic papers about data fusion were thematically analyzed, and the themes for their applications, methodologies, and challenges were extracted. To address RQ2 and RQ3, 44 DT frameworks were analyzed to extract their applications, core technologies, and challenges. In addition, a network map of the most prominent challenges hindering the seamless deployment of DT for smart civil infrastructure management is presented. To address RQ4 and to address some of the prominent challenges identified, the findings from all the sections are synthesized, and a conceptual lifecycle encompassing a DT framework for smart civil infrastructure management is presented based on concepts of multi-layer data fusion, IFC extension, blockchain, stakeholder engagement, openBIM, and GIS integration, and multi-level checks for quality assurance. The proposed framework facilitates enterprise-level asset management throughout its lifecycle.

2. Methods

This study applies a systematic literature review approach to synthesize relevant academic publications and case studies on DT for civil infrastructure management. Systematic review is a comprehensive approach for identifying, evaluating, and synthesizing relevant academic papers [27,28]. The rigorous approach of systematic review ensures the inclusion of relevant studies and facilitates identifying trends, gaps, and future research directions [29,30].

As shown in Figure 2, the research methodology in this study consists of five steps: (1) literature retrieval, (2) thematic analysis of the literature, (3) discussion of findings, (4) network mapping of challenges and gaps, and (5) development of conceptual DT framework for smart civil infrastructure management. This approach has been adopted in numerous prior research studies [15,20,31–33].

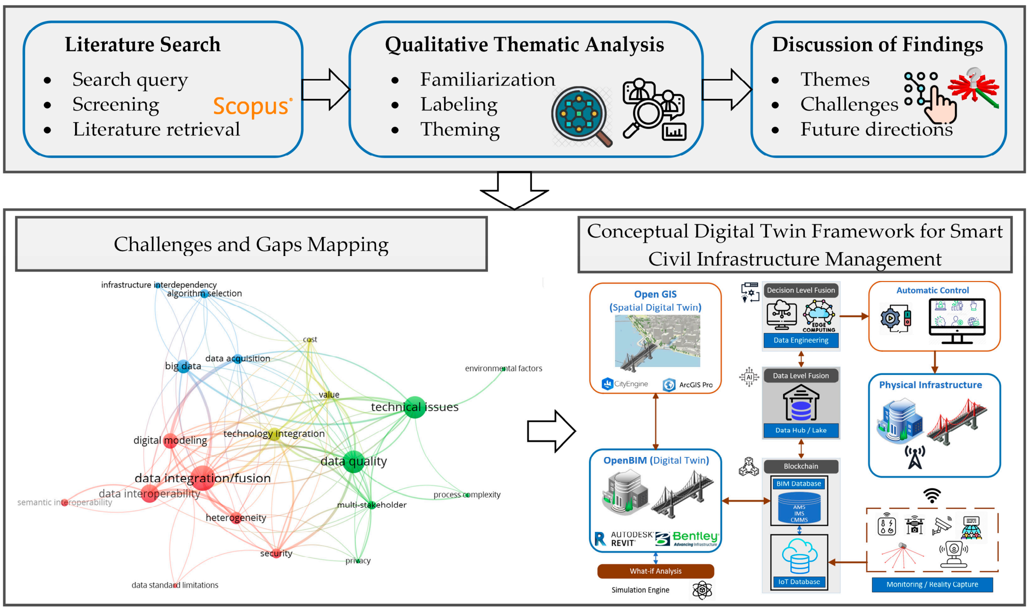

Figure 2. Research methodology.

Thematic analysis is a prominent approach for identifying and reporting data patterns and themes, revealing the basic concepts of the analyzed content and representing the fundamental ideas arising from specific research questions and objectives [34,35]. The thematic analysis approach in this study is adopted from Maguire and Delahunt [36] and is based on the six-phased framework proposed by Braun and Clarke [37] as follows: (1) becoming familiar with data, (2) generating initial codes, (3) searching for themes,

(4) reviewing themes, (5) defining themes, and (6) write-up. This study used an inductive thematic analysis approach, where the analysis is data-driven, and the identified themes are strongly related to the data and emerge naturally [37]. Microsoft Excel was used for data summarization and NVivo was used to code and classify the data. NVivo assists qualitative researchers in organizing, analyzing, visualizing, and reporting their data by providing tools and features to structure and organize the collected data [38].

To map challenges and gaps, this research used VOSviewer version 1.6.18, a tool that uses publication data to create maps for visualization and interpretation. In this study, the challenges from the analyzed literature publications were summarized and organized in a comma-separated values (csv) file and fed into VOSviewer. The co-occurrence analysis of challenges was conducted to visualize the research themes and trends of the targeted research domain quantitatively because co-occurrence shows the number of documents that contain the same challenge and are formed into clusters that allow for better representation and easy interpretation of the research theme results [39].

2.1. Literature Selection

The literature for systematic analysis was retrieved from Scopus and it was selected as the main database due to its reputation as a leading scientific abstract and indexing database; it also has a broader literature collection compared to its counterparts [18]. A comprehensive query-based search was performed in the Scopus database using keywords associated with DT and civil infrastructure management. Two main query blocks of DT and infrastructure were searched within article title, abstract and keywords. In the DT search string, the keywords "Digital Twin" OR "DT" OR "Digital Twins" OR "Digital-twin" OR "Digital Twinning" OR "Virtual Twin" OR " Virtual Counterpart" OR "Virtual Replica" were included. In the infrastructure management search string, the keywords of "Civil Infrastructure Management" OR "Infrastructure Management" OR "Infrastructure Asset Management" OR "Bridge" OR "Tunnel" OR "Railways" OR "Roads" OR "Ports" OR "Highway" were included, and it was integrated with DT by the AND command.

After identifying the keywords, a comprehensive query-based search was performed, and the potential papers were identified. To ensure the value of the systematic review and provide a comprehensive and precise explanation of the literature retrieval process, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 flow was employed. The PRISMA 2020 flow diagram provides a visual map of the stages of a systematic review, enhancing transparency; in addition, it allows readers to track decisions and understand how the initial literature search led to the final set of included studies [40]. The literature retrieval process is summarized in Figure 3. The period for literature search was set as from January 2012 to May 2023. Literature has been collected since 2012 because that is when DT emerged as a prominent technology and garnered significant research attention. The initial search resulted in 2141 papers from Scopus. Through automation filtering, the language was limited to English, the source type was limited to journal and conference proceedings and the subject area was limited to engineering, computer science, energy, decision science, and environmental science.

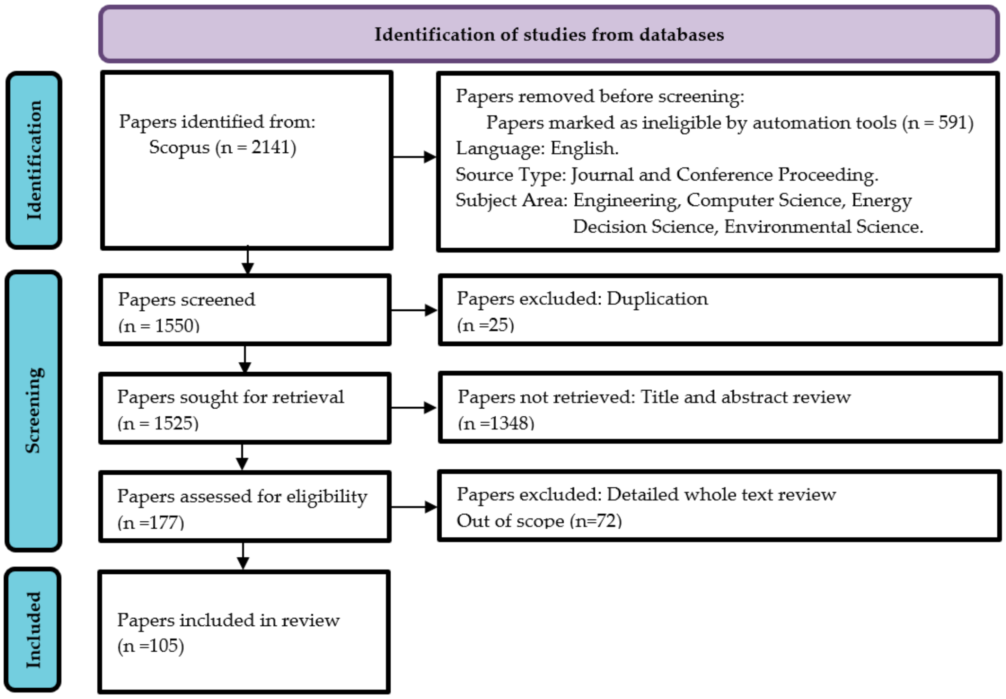

Figure 3. Literature retrieval flowchart based on PRISMA 2020 flow of a systematic review.

2.2. Literature Features on DT in Civil Infrastructure

Research on DT in civil infrastructure has been gaining momentum. Recently, there has been a significant surge in the number of studies conducted. In recent years, the number of studies has dramatically increased. As depicted in Figure 4, there is a clear trend in publication distribution. Notably, in the past three years, publications on DT in civil infrastructure have increased by more than four times, emphasizing the rising interest and immense potential of DT in intelligent infrastructure management. Figure 5a highlights that most publications on DT in civil infrastructure are within the fields of engineering and computer science. This underscores the significance of machines and computer-aided tools in advancing smart engineering solutions. Meanwhile, Figure 5b categorizes academic publications on DT in civil infrastructure from January 2012 to May 2023 based on the type of document source. The data reveals that 53% of the publications from this study are journal articles, while 47% are from conference proceedings.

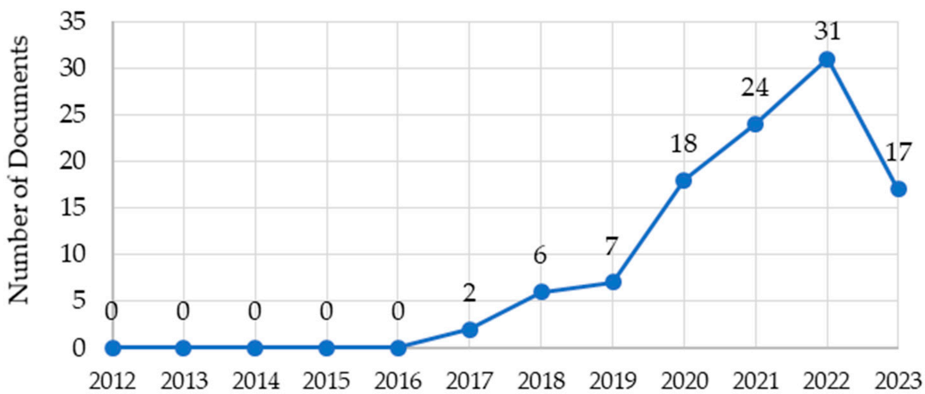

Figure 4. Number of documents published annually on DT in civil infrastructure (January 2012–May 2023).

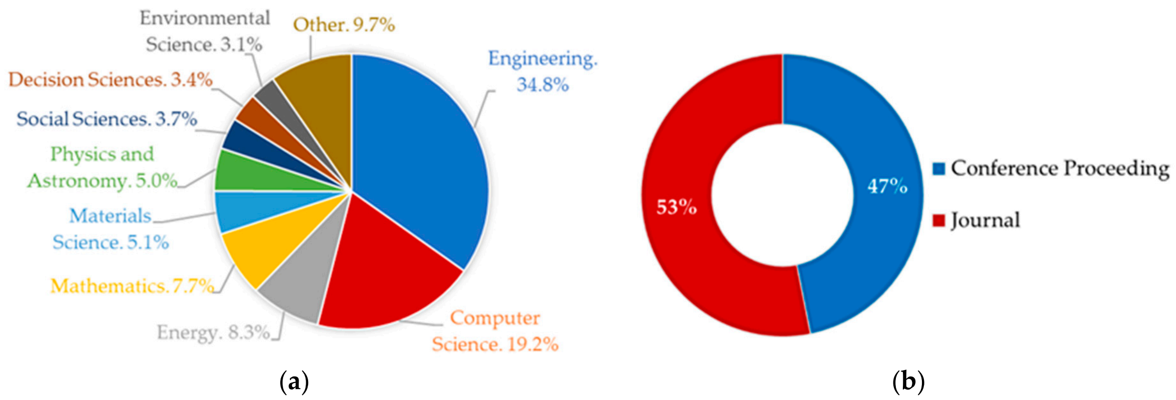

Figure 5. Distribution of publications on DT in civil infrastructure: (**a**) publications in various research fields; (**b**) document source type.

3. Findings

This section presents the findings from a thematic analysis of 12 literature review studies on DT application for civil infrastructure management, 13 data fusion studies and prominent DT frameworks from 44 studies. Microsoft Excel version 1808 was used for data structuring and summarization, and NVivo version 14.23.2 was used to code and classify the data. The approaches, findings, and challenges from all the identified studies were extracted and summarized in an Excel sheet. Then, the six-phased framework proposed by Braun and Clarke [37] was followed. The thematic analysis was performed as follows: (1) familiarization with the data was performed through critical reading and noting down initial themes, (2) the files were converted into text files and imported into NVivo for coding by collecting data relevant to each code, (3) the codes were collected into potential themes by gathering all the relevant data to a potential theme, (4) the themes were reviewed for accuracy, (5) themes were defined and named, and (6) the findings were plotted and described.

3.1. Literature Review Studies on DT for Infrastructure Management

Table A1, summarizes the research methodology, findings and challenges highlighted from 12 literature review studies about DT application for infrastructure management.

3.1.1. Literature Review Findings

Through the thematic analysis of the findings from the 12 studies focused on literature review and case studies in DT for civil infrastructure management, four primary themes emerged, which are shown in Figure 6, and briefly elaborated below.

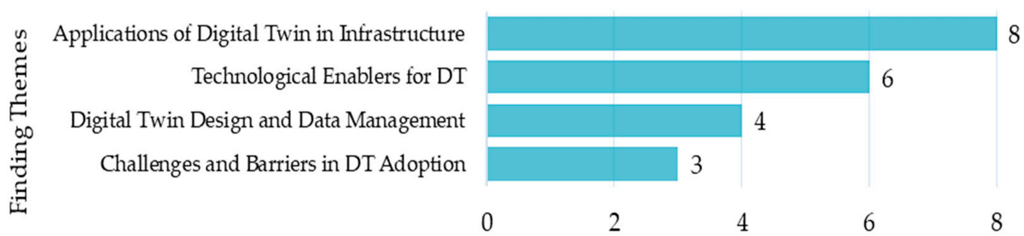

Figure 6. Occurrences of themes derived from analysis of the findings in 12 studies.

In the research of DT for civil infrastructure, several themes have emerged. Firstly, the applications of DT in infrastructure management have been explored in eight studies [20,21,32,33,41–44], which delve into its use in managing and optimizing various infrastructure systems, encompassing bridge monitoring, railway infrastructure management, emergency management, urban development, and smart city applications.

Secondly, the technological enablers for DT theme underscore the pivotal technologies that facilitate DT applications. This is evident in six studies [20–22,33,42,45] that discuss core technologies like BIM, IoT, UAVs, 3D surveying, AI, cloud storage, and computing. The third theme, DT design and data management, emphasized by four studies [44–47], highlights the foundational principles of DT design, data management, and system architecture considerations. These studies underscore the significance of a systems perspective, the distinction of DT from other technologies, and the pressing need for standardized interoperability solutions. Lastly, the challenges and barriers in DT adoption' theme brings to light the hurdles encountered in DT adoption, spanning technological to cultural challenges. Studies [44–46] pinpoint various challenges in assimilating DT into existing practices and systems, from the lack of standard definitions to cultural impediments and skill deficiencies.

3.1.2. Literature Review Challenges

To provide a holistic understanding of the challenges facing DT deployment, the challenges related to DT application for smart infrastructure management were extracted from the 12 studies that were focused on literature reviews and case studies. Thematic analysis was performed to identify core themes and patterns among extracted challenges. The results yield four main themes shown in Figure 7. The findings from the thematic analysis are as follows:

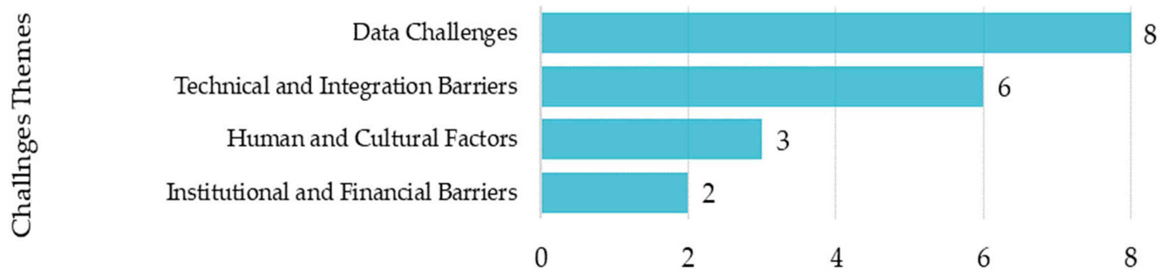

Figure 7. The occurrences of themes derived from analysis of challenges in 12 studies.

Data challenges are emphasized in eight out of 12 studies [20,22,32,41–45], highlighting the crucial role of data in the DT paradigm and the challenges in ensuring data security, integrity, and efficient management. Technical and integration barriers are discussed in six studies [21,33,41,42,44,45], underscoring the technical complexities that hinder DT implementation and the need for seamless systems and technology integration. Human and cultural factors are spotlighted in three studies [21,46,47], emphasizing the human-centric challenges and the importance of cultural acceptance in realizing the benefits of DT adoption. Additionally, institutional and financial barriers are addressed in two studies [21,42], pointing out the external challenges, including institutional and financial constraints, that impede the widespread adoption and implementation of DT.

3.2. Data Fusion

Data fusion plays a crucial role in decision-making, enhancing prediction and system optimization. Lee et al. [48] introduced a multi-sensor data fusion, utilizing a reconfigurable module with three fusion layers at data level, feature level, and decision level. The data layer refines the raw data, the feature layer configures a fusion tree, and the decision layer facilitates final decision-making using predetermined equations. Similarly, Hijji et al. [49] presented an intelligent hierarchical framework that utilizes 6G communication technologies, DL techniques, and mobile edge AI training. The proposed framework uses data level fusion and utilizes the convolution neural network (CNN) model that fuses imagery and sensory data to detect potholes. Alternatively, Wei et al. [23] introduced a decision-level data fusion model framework to improve prediction performance in quality control and predictive maintenance. The proposed framework transforms low-dimensional decisions from individual sensor data like temperature and vibration into high-dimensional ones, formulating the integration as a convex optimization problem. The approach is demonstrated in two cases: (1) quality control in additive manufacturing, where it predicts surface roughness, and (2) predictive maintenance in aircraft engines, where it estimates remaining useful life.

Wei et al. [23] emphasize that while decision-making is supported by traditional data analytics methods utilizing a single data source, accuracy is optimized by data fusion through the integration of multiple sources. Data fusion, integrating information from heterogeneous sources and multiple sensors, provides a more thorough representation of measurements and enhances prediction performance [24,25]. A significant gap exists in current predictive maintenance practices due to the dependence on single-source data as opposed to heterogeneous data, impacting data accuracy, reliability, adaptability, and the overall efficacy of engineering decision-making. The transformation of low-dimensional decisions from individual sensors into high-dimensional ones is necessitated for decision optimization through data fusion.

To provide a holistic understanding of data fusion for smart decision-making and to answer RQ1, this paper summarized the methodology, applications, and challenges of 13 academic publications on data fusion and integration for smart decision-making, as shown in Table A2. Additionally, a qualitative thematic analysis was performed to underscore the prominent themes in the data fusion methods, applications, and challenges.

The thematic analysis of the 13 data fusion and integration topics emphasized data fusion and collaboration, technological connectivity and integration and semantic understanding and ontology. To provide a more thorough evaluation of the studies, their methods, applications, and challenges are presented in the following sections.

3.2.1. Methods and Approaches of Analyzed Data Fusion/Integration Studies

The thematic analysis of the methodologies from the 13 studies that are focused on data fusion and data integration reveals four major themes that are shown in Figure 8, and briefly elaborated as follows:

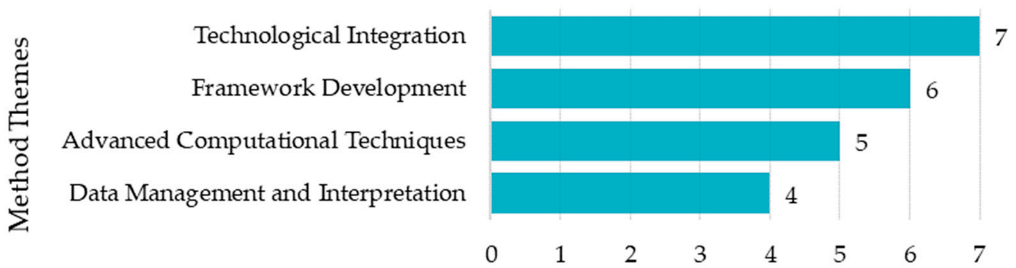

Figure 8. Occurrences of themes derived from methodologies in 13 data integration studies.

Technological integration, the most significant theme with seven occurrences, underscores methodologies that focus on integrating various technologies, such as BIM and IoT, or BIM and GIS. This theme also emphasizes data fusion techniques vital for extracting insights from heterogeneous data sources. With six occurrences, framework development highlights the complexity of civil infrastructures, which require various data sources for holistic decision-making. Due to heterogeneous data sources for various infrastructure assets, data fusion becomes challenging, emphasizing the creation of new computational or technological frameworks for specific applications. Advanced computational techniques, with five occurrences, underscores methodologies that utilize AI tools, such as ML and DL, to reduce computational complexity. Lastly, data management and interpretation, with four occurrences, focuses on methodologies that handle processing and managing data, including ontology-based methods, semantic integration, and risk assessment.

3.2.2. Applications of Analyzed Data Fusion/Integration Studies

The thematic analysis of the applications from the 13 studies that are focused on data fusion and data integration reveals four major themes that are shown in Figure 9, and briefly discussed as follows:

Figure 9. Occurrences of themes derived from applications in 13 data integration studies.

Infrastructure monitoring and management is the most prominent theme, with seven occurrences, emphasizing data fusion applications that concentrate on real-time monitoring, maintenance, and management of infrastructure assets like roads, bridges, and buildings. Technological integration and visualization, with six occurrences, highlights the fusion of diverse technologies, particularly data collection tools such as IoT, coupled with visualization tools like DT models for infrastructure asset management. Data-driven decision-making, having five occurrences, focuses on data-centric applications that utilize big data for informed decision-making, encompassing predictive maintenance and addressing missing data. Lastly, risk evaluation and prevention, with four occurrences, underscores applications that evaluate risks in various scenarios aiming to prevent potential issues.

3.2.3. Challenges of Analyzed Data Fusion/Integration Studies

The thematic analysis of the challenges from the 13 studies that are focused on data fusion and data integration reveals five major themes and patterns that are depicted in Figure 10, and briefly discussed as follows:

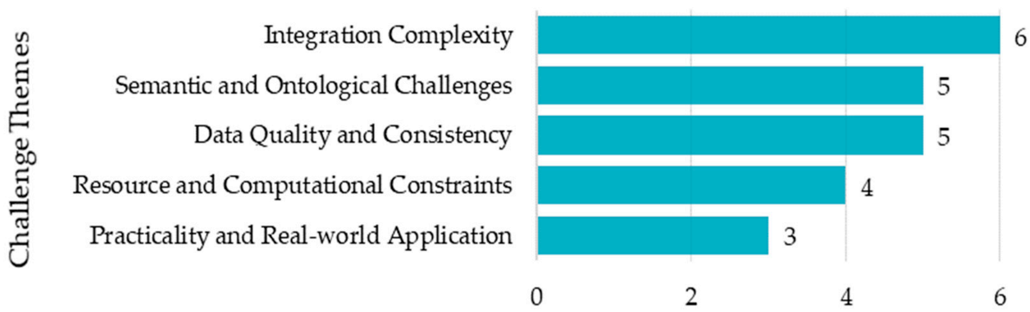

Figure 10. Occurrences of themes derived from analysis of challenges in 13 data integration studies.

Integration complexity was the most prominent theme with six occurrences, highlighting the challenges and complexities of integrating heterogeneous data sources, especially from different sensors, photogrammetry technologies, and conventional sources. Data quality and consistency, with five occurrences, discuss the challenges concerning the quality, consistency, and reliability of data used in the data fusion and integration process. Similarly, semantic, and ontological challenges, also with five occurrences, emphasize the difficulties in maintaining and interpreting the semantic features and structure of data to retain its profound meaning. Resource and computational constraints, with four occurrences, address the challenges tied to limited computational resources, particularly when managing big data, and the selection, implementation, and validation of appropriate algorithms. Lastly, practicality and real-world application, with three occurrences, discuss the disparity between theoretical knowledge and its real-world application, as well as the validation of actual data. This theme also points out the challenges of applying theoretical and conceptual knowledge in real-world scenarios, especially for data fusion-based DT applications in the infrastructure management domain.

The thematic analysis performed on challenges extracted from 13 data fusion and data integration studies revealed several themes and patterns. Integrating multisensory data due to source heterogeneity and ensuring seamless interoperability are recurring challenges. Furthermore, difficulties associated with data quality, missing data, and noisy data are significant. Moreover, challenges related to maintaining the semantic features of big data and the complexities of certain algorithms are evident. Big data is essential for smart infrastructure management and handling vast volumes and varieties of real-time data generated by users and devices is crucial; the concept of a DT for infrastructure is considered as an efficient way to organize and utilize this data [50]. Lastly, the practicality and real-world application of data fusion for smart infrastructure management and validation of actual data is challenging.

3.3. Digital Twin Frameworks

Researchers have been focused on DT for civil infrastructure management and studied digital twinning technologies, interoperability solutions, DT applications and challenges. Additionally, some of the studies proposed DT system architectures and frameworks for civil infrastructure management. To evaluate the capabilities of the current DT frameworks for civil infrastructure asset management, including their applications, technologies utilized, and challenges, to answer RQ2, this study performed a content analysis of 44 DT frameworks to extract their applications, core technologies and challenges. The applications, technologies utilized and challenges of implementing DT frameworks are outlined in Table A3.

The technologies are abbreviated in the table, and full forms of technologies not mentioned above in this paper are as follows: closed-circuit televisions (CCTVs), resource description framework (RDF), JavaScript object notation (JSON), extensible markup language (XML), extended process specification language (EXPRESS), and web ontology language (OWL) information and communications technology (ICT), you only look once (YOLO), deep simple online and real-time tracking (DeepSORT), light detection and ranging (LiDAR), extended reality (XR), Vuforia (an augmented reality software development kit), representational state transfer (REST), application programming interface (API), wireless sensor networks (WSNs), mixed reality (MR), construction operations building information exchange (COBie), sniffing omgewing/environmental tester (SNOET), non-destructive tests (NDTs), long-range wide area network (LoRaWAN), machine-to-machine (M2M), radio-frequency identification (RFID), weigh-in-motion (WIM), industrial internet of things (IIoT), semantic web (SWeb), Amazon web services (AWS), terrestrial laser scanning (TLS), mobile mapping system (MMS).

To draw holistic conclusions from the applications, technologies utilized, and challenges encountered in the prominent DT frameworks, a content and thematic analysis of each section is conducted, and the findings of each section are presented in the following sections.

3.3.1. Applications of Studied Digital Twin Frameworks

The thematic analysis of the applications from the 44 studies that presented DT framework for infrastructure management revealed six themes and patterns that are shown in Figure 11, and elaborated as follows:

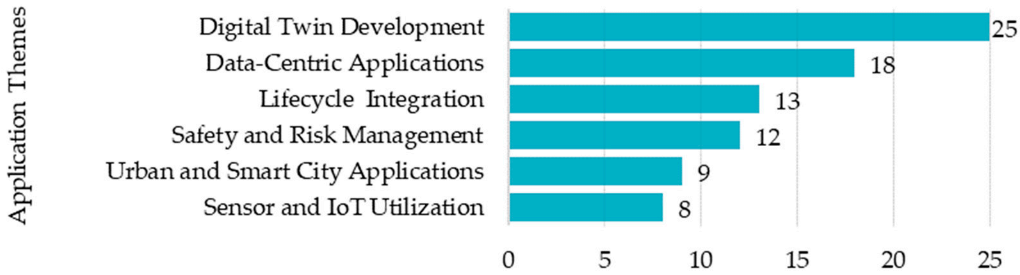

Figure 11. Occurrences of application themes derived from applications in 44 DT frameworks.

DT development emerged as the most prominent theme, with 25 studies emphasizing its applications in monitoring, optimization, and decision-making through digital twinning and comprehensive framework design. These studies underscored the development, implementation, and utilization of DT frameworks and models. Data-centric applications were also significant, with 18 studies discussing the role of real-time data acquisition, processing, and analysis in DT applications for real-time monitoring visualization, predictive maintenance, and smart decision-making. Lifecycle integration is crucial for smart infrastructure management, and 13 studies highlighted the importance of information continuity throughout the asset lifecycle and its integration with other systems for enhanced decision-making. Safety and risk management is paramount, especially since civil infrastructures are susceptible to natural disasters and uncertainties. Twelve studies emphasized the critical role of technology in ensuring infrastructure safety, managing risks, and addressing potential emergencies, particularly in infrastructure condition assessment and disaster management. Urban and smart city applications were spotlighted in nine studies, focusing on the application of DT in urban planning and the development and management of smart cities. Lastly, sensor and IoT utilization is fundamental in smart infrastructure management. Eight studies detailed the significant reliance of DT implementation on sensor technology and IoT for various DT applications.

3.3.2. Challenges of Studied Digital Twin Frameworks

The thematic analysis of the challenges encountered by 44 studies that proposed DT framework for civil infrastructure management yielded in eight themes that are depicted in Figure 12, and elaborated as follows:

Figure 12. Occurrences of challenge themes derived from challenges in 44 DT frameworks.

Data management and quality emerged as the most prominent theme, with 28 studies discussing challenges related to data collection, quality, and efficient management. The importance of accurate and high-quality data was a significant concern across most of these studies. Interoperability and system complexity was another major theme, with 22 out of 44 studies emphasizing the complexities of working with diverse systems and models, highlighting challenges in integrating different systems, working with complex models, and ensuring seamless interoperability. Technological limitations were cited in 20 studies, which pointed out challenges related to technologies, sensors, software, and platforms, mainly due to the limitations of current technologies in meeting the needs for full DT deployment for smart infrastructure management. Stakeholder and organizational challenges were also crucial, with 17 studies discussing the broader context of DT deployment, including challenges related to stakeholder collaboration, organizational structures, and socio-political dynamics. Environmental and external factors were highlighted by 15 studies, pointing out the uncertainties associated with civil infrastructures. These challenges are related to mapping accuracy, geospatial data, and other environmental factors that complicate DT deployment for smart civil infrastructure management. Knowledge and training were emphasized by 13 studies, noting the knowledge and skill gap as a significant factor complicating effective DT implementation in the civil infrastructure industry. The need for proper training, expertise, and efficient knowledge transfer is vital. Security and ethics were major concerns in 12 studies, underscoring challenges related to data privacy, security, and ethical considerations in the digital age. Lastly, business and value were discussed in seven studies, highlighting challenges related to cost, value, and return on investment, emphasizing the need for case studies evaluating the cost-benefit analysis of DT implementation for civil infrastructure management and proving its long-term impact and business value.

3.3.3. Core Technologies Utilized in the Studied DT Frameworks

The thematic analysis of the technologies utilized in the DT frameworks for infrastructure management revealed five themes that are depicted in Figure 13, and briefly discussed as follows:

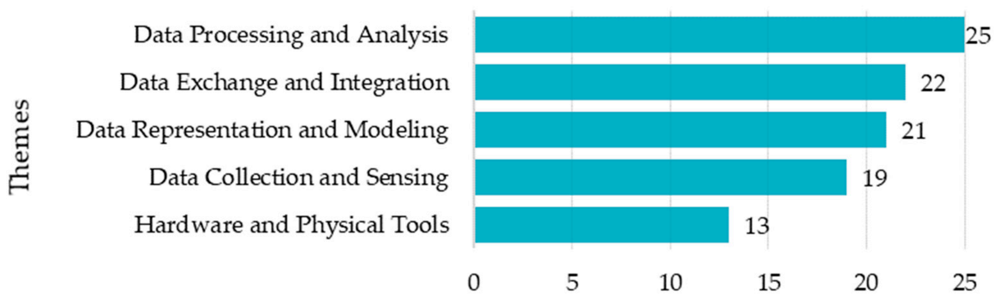

Figure 13. Occurrences of themes derived from technologies utilized in 44 DT frameworks.

Data processing and analysis was identified as the most prominent theme with 25 occurrences, emphasizing the crucial role of AI, ML, DL, cloud computing, edge computing, data mining, and pattern recognition in extracting insights from vast data collected from heterogenous sources. Following closely is the data exchange and integration theme with 22 occurrences, which emphasizes the importance of standards and formats like IFC, COBie, RDF, JSON, and XML schemas for ensuring smooth interoperability between various systems. The data representation and modeling theme, with 21 occurrences, underscores the significance of visualization and digital modeling technologies such as BIM, GIS, VR, AR, MR, and 3D models, making data more understandable and actionable, vital for DT implementation. Data collection and sensing, with 19 occurrences, stresses the essential role of reliable data-gathering tools like IoT, UAVs, cameras, LiDAR, and laser scanners in the DT paradigm. Lastly, the hardware and physical tools theme, with 13 occurrences, highlights the reliability and functionality of physical devices like Arduino, fiber optic sensors, laser rangefinders, and cameras. These devices must operate precisely to supply the DT with reliant data, and challenges like limited battery life and anomalous functionality can hinder successful DT implementation for smart civil infrastructure management.

The thematic analysis of the infrastructure management frameworks from the 44 studies revealed the application of advanced technologies across various stages. The most prominent technologies in various layers, including the data collection layer, data transfer layer, data processing and analysis layer, and data visualization layer, were extracted, and their significance was examined. DT is a data-driven approach and strongly relies on seamless data exchange. It is evident that there is a great need for seamless data integration that can be achieved through standardized data exchange tools throughout the asset lifecycle, from planning and construction to O&M.

3.4. Digital Twin Enabling Technologies

DT has five essential constituents: physical entity, virtual entity, connection, data, and service [51]. Lu et al. [52] presented a systems architecture for developing DT at the building and city level that included multiple layers of data acquisition, transmission, digital modeling, data/model integration, and service. It is essential to understand the required technologies that will be applied at each layer and provide the desired serviceability. Fuller et al. [16] performed a categorical review of DT literature in the research area of manufacturing, healthcare and smart cities and provided an evaluation of DT enabling technologies, challenges, and future research needs and stated that key enabler technologies for DT are AI, and industrial IoT. Madubuike et al. [13] provided a systematic review of research articles of DT application in construction and its comparison to other industries, it also provided a thematic analysis to address the aim of the study; the paper concludes that some smart technologies such as BIM, point cloud segmentation, AR, AI, ML, data analytics, and sensors are the key for feasible implementation of DT in the construction industry. Liu et al. [53] provided a comprehensive analysis of 240 academic documents about DT technologies and industrial applications and stated that DT concept includes: exact replica, high-fidelity, real-time and controllable. Similarly, Qi et al. [14] provided a review of DT enabling technologies and tools considering the five dimensions of physical, model, data, connections, and services and concluded that DT technologies are different for every industry and the users need to select their tools based on their specific field and scope.

To answer RQ3, the core technologies from the 44 DT framework studies were analyzed and the most prominent were identified. As mentioned above, Section 3.3.3 presents the core technologies utilized in the 44 DT frameworks and it also underscores some of the core DT enabling technologies. To further elaborate the most significant DT enabling technologies, Figure 14 highlights the most prominent technologies used in four stages of data collection, data processing, data exchange and data visualization. It is evident that DT applications for smart infrastructure management encompass a multi-faceted approach to data handling and representation. At the initial layer of data collection and sensing, the prominent technology utilized is IoT and sensors, with 27 occurrences. This is followed by UAVs/drones and cameras, with seven and five occurrences, respectively. AI technologies, including DL and ML, take the lead at the data processing and analysis layer with 18 occurrences. Cloud computing is also a significant player in this stage with seven occurrences, while structural health monitoring (SHM) using the finite element method (FEM) is noted two times. In the data exchange and integration layer, the IFC standard is the most prominent, with 10 occurrences. XML and WSNs both have three occurrences, and COBie is used in one study. Lastly, in the data representation and modeling layer, BIM stands out with 15 occurrences. The potential of BIM is evident and it can be employed throughout the asset lifecycle from the initial phase of construction to the O&M phase [54]. Three-dimensional models are also a key component, with eight occurrences, followed by AR/MR/VR and GIS, with five and three occurrences, respectively.

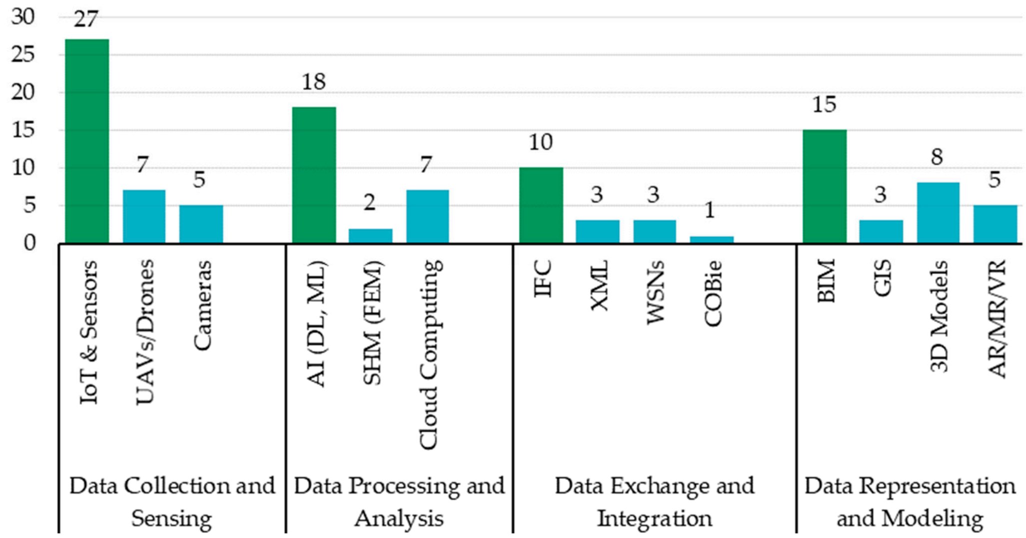

Figure 14. Occurrences of technologies at various stages of DT framework for civil infrastructure management. Extracted from 44 DT frameworks analyzed in this paper.

From the occurrences, we can see technologies like IoT, AI, IFC, and BIM are among the most frequently mentioned across the studies, indicating their prominence in DT applications for infrastructure management.

3.5. Data Exchange

In the DT paradigm for infrastructure management, the need for seamless data integration and exchange is evident. As presented in Sections 4.1.3 and 4.2, the most prominent technologies for data exchange and integration were found to be IFC, followed by XML, JSON, RDF, COBie, and WSNs. IFC offers an open, standardized data model adopted for the building and construction sector, ensuring interoperability across different software platforms. XML serves as a structured conduit for data exchange, bridging the gap between various information sources. JSON is recognized for its lightweight nature and is crucial for real-time data exchanges, especially in web-centric infrastructure management systems. RDF addresses semantic depth, enabling the intricate representation of relationships between different data entities, an essential feature for in-depth analytics and asset interactivity understanding. COBie facilitates the transition of project data, ensuring that infrastructure managers have immediate access to accurate asset details from various project stages. Meanwhile, WSNs play a vital role in real-time data collection and transmission, providing a seamless information flow from the physical infrastructure to its digital counterpart. Collectively, these technologies underscore the data exchange approaches in DT applications, facilitating a detailed and actionable digital replica of physical assets.

3.5.1. Industry Foundation Classes

As the findings in Section 3.4 show IFC is at the forefront of seamless data exchange and provides promising solutions for data interoperability; this study focusses on its development and needs.

IFC is evolving as a unified data model and exchange format for managing linear infrastructure data [55]. BuildingSMART indicates that the current IFC 4.3 standards support a range of infrastructures, including buildings, bridges, tunnels, railways, roads, ports, and waterways. Xia et al. [56] highlighted that the interoperability of BIM software is achieved through IFC, which provides details of building entities. However, while IFC is well-established in the building domain, it is less mature for other infrastructures [56,57]. Floros et al. [58] pinpoint two primary challenges in applying IFC to highway construction: its predominant focus on buildings with limited infrastructure support and its emphasis on the construction phase, indicating a shortage of classes for the O&M phase.

To address these gaps, several researchers have proposed extensions to the IFC standard. Extensions targeting road and highway construction and management have been suggested by multiple researchers, including [58–61]. A significant contribution from Floros et al. [58] was the IFC extension for highway asset management. This involved the conceptual mapping of the Asset Data Management Manuel (ADMM) using Unified Modeling Language (UML) diagrams, which were subsequently transformed into EXPRESS-G diagrams to align with IFC's structure. In a related effort, Ait-Lamallam et al. [60] proposed enhancing the IFC schema with semantics from the O&M phase of road infrastructures. This enhancement encompasses the addition of new object classes from the IFCInfra4OM ontology, the enrichment of existing IFC enumerations, and the establishment of relations between IFC and new classes. In the context of building management, Lu et al. [62] introduced a digital twin-supported anomaly detection system for asset monitoring, utilizing an extended IFC for daily O&M management. They adapted the IFC schema to include specific asset data, such as pumps (e.g., ifcpump), and employed ifcObject matching to link the BIM model of the pump with its corresponding sensor ID in the sensor system.

There is an eminent need for a unified standard because a significant challenge with data exchange is the loss of information during exchange from one standard to another. Floros and Ellul [63] emphasize that the loss of semantic information during the conversion process poses a significant challenge in highway construction data exchange. This is further complicated by issues like the conversion of curved surfaces, missing geometric features, and inaccurately geolocated geometries due to the utilization of local coordinate systems [64,65]. Additionally, Arroyo Ohori et al. [66] highlight topological challenges encountered during IFC to CityGML conversions, which are closely linked with geometric problems such as self-intersecting polygons and non-planar surfaces. Thus, there is need for a more robust IFC extension that includes classes for exchanging O&M data of civil infrastructure assets.

3.5.2. Industry Foundation Classes Status of Adoption

The adoption of the IFC in highway construction is gaining momentum among various entities. The American Association of State Highway and Transportation Officials (AASHTO) has recommended the adoption of the IFC Schema as the national standard for AASHTO States [67]. This move aims to coordinate schema development, identify gaps, resolve conflicts, and prevent duplication of efforts. Additionally, according to buildingSMART [68], other organizations such as State DOTs, the American Concrete Institute (ACI), and the American Institute of Steel Construction (AISC) embraced IFC-based information exchange.

On a more specific level, the Iowa Department of Transportation is leading research under the Transportation Pooled Fund Program (TPF-5(372)). This program is a collaboration of over 20 states, FHWA, and the AASHTO committee, which aims to establish a national standard. The research is focused on infrastructure structures, seeking to establish an open exchange of modeled bridge and structure data spanning the design, construction, and fabrication phases. A significant outcome of this pooled fund project is the creation of an IFC to construct a model view definition (MVD) for meeting one or more data exchange requirements.

3.5.3. Data Needs

Key components vital for IFC-based modeling are geometries, attributes, semantics, and relationships. The current IFC standard does not include all the required properties and relationships related to the O&M phase [60,69]. IFC lacks certain features for road construction compared to general buildings [56,57]. The O&M phase is still missing in the IFC schema and needs to be extended to support life cycle data, especially during the O&M phase of infrastructures.

To understand the necessity for the type of data that is needed during the O&M phase, it is essential to understand the specifics of data during the O&M phase. Patacas et al. [70] presented five key areas of deliverables vital for asset owners. These are legal aspects, including ownership and property boundaries; commercial data that include asset description, function, vendor data, and condition; financial data that encompass actual and replacement costs; technical specifics that underscore design parameters, asset dependencies, and commissioning dates and data; and managerial elements, including asset spatial data, warranties, and end-of-life data. In terms of the data requirements for various infrastructure assets, the needs for strategic decision-making can differ based on the purpose. However, the broader categories of data related to assets comprise physical attributes detailing asset semantics, material characteristics, and installation dates. The geographical location of the asset, its spatial connections to other assets, its maintenance history, and its condition data are also essential. Additionally, understanding an asset's remaining useful life is vital for predictive maintenance and budget allocation; similarly, financial data that provides insights into the costs incurred by the asset and projected future repair or renewal expenses, crucial for civil infrastructure asset management.

Some of the data types that are present in the IFC 4.3 schema for infrastructure asset management are annotations, geometrical properties, structural data, alignment, geotechnics, spatial data, utility networks, infrastructural relationships, earthworks, road signage, road features, rail power, rail signaling, rail track, rail telecoms, drainage and maritime elements [71,72]. However, it still lacks the necessary features to exchange the O&M-related data.

3.6. Challenges and Gaps

The challenges extracted from various DT studies that are focused on civil infrastructure management were summarized as keywords and fed into VOSviewer to identify co-occurrences; the threshold for keyword occurrences was set at three. A total of 20 of the 102 challenges met the criteria. The challenges that met this threshold were mapped in the keyword network and were visualized, as shown in Figure 15.

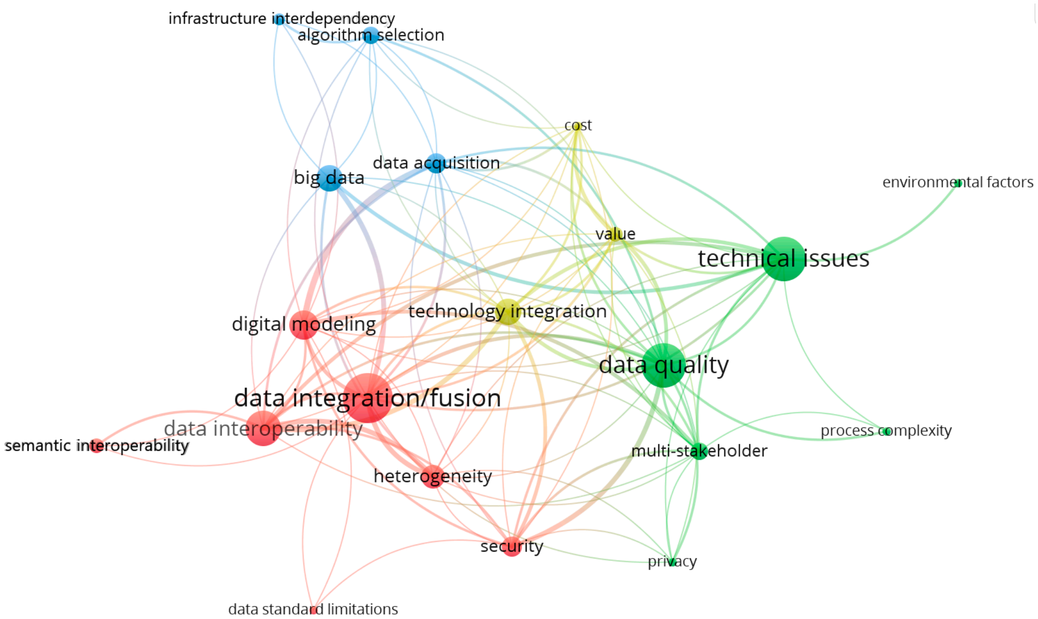

Figure 15. Network mapping of challenges and gaps in DT application for civil infrastructure management.

Each node represents one challenge and the color-coded node's size shows the challenge occurrences. The relatedness of a challenge to other challenge is indicated by the attributes of links, like total link strength. The strength of the link indicates the number of documents in which two challenges appear together. The distance between keywords reflects the level of relatedness between them. As shown in Table 1, the VOSviewer clustering technique was employed to group the challenges into four clusters: (1) data integration and security (red), (2) data quality and technical limitations (green), (3) data processing (blue), and (4) cost and value of technology (yellow). This finding indicates the most prominent challenges as data integration/fusion with 17 occurrences and 30 total link strength, data interoperability (12, 27), digital modeling (10, 26), data quality (15, 31), technical issues (15, 28), multi-stakeholder (6, 19), big data (9, 14), data acquisition (7, 22), algorithm selection (6, 11), technology integration (9, 27) and value (5, 20). The findings also suggest that semantic interoperability, technical issues, infrastructure interdependency, cost-benefit analysis and environmental factors are among the least focused-upon challenges and require further research to evaluate their holistic impact on smart civil infrastructure management. It is very interesting to see that data integration is very closely related to data interoperability and data heterogeneity; similarly, data quality suffers from technical issues with data acquisition tools.

Table 1. Most occurring challenges in DT application for civil infrastructure management.

Clusters and Their Challenges		Occurrences	Total Link Strength
Cluster 1: Data integration and security (red)			
1	Data integration/fusion	17	30
2	Data interoperability	12	27
3	Data standard limitations	3	3
4	Digital modeling	10	26
5	Heterogeneity	8	18
6	Security	7	21
7	Semantic interoperability	5	4
Cluster 2: Data quality and technical limitations (green)			
1	Data quality	15	31
2	Environmental factors	3	2
3	Multi-stakeholder	6	19
4	Privacy	3	8
5	Process complexity	3	4
6	Technical issues	15	28
Cluster 3: Data processing (Blue)			
1	Algorithm selection	6	11
2	Big data	9	14
3	Data acquisition	7	22
4	Infrastructure interdependency	4	5
Cluster 4: Cost and value of technology (yellow)			
1	Cost	3	16
2	Technology integration	9	27
3	Value	5	20

This paper extracted the most prominent challenges hindering the seamless deployment of DT for smart civil infrastructure management. To address some of the most significant challenges identified through the holistic analysis of the academic publications, this paper proposes a conceptual lifecycle encompassing DT framework for smart civil infrastructure management based on concepts of multi-layer data fusion, IFC extension, blockchain, stakeholder engagement, openBIM, and GIS integration, and multi-level checks for quality assurance.

In this study, several gaps are identified, such as the difficulty in integrating data due to data heterogeneity, seamless interoperability, difficulties associated with data quality, maintaining the semantic features of big data, technological limitations, and complexities with algorithm selection. However, a significant gap exists in current predictive maintenance practices for civil infrastructure management due to the dependence on single-source data as opposed to heterogeneous data, impacting data accuracy, reliability, adaptability, and the overall efficacy of engineering decision-making. The transformation of low-dimensional decisions from individual sensors into high-dimensional ones is necessitated for decision optimization through data fusion.

To propose a solution to some of the challenges identified in this study, this paper aims to establish a conceptual framework for harnessing DT technology with data fusion, to ensure the efficiency and resilience of civil infrastructures throughout their lifecycle. The proposed framework emphasizes multilayer data fusion, the integration of openBIM and GIS for immersive visualization and stakeholder engagement and adoption of extended IFC for data integration throughout the asset lifecycle.

4. A Conceptual Digital Twin Framework for Smart Civil Infrastructure Management

To answer RQ4, this section combines the needs for lifecycle management of civil infrastructure from the sections above and presents a comprehensive DT framework for smart civil infrastructure management. Asset management necessitates a framework that considers strategic plans and policies for future actions essential for maintaining asset functionality. This framework embodies an organization's grasp of concepts central to asset management [73]. An infrastructure network consists of numerous interdependent facilities, complicating intelligent decision-making [5]. For effective smart infrastructure management, integrating various infrastructure systems and leveraging data throughout the assets' entire life cycle is crucial [15]. This study introduces a framework for integrated smart infrastructure management, drawing from literature reviews, industry-proposed roadmaps, and asset lifecycle needs. It also highlights two primary components: (1) an interoperable digital twin modeling system architecture and (2) a lifecycle-focused smart infrastructure management framework based on data fusion, openBIM, and GIS integration.

4.1. Smart Infrastructure Management System Architecture

The integrated systems architecture, shown in Figure 16, consists of four layers: civil infrastructure network, including system breakdown and digital-physical components, interoperable data stream, services and goals, including performance measures, and stakeholders.

4.1.1. Civil Infrastructure Network

An infrastructure network is comprised of various interdependent systems and its functionality is impacted by the performance of each individual component in this network [5]. Civil infrastructure, including buildings, bridges, roads, pipelines, tunnels, and others are vital for the socioeconomic functionality of communities and are complex and critical to maintain [20]. Smart infrastructure management necessitates the integration of systems, facilities, and components [15]. Thus, the infrastructure network layer of system architecture for integrated smart infrastructure management integrates two components of the civil infrastructure system of systems and DT of facilities.

The civil infrastructure system of systems encompasses essential civil infrastructure systems like buildings, recreation places, utility systems, water and energy management, transportation, logistics, and other relevant infrastructures. These systems are simplified by categorizing them into facilities such as buildings, bridges, tunnels, ports, waterways, railways, and roads. On the other hand, the DT of facilities emphasizes the need for smart infrastructure management through digital transformation and the integration of real-time physical and digital systems. Given that most infrastructure lacks comprehensive digital models, there is a pressing need for digital transformation to create accurate models for effective monitoring and oversight. This process involves developing digital twins by breaking down infrastructure systems into sub-facilities and components.

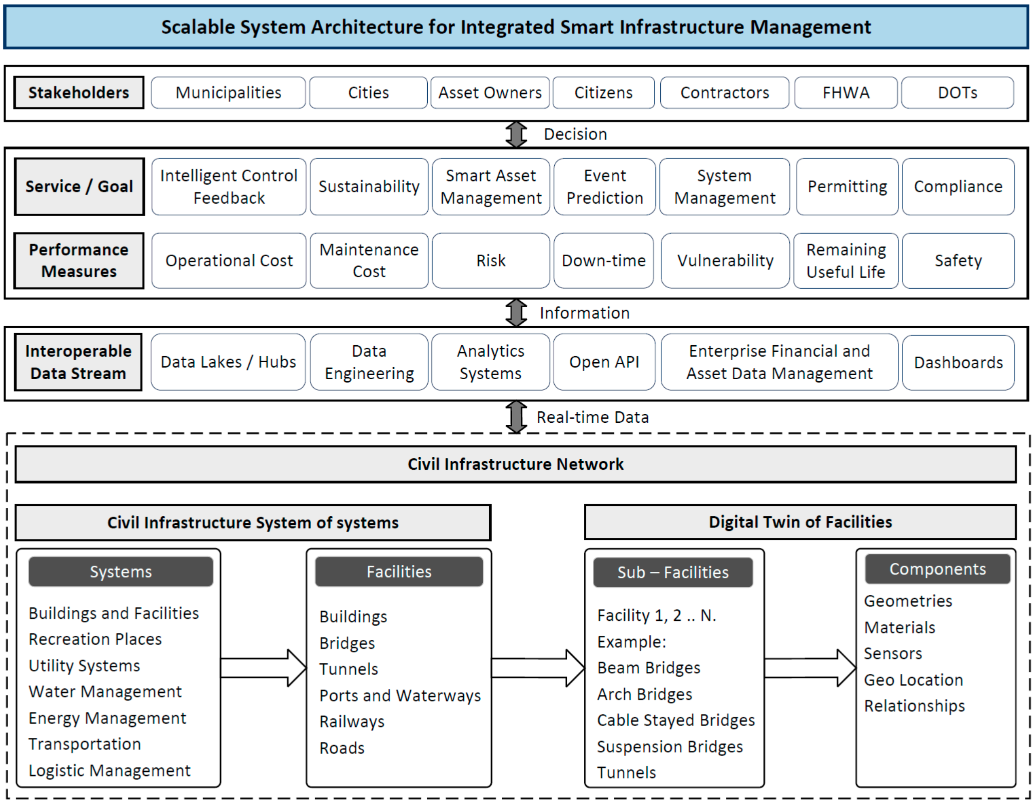

Figure 16. Systems architecture for scalable and integrated smart infrastructure management.

4.1.2. Interoperable Data Stream

Infrastructural asset operational and condition-related data are collected through expert inspections and continuous surveillance using IoT and photogrammetry tools [74]. The big data gathered in real-time is wirelessly transferred and stored in cloud-based data lakes and hubs. Furthermore, data is used as an engineering tool by utilizing AI tools such as ML and DL for analytics, enterprise financial data management, and asset data management and presented on dashboards for facility managers and stakeholders. The interoperable data stream layer facilitates data processing, normalization, fusion, AI-based analysis, and visualization for smart decision-making [15].

4.1.3. Service and Goal

In the smart infrastructure management system architecture, the service layer facilitates interaction between data, model and stakeholders, it also offers intelligent services and incorporates end-user feedback to boost performance [62]. In addition, performance indicators are also incorporated into the service layer as they are essential components of service delivery, the system architecture includes performance measures such as operational cost, maintenance cost, risk, down-time, vulnerability, remaining useful life and safety that are specified by stakeholders and incorporated into the decision-making process.

The service layer uses the information gathered from data processing for intelligent control feedback, smart asset management, event prediction, system management, permitting, and compliance checks. Furthermore, authorities and other stakeholders can use the service layer for resource allocation, remote monitoring, process optimization, automated municipal permitting, zoning, fire safety, and building code checks. Ultimately, DT helps stakeholders in achieving sustainable development and environmental protection goals.

4.1.4. Stakeholders

Smart asset management requires stakeholder involvement to ensure integrity, validity, and dynamic information exchange [75]. DT-managed projects require multiple stakeholder integration systems such as cities, municipalities, asset owners, citizens, contractors, the Federal Highway Administration (FHWA), and Departments of Transportation (DoT). Cities and municipalities manage a broad list of valuable public assets that are essential for economic functionality [6,76,77]. In addition, the FHWA oversees national highway policies and programs, and DoT manage and maintain transportation infrastructure within their respective states. Bringing authorities and citizens together will ensure better quality of life, inclusiveness, transparency, and sustainability [15].

4.2. Interoperable Digital Twin Modeling Systems Architecture

Civil infrastructure is deteriorating rapidly, necessitating intelligent monitoring and maintenance [78]. Considering the absence of comprehensive digital models in most infrastructures, it is crucial to undergo a digital transformation and develop accurate as-built models for effective monitoring and management [79]. To achieve smart infrastructure management, it is crucial to create effective systems architecture for digitizing assets and employing automated data analysis algorithms for automated decision-making. The interoperable digital twin modeling system architecture shown in Figure 17 presents the crucial steps needed to create compatible digital models during the planning phase and for existing assets (in the form of as-built models). The systems architecture is comprised of four main layers, (1) data management including standards, data encoding, data type, and data integration, (2) IFC extension including components and universal IFC extension, (3) digital modeling that includes data layers and parametric modeling, (4) standardization including IFC conversion and IFC check.

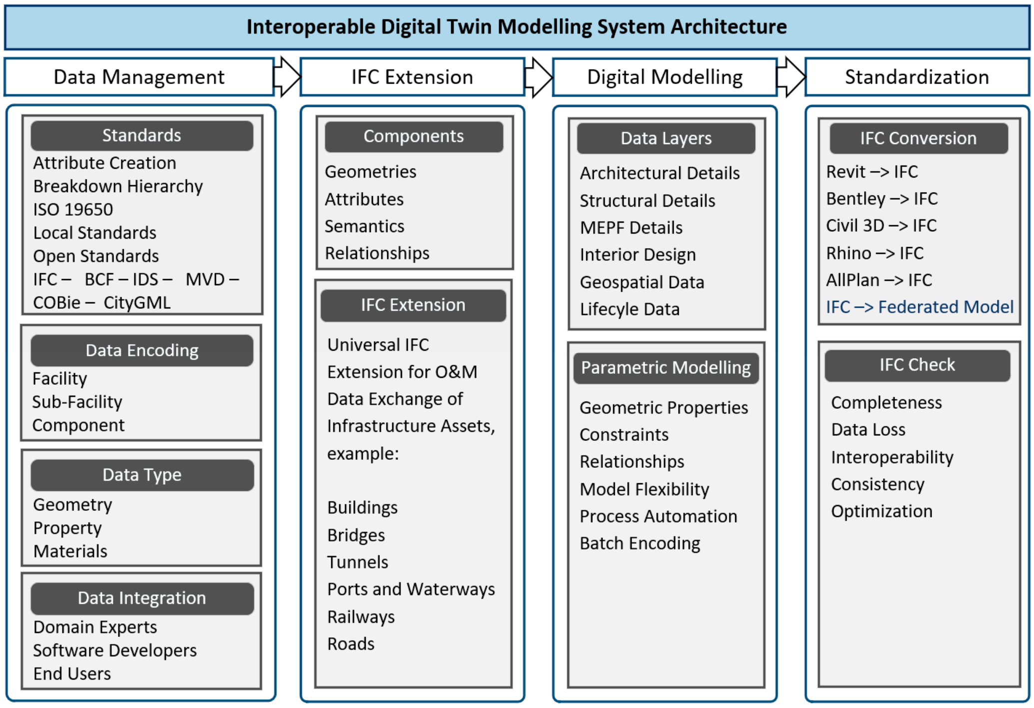

Figure 17. Systems architecture for interoperable digital twin modeling.

4.2.1. Data Management

Data is the most vital component in the DT paradigm; as data becomes integrated with DT it provides a chance to identify trends, assess interoperability, and comprehensively understand systems [80]. During the operation and maintenance phase of an asset, data management is a comprehensive tool that includes data acquisition, transfer, processing, and storage [81]. In the context of digital modeling, we only focus on the data necessary to create interoperable digital twins of assets. The data management layers include four components, namely: standards, data encoding, data type, and data integration.

At present, there is no specific standard that exclusively addresses the technical elements of digital twinning [82]. However, there are significant important international standards developed that guide the fundamentals of infrastructure asset management.

The International Organization for Standardization (ISO) is a non-governmental international standard development organization based in Geneva, Switzerland. ISO 55010 was published in 2019, including guidance on aligning financial and non-financial functions in asset management [77]. This new standard that integrates asset management finance and accounting activities can result in better controls, transparency, and improved measurement of performance indicators [77]. The ISO 19650 standard is a global guideline for handling information throughout the entire life cycle of a constructed asset using BIM [63]. Similarly, the Asset Management Landscape is a manual that is developed by the Global Forum on Maintenance and Asset Management (GFMAM). The Asset Management Landscape is "a framework that enables asset management knowledge and practices to be compared, contrasted, and aligned around a mutual understanding of the discipline of asset management" [83]. Similarly, the International Infrastructure Management Manual (IIMM) is one of the most widely used manuals in the world [77]. IIMM was published by Zealand Asset Management Support (NAMS) and is owned by the Institute of Public Works Engineering Australia (IPWEA). The fifth edition of the manual was published in 2015 and incorporates the ISO standards. The ISO standards provide insights on what to do and the IIMM manual provides guidance on how to do it [77].

Alternatively, a lot of efforts have been focused on developing open standards for information exchange throughout the asset life cycle. BuildingSMART manages the BIM Collaboration Format (BCF) that facilitates the communication of model-based issues between various BIM applications, using IFC models shared among project collaborators and Model View Definition (MVD) that represents a particular application level of IFC designed to enable a specific use or workflow. There are numerous other open standards that can be utilized for data exchange, such as Information Delivery Specification (IDS), COBie and CityGML, which is an open standardized data model and interchange format for storing digital 3D representations of cities and landscapes.

The systems architecture presented In this paper is focused on converting all the necessary complements of infrastructure assets into an IFC-based federated model to ensure seamless interoperability. Neves et al. [55] state that IFC is being developed as a single data model and a neutral exchange format to create, integrate, or merge and manage linear infrastructure data. BuildingSMART defines IFC as "a standardized, digital description of the built environment, including buildings and civil infrastructure. It is an open, international standard (ISO 16739-1:2018), meant to be vendor-neutral, or agnostic, and usable across a wide range of hardware devices, software platforms, and interfaces for many different use cases" [84]. IFC is widely embraced by governmental agencies and software vendors as a means of information exchange.

Data encoding is a crucial process in digital twinning, involving the conversion of data from diverse standards into an interoperable format for creating a digital replica of physical assets. This standardized data includes information from facility to component levels and enables real-time monitoring, predictive analysis, and control feedback. Data types play a pivotal role, particularly in 3D geometry, vital for digital twin applications in fields like architectural design and asset management [85]. These data encompass asset geometry, materials, and properties. Data integration becomes essential after standardization and data type identification, allowing domain experts, software developers, and end users to collaborate seamlessly on a common platform, ensuring interoperability and efficient utilization.

4.2.2. IFC Extension

Key components that are vital for IFC-based modeling are geometries, attributes, semantics and relationships. The current IFC standard does not include all the required properties and relationships related to the O&M phase [60,69]. IFC still lacks certain features and functionalities for road construction elements compared to buildings in general [56,57]. Floros et al. [58] highlight two key challenges in applying IFC to highway construction: its primary focus on buildings with limited infrastructure support, and its information exchange largely targeting the construction phase, thereby revealing a lack of classes for the O&M phase. According to buildingSMART the current IFC 4.3 standards include bridges, tunnels, ports and waterways, railways, and roads. However, the O&M phase is still missing and the IFC schema needs to be extended to support life cycle data. Thus, it is essential to create IFC extensions that will support information exchange during the O&M phase of infrastructural projects.

4.2.3. Digital Modeling

Digital models encompass all the important data related to assets, including architectural, structural, mechanical, electrical, plumbing, and fire protection details; they also include interior design, geospatial, and life cycle data. To combine all the data layers in one model, it is essential to perform parametric modeling that addresses geometric properties, constraints, relationships, model flexibility, process automation, and batch encoding for repetitive operations. Parametric modeling is vital for developing BIM models for the whole life cycle application and facilitates intelligent facility management [86].

4.2.4. Standardization

The last and especially crucial step in the systems architecture for creating interoperable digital twin models is the standardization and creation of an IFC-based federated model. All the individual models that might be generated in various platforms need to be converted into a single open data format of IFC, creating the federated data model that will ensure seamless interoperability and information flow throughout the asset lifecycle. By leveraging the federation approach, data can be reused within their specific domains, preserving the integrity of each data model. This methodology not only addresses the complexities of multiscale data but also promotes the generalization and repeatability of interconnected open data models. To validate the federated data modeling and to optimize the process, it is essential to perform automated IFC checks to ensure the completeness, consistency, and interoperability of the model and prevent data loss.

4.3. Smart and Scalable Civil Infrastructure Lifecycle Management Framework Based on Data Fusion and OpenBIM and GIS Integration

Traditional civil infrastructure asset management systems use standard classifications for managing assets and do not integrate information from all the phases of the asset lifecycle [9,11]. Asset management through the lifecycle requires digital continuity of the data along different phases of the facility, enabling predicting facility performance and making smart maintenance decisions [12]. Thus, there is an eminent need for modernization in asset management to achieve smart and resilient infrastructure systems. This paper outlines a robust framework, shown in Figure 18, for managing civil infrastructure that can be applied across the entire lifecycle of an asset, encompassing essential components from initial planning and design to construction, operation, and maintenance.

The proposed framework is adaptable and can be tailored to various kinds and sizes of infrastructure assets. It operates through a central data hub, which serves as the sole repository for information gathered from diverse databases, including BIM, IoT, and asset management databases. This data is then processed and analyzed using edge and cloud computing within the hub. Moreover, the framework allows for multi-level data fusion. At the data hub, data-level fusion integrates information from different sources for decision-making, while decision-level fusion at the data engineering layer amalgamates various decision outcomes for optimization purposes.

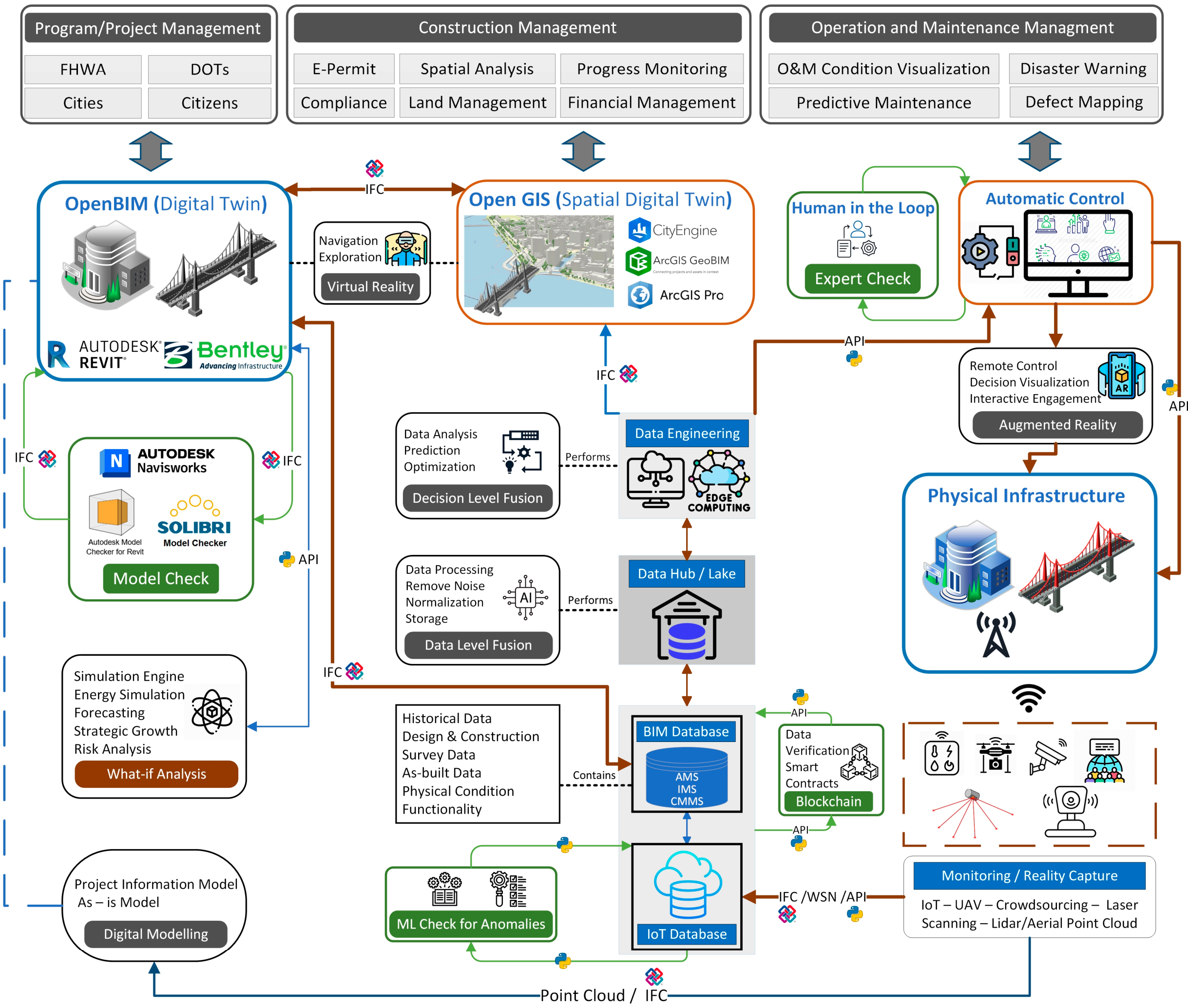

Figure 18. Digital twin-based smart civil infrastructure life cycle management framework.

The suggested framework is structured into several layers: a monitoring and reality capture layer; a layer containing BIM, IoT, and asset management databases; a data hub or data lake layer for data level fusion and a single source of fact; a data engineering layer for analysis and decision level fusion; a visualization layer that includes an automatic control dashboard and open GIS; and an openBIM layer. Alongside these layers, various checks and validations are carried out at different stages. For example, machine learning is used to detect anomalies in IoT data, model checks ensure the completeness of the openBIM model, blockchain technology safeguards data security and privacy, and expert checks are implemented to maintain human oversight and incorporate professional judgment in crucial decision-making processes. Additionally, a simulation engine is employed for forecasting and risk analysis through 'what-if' scenarios. Virtual reality (VR) is used for model navigation and exploration, while augmented reality (AR) facilitates decision visualization, interactive engagement, and remote control.

4.3.1. Monitoring and Reality Capture Layer

The first and most important constituent of DT is real-time data acquisition. IoT technologies, including sensors, video cameras, RFID devices, barcodes, and QR codes, enable the seamless gathering and perception of real-time information [14]. As the primary driving force behind DT, IoT connects the physical entity to data-sensing systems, allowing the DT to transform the collected data into optimized processes that yield tangible business results. This connection plays a crucial role in modern infrastructure management by enhancing efficiency and decision-making. Furthermore, IoT streamlines automation in data acquisition and integration, gathering real-time data from physical assets through sensors and sharing this substantial data with other systems via the Internet. This integration fosters a more responsive and adaptive approach to infrastructure management, aligning with the evolving needs of the industry.

In addition to IoT, there are various other technologies that play crucial roles in DT applications for smart infrastructure management both during operation and for the creation of as-built/as-is models. Data collection for the purpose of DT modeling and asset monitoring is facilitated through a range of tools, such as unmanned aerial vehicles (UAVs), point-cloud scanning, localized laser scanning, and photogrammetry tools [52]. Moreover, laser scanners and LiDAR are employed to acquire on-site point clouds for DT modeling [87]. During the O&M phase, image-based SHM can facilitate monitoring, measuring, automation and efficiency and fostering 3D modeling [88].

Another especially important source of information that also ensures citizen engagement is crowdsourcing. In the context of urban development and infrastructure management, crowdsourcing can be realized through citizen sensing. This innovative approach enlists city residents in the deployment of sensors and the collection of data, utilizing tools such as location-tracking apps, smart devices, and community projects. Additionally, the integration of maintenance QR codes, mobile phone applications, and GPS localization through end-user engagement enhances the stakeholder stratification, efficiency, and accuracy of asset management. Together, these technologies foster a more responsive and interconnected urban environment, leveraging the collective input of the community to drive informed decision-making and sustainable development. Real-time data acquisition and transmission is crucial for smart asset monitoring and reality capture of as-is condition assets.

4.3.2. Data Management Layer

The data collected through monitoring and reality capture tools is transferred wirelessly in real-time into a cloud-based IoT database. To ensure IoT data quality and accuracy, ML checks are performed on the IoT database to validate the acquired data and detect anomalies. The ML algorithms will be trained to cross-validate data from various sources of data collection tools and detect abnormalities in captured data. The IoT database is integrated with a cloud-based BIM database that includes information from the digital model and asset management activities. The BIM database contains historical data, design and construction data, as-built data, physical condition data and current functionality. Furthermore, to ensure data security and privacy, blockchain technology is used at the database level for data verification and privacy control. Blockchain has been proven to be an effective tool for wireless-based data transfer. In addition, as found by Sadri et al. [89], integrating blockchain and IoT networks facilitates decentralizing intelligence across the system and allows IoT data to be processed locally, which will eliminate single points of failure inherent in traditional systems. Liu et al. [90] states that blockchain is vital for securing various transactions, enhancing trust during digital transformation, and effectively handling human-related concerns like privacy in cooperative endeavors. Awan et al. [91] proposed the ZAIB (Zero-Trust and ABAC for IoT using Blockchain) framework to enhance security within the IoT domain. The presented approach works on a zero-trust model, verifying every device input or action, and utilizes attribute-based access control (ABAC) for fine-grained data access. ZAIB uses blockchain technology to ensure anonymous registrations and unalterable activity logs; furthermore, the InterPlanetary File System (IPFS) is used to protect all IoT-generated attributes and data. Additionally, the proposed framework also implements real-time monitoring and dynamic policy generation mechanisms that contribute to end-to-end security enforcement of data.

The information from BIM, IoT and asset management databases is integrated with the data hub which is the central database for the whole DT framework and all the asset-related information can be retrieved from the data hub. Additionally, AI tools are used to process data in the data hub for noise removal, normalization, and data level fusion.

4.3.3. Data Engineering Layer

At the data engineering layer, AI tools such as ML and DL are utilized to perform data analysis using cloud computing and edge computing. Infrastructure projects are complex and will require computation and analysis at segregated levels. Edge computing, by utilizing the DT and IoT paradigm, can provide accelerated predictive maintenance decisions by conducting predictive analytics near the data source, thereby accelerating analytics process and adding scalability to the system [92]. Edge computing in the domain of DT for infrastructure asset management enables real-time data analysis at or near the source of data generation; thus, facilitating immediate decision-making, such as detecting flaws, predictive maintenance and performance optimization. At the central database, decision-making will be made more robust by using decision-level fusion for event prediction and optimization purposes.

4.3.4. Visualization Layer

Analysis results from the data engineering layer will be displayed on user-friendly interfaces and dashboards. The crucial decisions made by the DT system will be integrated with human supervision to ensure humans are part of the process. Ibanez et al. [93] state that an innovative machine-learning model can handle around 80% of a given problem, while 19% of instances necessitate human intervention, and the residual 1% is random. Furthermore, Agnisarman et al. [94] proposed that automation-enabled infrastructure inspection systems should be viewed as socio-technical systems, involving both humans and technology, with human agents being integral to the system's architecture.

To better visualize and integrate the decision into real-world environment, AR is employed for decision visualization, interactive engagement and remote control; for instance, during emergency fire evacuation, AR could be used to show the optimal route and guide the occupant to safety; in addition, during the construction phase, AR helps track the progress in real-time by superimposing the virtual model that shows work completed in the real-world physical space [95,96].

4.3.5. OpenBIM Layer

BIM has been widely accepted as a virtual component of the DT system. The BIM model is the digital representation of a built object and includes information regarding its functional characteristics [45]. BIM models include semantically rich information regarding assets. BIM characterizes geometric information, spatial relationships, quantities, cost estimates, material inventories, and schedules; in addition, BIM facilitates visualization, fabrication/shop drawings, construction sequencing, conflict/collision detection, and forensic analysis [97].

The BIM modeling method in the proposed framework in this paper is based on openBIM technology that is modeled and stored in the cloud and can be accessed through web-based applications. Furthermore, the openBIM model is geolocated on the GIS map to create the open GIS digital twin that links the BIM model with spatial data. The information from openBIM is transferred to open GIS in real-time through IFC and any changes in the BIM model will be updated in the GIS model for visualization and information querying in a spatial context. As the model keeps updating in real-time and the latest information becomes integrated, model checks will be utilized to ensure BIM model accuracy and information completeness. Furthermore, VR is utilized at the openBIM layer to navigate the model and explore features. VR is an information and content-rich full digital representation of real world [98]. Moreover, simulation engines are utilized at the openBIM and open GIS layer to conduct what-if analysis for the purpose of forecasting, risk prediction, energy management and strategic planning.

4.3.6. Service Layer

The framework of DT for smart civil infrastructure management that integrates openBIM and GIS and employs multi-level data fusion across the whole lifecycle of the asset provides extensive serviceability. This framework will provide program and project management services to FHWA, DoTs, cities and citizens aiding with strategic planning and financial management by providing comprehensive information from the planning phase through construction and operation. During infrastructure construction, it enables automatic permitting, code compliance checks, spatial analysis, and progress monitoring. During the O&M phase, the framework will offer the functionalities of O&M condition visualization, predictive maintenance, disaster warning, defect mapping and condition rating.

5. Discussion

DT emphasizes the integration of physical and virtual entities, facilitating real-time data acquisition and integration. The evolution of Industry 4.0 technologies, including IoT, AI, cloud computing, and simulation tools, has further encouraged the development and application of DT. This paper highlights the transformative potential of DT in providing real-time monitoring and data-driven decision-making for civil infrastructure.

5.1. Current State of DT for Civil Infrastructure Management

5.1.1. The Need for Digital Transformation in Civil Infrastructure Management

Civil infrastructure systems, such as roads, buildings, and pipelines, are foundational to modern societies, ensuring essential services like transportation, shelter, and clean water. Smart management of these assets requires digital continuity of data across different phases for predictive asset performance and smart maintenance decisions. However, the current management systems, primarily CMMS and DSS, are heavily reliant on historical data and manual inputs. This reliance results in inefficiencies and inaccuracies, especially given the rapid deterioration of infrastructure assets. Thus, there is an urgent need for a digital transformation to ensure smart and resilient civil infrastructure.

5.1.2. Data Fusion and Integration

Data fusion plays a pivotal role in decision-making, prediction, and system optimization. Various studies emphasize the importance of multi-sensor data fusion, with layers focusing on refining raw data, configuring fusion trees, and facilitating decision-making. A significant gap exists in current predictive maintenance practices for civil infrastructure management due to the dependence on single-source data as opposed to heterogeneous data, impacting data accuracy, reliability, adaptability, and the overall efficacy of engineering decision-making. The transformation of low-dimensional decisions from individual sensors into high-dimensional ones is necessitated for decision optimization through data fusion. The thematic analysis reveals a significant emphasis on technological integration to derive insights from various data sources. Advanced computational techniques, such as ML and DL, are crucial for data integration and management. The applications of data fusion highlight its role in infrastructure monitoring, management, and visualization. However, challenges such as integrating multisensory data, maintaining data quality, and applying theoretical knowledge in real-world scenarios persist and need to be the focus of future research.

5.1.3. Potential Digital Twin Frameworks

Current civil infrastructure management systems face challenges related to data management, interoperability, and integration across asset lifecycle phases. This study analyzed 44 DT frameworks for civil infrastructure management and identified several themes and patterns. The most prominent theme was the digital twinning and framework design, emphasizing the development, implementation, and utilization of DT frameworks. Data-centric applications highlighted the importance of real-time data acquisition, processing, and analysis for monitoring, predictive maintenance, and decision-making. The significance of integrating information throughout the asset lifecycle for improved decision-making was evident. Lastly, the role of real-time sensing and data collection through sensor technologies and IoT was emphasized. In terms of challenges, data management and quality emerged as the most prominent themes, emphasizing the importance of accurate and high-quality data. Interoperability and system complexity were also highlighted, underscoring the challenges of integrating different systems and ensuring seamless interoperability. Technological limitations, stakeholder and organizational challenges, environmental factors, knowledge and training gaps, security and ethics, and business value were other challenges identified. Future research needs to focus on addressing these challenges for reliant DT framework development.

5.1.4. Core Digital Twin Technologies

In this study, five main themes related to the technologies utilized in DT frameworks were identified. Data processing and analysis were the most prominent, emphasizing the role of AI, ML, cloud computing, and pattern recognition. Data exchange and integration highlighted the importance of standards and formats for interoperability. Data representation and modeling emphasized visualization and digital modeling technologies like BIM, GIS, and 3D models. Data collection and sensing focused on real-time data-gathering tools like IoT, UAVs, and cameras. AR/VR were highlighted for their potential in visualizing, simulating, and interacting with infrastructure models in real-time. Lastly, the reliability and functionality of physical devices and tools for data collection and transfer were underscored.

5.1.5. Data Exchange Standards and Challenges

The DT paradigm for infrastructure management necessitates seamless data integration and exchange, with IFC emerging as a prominent technology. IFC offers a standardized data model for the building and construction sector but requires further development for broader infrastructure applications. Challenges in data exchange include the loss of information during transitions between standards. The adoption of IFC in highway construction is growing, but there is a need for a unified standard that encompasses all phases of infrastructure management, especially the O&M phase.

To sum up, this study comprehensively analyzes DT frameworks for civil infrastructure management, highlighting the applications, challenges, and core technologies utilized. Moreover, the emphasis on digital twinning and framework design underscores the growing importance of DT in infrastructure management. Furthermore, the challenges identified, particularly data management and interoperability, highlight areas that need further research and development. The prominence of technologies like IoT, AI, BIM, and AR/VR indicates their critical role in the future of civil infrastructure management. Moreover, this study highlights the multi-faceted approach required for effective DT implementation, emphasizing the need for seamless data integration, real-time monitoring, and advanced technological solutions. Also, the analysis underscores the significance of data fusion and integration in digital twin data integration. It is essential to focus on technological integration, advanced computational techniques, and the challenges faced in real-world applications. The role of IFC in data exchange is evident, but its comprehensive application across all infrastructure phases requires further development and standardization.

5.2. Conceptual Digital Twin Framework for Smart Civil Infrastructure Management

To address some of the identified challenges of managing the lifecycle of civil infrastructure, which is becoming increasingly complex due to the vast interdependencies of various facilities, this paper proposes a novel DT framework for integrated smart infrastructure management. This framework integrates advanced technologies like openBIM, GIS, and blockchain to ensure seamless data integration, multi-level data fusion, and robust data security. The proposed framework aims to provide a scalable and integrated approach to smart infrastructure management throughout the asset's lifecycle.

This paper Introduces a comprehensive system architecture for integrated smart infrastructure management. This architecture is derived from a holistic review of existing literature, industry roadmaps, and asset lifecycle management needs. Two primary components are highlighted: the interoperable digital twin modeling system architecture and the lifecycle encompassing smart infrastructure management framework based on data fusion and the integration of openBIM and GIS.

The integrated systems architecture is divided into four layers: civil infrastructure network, interoperable data stream, services and goals, and stakeholders. Each layer plays a crucial role in the overall framework. The civil infrastructure network emphasizes the interdependence of various systems, highlighting the importance of integrating these systems for smart decision-making. The interoperable data stream layer focuses on the collection, storage, and analysis of data using advanced tools like IoT and AI. The service and goal layer is crucial for interaction between data, models, and stakeholders, ensuring that performance measures align with stakeholder specifications. Lastly, the stakeholder layer emphasizes the importance of involving various stakeholders, from cities and municipalities to federal agencies, in the asset management process. Furthermore, this study presents the essentials of interoperable digital twin modeling system architecture. It underscores the urgency of digital transformation in the realm of civil infrastructure, given the rapid deterioration of these assets. The architecture is divided into four main layers: data management, IFC extension, digital modeling, and standardization. Each layer plays an essential role in ensuring the creation of accurate digital models of infrastructure assets, which are essential for effective monitoring and management.

Lastly, this study introduces a robust framework for managing civil infrastructure throughout its lifecycle. This framework is adaptable and integrates data from various sources, including BIM, IoT, and asset management databases. The framework operates through a central data hub, facilitating multi-level data fusion. The framework is structured into several layers, including monitoring and reality capture, data management, data engineering, visualization, and openBIM. Each layer plays a specific role, from real-time data acquisition to visualization and decision-making.

This paper presents a comprehensive and scalable framework for smart civil infrastructure management using a digital twin paradigm. The proposed framework integrates various technologies, including IoT, AI, BIM, and GIS, to provide a data-driven solution for asset management throughout its lifecycle. The emphasis on stakeholder involvement, data fusion, and real-time monitoring underscores the importance of a collaborative and data-driven approach to infrastructure management in the digital era.

6. Conclusions

The systematic review of 105 academic publications in this research provides a comprehensive insight into data fusion and DT frameworks, including their applications, enabling technologies, and the challenges they face in civil infrastructure management. This study highlights the crucial need for data fusion from heterogeneous sources for data-driven civil infrastructure management. Furthermore, it underscores the pivotal need for a digital transformation from traditional management systems, which rely heavily on historical data and manual processes, to more modern, efficient systems. These traditional systems are becoming increasingly inadequate in addressing the complexities of modern infrastructure challenges. The revolutionary potential of DT technology is profound, with its capabilities in real-time data acquisition, integration, and historical evolution. However, gaps such as data management issues, the lack of standardization, interoperability challenges, and technological limitations persist. Key technologies, including IoT, AI, BIM, AR/VR, openBIM, GIS, and blockchain, are crucial enablers facilitating real-time data acquisition, predictive analysis, immersive visualization, and robust security. This paper provides a conceptual framework for harnessing DT technology and its crucial role for smart civil infrastructure management; the proposed framework aims to increase data accuracy, reliability, adaptability, and further effectiveness of engineering decision-making while also underscoring the need for continuous evolution and addressing the existing challenges.

Author Contributions: Conceptualization, O.H. and H.L.; methodology, O.H. and H.L.; software, O.H.; validation, O.H., H.L. and O.A.; formal analysis, O.H.; investigation, O.H.; resources, O.H.; data curation, O.H.; writing—original draft preparation, O.H.; writing—review and editing, O.H., H.L., O.A., M.A., A.H. and A.A.; visualization, O.H.; supervision, H.L. and O.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Tables supplemental to the main text.

Table A1. Methods, findings and challenges of potential literature review studies.

Paper	Title	Methodology	Findings	Challenges
[20]	Digital twin in civil infrastructure emergency management: A systematic review.	Systematic literature review of 174 papers on DT for emergency management of civil infrastructure EMCI.	DT in EMCI through four stages of lifecycle reinforcement, virtue planning, real-time assessment, collaboration. DT needs fast data collection through sensing tools, DT utilizes AI to predict disaster.	Semantic rich digital modeling, cybersecurity issues in DT development, data quality in DT models, prediction accuracy.
[21]	Bridge management through digital twin-based anomaly detection systems: A systematic review.	Systematic literature review of 76 papers on bridge management through DT-based anomaly detection	Classified findings within themes: dridge DTs, BrIM, FEM, BHM, AI, UAVs, satellite monitoring, and other DT-related technologies.	Software interoperability, anomaly-detection algorithms, DT integration, data quality, cost, limitations, institutional barriers, resistance to change.
[47]	Design and implementation of a smart infrastructure digital twin.	Literature review and case study	Emphasizes systems perspective and data management in digital twin design.	Multidisciplinary nature, lack of processes, systems perspective, non-technical considerations.
[45]	Digital twin and its implementations in the civil engineering sector.	Systematic literature review of 134 papers on DT in civil engineering sector	Clarifies DT concept, differentiates from BIM and CPS, and highlights challenges in DT creation using advanced 3D surveying technologies.	DT creation challenges, limitations in virtual parts creation due to data acquisition, processing, modeling methods, and tools.
[22]	Digital twinning of civil infrastructures: Current state of model architectures, interoperability solutions, and future prospects.	Systematic review of 85 papers, mixed qualitative and quantitative methods with content analysis	Highlights versatility of BIM and IoT for IDTs, need for complex architectures, edge-based solutions for simple IDTs, and standardization for interoperability.	Data security, lack of DT standard, data latency, user interface issues.
[46]	Digital twins in infrastructure: definitions, current practices, challenges and strategies.	Qualitative analysis, semi-structured interviews with experts	Discusses definitions, practices, challenges, strategies, and workforce related to digital twins in infrastructure.	Technology adoption, cultural acceptance, workforce skills, data challenges, human factors.
[41]	Review of digital twins for constructed facilities.	Systematic review of 53 papers with content analysis	Recommends DTs for decision-making in construction, operation, and asset management; identifies nine DT application areas in construction.	Data integrity, interoperability, absence of robust models, data inaccessibility, data acquisition and heterogeneity.

Table A1. *Cont.*

Paper	Title	Methodology	Findings	Challenges
[42]	Smart infrastructure: A vision for the role of the civil engineering profession in smart cities.	State-of-the-art comprehensive review of smart technologies in civil engineering	Emphasize potential of smart city programs and technologies like sensors, IoT, big data analytics; emphasize role of civil engineers in smart cities development.	Technical, financial, social constraints, data management, privacy concerns, appropriate technology use.
[33]	Digital systems in smart city and infrastructure: Digital as a service.	Comprehensive review and conceptual paper on digital systems in smart cities with a focus on Digital as a Service (DaaS)	Discusses digitalization's potential in smart infrastructure and cities, introduces DaaS concept, and predicts next Industrial Revolution based on AI, IoT, cloud, and more.	Smart city implementation challenges, technical interoperability, system virtualization, cybersecurity, intellectual property protection.
[44]	The potential for digital twin applications in railway infrastructure management.	Review of DT applications in railway infrastructure with discussions with engineers	Highlights benefits of digital twins in railway infrastructure management, data processing, and slow adoption in the railway sector.	Information integration, maintenance paradigm validation, processing large sensor data volumes.
[32]	Developing human-centered urban digital twins for community infrastructure resilience: A research agenda.	Scoping review of 91 papers on human-centered urban DTs with a four-stage analysis	UDTs offer 3D visualization, augmented reality, and prediction for urban transformation with emphasis on simulation.	Varying UDT definitions, managing geospatial data, integrating diverse datasets.
[43]	Digital twins in asset management: Potential application use cases in rail and road infrastructures.	Review and case study on feedback from train sensors on rail track and track sensor data for speed adjustment	Discusses DT technology and signaling simulation center for the Singapore Downtown line by Siemens Mobility.	Faults in switches/crossings, track defects, stiffness in track foundation, operational risks, processing large sensor data volumes.

Table A2. Methods, applications, and challenges from 13 data fusion and integration studies.

Paper	Title	Methodology	Applications	Challenges
[49]	6G connected vehicle framework to support intelligent road maintenance	DL for pothole detection using imagery and sensory data fusion. Cost-effective data collection and intelligent hierarchical framework.	Real-time pothole notifications, route optimization, and legal claim support for insurance.	Inconsistent road inspections, input signal limitations, and privacy concerns in analytics.
[99]	Collaborative fault diagnosis using multisensory fusion with stacked wavelet auto-encoder and flexible weighted assignment of fusion strategies.	Multi-sensor fusion for fault diagnosis using stacked wavelet auto-encoder and enhanced voting fusion.	Risk assessment for planetary gearboxes in industrial equipment.	Multisensory data integration, fusion of maintenance strategies, and reliance on subjective information.
[100]	A unified ontology-based data integration approach for the internet of things.	Semantic integration for heterogeneous data modeling. Unified ontology schema and data unification layer.	Smart homes, healthcare, industry, security, smart grids, and future transportation systems.	Heterogeneity in real-time apps and IoT device resource limitations.
[24]	Application of data fusion via canonical polyadic decomposition in risk assessment of musculoskeletal disorders in construction: procedure and stability evaluation.	Data fusion using canonical polyadic decomposition for risk assessment. Comparison of results from different datasets.	Risk assessment for musculoskeletal disorders in roofing workers. Handling missing data across fields.	Handling missing data, dynamic motion effects, and obstructions in motion-capture.
[101]	BIM-based infrastructure asset management using semantic web technologies and knowledge graphs.	BIM infrastructure integration. Cross-domain container and extendable system architecture.	Concrete bridge inspection and road pavement maintenance decision-making.	Accelerated asset deterioration due to global change and gap in BIM optimal usage.

Table A2. *Cont.*

Paper	Title	Methodology	Applications	Challenges
[25]	Data fusion and machine learning for industrial prognostics and health management: A review.	Data fusion and ML algorithms for data pre-processing, pattern recognition, feature engineering.	Infrastructure health monitoring and data handling from monitoring tech.	Increase in data volume, ML technique selection, and environmental data impact.
[74]	Data-driven predictive maintenance planning framework for MEP components based on BIM and IoT using machine learning algorithms.	BIM and IoT-based framework for FMM.	Predictive maintenance using BIM and IoT.	Algorithm selection, prediction methods, and model training.
[23]	Decision-level data fusion in quality control and predictive maintenance.	Computational framework for decision-level fusion.	QC in manufacturing and aircraft engine predictive maintenance.	Sensor selection, noisy data, and computational complexity.
[102]	Integrating heterogeneous stream and historical data sources using SQL.	Data integration framework using SQL queries.	Monitoring data from sensors, IoT, logs, social networks, etc.	Data volume, integration challenges, and querying heterogeneous data.
[63]	Loss of information during design and construction for highways asset management: A GeoBIM perspective.	BIM and GIS integration for highway asset management.	GeoBIM for highway asset management.	Interoperability, semantic information loss, geometry conversion.
[48]	Multi-sensor data fusion with a reconfigurable module and its application to unmanned storage boxes.	Computational complexity reduction via selective gate module coupling.	Monitoring of unmanned storage boxes.	Maintaining unique sensor data characteristics.
[103]	Ontology-based data integration and sharing for facility maintenance management.	Ontology-based approach for information interoperability in AEC/FM.	FMM with BIM and IoT.	Interoperability, semantic information loss, and ontology validation.
[104]	Toward smart-building digital twins: BIM and IoT data integration.	BIM-IoTDI framework for BIM and IoT data integration.	DT for real-time building monitoring and visualization.	Semantic interoperability and real-building data validation.

Table A3. Applications, technologies utilized and challenges of studied DT frameworks.

Paper	Title	Applications	Technologies Utilized	Challenges
[105]	A framework for simulating the suitability of data usage in designing smart city services.	Data usage simulation framework for smart city service design.	Sensors (CCTV, traffic, mobile, human)	Data detail identification, data collection limitations.
[106]	A framework utilizing modern data models with ifc for building automation system applications.	IFC integration with modern data models for building automation.	RDF, JSON, IFC	EXPRESS to OWL mapping, IFC schema/data issues.
[107]	A scalable cyber-physical system data acquisition framework for the smart built environment.	Data acquisition for smart built environments and IoT-enabled cities.	Cloud databases, XML, BIM, IoT, AI.	Data interoperability, underutilized data, connectivity/accessibility.
[15]	Framework for using data as an engineering tool for sustainable cyber-physical systems.	Sustainable cyber-physical systems framework for smart infrastructure.	AI (DL, ML), ICT, IoT	Stakeholder ambiguity, data source issues, purpose misalignment.

Table A3. *Cont.*

Paper	Title	Applications	Technologies Utilized	Challenges
[108]	An example of digital twins for bridge monitoring and maintenance.	DT-based bridge monitoring using UAVs, cameras and sensors.	UAVs, cameras, YOLO, DeepSORT, Sensors.	Vehicle detection and tracking, location conversion, real-time estimation.
[87]	A novel approach to construct digital twins for existing highways based solely on available map data.	Digital representation and twin for highway management.	Digimap topographies, Civil 3D, IFC	Map platform choice, data quality, data obstructions, approach limits.
[109]	Creation of a mock-up bridge digital twin by fusing intelligent transportation systems (ITS) data into bridge information model (BrIM).	DT of bridge with Weigh-in-motion data; safety and cost benefits.	Arduino, Bexel Manager, BrIM, IFC.	Arduino tech challenges, AECO interoperability, load cell sensitivity.
[110]	Data sharing framework for digital infrastructure management utilizing eo data.	Digital infrastructure management and disaster response.	ML, big data, remote-sensing, UAV, LiDAR	Disaster event challenges, infrastructure impact.
[111]	Developing a city-level digital twin—propositions and a case study.	Real-time traffic management and AI-based pattern identification.	AI, ML.	Non-technical factor understanding, socio-political causes, urban challenge
[112]	Developing a web-based BIM asset and facility management system of building digital twins.	For AECO/FM sectors; integrates building assets throughout lifecycle.	BIM, Unreal Engine, web real-time.	Barriers and inconsistency in data sharing, unreliable operation data.
[52]	Developing a digital twin at building and city levels: case study of west Cambridge campus.	Collaboration, visualization and O&M management of building and city.	AI, BIM, ICTs, cloud computing, IoT, IFC	Data integration and synchronization, big data management, data quality.
[113]	Digital twin as a service (DTaaS) in industry 4.0: An architecture reference model	DT for wetland maintenance and real-time monitoring.	IoT, AR, big data, XR, ML, Vuforia.	Integration, physical-digital-human interactions, value-cost trade-off.
[114]	Digital twin-driven intelligence disaster prevention and mitigation for infrastructure: advances, challenges, and opportunities.	DT and Intelligence disaster prevention/mitigation integration.	IoT, BIM, UAV, ML, DL, IFC.	Data development, real-time data, system-stage collaboration.
[47]	Design and implementation of a smart infrastructure digital twin.	Tools for structural behavior visualization on 3D bridge model.	Sensors, docker, REST interface, API	Multidisciplinary collaboration, digital twinning, non-technical issues.
[115]	Towards civil engineering 4.0: Concept, workflow and application of digital twins for existing infrastructure.	Framework for civil infrastructure predictive maintenance and analytics;	SHM, WSNs, ML, AI, API.	Data collection issues, software integration, DT application barriers.

Table A3. *Cont.*

Paper	Title	Applications	Technologies Utilized	Challenges
[116]	A digital twin uses classification system for urban planning and city infrastructure management.	Digital twin uses classification system framework; visualization and public consultation tools.	VR, AR, MR, AI, ML.	Framework diversity, DT knowledge transfer, machine-readability, automation challenges.
[117]	A digital twin-based decision analysis framework for operation and maintenance of tunnels.	Decision support for tunnel O&M.	COBie, IFC Semantic Web.	Twin data association, semantic association expression.
[118]	Operational modal analysis as a support for the development of digital twin models of bridges.	Digital twin model for bridge condition-based maintenance.	Dynamic tests, NDTs, finite element model.	Dynamic test accuracy, sensor layout instrumentation, synchronizing data.
[119]	Digital twinning approach for transportation infrastructure asset management using UAV data.	Infrastructure distress visualization and inspector comments.	UAVs, photogrammetry, 3D.	Platform limitations, aerial photogrammetry.
[120]	Digital twins for safe and efficient port infrastructure management.	Infrastructure management with digital twins and mixed reality.	UAVs, mixed reality, AI, ML.	Safety, data processing, data sharing, data quality, system integration.
[121]	Digital twin of road and bridge construction monitoring and maintenance.	Road and bridge management; multiple applications.	IoT, AI, big data, sensors, BIM, GIS.	Map availability, security system, dashboard speed.
[122]	Digital twinning of lap-based marathon infrastructure.	Real-time environmental monitoring for marathons.	SNOET, LoRaWAN, Hovermap LiDAR.	Electrical issues with SNOET.
[123]	Digital twin technology for bridge maintenance using 3D laser scanning: A review	Bridge management and 3D modeling based on digital twins.	Laser scanner, UAV, LiDAR, BIM, NDTs, IFC	Raw data transformation, information standardization.
[26]	Federated data modeling for built environment digital twins.	Real-time monitoring and data-driven decision tools for buildings.	IoT, robotics, AR, MR, VR, AI, BIM, IFC.	Information/process clarity, fragmented data, interoperability.
[124]	Framework of a smart local infrastructure management system.	Subway tunnel monitoring and disaster prevention.	M2M, Wi-Fi sensor network, RFID.	Sensor network implementation, data collection.
[125]	Identifying maturity dimensions for smart maintenance management of constructed assets: A multiple case study	Integration and digitalization in corporate facilities management.	Sensor tech, RFID, IoT.	Construction client and building operation function integration.
[126]	Infrastructure BIM platform for lifecycle management	Web-based BIM platform for infrastructure management.	BIM, AI, SHM, robots, UAVs, IFC.	Real-time data and data acquisition, time-series data processing.
[127]	Integrated management of bridge infrastructure through bridge digital twins: A preliminary case study.	Road and bridge lifecycle management; ITS and WIM systems.	BIM, WIM data integration.	Non-interoperable systems, integration, real-time communication.

Table A3. *Cont.*

Paper	Title	Applications	Technologies Utilized	Challenges
[128]	A digital twin of bridges for structural health monitoring.	Digital twin for bridge monitoring and real-time data management.	WSNs, IIoT, Gaussian process.	Large dataset handling, data querying, software interoperability.
[129]	Applications of machine learning and computer vision for smart infrastructure management in civil engineering.	Traffic and occupancy detection using sensors and machine learning.	ML, computer vision, neural Network.	Multi-channel information integration, model complexity.
[130]	Multi-domain ubiquitous digital twin model for information management of complex infrastructure systems.	Infrastructure real-time monitoring and dynamic control.	IoT, AI, VR, cloud computing.	Automatic control, stage communication, IoT data fusion.
[131]	Ontology-based modelling of lifecycle underground utility information to support operation and maintenance.	Underground utility data conversion and maintenance work.	GIS, BIM, AR and IoT, SWeb, Ontology, IFC.	Heterogeneous data, data exchange, data management, decision-making.
[132]	Open urban and forest datasets from a high-performance mobile mapping backpack—a contribution for advancing the creation of digital city twins.	Urban localization, 3D reconstruction and scene analysis.	BIMAGE backpack MMS, LiDAR.	Challenging environments, georeferencing methods, accuracy.
[133]	Participatory sensing and digital twin city: Updating virtual city models for enhanced risk-informed decision-making.	Monitoring city systems and risk-informed decision-making.	Participatory sensing, 3D city models, GIS.	Sensor-based information, geospatial localization.
[134]	A hybrid predictive maintenance approach for CNC machine tool driven by digital twin.	Predictive maintenance for CNC machine tools.	ML, dynamometer, Sensors.	CNC machine tool complexity, data acquisition, algorithm selection.
[43]	Digital twins in asset management: potential application use cases in rail and road infrastructures.	Train and track sensor feedback for rail safety.	Siemens Mobility signaling simulation.	Switch faults, track defects, operational risks, data processing.
[135]	Real-time participatory sensing-driven computational framework toward digital twin city modeling.	Real-time digital twin city modeling and infrastructure updates.	IoT, AWS cloud, mobile app.	Mapping accuracy, semantic segmentation enhancement.
[5]	Resource allocation framework for optimizing long-term infrastructure network resilience.	Resource allocation for infrastructure resilience.	Agent-based modeling, deep Q-learning.	Resilience considerations, infrastructure interdependencies.
[136]	Smart and automated infrastructure management: A deep learning approach for crack detection in bridge images.	Civil infrastructure monitoring and damage detection.	DL (YOLOv5), image processing.	Limited image dataset, crack recognition and dimensions.

Table A3. *Cont.*

Paper	Title	Applications	Technologies Utilized	Challenges
[137]	Smart infrastructure: A research Junction.	Road safety and training for automated driving systems.	Sensors, Detectron2, Triangulation.	Camera calibration, perception models, seasonal conditions.
[138]	Technological infrastructure management models and methods based on digital twins	Maintenance cost minimization and grid safety improvement.	DT, ontological model.	DT creation for large-scale infrastructure, multi-step processes.
[139]	Integration of TLS-derived bridge information modeling (BrIM) with a decision support system (DSS) for digital twinning and asset management of bridge infrastructures.	Bridge management, terrestrial laser scanning application and DSS integration.	TLS, BrIM, DSS, Ms. Visual Studio, Tekla Open API.	Inspection subjectivity, management decision reliability, environmental aggression.
[140]	Towards a hybrid twin for infrastructure asset management: Investigation on power transformer asset maintenance management.	Grid asset management and real-time operational decisions.	Physics-based models, hybrid-twin model.	Model explanation, prediction certification, extrapolation issues.
[74]	Data-driven predictive maintenance planning framework for MEP components based on BIM and IoT using machine learning algorithms.	BIM and IoT-based framework for FMM.	BIM, IoT, ML.	Algorithm selection, prediction methods, model training.

References

1. Osman, H. Agent-based simulation of urban infrastructure asset management activities. *Autom. Constr.* **2012**, *28*, 45–57. [CrossRef]
2. Zavadskas, E.K.; Turskis, Z.; Šliogerienė, J.; Vilutienė, T. An integrated assessment of the municipal buildings' use including sustainability criteria. *Sustain. Cities Soc.* **2021**, *67*, 102708. [CrossRef]
3. Abu-Samra, S.; Ahmed, M.; Amador, L. Asset management framework for integrated municipal infrastructure. *J. Infrastruct. Syst.* **2020**, *26*, 04020039. [CrossRef]
4. Chyad, A.M.; Abudayyeh, O.; Zakhil, F.; Hakimi, O. Deterioration Rates of Concrete Bridge Decks in Several Climatic Regions. In Proceedings of the IEEE International Conference on Electro Information Technology, Rochester, MI, USA, 3–5 May 2018; pp. 65–68. [CrossRef]
5. Sun, J.; Han, Z.; Zhang, Z. Resource allocation framework for optimizing long-term infrastructure network resilience. *J. Infrastruct. Syst.* **2023**, *29*, 04022048. [CrossRef]
6. Al-Kasisbeh, M.R.; Abudayyeh, O. Municipality Asset Management: Asset Types and Effective Management Decision Using GIS. In Proceedings of the Construction Research Congress 2018, New Orleans, LA, USA, 2–4 April 2018; pp. 273–280.
7. Shahata, K.; El-Zahab, S.; Zayed, T.; Alfalah, G. Rehabilitation of municipal infrastructure using risk-based performance. *Autom. Constr.* **2022**, *140*, 104335. [CrossRef]
8. Dziedzic, R.; Amador, L.; An, C.; Chen, Z.; Eicker, U.; Hammad, A.; Nasiri, F.; Nik-Bakht, M.; Ouf, M.; Moselhi, O. A Framework for Asset Management Planning in Sustainable and Resilient Cities. In Proceedings of the IEEE International Symposium on Technology and Society (ISTAS), Waterloo, ON, Canada, 28–31 October 2021; IEEE: Piscataway, NJ, USA, 2021; Volume 5, pp. 1–10. [CrossRef]
9. Caldera, S.; Mostafa, S.; Desha, C.; Mohamed, S. Exploring the role of digital infrastructure asset management tools for resilient linear infrastructure outcomes in cities and towns: A Systematic literature review. *Sustainability* **2021**, *13*, 11965. [CrossRef]
10. Al-Kasasbeh, M.; Abudayyeh, O.; Liu, H. A unified work breakdown structure-based framework for building asset management. *J. Facil. Manag.* **2020**, *18*, 437–450. [CrossRef]
11. Al-Kasasbeh, M.; Abudayyeh, O.; Liu, H. An integrated decision support system for building asset management based on BIM and work breakdown structure. *J. Build. Eng.* **2021**, *34*, 101959. [CrossRef]
12. Macchi, M.; Roda, I.; Negri, E.; Fumagalli, L. *Exploring the Role of Digital Twin for Asset Lifecycle Management*; International Federation of Automatic Control (IFAC); Elsevier: Amsterdam, The Netherlands, 2018; Volume 51, pp. 790–795.
13. Madubuike, O.C.; Anumba, C.J.; Khallaf, R. A review of digital twin applications in construction. *J. Inf. Technol. Constr.* **2022**, *27*, 145–172. [CrossRef]

14. Qi, Q.; Tao, F.; Hu, T.; Anwer, N.; Liu, A.; Wei, Y.; Wang, L.; Nee, A.Y.C. Enabling technologies and tools for digital twin. *J. Manuf. Syst.* **2021**, *58*, 3–21. [CrossRef]
15. Broo, D.G.; Schooling, J. A framework for using data as an engineering tool for sustainable cyber-physical systems. *IEEE Access* **2021**, *9*, 22876–22882. [CrossRef]
16. Fuller, A.; Fan, Z.; Day, C.; Barlow, C. Digital Twin: Enabling technologies, challenges and open research. *IEEE Access* **2020**, *8*, 108952–108971. [CrossRef]
17. Deng, M.; Menassa, C.C.; Kamat, V.R. From BIM to Digital Twins: A systematic review of the evolution of intelligent building representations in the AEC-FM industry. *J. Inf. Technol. Constr.* **2021**, *26*, 58–83. [CrossRef]
18. Hakimi, O.; Liu, H.; Abudayyeh, O. Digital twin-enabled smart facility management: A bibliometric review. *Front. Eng. Manag.* **2023**, 1–18. [CrossRef]
19. Almatared, M.; Liu, H.; Tang, S.; Sulaiman, M.; Lei, Z.; Li, H.X. Digital Twin in the Architecture, Engineering, and Construction Industry: A Bibliometric Review. In Proceedings of the Construction Research Congress 2022, Arlington, VA, USA, 9–12 March 2022. [CrossRef]
20. Cheng, R.; Hou, L.; Xu, S. A review of digital twin applications in civil and infrastructure emergency management. *Buildings* **2023**, *13*, 1143. [CrossRef]
21. Jiménez Rios, A.; Plevris, V.; Nogal, M. Bridge management through digital twin-based anomaly detection systems: A systematic review. *Front. Built Environ.* **2023**, *9*, 1176621. [CrossRef]
22. Naderi, H.; Shojaei, A. digital twinning of civil infrastructures: Current state of model architectures, interoperability solutions, and future prospects. *Autom. Constr.* **2023**, *149*, 104785. [CrossRef]
23. Wei, Y.; Wu, D.; Terpenny, J. Decision-level data fusion in quality control and predictive maintenance. *IEEE Trans. Autom. Sci. Eng.* **2020**, *18*, 184–194. [CrossRef]
24. Dutta, A.; Breloff, S.P.; Dai, F.; Sinsel, E.W.; Warren, C.M.; Carey, R.E.; Wu, J.Z. Application of data fusion via canonical polyadic decomposition in risk assessment of musculoskeletal disorders in construction: Procedure and stability evaluation. *J. Constr. Eng. Manag.* **2021**, *147*, 04021083. [CrossRef]
25. Wang, H.; Barone, G.; Smith, A. Current and future role of data fusion and machine learning in infrastructure health monitoring. *Struct. Infrastruct. Eng.* **2023**, *17*, 11. [CrossRef]
26. Moretti, N.; Xie, X.; Garcia, J.M.; Chang, J.; Parlikad, A.K. Federated data modeling for built environment digital twins. *Comput. Civ. Eng.* **2023**, *37*, 04023013. [CrossRef]
27. Giannakos, M.N.; Mikalef, P.; Pappas, I.O. Systematic literature review of e-learning capabilities to enhance organizational learning. *Inf. Syst. Front.* **2022**, *24*, 619–635. [CrossRef] [PubMed]
28. Lee, I.; Mangalaraj, G. Big data analytics in supply chain decarbonisation: A Systematic literature review and future research directions. *Int. J. Prod. Res.* **2022**, 1–21. [CrossRef]
29. Ashraf, M.A.; Yang, M.; Zhang, Y.; Denden, M.; Tlili, A.; Liu, J.; Huang, R.; Burgos, D. A systematic review of systematic reviews on blended learning: Trends, gaps and future directions. *Psychol. Res. Behav. Manag.* **2021**, *14*, 1525–1541. [CrossRef]
30. Hung, W.; Dolmans, D.H.J.M.; van Merriënboer, J.J.G. A review to identify key perspectives in pbl meta-analyses and reviews: Trends, Gaps and future research directions. *Adv. Health Sci. Educ.* **2019**, *24*, 943–957. [CrossRef]
31. Zhao, J.; Feng, H.; Chen, Q.; de Soto, B.; Garcia de Soto, B. Developing a conceptual framework for the application of digital twin technologies to revamp building operation and maintenance processes. *J. Build. Eng.* **2022**, *49*, 104028. [CrossRef]
32. Ye, X.; Du, J.; Han, Y.; Newman, G.; Retchless, D.; Zou, L.; Ham, Y.; Cai, Z. Developing human-centered urban digital twins for community infrastructure resilience: A research agenda. *J. Plan. Lit.* **2022**, *38*, 187–199. [CrossRef]
33. Serrano, W. Digital systems in smart city and infrastructure: Digital as a service. *Smart Cities* **2018**, *1*, 134–154. [CrossRef]
34. Gupta, S.; Sharma, A.K. Evolution of infrastructure as an asset class: A systematic literature review and thematic analysis. *J. Asset Manag.* **2022**, *23*, 173–200. [CrossRef]
35. Castleberry, A.; Nolen, A. Thematic analysis of qualitative research data: Is it as easy as it sounds? *Curr. Pharm. Teach. Learn.* **2018**, *10*, 807–815. [CrossRef]
36. Maguire, M.; Delahunt, B. Doing a thematic analysis: A practical, step-by-step guide for learning and teaching scholars. *IEEE Trans. Ind. Appl.* **2017**, *3*, 3135–3140. [CrossRef]
37. Braun, V.; Clarke, V. Using thematic analysis in psychology. *Qual. Res. Psychol.* **2006**, *3*, 77–101. [CrossRef]
38. Dhakal, K. NVivo: A qualitative data analysis soft- ware tool. *J. Med. Libr. Assoc.* **2022**, *110*, 270–272. [CrossRef] [PubMed]
39. Jan van Eck, N.; Waltman, L. VOSviewer Manual. 2022. Available online: https://www.vosviewer.com/documentation/Manual_VOSviewer_1.6.18.pdf (accessed on 10 January 2023).
40. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *Int. J. Surg.* **2021**, *88*, 105906. [CrossRef]
41. Khallaf, R.; Khallaf, L.; Anumba, C.J.; Madubuike, O.C. Review of digital twins for constructed facilities. *Buildings* **2022**, *12*, 2029. [CrossRef]
42. Berglund, E.Z.; Monroe, J.G.; Ahmed, I.; Noghabaei, M.; Do, J.; Pesantez, J.E.; Khaksar Fasaee, M.A.; Bardaka, E.; Han, K.; Proestos, G.T.; et al. Smart Infrastructure: A Vision for the role of the civil engineering profession in smart cities. *J. Infrastruct. Syst.* **2020**, *26*, 03120001. [CrossRef]

43. Vieira, J.; Clara, J.; Patrício, H.; Almeida, N.; Martins, J.P. Digital twins in asset management: Potential application use cases in rail and road infrastructures. In *15th WCEAM Proceedings*; Lecture Notes in Mechanical Engineering Series; Springer: Cham, Switzerland, 2022. [CrossRef]
44. Doubell, G.C.G.C.; Kruger, K.; Basson, A.H.A.H.; Conradie, P. The potential for digital twin applications in railway infrastructure management. In *15th WCEAM Proceedings*; Lecture Notes in Mechanical Engineering Series; Springer: Cham, Switzerland, 2022; pp. 241–249. [CrossRef]
45. Jiang, F.; Ma, L.; Broyd, T.; Chen, K. Digital twin and its implementations in the civil engineering sector. *Autom. Constr.* **2021**, *130*, 103838. [CrossRef]
46. Broo, D.G.; Schooling, J. Digital twins in infrastructure: Definitions, current practices, challenges and strategies. *Int. J. Constr. Manag.* **2021**, *23*, 1254–1263. [CrossRef]
47. Gürdür Broo, D.; Bravo-Haro, M.; Schooling, J. Design and implementation of a smart infrastructure digital twin. *Autom. Constr.* **2022**, *136*, 104171. [CrossRef]
48. Lee, S.K.; Hong, S.H.; Jun, W.H.; Hong, Y.S. Multi-sensor data fusion with a reconfigurable module and its application to unmanned storage boxes. *Sensors* **2022**, *22*, 5388. [CrossRef]
49. Hijji, M.; Iqbal, R.; Pandey, A.K.; Doctor, F.; Karyotis, C.; Rajeh, W.; Alshehri, A.; Aradah, F. 6G connected vehicle framework to support intelligent road maintenance using deep learning data fusion. *IEEE Trans. Intell. Transp. Syst.* **2023**, *24*, 7726–7735. [CrossRef]
50. Kussl, S.; Wald, A. Smart mobility and its implications for road infrastructure provision: A systematic literature review. *Sustainability* **2023**, *15*, 210. [CrossRef]
51. Tao, F.; Zhang, H.; Liu, A.; Nee, A.Y.C. Digital Twin in Industry: State-of-the-Art. *IEEE Trans. Ind. Informatics* **2019**, *15*, 2405–2415. [CrossRef]
52. Lu, Q.; Parlikad, A.K.; Woodall, P.; Don Ranasinghe, G.; Xie, X.; Liang, Z.; Konstantinou, E.; Heaton, J.; Schooling, J. Developing a digital twin at building and city levels: Case study of west cambridge campus. *J. Manag. Eng.* **2020**, *36*, 05020004. [CrossRef]
53. Liu, M.; Fang, S.; Dong, H.; Xu, C. Review of digital twin about concepts, technologies, and industrial applications. *J. Manuf. Syst.* **2021**, *58*, 346–361. [CrossRef]
54. Nizam, K.S.; Yu, C.; Mardhiyah, A.N. Green building construction: A systematic review of BIM utilization. *Buildings* **2022**, *12*, 1205.
55. Neves, J.; Sampaio, Z.; Vilela, M. A Case study of BIM implementation in rail track rehabilitation. *Infrastructures* **2019**, *4*, 8. [CrossRef]
56. Xia, H.; Liu, Z.; Efremochkina, M.; Liu, X.; Lin, C. Study on city digital twin technologies for sustainable smart city design: A Review and bibliometric analysis of geographic information system and building information modeling integration. *Sustain. Cities Soc.* **2022**, *84*, 104009. [CrossRef]
57. Meža, S.; Mauko Pranjić, A.; Vezočnik, R.; Osmokrović, I.; Lenart, S. Digital twins and road construction using secondary raw materials. *J. Adv. Transp.* **2021**, *2021*, 1–12. [CrossRef]
58. Floros, G.S.; Boyes, G.; Owens, D.; Ellul, C. Developing IFC for Infrastructure: A Case Study of Three Highway Entities. *ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci.* **2019**, *4*, 59–66. [CrossRef]
59. Soilán, M.; Justo, A.; Sánchez-Rodríguez, A.; Riveiro, B. 3D point cloud to BIM: Semi-automated framework to define IFC alignment entities from MLS-acquired LiDAR data of highway roads. *Remote Sens.* **2020**, *12*, 2301. [CrossRef]
60. Ait-Lamallam, S.; Yaagoubi, R.; Sebari, I.; Doukari, O. Extending the Ifc Standard to Enable Road Operation and Maintenance Management through OpenBIM. *ISPRS Int. J. Geo-Inf.* **2021**, *10*, 496. [CrossRef]
61. Justo, A.; Soilán, M.; Sánchez-Rodríguez, A.; Riveiro, B. Scan-to-BIM for the infrastructure domain: Generation of IFC-complaint models of road infrastructure assets and semantics using 3D point cloud data. *Autom. Constr.* **2021**, *127*, 103703. [CrossRef]
62. Lu, Q.; Xie, X.; Parlikad, A.K.; Schooling, J.M. Digital twin-enabled anomaly detection for built asset monitoring in operation and maintenance. *Autom. Constr.* **2020**, *118*, 103277. [CrossRef]
63. Floros, G.S.; Ellul, C. Loss of Information During Design & Construction for Highways Asset Management: A GeoBIM Perspective. *ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci.* **2021**, *8*, 83–90. [CrossRef]
64. Biljecki, F.; Tauscher, H. Quality of BIM-GIS Conversion. *ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci.* **2019**, *4*, 35–42. [CrossRef]
65. Noardo, F.; Arroyo Ohori, K.; Biljecki, F.; Krijnen, T.; Ellul, C.; Harrie, L.; Stoter, J. Geobim Benchmark 2019: Design and Initial Results. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.-ISPRS Arch.* **2019**, *42*, 1339–1346. [CrossRef]
66. Ohori, K.A.; Biljecki, F.; Diakité, A.; Krijnen, T.; Ledoux, H.; Stoter, J. Towards an Integration of GIS And BIM Data: What are the Geometric and Topological Issues? *ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci.* **2017**, *4*, 1–8. [CrossRef]
67. AR-1-19, A.R. Adoption of Industry Foundation Classes (IFC) Schema as the Standard Data Schema for the Exchange of Electronic Engineering Data. 2019. Available online: https://data.transportation.org/wp-content/uploads/sites/44/2022/05/AR-1-19-IFC-Schema-Resolution-Board-Adopted-FINAL.pdf (accessed on 5 September 2023).
68. BuildingSMART, USA. IFC Open Standard Specifications in the US 2023. Available online: https://www.buildingsmartusa.org/about/openbim/openbim-in-the-us/ (accessed on 4 September 2023).
69. Motamedi, A.; Hammad, A.; Asen, Y. Knowledge-Assisted BIM-based visual analytics for failure root cause detection in facilities management. *Autom. Constr.* **2014**, *43*, 73–83. [CrossRef]

70. Patacas, J.; Dawood, N.; Greenwood, D.; Kassem, M. Supporting building owners and facility managers in the validation and visualisation of asset information models (AIM) through open standards and open technologies. *J. Inf. Technol. Constr.* **2016**, *21*, 434–455.
71. Moon, H.; Borrmann, A.; Jaud, Š.; Muhič, S.; Marquez, A.; Shin, J.; Won, J.; Anderson, K.; Hyvärinen, J.; Wikström, L.; et al. BSI UML Model Report—Part 5—UML Model Report for Road Elements. 2020. IFC Road P. pp. 1–124. Available online: https://www.buildingsmart.org/wp-content/uploads/2020/06/IR-CS-WP2-UML_Model_Report_Part-5_.pdf (accessed on 15 August 2023).
72. Alfieri, E.; Marschal, C.; Perin, M.; Esser, S.; Zhang, C.; Hulin, F.; Liebich, T. BSI UML Model Report—Part 4 UML Model Report for Railway Elements. IFC Rail—Railway Room—FC Infra Program Office. 2020, pp. 1–154. Available online: https://www.buildingsmart.org/wp-content/uploads/2020/06/IR-CS-WP2-UML_Model_Report_Part-4_.pdf (accessed on 15 August 2023).
73. Silva Schmidt Zucco, A. Infrastructure Asset Management Readiness Assessment of Ontario Municipal Water Utilities. Master's thesis, University of Waterloo, Waterloo, ON, Canada, 2020; p. 84.
74. Cheng, J.C.P.; Chen, W.; Chen, K.; Wang, Q. Data-driven predictive maintenance planning framework for MEP components based on BIM and IoT using machine learning algorithms. *Autom. Constr.* **2020**, *112*, 103087. [CrossRef]
75. Lu, Q.; Xie, X.; Parlikad, A.K.; Schooling, J.M.; Konstantinou, E. Moving from building information models to digital twins for operation and maintenance. *Proc. Inst. Civ. Eng.-Smart Infrastruct Constr.* **2021**, *174*, 46–56. [CrossRef]
76. Dalzeil, A. *Municipal Infrastructure Asset Inventories: A Guide for Municipalities*; PEI Infrastructure Secretariat: Charlottetown, PE, Canada, 2014. Available online: https://www.gov.pe.ca/photos/original/tir_assetinvent.pdf (accessed on 25 August 2023).
77. Hanif, N.; Lombardo, C.; Platz, D.; Chan, C.; Machano, J.; Pozhidaew, D.; Balakrishnan, S. *Managing Infrastructure Assets for Sustainable Development: A Handbook for Local and National Governments*; United Nations: New York, NY, USA, 2021. [CrossRef]
78. Shim, C.-S.; Dang, N.-S.; Lon, S.; Jeon, C.-H. Development of a bridge maintenance system for prestressed concrete using 3D digital twin model. *Struct. Infrastruct. Eng.* **2019**, *15*, 1319–1332. [CrossRef]
79. Lu, R.; Brilakis, I. Digital twinning of existing reinforced concrete bridges from labelled point clusters. *Autom. Constr.* **2019**, *105*, 102837. [CrossRef]
80. Broo, D.G.; Schooling, J. Towards data-centric decision making for smart infrastructure: Data and its challenges. International Federation of Automatic Control. *IFAC-PapersOnLine* **2020**, *53*, 90–94. [CrossRef]
81. Law, K.H.; Smarsly, K.; Wang, Y. Sensor Data Management Technologies for Infrastructure Asset Management. In *Sensor Technologies for Civil Infrastructures*; Woodhead Publishing Series in Electronic and Optical Materials; Woodhead Publishing: Cambridge, UK, 2014; Volume 1, pp. 3–32. [CrossRef]
82. Rathore, M.M.; Shah, S.A.; Shukla, D.; Bentafat, E.; Bakiras, S. The Role of AI, Machine Learning, and Big Data in Digital Twinning: A Systematic Literature Review, Challenges, and Opportunities. *IEEE Access* **2021**, *9*, 32030–32052. [CrossRef]
83. *The Asset Management Landscape the Asset Management Landscape*; Global Forum: Deerfield Beach, FL, USA, 2014; Volume 2, ISBN 978-0-9871799-2-0.
84. Parisi, F.; Mangini, A.M.; Fanti, M.P. Enabling Technologies for Smart Construction Engineering: A Review. *IEEE Int. Conf. Autom. Sci. Eng.* **2020**, *2020*, 1546–1551. [CrossRef]
85. Vite, C.; Horvath, A.-S.A.S.; Neff, G.; Møller, N.L.H.H. Bringing Human-Centredness to Technologies for Buildings: An Agenda for Linking New Types of Data to the Challenge of Sustainability. In *Proceedings of the ACM International Conference Proceeding Series*; Association for Computing Machinery: New York, NY, USA, 2021.
86. Luka, A.; Guo, Y. Plantingsmart: The parametric approach for trees in bim with full lifecycle application. *J. Digit. Landsc. Archit.* **2021**, *2021*, 370–380. [CrossRef]
87. Jiang, F.; Ma, L.; Broyd, T.; Chen, W.; Luo, H. Building digital twins of existing highways using map data based on engineering expertise. *Autom. Constr.* **2022**, *134*, 104081. [CrossRef]
88. Payawal, J.M.G.; Kim, D.K. Image-based structural health monitoring: A systematic review. *Appl. Sci.* **2023**, *13*, 968. [CrossRef]
89. Sadri, H.; Yitmen, I.; Tagliabue, L.C.; Westphal, F.; Tezel, A.; Taheri, A.; Sibenik, G. Integration of blockchain and digital twins in the smart built environment adopting disruptive technologies—A systematic review. *Sustainability* **2023**, *15*, 3713. [CrossRef]
90. Liu, H.; Han, S.; Zhu, Z. Blockchain technology toward smart construction: Review and future directions. *J. Constr. Eng. Manag.* **2023**, *149*, 03123002. [CrossRef]
91. Awan, S.M.; Azad, M.A.; Arshad, J.; Waheed, U.; Sharif, T. A blockchain-inspired attribute-based zero-trust access control model for IoT. *Information* **2023**, *14*, 129. [CrossRef]
92. Damant, L.; Forsyth, A.; Farcas, R.; Voigtländer, M.; Singh, S.; Fan, I.S.; Shehab, E. Exploring the Transition from Preventive Maintenance to Predictive Maintenance within ERP Systems by Utilising Digital Twins. In *Proceedings of the Advances in Transdisciplinary Engineering*; IOS Press BV: Clifton, VA, USA, 20 October 2021; Volume 16, pp. 171–180.
93. Ibáñez, L.D.; Reeves, N.; Simperl, E. Crowdsourcing and human-in-the-loop for IoT. In *Internet Things from Data to Insight*; Wiley Telecom: Hoboken, NJ, USA, 2019; pp. 91–105. [CrossRef]
94. Agnisarman, S.; Lopes, S.; Chalil Madathil, K.; Piratla, K.; Gramopadhye, A. A survey of automation-enabled human-in-the-loop systems for infrastructure visual inspection. *Autom. Constr.* **2019**, *97*, 52–76. [CrossRef]
95. Schiavi, B.; Havard, V.; Beddiar, K.; Baudry, D. BIM data flow architecture with AR/VR technologies: Use cases in architecture, engineering and construction. *Autom. Constr.* **2022**, *134*, 104054. [CrossRef]

96. Zhu, Y.; Li, N. Virtual and augmented reality technologies for emergency management in the built environments: A state-of-the-art review. *J. Saf. Sci. Resil.* **2021**, *2*, 1–10. [CrossRef]
97. Azhar, S. Building information modeling (BIM): Trends, benefits, risks, and challenges for the AEC industry. *Leadersh. Manag. Eng.* **2011**, *11*, 241–252. [CrossRef]
98. Hisrich, R.D.; Soltanifar, M. *Digital Entrepreneurship, Future of Business and Finance*; National University of Singapore: Singapore, 2021; ISBN 9783030539139.
99. Shao, H.; Lin, J.; Zhang, L.; Galar, D.; Kumar, U. A novel approach of multisensory fusion to collaborative fault diagnosis in maintenance. *Inf. Fusion* **2021**, *74*, 65–76. [CrossRef]
100. Swar, A.; Khoriba, G.; Belal, M. A unified ontology-based data integration approach for the internet of things. *Int. J. Electr. Comput. Eng.* **2022**, *12*, 2097–2107. [CrossRef]
101. Hagedorn, P.; Liu, L.; König, M.; Hajdin, R.; Blumenfeld, T.; Stöckner, M.; Billmaier, M.; Grossauer, K.; Gavin, K. BIM-enabled infrastructure asset management using information containers and semantic web. *J. Comput. Civ. Eng.* **2023**, *37*, 04022041. [CrossRef]
102. Amará, J.; Ströele, V.; Braga, R.; Dantas, M.; Bauer, M. Integrating heterogeneous stream and historical data sources using SQL. *J. Inf. Data Manag.* **2022**, *13*, 191–206. [CrossRef]
103. Chen, W.; Das, M.; Chen, K.; Cheng, J.C.P. Ontology-Based Data Integration and Sharing for Facility Maintenance Management. *Constr. Res. Congr.* **2020**, *007*, 809–818.
104. Eneyew, D.D.; Capretz, M.A.M.; Bitsuamlak, G.T. Towards smart building digital twins: BIM and IoT data integration. *IEEE Access* **2022**, *10*, 130487–130506. [CrossRef]
105. Jang, H.; Ryu, H.; Kwahk, J. A framework for simulating the suitability of data usage in designing smart city services. *J. Urban Plann. Dev.* **2023**, *149*, 1–14. [CrossRef]
106. Tang, S.; Shelden, R.D. A Framework Utilizing Modern Data Models with IFC for Building Automation System Applications. *Constr. Res. Congress* **2020**, *7*, 809–818.
107. Gao, X.; Pishdad-Bozorgi, P.; Shelden, R.D.; Tang, S. A scalable cyber-physical system data acquisition framework for the smart built environment. *Comput. Civ. Eng.* **2019**, *2019*, 105–113.
108. Zhou, C.; Xiao, D.; Hu, J.; Yang, Y.; Li, B.; Hu, S.; Demartino, C.; Butala, M. *An Example of Digital Twins for Bridge Monitoring and Maintenance: Preliminary Results*; Springer International Publishing: New York, NY, USA, 2022; Volume 200, ISBN 9783030918767.
109. Adibfar, A.; Costin, A.M. Creation of a mock-up bridge digital twin by fusing intelligent transportation systems (ITS) Data into Bridge Information Model (BrIM). *J. Constr. Eng. Manag.* **2022**, *148*, 04022094. [CrossRef]
110. Kwak, Y.J. Data Sharing Framework for Digital Infrastructure Management Utilizing EO Data. In Proceedings of the IGARSS 2022–2022 IEEE International Geoscience and Remote Sensing Symposium, Kuala Lumpur, Malaysia, 17–22 July 2022; pp. 5230–5231. [CrossRef]
111. Wan, L.; Nochta, T.; Schooling, J.M. Developing a City-Level Digital Twin—Propositions and a Case Study. In Proceedings of the International Conference on Smart Infrastructure and Construction 2019, ICSIC 2019: Driving Data-Informed Decision-Making, Cambridge, MA, USA, 8–10 July 2019; pp. 187–193. [CrossRef]
112. Yan, J.; Yin, K.; Lu, Q.; Shen, X. Developing a web-based BIM asset and facility management system of building digital twins. *Comput. Civ. Eng.* **2021**, 490–497.
113. Aheleroff, S.; Xu, X.; Zhong, R.Y.; Lu, Y. Digital twin as a service (DTaaS) in industry 4.0: An architecture reference model. *Adv. Eng. Inform.* **2021**, *47*, 101225. [CrossRef]
114. Yu, D.; He, Z. *Digital Twin-Driven Intelligence Disaster Prevention and Mitigation for Infrastructure: Advances, Challenges, and Opportunities*; Springer: Dordrecht, The Netherlands, 2022; Volume 112, p. 6789. ISBN 0123456789.
115. Pregnolato, M.; Gunner, S.; Voyagaki, E.; De Risi, R.; Carhart, N.; Gavriel, G.; Tully, P.; Tryfonas, T.; Macdonald, J.; Taylor, C. Towards civil engineering 4.0: Concept, workflow and application of digital twins for existing infrastructure. *Autom. Constr.* **2022**, *141*, 104421. [CrossRef]
116. Al-Sehrawy, R.; Kumar, B.; Watson, R. A digital twin uses classification system for urban planning & city infrastructure management. *J. Inf. Technol. Constr.* **2021**, *26*, 832–862. [CrossRef]
117. Yu, G.; Wang, Y.K.Y.; Mao, Z.; Hu, M.; Sugumaran, V.; Wang, Y.K.Y. A digital twin-based decision analysis framework for operation and maintenance of tunnels. *Tunn. Undergr. Sp. Technol.* **2021**, *116*, 104125. [CrossRef]
118. Nicoletti, V.; Martini, R.; Carbonari, S.; Gara, F. Operational modal analysis as a support for the development of digital twin models of bridges. *Infrastructures* **2023**, *8*, 24. [CrossRef]
119. Congress, S.S.C.; Puppala, A.J.; Sarat, S.; Congress, C.; Puppala, A.J.; Asce, F.; Chair, F.W. Digital Twinning Approach for Transportation Infrastructure Asset Management Using UAV Data. In Proceedings of the International Conference on Transportation and Development, Atlanta, GA, USA, 15–18 June 2021.
120. Lovelace, B.; Hafer, R.; Aryal, B. Digital Twins for Safe and Efficient Port Infrastructure Management. In Proceedings of the Ports 2022: Port Engineering—Papers from Sessions of the 16th Triennial International Conference, Honolulu, HI, USA, 18–21 September 2022; Volume 2, pp. 592–600.
121. Hidayat, F.; Supangkat, S.H.; Hanafi, K. Digital Twin of Road and Bridge Construction Monitoring and Maintenance. In Proceedings of the ISC2 2022—8th IEEE International Smart Cities Conference, Pafos, Cyprus, 26–29 September 2022. [CrossRef]

122. Broekman, A.; Steyn, W.J.M. Digital Twinning of Lap-Based Marathon Infrastructure. In Proceedings of the 2021 Rapid Product Development Association of South Africa—Robotics and Mechatronics—Pattern Recognition Association of South Africa (RAPDASA-RobMech-PRASA), Pretoria, South Africa, 3–5 November 2021. [CrossRef]
123. Hosamo, H.H.; Hosamo, M.H. Digital twin technology for bridge maintenance using 3D laser scanning: A review. *Adv. Civ. Eng.* **2022**, *2022*, 2194949. [CrossRef]
124. Xie, H.Y.; Liang, T.T.; Babiceanu, R.F.; Lu, C.W. Framework of a smart local infrastructure management system. *Appl. Mech. Mater.* **2013**, *357–360*, 2388–2392. [CrossRef]
125. Johannes, K.; Theodorus Voordijk, J.; Marias Adriaanse, A.; Aranda-Mena, G. Identifying maturity dimensions for smart maintenance management of constructed assets: A multiple case study. *J. Constr. Eng. Manag.* **2021**, *147*, 05021007. [CrossRef]
126. Jang, K.; Kim, J.W.; Ju, K.B.; An, Y.K. Infrastructure BIM platform for lifecycle management. *Appl. Sci.* **2021**, *11*, 10310. [CrossRef]
127. Adibfar, A.; Costin, A.M.A.M. Integrated management of bridge infrastructure through bridge digital twins: A preliminary case study. *Comput. Civ. Eng.* **2021**, *2021*, 358–365. [CrossRef]
128. Ye, C.; Butler, L.; Calka, B.; Iangurazov, M.; Lu, Q.; Gregory, A.; Girolami, M.; Middleton, C. A Digital Twin of Bridges for Structural Health Monitoring. In Proceedings of the 12th International Workshop on Structural Health Monitoring, Hangzhou, China, 19–23 October 2019; Volume 1.
129. Mitra, S. *Applications of Machine Learning and Computer Vision for Smart Infrastructure Management in Civil Engineering*; Visvesvaraya National Institute of Technology: Maharashtra, India, 2010.
130. Jiang, Y.; Li, M.; Wu, W.; Wu, X.; Zhang, X.; Huang, X.; Zhong, R.Y.; Huang, G.G.Q. Multi-domain ubiquitous digital twin model for information management of complex infrastructure systems. *Adv. Eng. Informatics* **2023**, *56*, 101951. [CrossRef]
131. Wang, M. Ontology-based modelling of lifecycle underground utility information to support operation and maintenance. *Autom. Constr.* **2021**, *132*, 103933. [CrossRef]
132. Blaser, S.; Meyer, J.; Nebiker, S. Open Urban and Forest Datasets from a High-Performance Mobile Mapping Backpack—A Contribution for Advancing the Creation of Digital City Twins. In Proceedings of the International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences—ISPRS Archives, Nice, France, 28 June 2021; Volume 43, pp. 125–131.
133. Ham, Y.; Kim, J. Participatory sensing and digital twin city: Updating virtual city models for enhanced risk-informed decision-making. *J. Manag. Eng.* **2020**, *36*, 04020005. [CrossRef]
134. Luo, W.; Hu, T.; Ye, Y.; Zhang, C.; Wei, Y. A hybrid predictive maintenance approach for CNC machine tool driven by digital twin. *Robot. Comput. Integr. Manuf.* **2020**, *65*, 101974. [CrossRef]
135. Kim, J.; Ham, Y. Real-Time Participatory Sensing-Driven Computational Framework toward Digital Twin City Modeling. *Constr. Res. Congr.* **2022**, *3–C*, 964–973. [CrossRef]
136. Inam, H.; Islam, N.U.; Akram, M.U.; Ullah, F. Smart and automated infrastructure management: A deep learning approach for crack detection in bridge images. *Sustainability* **2023**, *15*, 1866. [CrossRef]
137. Hetzel, M.; Reichert, H.; Doll, K.; Sick, B. Smart Infrastructure: A Research Junction. In Proceedings of the 2021 IEEE International Smart Cities Conference, ISC2 2021, 2021–2024, Manchester, UK, 7–10 September 2021. [CrossRef]
138. Grebenyuk, G.G.G.; Kalyanov, G.N.G.N.; Kovalyov, S.P.S.P.; Krygin, A.A.A.A.; Lukinova, O.V.O.V.; Nikishov, S.M.S.M. Technological Infrastructure Management Models and Methods Based on Digital Twins. In *Proceedings of the Proceedings of 2021 14th International Conference Management of Large-Scale System Development, MLSD 2021*; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2021.
139. Mohammadi, M.; Rashidi, M.; Yu, Y.; Samali, B. Integration of tls-derived bridge information modeling (BrIM) with a decision support system (DSS) for digital twinning and asset management of bridge infrastructures. *Comput. Ind.* **2023**, *147*, 103881. [CrossRef]
140. Kestelyn, X.; Denis, G.; Champaney, V.; Hascoet, N.; Ghnatios, C.; Chinesta, F. Towards a Hybrid Twin for Infrastructure Asset Management: Investigation on Power Transformer Asset Maintenance Management. In Proceedings of the ARWtr 2022—Proceedings: 2022 7th Advanced Research Workshop on Transformers, Baiona, Spain, 24–26 October 2022; pp. 109–114. [CrossRef]