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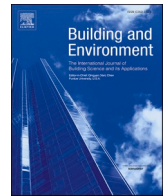
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Integrating digital twin technologies for maintenance 4.0 in the building industry: A review and conceptual framework

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ABSTRACT

The building industry is facing increasing demands for sustainable and efficient maintenance practices, driven by advancements in Industry 4.0 technologies. Maintenance 4.0 emphasizes proactive maintenance strategies, including Condition-based Maintenance (CbM) and Predictive Maintenance (PdM), significantly enhanced by Digital Twin (DT) technology. DT enables the real-time monitoring, simulation, and optimization of building assets, offering substantial improvements in asset management, energy efficiency, and system longevity. However, integrating these technologies into the building industry's maintenance processes remains a challenge. This paper provides a comprehensive review of current research on DT-enabled Maintenance 4.0, presenting a conceptual framework that integrates enabling technologies and outlines their technological pipelines. It discusses the state-of-the-art methodologies, challenges, and future directions for the implementation of Maintenance 4.0 in the building sector, highlighting the potential of DT systems in optimizing maintenance strategies and enhancing decision-making. The study identifies key areas for further research, including data standardization, AI integration, and hybrid modeling approaches.

1. Introduction

The building industry has become a priority in sustainability efficiency initiatives due to its substantial energy consumption and environmental impact [1], while the maintenance costs constitute approximately 65% of the annual facility management expenses [2]. Maintenance 4.0 represents a significant evolution in the maintenance industry, integrating condition-based and predictive procedures to enhance system sustainability and operational efficiency [3]. In the building industry, this approach is grounded in the evaluation of both occupant comfort and building performance, aiming to develop advanced operational schedules for structures, facilities, and indoor environments [4].

Condition-based Maintenance (CbM) and Predictive Maintenance (PdM) exemplify transformative approaches within Maintenance 4.0, seamlessly integrating with the capabilities of Digital Twin (DT) technology. As one of the representative technologies of Industry 4.0, DT is regarded as a comprehensive solution for demonstrating, operating,

maintaining, and optimising building-related assets. DT leverages and integrates a variety of advanced technologies, including the Internet of Things (IoT), Artificial Intelligence (AI), and Building Information Modelling (BIM) [5], enabling the digitalisation of building assets and lifecycle management [6]. It shows robust potential in the establishment of the Maintenance 4.0 Platform, allowing for real-time bi-directional data integration, high-quality model visualisation, and various function coordination. Maintenance and management notifications are provided on the virtual twin platform, while the data and information are acquired through the physical system [7]. This emerging paradigm underscores a significant shift towards more proactive and data-driven maintenance practices, allowing a timely and advanced schedule of maintenance operations, significantly reducing unplanned downtimes and optimising the use of both technological and human resources [8].

Recent advancements in the automated platform and data-driven functions have broadened the scope, enabling the implementation of a more proactive maintenance paradigm in the building industry. However, achieving intelligent building management is still a complex issue

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because comprehensive information is required (e.g., operating data, maintenance records, metadata, etc.), and multiple technologies will be adopted (e.g., sensors, scanners, cameras, etc.). Keeping data interoperability and system integrity is the key challenge during the practical deployment. Firstly, the requisite data typically resides within siloed systems that are neither thoroughly utilised nor integrated [9,10]. Besides, most existing studies and solutions are developed for single systems, while data and platforms are not well-integrated or analysed. Single data collection systems can support multiple functions when integrated with different algorithms. Consequently, this paper aims to address this gap by providing a state-of-the-art survey of the conceptual framework and enabling technologies necessary for the achievement of Maintenance 4.0 in the building industry from a DT perspective. Furthermore, a unified framework has been formulated within the DT structure to integrate enabling technologies and facilitate the pipeline deployment. Finally, potential challenges and future directions are identified from technology maturity and commercialised perspectives.

The structure of this paper is organised as follows: Section 2 details the article searching process and analyses current research trends. Section 3 explores the benefits and adoption of DT architecture for Maintenance 4.0 in the building industry. Section 4 develops a conceptual framework highlighting the technological pipeline and systematic integration methodology. Section 5 evaluates the technological maturity and deployment feasibility based on the systematic review. Finally, Section 6 concludes by summarising the contributions of this work and discussing future directions.

2. Research methodology

This study conducts a systematic review (SR) of DR-enabled Maintenance 4.0 solutions within the building industry, encompassing surveys, frameworks, case studies, and implemented applications. A systematic review differs from a narrative review by employing a transparent, reproducible, and auditable process that minimises selection bias and ensures traceable synthesis of evidence [11]. The publications between 2019 and October 2025 are used for evidence synthesis, while older materials are cited for theoretical support, thereby

improving interpretability and transparency. The review process follows the PRISMA guidelines [12], integrating bibliometric and qualitative synthesis to reveal the technological, methodological, and conceptual progress of DT-enabled PdM in the built environment. Because PdM and DT concepts originated in manufacturing and cyber-physical domains, this cross-industry adaptation requires both theoretical synthesis and evidence-based mapping of enabling technologies.

2.1. Publications identification process

Literature search and screening were conducted to ensure comprehensive and up-to-date coverage, encompassing publications from 2019 to 2025.10 on DT-related advancements in building maintenance. Following the PRISMA protocol (Fig. 1), the **Web of Science (WoS)** served as the primary database owing to its rigorous indexing and topic-based query capability, while **Scopus** was concurrently employed as a complementary source to enhance retrieval completeness and cross-validation accuracy.

- The Pseudo-code for keyword combination search was as follows: (“*Predictive Maintenance*” OR “*Condition-based Maintenance*”) AND (“*Digital Twin*” OR “*Cyber-Physical System*”) AND (“*Building Industry*” OR “*Construction Industry*”).
- Search filters were applied as follows: (*Time Span* = 2019-2025.10), (*Language* = English), (*Source* = Journal OR Conference)

Subsequently, the abstract and full text were examined using the following inclusion criteria to ensure the searching rigor and maintain thematic relevance.

- Relevance of domain: Studies addressing DT-driven PdM or CbM for building structures, building facilities, or indoor environmental systems.
- Technological contribution: Presence of DT-related enabling technologies, such as IoT-based data acquisition, BIM integration, AI algorithms, and virtual simulation.

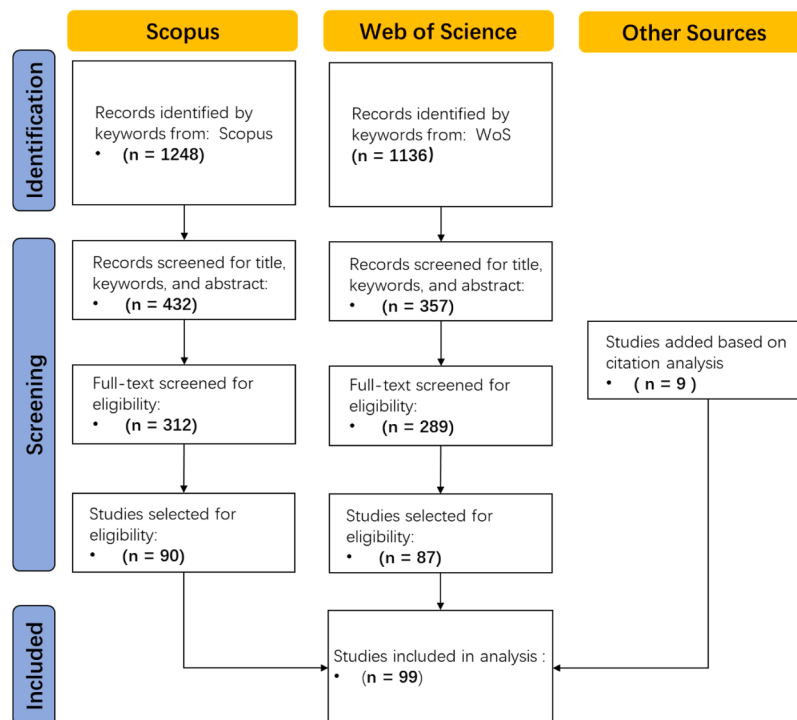


Fig. 1. PRISMA diagram for the systematic review.

- Evidence type: Conceptual frameworks, architecture proposals, prototype demonstrations, and validated case studies.
- Transparency: Explicit methodological description allowing replication of the proposed workflow or architecture.
- Publication quality: Indexed peer-reviewed journals or reputable conferences with verifiable DOI.

Finally, the above thorough search process led to the identification of 99 related articles for in-depth analysis.

2.2. Bibliometric analysis

The bibliometric analysis complements the systematic review by providing a quantitative overview of research dynamics in DT-enabled Maintenance 4.0. Based on the latest searching, Fig. 2 shows a sustained increase in annual outputs, with 19 papers already identified for 2025. The dash projection further indicates that the final 2025 total is expected to reach approximately 23 to 25 publications, highlighting the continuing growth of DT and PdM research in the building sector that aligns with the global momentum of Construction 4.0 research.

A total of 99 core studies were identified across 49 peer-reviewed journals and conferences. As summarised in Table 1, *Buildings* emerged as the leading publication outlet, contributing seven papers. This was followed by *Automation in Construction*, *Energy and Buildings*, *Journal of Building Engineering*, and *Sustainability (Switzerland)*, each publishing four articles. Additionally, *Frontiers in Built Environment* and *Scientific Reports* contributed three papers each. Collectively, these distributions highlight the multidisciplinary nature of the research, spanning domains such as the built environment, construction automation, energy efficiency, and sustainability.

Fig. 3 presents the distribution of publications across various research fields, showcasing the interdisciplinary nature of the studies. *Engineering* dominates with 38%, followed by *Computer Science* at 18%, underscoring their leading roles in technological development and system integration. Other notable fields include *Social Sciences* (8%), *Energy* (6%), *Materials Science* (5%), and *Environmental Science* (4%). In addition, studies focusing on structural components such as façade durability and pavement performance emerge from more specialized domains, including *Earth and Planetary Sciences*, *Chemical Engineering*, and *Materials Science*, each contributing 3% or less to the total body of research.

Geographically, as illustrated in Fig. 4, the research exhibits a strong concentration in Europe, led by Italy and the United Kingdom, each contributing 16 studies. Other major contributors include the United States (11), Australia and Germany (9 each), followed by Sweden (8), and Denmark and Norway (6 each). These regions are characterised by mature infrastructure systems, well-established maintenance standards, and advanced digitalisation strategies. In contrast, emerging contributions from Asia, notably China (5), Singapore and Japan (3 each), and South Korea (1), reflect a rapid shift toward data-driven and maintenance-intensive digital transformation. The growing participation from developing regions, including South Africa, Brazil, and Malaysia, further underscores the expanding global relevance of DT and

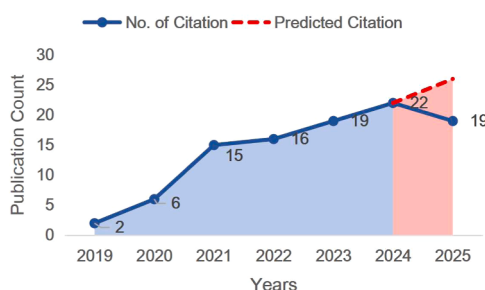


Fig. 2. Number of publications (2019–2025.10).

Table 1

Highest sourced journals presented in the review.

Journal	Counts
Buildings	7
Automation in Construction	4
Energy and Buildings	4
Journal of Building Engineering	4
Sustainability Switzerland	4
Frontiers in Built Environment	3
Scientific Reports	3

PdM research in the built environment.

Collectively, these bibliometric findings delineate the global landscape, disciplinary diversity, and regional evolution of DT-enabled Maintenance 4.0 research. They underscore the expanding academic recognition of this field and provide a foundation for the structured, evidence-based synthesis developed in the subsequent sections.

2.3. Evidence coding and analytical dimensions

All 99 selected studies were systematically examined using a structured five-dimensional coding framework designed to ensure methodological transparency and reproducibility. As shown in Table 2, each publication was analysed across the following dimensions: asset type, data stream, algorithmic approach, and technology readiness level (TRL), collectively representing the technological scope, methodological depth, and practical maturity of DT-enabled maintenance research in the building industry. The coding process involved a comprehensive review of each article to extract and categorise key features within these dimensions, enabling consistent cross-study comparison and supporting future quantitative or meta-analytical synthesis. The evidence map reveals that most studies focus on facility-level or environmental assets supported by sensor-based and BIM-integrated data, while deep-learning and hybrid algorithms dominate PdM modelling. However, few works have progressed beyond prototype validation, indicating that DT applications in building maintenance remain at an early-to-intermediate maturity stage.

2.4. Risk-of-bias and quality appraisal

To enhance methodological rigour and ensure the reliability of this systematic review, a risk-of-bias and quality appraisal was performed for all included studies using the Mixed Methods Appraisal Tool (MMAT, 2018). The MMAT provides a structured approach for evaluating methodological soundness across diverse empirical designs, which is particularly relevant to interdisciplinary research integrating engineering, computer science, and building management perspectives.

Each of the 99 reviewed studies was independently assessed against five quality criteria:

- Clarity of research objectives – whether the study articulates a precise and coherent research aim.
- Adequacy of data collection – the suitability and transparency of IoT, BIM, or experimental datasets used.
- Transparency of analytical methods – completeness of algorithmic, simulation, or modelling descriptions.
- Validity of findings – robustness of results supported by verification, cross-validation, or comparative benchmarking.
- Replicability of the DT framework – accessibility and reproducibility of data, models, or workflow documentation.

Each criterion was rated on a five-point ordinal scale (1 = poor, 5 = excellent). Mean scores were calculated for each study, and inter-reviewer agreement exceeded 90%, indicating strong reliability of evaluation. The results (Table 3) reveal that most studies achieved high methodological quality, with notable strengths in research clarity and

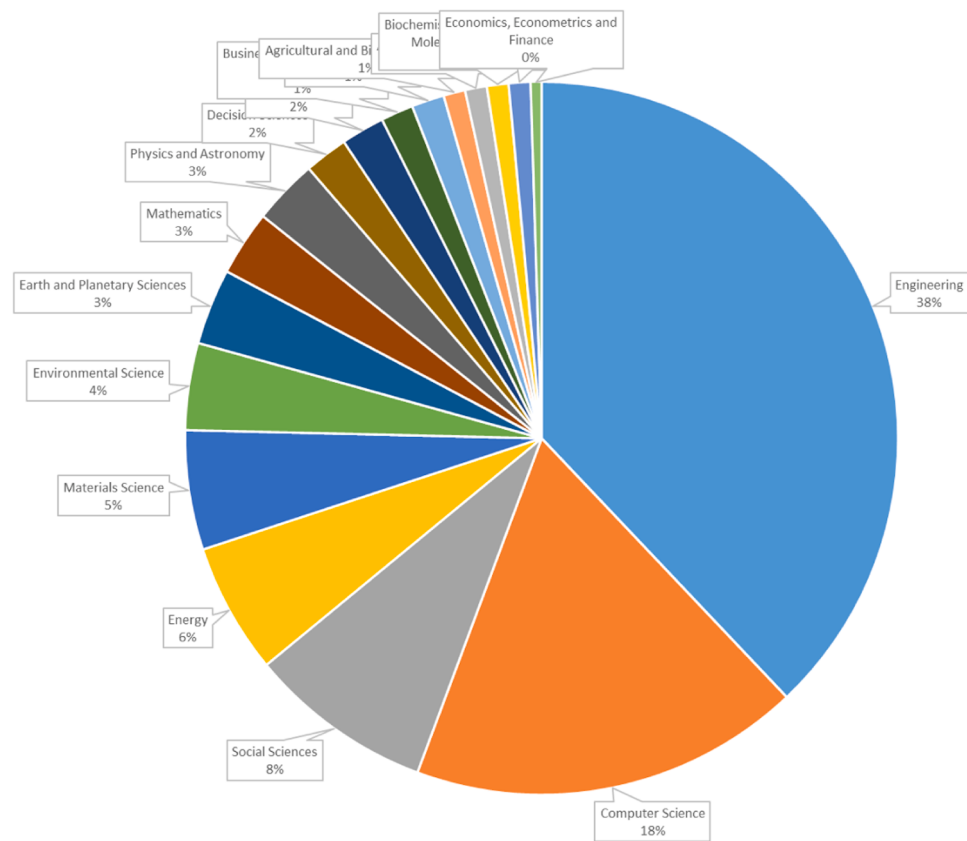


Fig. 3. Publication distribution of research field.

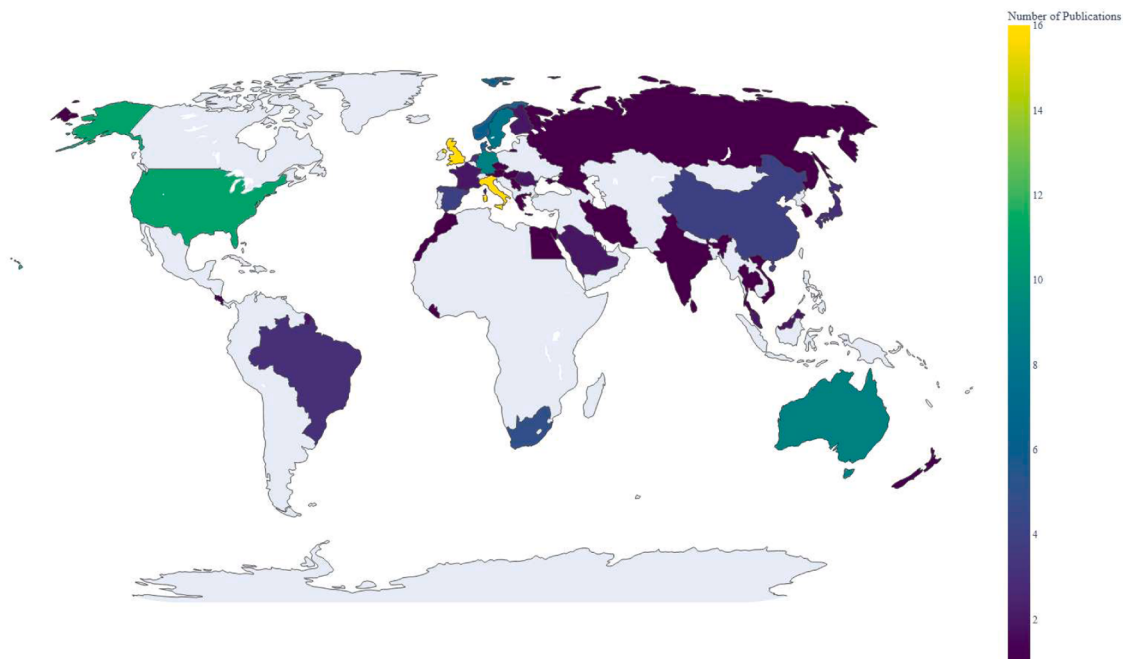


Fig. 4. Publication count categorized by countries.

analytical transparency. However, common weaknesses remain in data availability and replicability, particularly among AI-driven case studies relying on proprietary or closed datasets.

These results confirm that the reviewed literature exhibits moderate to high methodological quality, demonstrating coherent objectives and

credible analytical approaches. Nonetheless, future DT-enabled maintenance research should place greater emphasis on open data accessibility, transparent algorithmic documentation, and standardised evaluation protocols to further reduce potential bias and strengthen cross-study comparability.

Table 2
Analytical dimensions.

Coding Dimension	Description	Typical Examples
Asset Type	Physical or functional building components targeted by the DT solution.	Structure, HVAC, facade, road, pavement, indoor environment.
Data Stream	Origin of input data used in the DT loop.	IoT sensors, BIM models, historical records, maintenance logs.
Algorithm Type	Analytical or predictive technique employed.	ML (LSTM, CNN, Autoencoder), statistical regression, rule-based model, hybrid AI.
Technology Readiness Level (TRL)	Practical maturity of the technology.	TRL3–prototype, TRL5–demonstration, TRL7–pilot.

Table 3
MMAT-based quality assessment summary.

Quality Criterion	Average Score	No. of Studies	Key Observations
Clarity of research objectives	4.5	89 (90.0 %)	Aims are generally well defined and contextualised.
Adequacy of data collection	4.2	72 (72.7 %)	IoT/BIM datasets are robust but not always fully disclosed.
Transparency of analytical methods	4.4	77 (77.8 %)	Algorithms and model workflows are clearly reported in most papers.
Validity of findings	3.9	71 (71.7 %)	Cross-validation is used in several studies but not consistently.
Replicability of DT framework	3.8	59 (59.6 %)	Limited sharing of data or code restricts reproducibility.

3. Pattern analysis

This section presents a comprehensive technical practice analysis based on the systemic review, classifying existing studies into review, survey, framework, prototype system, and case study according to their technological maturity. The study provides insight into the practicality and applicability of DT-enabled Maintenance 4.0 technologies in the building industry and highlights trends and patterns within the research community.

3.1. Category definitions

To facilitate a clear understanding, the existing studies are categorised by following benchmarks, and the distribution of collected studies is presented in Fig. 5.

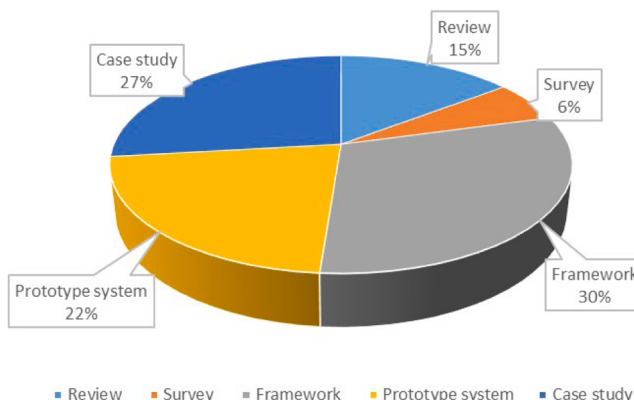


Fig. 5. The distribution of article categories.

- **Review:** A review study synthesises existing research on a particular topic, identifying key themes, gaps, and future directions to provide a comprehensive overview of the current knowledge and state-of-the-art technologies.
- **Survey:** Survey studies collect and analyse data from a specific group of respondents to gather insights, opinions, or behaviours related to the research topic, facilitating the understanding of the adoption, challenges, and potential of new technologies
- **Framework:** Framework studies propose structured approaches or models for implementing or understanding specific technologies or processes, which often include theoretical constructs and practical guidelines.
- **Prototype System:** Prototype system studies involve the development and testing of preliminary versions of new technologies or systems, which are used to validate concepts, functionalities, and performance before industrial deployment. The DT systems in these studies are generally at the laboratory stage compared with case study research.
- **Case Study:** Case studies provide in-depth examinations of specific instances where a technology or process has been applied. They often involve real-world implementations and provide detailed insights into practical applications, benefits, and challenges.

3.2. Analysis and patterns

Based on the above benchmarks, Table 4 summarises the technical practice of existing studies. A significant observation is that most studies fall into the framework and case study categories, which are essential for establishing foundational principles and methodologies that guide the development and application of DT technologies in building maintenance. The high number of studies in this category indicates active experimentation and innovation, reflecting the industry's efforts to transition from theoretical models to practical applications.

In contrast, review and survey studies remain relatively limited

Table 4
Overview of studies distribution on technical practice.

Type	Reference distribution
Review	[13–25]
Survey	[26–31]
Framework	[4,32–59]
Prototype system	[60–79]
Case study	A school building, Sungkyunkwan University, South Korea [80], I4Helse and Tvedestrand building, Norway [81], A transport network, Salerno, Southern Italy [82], Institute for Manufacturing building, University of Cambridge, UK, [83], A conference room, Pythagoras AB company, Stockholm, Sweden [84], Montana Creek Bridge, USA [85], Austrian federal railways [86], 500 kV Wujiaochang substation project, China [87], Engineering 4.0 campus, Pretoria, South Africa [88], A building complex, Brazilian University, Brazil [89], Conveyor system, Dalrymple Bay Coal Terminal, Queensland, Australia [90], Zhongcheng Village Bridge, Zhejiang Province, China [91], Xinyi Line, Taipei Metro, Taipei [92], The building façade, an office building, Aalto University, Finland [93], The Alan Reece building, University of Cambridge, UK [94], The port, Ventotene, Italy [95], Humanitas Hospital, Milan, Italy [96], Rione Rinascimento complex, Rome, Italy [97], Mohammed VI Bridge, Morocco [98], Scandinavian-Mediterranean Connecting Europe Facility corridor, Italian highway A24, Italy [99] Snow galleries, Iron Ore railway, Northern Sweden [100] Concrete plant Ngonje, Slovenia [101]

compared with technical and case-based research. Review papers synthesise existing knowledge, identify research gaps, and guide future directions. Although their overall number is modest, the proportion of reviews has increased in recent years (2024-2025), reflecting the maturation of the field and the accumulation of sufficient empirical evidence to support systematic synthesis and framework development. This trend is further driven by the growing integration of AI, BIM, and IoT within digital twin research, prompting scholars to consolidate and categorise emerging knowledge. On the other hand, survey studies collect insights from specific respondent groups, offering valuable evidence on the adoption, challenges, and potential of DT technologies. Their scarcity suggests an opportunity for more industry-oriented surveys to capture real-world implementation perspectives and support evidence-based advancement.

Case studies provide essential insights into the real-world implementation of Digital Twin (DT) technologies. As summarised in the accompanying table, most identified cases originate from Europe, reflecting the region's extensive infrastructure and advanced maintenance requirements. A consistent pattern is observed in that nearly all these studies are supported by universities or government initiatives, indicating that DT applications in the built environment largely remain in the experimental or pilot stage. Besides, recent publications demonstrate a notable shift toward practical industrial applications. For example, a study on a mid-sized concrete plant illustrates how a DT system integrating sensor data, real-time monitoring, and predictive analytics can enhance operational efficiency, reduce waste, and improve maintenance forecasting [101]. Such emerging cases signal a gradual transition from research-led prototypes to industry-driven deployments, suggesting that DT technologies are moving closer to commercial viability and large-scale adoption within the construction sector.

4. Concepts and embracement of digital twin

This section introduces the development of DT technology, detailing its progression from the initial stage to advanced applications. Besides, it explores the integration of DT for Maintenance 4.0 in the building industry, highlighting how these innovations are transforming maintenance practices.

4.1. Concept evolution of digital twin

The concept of DT was first proposed in 2002 by Grieves [102] during his presentation of product family design. Although various definitions exist, the DT system contains physical and digital counterparts with their interconnections system [103]. Originally utilised as an economical method for the simulation of NASA rockets under different conditions, DT has undergone significant technological advancements and broadened its range of applications. According to current literature, DT-related enabling technologies have grown exponentially over time, with their concepts continuously evolving and transforming [103]. Notably, some projects labelled as DT do not fully adhere to the mainstream definition [104], instead falling into three categories, as shown in Fig. 6: digital model, digital twin, and intelligent digital twin [105]. A digital model represents a static digital replica of a physical object or

system primarily used for design and analysis [106]. As ICT developed, the DT energy developed with its dynamic nature, real-time data interactions, and bidirectional information communication [107]. Finally, the intelligent DT incorporates data-driven models such as advanced analytics and AI to enhance the decision-making process. This progression reflects the increasing complexity and capabilities of DT systems, transforming from basic representations to sophisticated, intelligent systems that drive significant improvements in various industries.

4.2. Embracement of digital twin for maintenance 4.0 in the building industry

The emerging maintenance paradigm during Industry 4.0 is conceptualised as Maintenance 4.0 [108]. Advanced strategies derived from Industry 4.0, such as fault detection, failure prediction, energy optimisation, etc., are implemented and assimilated to CbM and PdM when they suggest maintenance activities. As depicted in Fig. 7, the adoption of Maintenance 4.0 in the building industry marks a transformative shift over the whole building lifecycle with unique requirements on data scope, methodology, and virtual modelling [109]. The DT framework serves as the cornerstone in this context to facilitate proactive maintenance strategies and ensure timely interventions. Unlike manufacturing, the virtual replica of the building system accommodates intricate interactions between structural, mechanical, electrical, and environmental systems [110,111]. By integrating diverse data streams from sensor systems and maintenance records, the methodology emphasises long-term asset management, safety, and sustainability, which are developed to improve maintenance performance. Finally, the dynamic solution is generated from the digital model based on data analysis and an intelligent algorithm to provide guidance for physical operation and schedule planning.

Embracing DT technology for Maintenance 4.0 in the building industry requires a synergistic approach that leverages advancements in communication, virtualisation, and computation [112]. These innovations enable more efficient, accurate, and proactive maintenance strategies, ultimately enhancing the longevity and performance of building assets. By integrating these cutting-edge technologies, the industry can achieve significant improvements in asset management, operational efficiency, and sustainability. The reference summary in

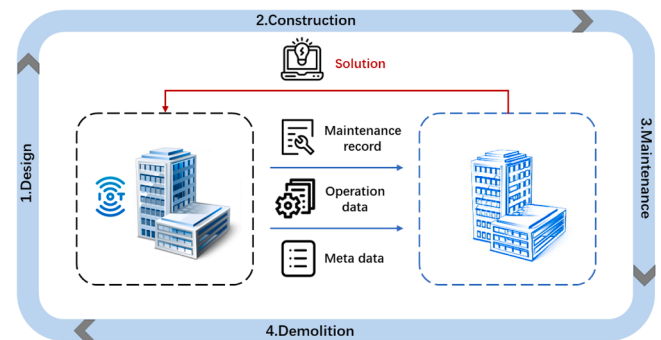


Fig. 7. Maintenance 4.0 in the building industry.

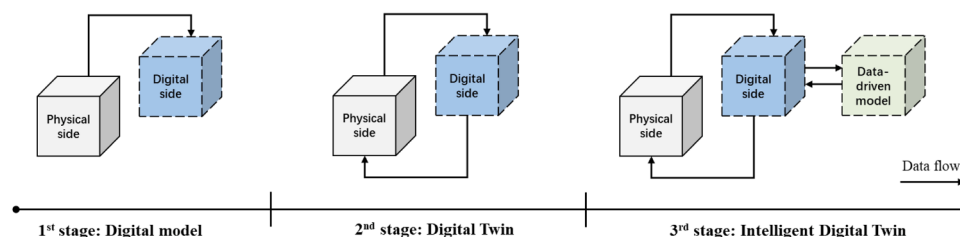


Fig. 6. Concept revelation of digital twin.

Table 5
Technology stack for DT embracement.

Structure	Facilities	Environment
Virtualisation • An interactive DT visualisation for life cycle asset monitoring [60]; • Time consumption reduction during DT model creation depending on reliable quality measures [61]; • 360° inspections depending on high-resolution 3D models and aerial imagery [85]; • Continuous road condition visualisation using data from LiDAR, photogrammetry, and drone video [88]; • DT model integrated BIM and inspection system [91]; • Comprehensive infrastructure DT updated with multisource and multitemporal data [98]; • Uncertainty-aware point cloud segmentation [118].	• Integrated video surveillance system and DT-related subsystem [87]; • Combine historical data and synthetic data into situ simulation [90]; • BIM and GIS integration model for energy consumption and carbon footprint [92]; • BIM integration with IoT alert system for condition and facility visualisation [46]; • EU-funded IoTwins platform facilitating hybrid DT system [47]; • Modelling approach with little hardware resources requirement [67]; • Graph-based virtual representation of legacy systems and digital models [76].	• Integrated BIM and terrain model, including design information and routine updates [82]; • As-built BIM model incorporates IoT and AI [34]; • Georeferenced photographs-based infrastructure digital model [95]; • Modelling framework and component design on PdM solution [49]; • Immersive AR digitalised platform to enhance user experience and presentations [50]; • Cloud-based life-cycle monitoring and visualisation of carbon intensity and resource consumption [63]; • AR-enhanced DT system focusing on indoor climate [83]; • Galata-driven environmental factors monitoring system [119]; • Multi-dimensional model and interactive simulation [58]; • Pre-made BIM model and DT protocols [101].
Computation • Robust and automated façade segmentation using point cloud data [80]; • Four-stage holistic assessment for maintenance planning [86]; • Extended DT creation in building life cycle management [93]; • Classic ML model comparison study on PdM performance on track structure [53]; • AI clustering and hazard index calculation-based decision support techniques for road maintenance [99]; • Improved decision making based on the integration of SHM data and 3D digital model [100]; • Robust decision-making support for multi-criteria ready-mix concrete supply chain effective management [78].	• Operation errors removal through feature extraction and ML techniques [4]; • Ensemble ML model for malfunction expedite detection [81]; • Automated risk detection and mitigation, including obstacles and human activity [40]; • Maintenance schedule prioritisation through hidden risk analysis [66]; • Systemic empirical knowledge-enhanced neural network model for automatic failure management [42]; • Reinforcement learning approach improving maintenance schedule based on track inspection [69]; • RNN-based surrogate model for dynamic maintenance optimisation [52]; • Explainable unsupervised deep learning model for failure detection [41]; • Semi-supervised model for failure prediction [120]; • Ontology-based decision support model [77].	• Predict and optimise occupant's comfort by combining statistic and ML models [32]; • AI-driven reasoning and service process for automatic building management system [36]; • Ensemble classifier learning algorithm tailored for imbalance scenarios during three-stage CBM [64]; • Ensemble failure prediction algorithm for indoor air quality [65]; • Combination of clustering ML and rule-based strategies for malfunction reduction [97].
Communication • Unified data storage and retrieval leveraging multiple blueprints [43]; • Integrated data collection architecture [44]; • Low-power and lightweight monitoring [70]; • Low-cost data exchange between cyber and physical [71]; • DT-oriented Industrial IoT Network covering sensors and actuators [39]; • Low-cost IoT design for concrete structure vibration monitoring [68].	• Automated data stream ageing feature extraction during remote monitoring [62]; • Data provenance model on a blockchain-based DT for improved reliability and trustworthiness [84]; • Information centralisation enabled by BIM and IoT [89]; • Evogy Simon monitoring for result-oriented product service system [96]; • Knowledge graph-based data management workflow [45]; • Introduces system dynamics into "Traintrack interaction [48]; • Blockchain-based digital twin data provenance [121].	• Novel IFC-based data structure, including operational data [33]; • Data access with digital building logbook using semantic web technology [94]; • Heterogeneous data integration architecture supporting intelligent data query [51]; • Copula data generation method [72]; • Blockchain and AI driven integrated management system [79].

Table 5 is according to the core concern and innovation focus of the reference, and the survey and review paper are excluded.

4.2.1. Virtualisation

Heterogeneous data and domain knowledge gathered from the on-site operation, as well as the decision support information generated after the intelligent computation, need to be modelled and delivered through the virtual platform [113]. As indicated in Table 5, BIM technology is employed as the key enabler to centralise the modelling across different building-related assets, while virtualisation advancements for structure, facilities, and environments show various requirements on technical specifications and design preferences.

For the building industry, visualisation and inspection serve as fundamental activities underpinning more advanced capabilities. With

the development of ICT, diverse data collection methods such as IoT systems, aerial photography, and LiDAR technology are utilised to enrich the information for the establishment and updating of digital layers [88]. Furthermore, integrating historical and synthetic data helps address data deficiencies during the modelling process [90]. A more comprehensive and high-fidelity 3D model can be generated in the DT solution depending on continued and accurate data exchange [98,85]. Besides, efficient and cost-effective modelling has garnered significant interest from researchers. For instance, Vassilev et al. [61] introduced reliable quality measure metrics to reduce time consumption, while Carotenuto et al. [67] developed innovative modelling techniques with lower hardware requirements.

Additionally, various functions like life cycle management are implemented across different assets, including building structures [60],

facilities [87], and environment [63], leveraging virtualisation platforms. As a pivotal technology for DT in the building industry, BIM is mainly utilised as the centralised platform for virtualising related assets and different technologies are integrated to provide a comprehensive digital target [91]. BIM-IoT integration for condition and facility visualisation is the most common method [46], while further advancements include BIM-GIS integration for building sustainability improvement [92], BIM-terrain model combination [82], and a hybrid DT system platform facilitated by EU-funded initiatives [47]. Sadri et al. [34] enhanced the as-built BIM with IoT and AI technologies, providing a new modelling perspective to establish DT systems for existing buildings without an as-designed model. Apart from BIM, emerging technologies such as georeferenced-based digital models [95] and immersive AR-enhanced systems [50,83] are explored to improve user experience and presentation. Overall, virtualisation enables the seamless integration and simulation of physical and digital assets, facilitating real-time monitoring, analysis, and optimisation of various processes and systems.

4.2.2. Computation

The computational aspect of the DT system is employed for data analytics and solution generation, facilitating intelligent decision-making and customised service [34]. As illustrated in Table 5, most research focuses on building facilities due to their similarity to manufacturing processes, which have been extensively studied. Conversely, research on structural and environmental applications is less prevalent, as these represent unique scenarios in the building industry. Extracting practical knowledge from heterogeneous data is challenging, making it essential to identify appropriate methodologies and tools for achieving and optimising the target function, which is crucial to DT construction.

Classical ML models, such as clustering and regression algorithms, are commonly applied to fundamental tasks like occupants' comfort improvement [32], building management automation [36,93], and maintenance scheduling [53,99]. Furthermore, advanced functions utilised deep learning methods, including explainable unsupervised models [41], RNN-based methods [52], and reinforcement learning [69]. Besides, M. Jasiulewicz-Kaczmarek and A. Gola [4] enhanced the feature extraction process to reduce the operation errors, while Lin et al. [64] developed an ensemble learning method tailored for imbalance. Failure prediction commonly demands higher algorithmic and analytical ability than management optimisation because of its real-time reliability requirements. Existing studies on failure reduction are mainly implemented on facilities [40,81] and environment [65,97], with structural-related studies focusing more on the management optimisation level [80]. Integrating the data-driven and model-driven methods enhances the failure management performance. For example, Weerapura et al. [42] incorporated empirical knowledge into the neural network design, while S. Agostinelli and F. Cumo [97] combined ML solutions and rule-based strategies. Employing robust and automated computational algorithms in building maintenance and management ensures comprehensive evaluation, improves predictive accuracy, and supports proactive decision-making.

4.2.3. Communication

Communication in DT architecture contains data acquisition and transmission, enabling seamless data exchange and integration across physical and virtual twins [114]. Existing studies aim to enhance the collection, storage, retrieval, and exchange of data information, covering the system architecture, communication protocols, and cloud platforms. Innovative studies and experiments are mainly achieved through unified implementation and the integration of a multi-sourced pipeline [115]. According to Table 5, communication-related research is evenly distributed across three types of assets in the building industry, demonstrating its cornerstone function during the establishment of the DT system.

Significant advances include both the macro-full process

improvement of the entire data stream and the tailored upgrading of subsystems. Sophisticated data processing capabilities are required for DT implementation in the building industry due to the increasingly complex and diverse data sources. As the technical basement, the unified data processing pipeline got the primary attention of the academic area, covering integrated architecture for data collection [20], storage and retrieval [21] process, and intelligent data query solutions [51]. Specifically, Lu et al. [33] integrated operational data into the proposed IFC-based data structure, while Fialho et al. [89] developed an innovative information centralisation architecture combining BIM and IoT systems. Furthermore, emerging technologies such as blockchain, semantic modelling, and knowledge graphs are being utilised to enhance data security [25], optimise data management [26], and facilitate data access [94]. Additionally, Machine Learning (ML) techniques are being integrated into the data stream process to enhance feature extraction [62,116] and data augmentation [72], further optimising the efficiency and effectiveness of data analysis in the building industry [117]. For hardware improvement, notable efforts include the development of low-power and sustainable sensor systems [48,70,71], as well as a new design paradigm for communication systems, particularly oriented from DT and results service perspectives [39,96]. The above development and implementation of advanced communication systems ensures robust data transfer and integration across various components of the DT system.

5. Application in the building industry

5.1. Concept of building industry

The building industry involves the building lifecycle and building-related assets. The framework specifically targets the maintenance stage and seeks to enhance the entire building lifecycle by applying the identified intelligent solutions and improvements. As shown in Table 6, the building lifecycle starts from the initial design phase, progresses through the on-site construction, extends into the operation and maintenance, and ultimately ends with demolitions.

5.2. Implementation in building industry

Regarding the associated assets and systems, the framework considers various implementations identified through a comprehensive literature review. Application scenarios include the building structure, mechanical, electrical, and plumbing (MEP) components, transport infrastructure, HVAC system, lighting systems, indoor comfort, indoor air quality, and building complex, while functions ranging from condition monitoring to resource optimisation are implemented on the above targets. The detailed distribution of these assets and functions is presented in Table 7. To ensure the accuracy of the description, only studies that explicitly identified the assets and functions were included in the summary. For example, studies that mentioned facilities or infrastructures without clear explanations were excluded [49,50,52].

Table 6
Building lifecycle.

Life stage	Definition
Design	Conceptualisation, planning, and detailed design of the building, encompassing architectural, structural, and engineering considerations.
Construction	Actual construction activities on the site involve the assembly of building materials, installation of systems, and coordination of various trades.
Operation & maintenance	Daily management, use, and ongoing upkeep of the building, as well as regular repair and optimisation to maintain functionality, safety, and performance standards.
Demolition	Systematic deconstruction and removal of the building at the end of its useful life, including recycling and disposal of materials.

Table 7
Summary of assets and functions.

Categories	Application assets	Refs.	Function
Facility	Water supply system	[66]	Failure conditions assessment
	HVAC system	[96]	Energy management
		[45]	Energy system monitoring and maintenance services
		[4]	Automatic fault detection and diagnostics
		[79]	Automated, blockchain-enabled smart facility management
	Pump system	[76]	Remaining Useful Life (RUL) tracking
		[33]	Anomaly detection
		[35]	Predictive maintenance
		[83]	Temperature abnormalities monitoring
	Lighting system	[89]	Lighting performance information delivering and anticipation
Structure	Drilling robot	[40]	Safety improvement and real-time monitoring
	Bridge structure	[60]	Structural health monitoring
		[27]	Inspection and maintenance
		[61]	Condition monitoring
		[90]	Real-time structural performance monitor
		[91]	Vulnerability assessment and risk-based maintenance planning
		[85]	Condition inspection
		[91]	Vulnerability assessment and risk-based maintenance planning
	Railway track	[53]	Track geometry parameters prediction and railway track maintenance
		[86]	Condition assessment and life cycle analysis
		[92]	Sustainability and resilience improvement
		[48]	Long-term rail surface damage prediction
	Road pavement	[69]	Maintenance activities reduction
		[98]	Real-time monitoring and maintenance
		[99]	Road inspection and maintenance
	Reinforced concrete unit	[122]	Unbound road pavement management
		[68]	Structural health monitoring and predictive maintenance
		[51]	Asset maintenance tracking and equipment failure prediction
	Facade element	[78]	Production and supply chain optimization
		[80]	Building facade segmentation
		[93]	Energy savings and reliability improvement
	Water infrastructure	[44]	Maintenance prioritisation based on surveillance program and prediction modelling
Environment	Indoor air quality	[65]	Failure prediction
		[94]	Health-based maintenance prioritisation
		[58]	Indoor environment quality prediction ratio
	Non-residential building	[32]	Fault detection and prediction
	Residential buildings	[81]	Occupant comfort improvement
	University laboratory	[83]	Temperature abnormalities monitoring and inspection
	Hospital building	[63]	Building component reuse
	Substation	[87]	Diagnostic prediction
	Port	[95]	Security control and pollution reduction
	Precast concrete plant	[42]	Operational risk management and anomaly detection
	HVAC plant	[46]	Real-time monitoring and anomaly detection

6. Unified framework and techniques pipeline

This section proposes a DT-enabled Maintenance 4.0 framework for the building industry, as illustrated in Fig. 8. The framework integrates key enabling technologies from the DT perspective to enhance intelligence, efficiency, and interoperability during the maintenance phase of the building lifecycle. The framework positions maintenance as the central phase at the bottom, emphasising its role in supporting and informing other lifecycle stages such as design, construction, and demolition through continuous feedback enabled by DT technologies.

6.1. Digital twin system

The framework in Fig. 9 delineates the DT-enabled Maintenance 4.0 in the building industry through a layered architecture, encompassing data collection, data processing, the intelligent model, and the virtualisation platform. Each subcomponent within this architecture is supported by cloud deployments, ensuring scalability and interactivity during implementation.

6.1.1. Data collection

Data collection serves as the foundational layer that enables the creation of an accurate and dynamic virtual representation of physical assets and the generation of decision-support information [123,124]. According to the systemic review, the data source involves gathering operation data, attribute data, and evaluation data from various sources, such as IoT sensors, BIM systems, and failure records.

The detailed data framework summarised from the systemic review is demonstrated in Fig. 9. Operation data includes real-time operating metrics and usage statistics such as temperature, humidity levels, occupancy and equipment status, among others, which provides a dynamic and continuous overview of the system performance [125]. Attribute data pertains to the static metadata associated with the target asset, encompassing detailed information such as the building's dimensions, architectural design, and other physical characteristics of facilities and the environment [126]. This data forms the foundational understanding of the inherent properties and capabilities of the target. Evaluation data primarily consists of maintenance records and stakeholders' feedback. Maintenance records detail the history of repairs, replacements, and upgrades, while stakeholders' feedback offers qualitative insights from users, operators, and maintenance personnel regarding the assets's functionality and performance. This information is crucial for providing significant objective standards during the training and establishment of the intelligent model [94].

6.1.2. Data processing

Data processing plays a pivotal role in transforming raw data into actionable insights for the DT establishment, enabling the seamless integration and utilisation of diverse data sources to support intelligent modelling and decision-making [127]. As illustrated in Fig. 8, it encompasses a series of critical steps, including data cleaning, data integration, data transformation, feature engineering, and data security. In addition to the above standard procedures, it is essential to address emerging considerations specific to building maintenance scenarios, which are critical for advancing the field and ensuring the effectiveness of DT-enabled maintenance strategies in the contemporary building industry.

6.1.2.1. Data from BIM models. BIM is integral to the advanced maintenance of the building industry [77], which provides a centralised repository for all building-related information, enabling a holistic view for real-time monitoring, PdM, and efficient resource allocation. As shown in Fig. 10, both structured and unstructured data play a crucial role in the comprehensive management of building information. Integrating these data types enhances the richness and utility of the BIM model,

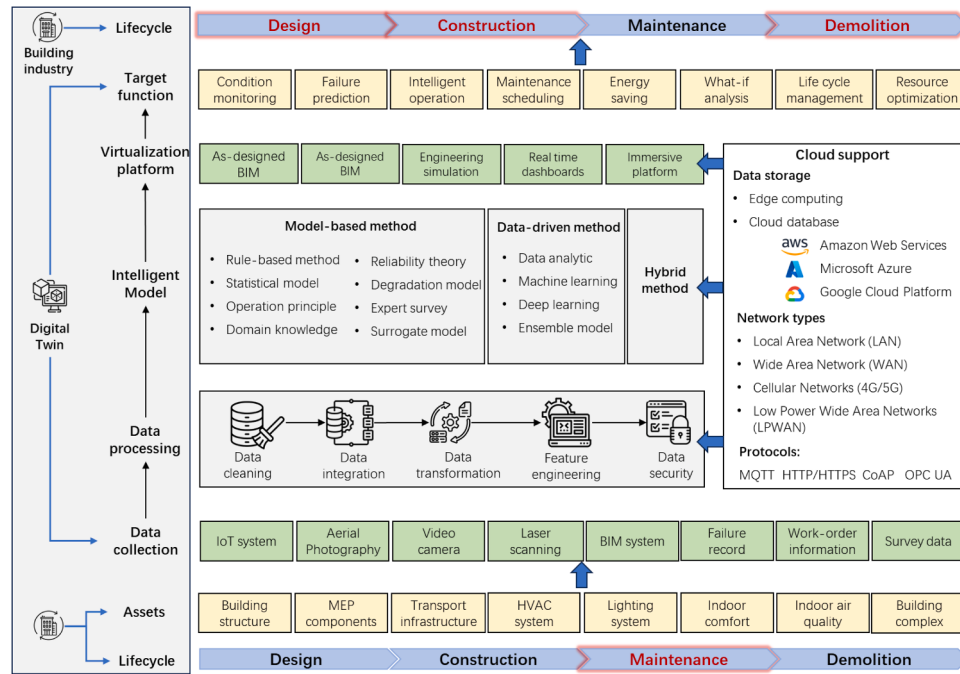


Fig. 8. Digital twin-enabled maintenance 4.0 framework in the building industry.

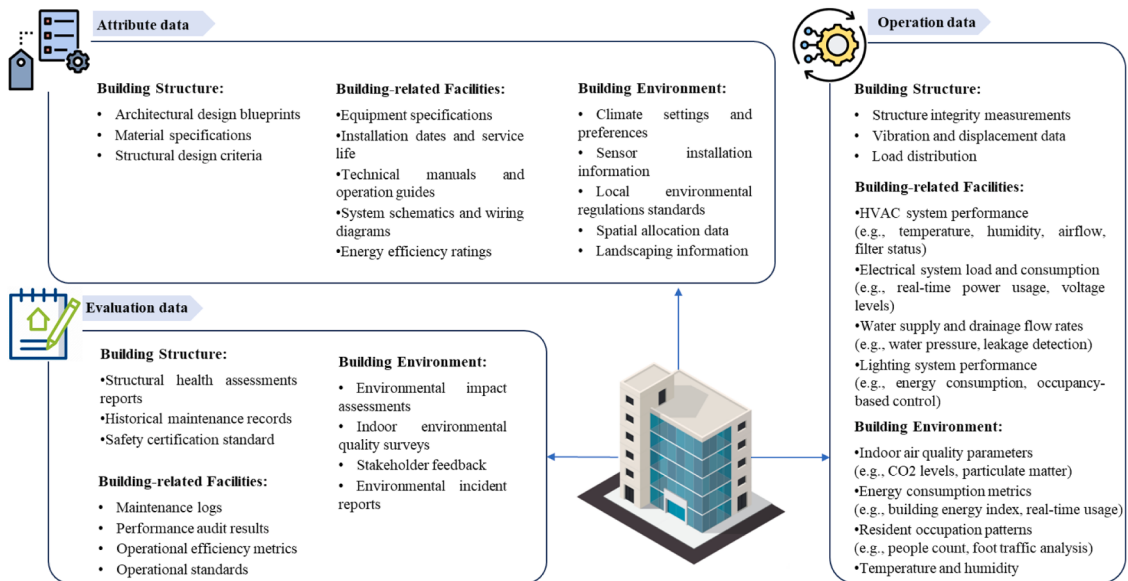


Fig. 9. The systemic overview of data distribution in digital twin-enabled maintenance 4.0 in the building industry.

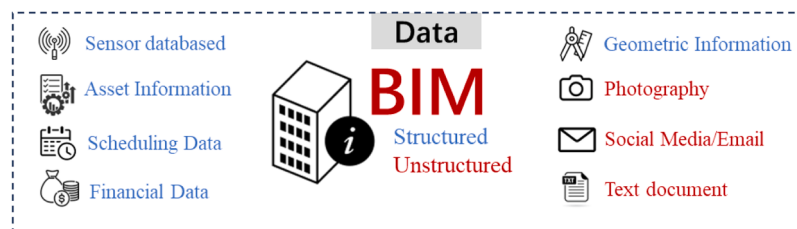


Fig. 10. Data from BIM models.

allowing for better decision-making and more effective building management [128]. For example, incorporating site photographs into the BIM model to create a visual timeline of construction progress, helping to identify potential issues and ensure quality control.

Beyond the as-designed BIM, as-built BIM is increasingly significant in the implementation of maintenance solutions [129]. As-built BIM accurately represents the actual construction, including unplanned modifications made during the construction process, while the data in as-built BIM provides up-to-date information on the building's current state. By leveraging as-built BIM, advanced maintenance solutions are significantly enhanced for existing buildings, which often lack digital models and have substantial maintenance demands [130]. Additionally, maintenance teams can accurately track the building's condition, anticipate potential issues, and streamline maintenance workflows [131]. In conclusion, the integration of both as-designed and as-built BIM models into building maintenance strategies is essential for modernising the maintenance approach. This comprehensive data view supports improved decision-making, operational efficiency, and extended building lifespans through timely and effective interventions.

6.1.2.2. Data integration using IFC, COBie, and JSON. Data integration between different subsystems is a critical characteristic for building-related maintenance [37]. In existing studies, three important methods for data mapping and integration in building maintenance are Industry Foundation Classes (IFC), Construction Operations Building Information Exchange (COBie), and JavaScript Object Notation (JSON). Moreover, the data interactivity and interoperability between BIM, sensor networks, and maintenance record systems have garnered significant research attention, with numerous studies exploring unified data formats for building maintenance [132,133].

IFC is an open, standardised data format that enables the sharing of BIM data across different software platforms [134]. It ensures interoperability, allowing various stakeholders to access and use the same data seamlessly. COBie is a data schema used to capture and deliver building information, particularly during the handover from construction to operation [135]. It includes details on building assets, such as equipment lists, warranties, and maintenance schedules, making it easier to manage building maintenance activities. JSON is a lightweight data-interchange format that is easy to read and write and is commonly used for data exchange between web applications and servers [136]. In the context of building maintenance, JSON can integrate data from sensors and facility management systems with BIM data, providing a unified dataset for maintenance activities. Fig. 11 presents data samples of a wall structure represented through IFC, COBie, and JSON formats, respectively. These examples are simplified to emphasise the differences in representation. In practical applications, each format would encompass more detailed and specific information tailored to its particular use case and standards.

The above data processing and integration techniques allow for the development of sophisticated maintenance strategies, ultimately

enhancing the performance and longevity of building assets. The synergy between IFC, COBie, and JSON not only facilitates efficient data management but also supports the creation of intelligent models that drive improved decision-making and operational efficiency in the building industry [137].

6.1.3. Intelligent model

The intelligent model plays a pivotal role in the proposed framework by serving as the core analytical engine that drives advanced maintenance strategies [17]. According to Fig. 8, the methodology can be categorised into model-based methods, data-driven methods, and hybrid methods. As illustrated in Table 8, model-based methodologies, such as rule-based algorithms, statistical models, and reliability theory, leverage domain knowledge and theoretical frameworks to provide structured and interpretable insights into system behaviour [138]. However, the effectiveness is often limited by the accuracy of the underlying models and assumptions, and they may struggle to adapt to complex, dynamic environments. Consequently, data-driven methods, including ML, deep learning, and data analytics, allow for the processing of large datasets to uncover hidden patterns and predictive insights [139]. Nevertheless, their reliance on extensive datasets and computational resources, coupled with potential issues in interpretability and transparency, poses significant challenges. To ensure a robust and adaptive maintenance solution, hybrid methods are being explored to combine the predictive

Table 8

Model-based VS data-driven method in maintenance 4.0.

	Model-based	Data-driven
Data	Architectural drawings, Facilities specifications, Material properties	Operation data, Attribute data, Maintenance logs
Techniques	Physical/mathematical models, Simulations	Machine learning, Statistical analysis
Approach	Simulating equipment behaviour and degradation based on detailed knowledge of physical principles and mechanisms.	Identifying patterns and trends in large volumes of data from sensors and logs.
Example	Structural health monitoring using stress-strain relationships	HVAC system failure prediction using historical and real-time performance data
Limitations	- Limited scalability due to the need for detailed models for each system. - Slower response time due to reliance on model analysis. - Highly dependent on specialised engineering skills, domain-specific knowledge, and experience - Limited by simplified model design and ideal parameters assumptions.	- Higher initial investment in data big data infrastructure. - Laborious and expensive data labelling efforts. - Highly dependent on the data quality and availability

<pre>#1 = IFCWall('2xvGm5e8D9u8xZqMaEgV', #2, 'Wall', 'A simple wall', 'MyWall', #3, #4, \$); #2 = IFCOWNERHISTORY(#5, #6, \$, .ADDED., #7, #8, #9, 1518490000); #3 = IFCPRODUCTDEFINITIONSHAPE(\$, #10); #4 = IFCLOCALPLACEMENT(\$, #11); #5 = IFCAPPLICATION(#6, '1.0', 'Building Designer', 'Wall App'); #6 = IFCORGANIZATION(\$, 'My Organization', \$, \$, \$); #7 = IFCPERSONANDORGANIZATION(#8, #6, \$); #8 = IFCPERSON(\$, 'Smith', 'John', \$, \$, \$, \$, \$); #9 = IFCMEASUREWITHUNIT(IFCPOSITIVELENGTHMEASURE(5.0), #12); #10 = IFCSHAPEPRESENTATION(#13, 'Body', 'SweptSolid', (#14)); #11 = IFCAXIS2PLACEMENT3D(#15, \$, \$); #12 = IFCUNITASSIGNMENT((#16)); #13 = IFCCOORDINATESYSTEM('3D'); #14 = IFCLOUORRGB('Red', 1.0, 0.0, 0.0); #15 = IFCORIGIN(\$, \$, \$); #16 = IFCSTUNIT(.LENGTHUNIT, .METRE.);</pre>	<pre>### Type Data ### Type: Wall Name: Wall001 Description: A simple wall Category: Exterior AssetType: Wall ### Component Data ### Component: Wall Name: Wall001 Type: Wall Description: Exterior Wall Location: First Floor Manufacturer: ABC Corp ModelNumber: W-001 SerialNumber: 12345 InstallationDate: 2024-01-01</pre>	<pre>{ "type": "Wall", "name": "Wall001", "description": "A simple wall", "category": "Exterior", "properties": { "material": "Concrete", "length": 5.0, "height": 3.0, "thickness": 0.2 }, "location": { "floor": "First Floor", "coordinates": { "x": 10, "y": 20, "z": 0 } }, "manufacturer": { "name": "ABC Corp", "modelNumber": "W-001", "serialNumber": "12345", "installationDate": "2024-01-01" } }</pre>
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Fig. 11. Wall sample of IFC, COBie, and JSON.

accuracy of data-driven methods with the contextual understanding provided by model-based methods [108]. This approach demonstrates improved performance and broader applicability during the practical implementation.

6.1.4. Virtualisation platform

The visualisation platform layer in the framework depicted in Fig. 8 integrates various tools and technologies to create a comprehensive and interactive representation of the target building-related asset, aiding in effective decision-making and operational efficiency [140]. The presented platform summarised from existing studies includes:

- (1) As-designed BIM: The BIM model captures the initial design specifications and construction details, providing a digital representation of the building's physical and functional characteristics [141].
- (2) As-built BIM: The as-built model is reconstructed using laser scanning and AI engineering after the building has been completed, which accurately reflects the actual conditions of the finished building, incorporating any changes made during the construction process [142].
- (3) Engineering Simulation: Professional software such as Matlab, EnergyPlus, TRNSYS, and DesignBuilder allow for the virtual testing and analysis of building components and systems under various conditions, helping to predict performance and identify potential issues before they arise [143].
- (4) Real-time Dashboards: These platforms provide up-to-date information and analytics, such as key performance indicators, maintenance schedules, energy usage, and other critical metrics, enabling stakeholders to monitor the building's performance and status in real-time [144].
- (5) Immersive Platform: This includes technologies such as virtual reality (VR) and augmented reality (AR) that offer immersive experiences for users. These platforms can be used for virtual walkthroughs, training, and remote collaboration, enhancing understanding and engagement with the building data [15].

The visualisation platform layer ensures that data acquired from various sources and decision-support information generated in the intelligent model layer are presented in a user-friendly and actionable format. Fig. 12 illustrates the example platform established by the authors in their experiment. The as-built BIM is displayed on the proposed iScan2BIM platform [145], while the as-designed BIM is shown using the XbimXplore software [129]. The immersive building environment is generated using Unity and HoloLens, and the real-time dashboard is deployed on a web-based platform. By providing these advanced visualisation tools, the layer supports better planning, monitoring, and management of building maintenance activities, ultimately contributing to the efficiency and sustainability of building operations [146].

6.1.5. Cloud support

Cloud support is essential for the efficient storage, processing, and accessibility of data with the DT-enabled Maintenance 4.0 ecosystem for the building industry [147]. The cloud system provides robust infrastructure and services that enhance data management and integration across various stages of the building lifecycle, from design to demolition [148]. Table 9 presents a comprehensive overview of the cloud support stack that underpins the DT-enabled Maintenance 4.0 in the building industry. It encompasses data transmission, data storage, and data processing technologies. The data transmission section highlights secure and efficient communication protocols, including MQTT, HTTP/HTTPS, CoAP, and OPC UA, along with various network types like LAN, WAN, 4G/5G, and LPWAN, which facilitate reliable data transfer across different environments [149]. The data storage section emphasises the role of edge computing for initial processing close to data sources and centralised cloud databases provided by Amazon Web Services, Microsoft Azure, and Google Cloud Platform for large-scale data management [150]. The data processing section covers edge processing for preliminary data handling and cloud processing using scalable infrastructures, including big data frameworks like Hadoop and Apache Spark, stream processing tools such as Apache Kafka and AWS Kinesis, and serverless computing services like AWS Lambda and Azure Functions. This technological stack ensures efficient data management, processing, and accessibility, enhancing the effectiveness of building

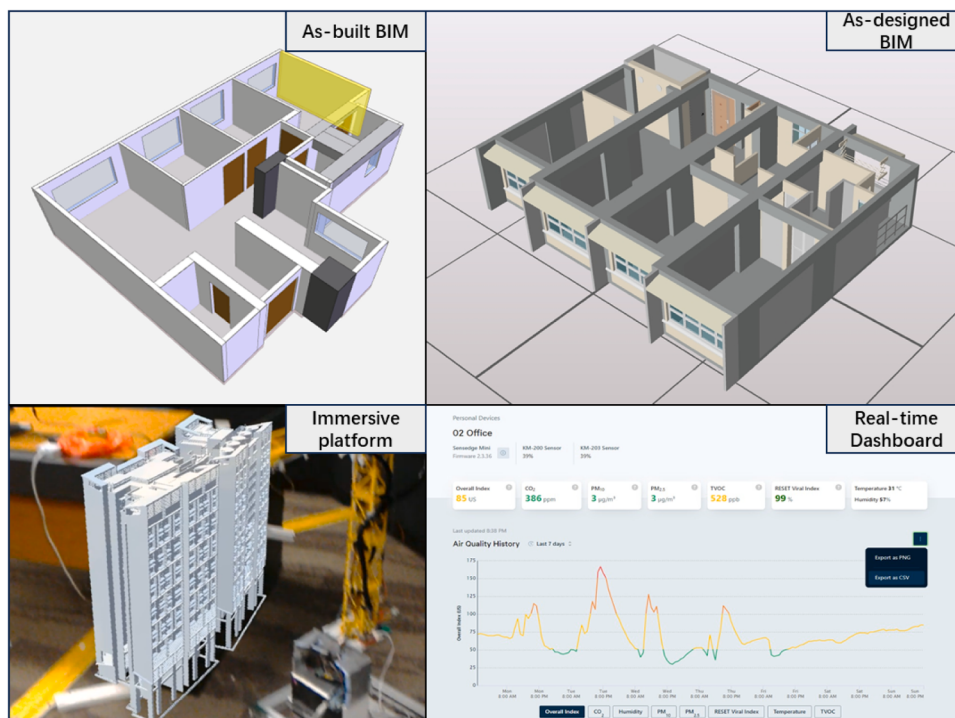


Fig. 12. Virtualisation platform established by authors.

Table 9
Technology stack in cloud support layer.

Data transmission	Communication Protocols: Ensures secure and efficient data exchange. MQTT (Message Queuing Telemetry Transport): Lightweight, publish-subscribe network protocol suitable for remote monitoring. HTTP/HTTPS: Used for web-based communication, ensuring secure data transfer. CoAP (Constrained Application Protocol): Designed for low-power, low-bandwidth devices. OPC UA (Open Platform Communications Unified Architecture): Standard for industrial automation, ensuring interoperability. Network Types: Facilitates reliable data transfer across various environments. Local Area Network (LAN): Used within a factory or industrial site. Wide Area Network (WAN): For data transmission over long distances. Cellular Networks (4G/5G): For remote locations and mobile assets. Low Power Wide Area Networks (LPWAN): For IoT devices with low data rates over long ranges (e.g., LoRaWAN, Sigfox).
Data storage	Edge Computing: Initial processing and storage close to the data source to reduce latency and bandwidth usage. Cloud Database: Centralized storage for large-scale data processing and analysis. Amazon Web Services (AWS): Offers databases like Amazon RDS, DynamoDB, and S3 for storage. Microsoft Azure: Provides Azure SQL Database, Cosmos DB, and Blob Storage. Google Cloud Platform (GCP): Includes Google Cloud Storage, Firestore, and BigQuery.
Data processing	Edge Processing: Preliminary data processing at the edge to filter, aggregate, and preprocess data before sending it to the cloud. Cloud Processing: Advanced data processing using scalable cloud infrastructure. Big Data Processing Frameworks: Apache Hadoop, Apache Spark. Stream Processing: Apache Kafka, AWS Kinesis. Serverless Computing: AWS Lambda, Azure Functions for event-driven processing.

lifecycle management within the digital twin framework.

Fig. 13 illustrates the comprehensive sequence of processes within this ecosystem, beginning with data collection from a variety of sources, which are subsequently transferred to the cloud database through the network. Following storage, disparate raw data are processed into suitable data and advanced data analysis methods, including ML and neural networks, are employed to extract meaningful insights from the integrated data. These insights are subsequently visualised through dashboard-enabled methodology, providing stakeholders with intuitive and actionable information. Finally, this process culminates in informed decision-making by industry professionals, who leverage the visualised data to optimise maintenance strategies, enhance operational efficiency, and ensure the sustainable management of building assets throughout their lifecycle.

6.2. Comparative interpretation and novelty analysis

The analytical review of 81 studies demonstrates a clear differentiation in research design, asset orientation, and evaluation methodology, indicating the growing methodological maturity of DT-enabled Maintenance 4.0 research. Conceptual and prototype investigations

constitute the majority of existing works, whereas fully validated case studies remain comparatively limited. The findings reveal distinct modelling preferences across asset categories: data-driven approaches are predominantly applied to dynamic environmental and HVAC systems, while hybrid physics-based and artificial intelligence methods are more prevalent in structural and safety-critical applications. In addition, the reviewed studies employ heterogeneous performance indicators, resulting in inconsistency and reduced comparability across domains. To overcome these limitations, the proposed framework establishes a systematic interpretation that integrates study design, asset domain, and evaluation metrics into a coherent analytical structure, as summarised in Table 10.

Although numerous studies have proposed high-level data-model-visualisation frameworks for DT-enabled maintenance, the proposed framework advances the field through three key aspects: *firstly*, it achieves evidence-based synthesis by being empirically derived from the comparative analysis of 99 systematically coded studies, integrating methodological patterns across asset types, algorithmic designs, and technological readiness levels to ensure analytical rigor and practical relevance; *secondly*, it introduces a bidirectional learning mechanism in which analytical outputs dynamically refine sensing strategies, fault thresholds, and maintenance scheduling, transforming linear maintenance processes into adaptive, self-optimising loops; and *thirdly*, it ensures scalable interoperability through modular integration of IoT, BIM, and cloud-edge infrastructures, supported by open standards such as IFC, COBie, and MQTT, enabling deployment across single assets and multi-building systems. Collectively, these advancements establish the framework as a data-driven, feedback-adaptive, and scalable methodology that operationalises Digital Twin-enabled Maintenance 4.0 beyond conceptual abstraction.

7. Conclusion and future discussion

The advanced maintenance paradigm has become increasingly vital in the building industry, driven by the urgent need to ensure structural integrity, operational efficiency, and sustainability throughout the building lifecycle [108]. The rapid advancement of Industry 4.0 has accelerated the convergence of Maintenance 4.0 and Construction 4.0, promoting proactive and intelligent maintenance approaches across the built environment. As a pivotal enabling technology, the DT paradigm enhances the continuous monitoring, simulation, and optimisation of physical assets through real-time information exchange and AI-enabled decision support [151]. This research makes progress beyond existing studies by systematically integrating dispersed DT-related maintenance research into a coherent, multi-dimensional framework, thereby contributing to the field through a structured threefold advancement.

- **Comprehensive Knowledge Integration:** A systematic review of 99 academic sources was conducted to identify and classify enabling technologies, technological pipelines, and deployment strategies within DT-enabled Maintenance 4.0. This integration consolidates fragmented findings into a cohesive knowledge system, providing a structured foundation that has been lacking in previous research.
- **Unified Framework Development:** A novel DT-enabled Maintenance 4.0 framework is proposed, encompassing the entire technological hierarchy from communication and data acquisition to computational analytics, intelligent modelling, and visualisation, all supported by scalable cloud infrastructure. Compared with previous studies that focused on single functions or domains, this framework

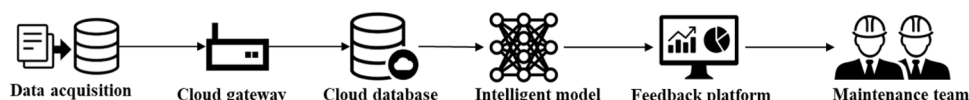


Fig. 13. Data flow diagram.

Table 10
Comparative interpretation across study designs, assets, and metrics.

Dimension	Key Findings from Reviewed Studies	Interpretation within the Unified Framework
Study Design	<i>Conceptual frameworks:</i> theoretical discussions of data flow and system architecture. <i>Prototype implementations:</i> integration of sensing, modelling, and cloud-based analytics for validation under controlled conditions. <i>Pilot projects:</i> real-site applications assessing prediction reliability and lifecycle performance.	The hierarchical progression from conceptual formulation to pilot deployment is mirrored in the framework's layered structure, encompassing communication, computation, intelligence, and visualisation layers supported by cloud infrastructure.
Asset groups	<i>HVAC and environmental systems:</i> comfort optimisation, energy efficiency, and anomaly prediction. <i>Structural and façade assets:</i> deformation, fatigue, and reliability analysis. <i>Facility and infrastructure subsystems:</i> utilities, lighting, and electrical management.	The framework integrates these heterogeneous domains through a multi-level intelligence layer that bridges data-driven analytics and physics-based reasoning, enabling cross-domain adaptability and unified decision-making.
Evaluation Metrics	- Environmental and HVAC studies utilise statistical indices such as accuracy, precision, and RMSE. - Structural applications emphasise reliability indices, degradation thresholds, and safety factors. - Facility-related studies apply lifecycle cost and energy indicators.	The framework aligns predictive metrics with data-driven models, diagnostic metrics with hybrid reasoning, and prescriptive metrics with maintenance optimisation to ensure consistent and comparable performance evaluation.

unifies multi-disciplinary technologies and demonstrates their interoperability across building structures, facilities, and environmental systems.

- **Comparative Progress and Maturity Evaluation:** By categorising existing studies into review, framework, prototype, and case study types, this research provides a technology maturity analysis that clarifies how the field has evolved from conceptual proposals toward implementable systems. This classification highlights the concrete progress achieved and identifies critical gaps hindering large-scale industrial adoption.

Among examined studies, about 20% studies focused on data standardisation issues, 50% examined AI-driven modelling, and 30% proposed hybrid or integrated approaches, thereby offering quantitative evidence for the above three major conclusions. Collectively, these findings confirm that while research on DT-enabled maintenance has made substantial progress in modelling and integration, it lacks standardised metrics, validated cross-domain benchmarks, and large-scale industrial replication. Future work should therefore prioritise:

- The standardisation of data protocols covering structure, facilities, and environment is essential for ensuring interoperability and consistency across different systems and platforms [127].
- The implementation of interpretable AI is crucial for enhancing transparency and trust in AI-driven decisions.
- Furthermore, the development of hybrid models is necessary to leverage the strengths of model-based and data-driven approaches, providing more robust and versatile solutions [152].
- The advancement of high-precision modelling is required to accurately capture and simulate intricate details, thereby enabling more effective and efficient management of complex tasks [153]. The above efforts will collectively drive significant progress in the field.

The above analysis demonstrates the practical usefulness of this study. The proposed framework not only integrates the technological ecosystem of DT-enabled Maintenance 4.0 but also serves as a reference architecture for developing intelligent maintenance platforms with cross-domain data interoperability. The findings offer actionable insights for researchers and practitioners to design scalable AI-supported systems capable of predictive decision-making and self-optimising operations in real-world building environments.

CRediT authorship contribution statement

Wei Hu: Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yifu Ou:** Writing – review & editing, Formal analysis. **Haiyi Liu:** Writing – review & editing, Validation. **Peizhou Ni:** Writing – review & editing, Visualization. **Cheng Chang:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization.

Declaration of competing interest

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

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Data availability

Data will be made available on request.

References

- [1] H.H. Hosamo, M.S. Tingstveit, H.K. Nielsen, P.R. Svennevig, K. Svidt, Multiobjective optimization of building energy consumption and thermal comfort based on integrated BIM framework with machine learning-NSGA II, *Energy Build.* 277 (2022) 112479, <https://doi.org/10.1016/j.enbuild.2022.112479>.
- [2] R. Sacks, R. Sacks, C. Eastman, G. Lee, G. Lee, PM. Teicholz, PM. Teicholz, *BIM Handbook: A Guide to Building Information Modeling for Owners, Designers, Engineers, Contractors, and Facility Managers*, Wiley, 2018, <https://doi.org/10.1002/9781119287568>.
- [3] C.J. Turner, J. Oyekan, L. Stergioulas, D. Griffin, Utilizing industry 4.0 on the construction site: challenges and opportunities, *IEEE Trans. Industr. Inform.* 17 (2021) 746–756, <https://doi.org/10.1109/TII.2020.3002197>.
- [4] H.H. Hosamo, P.R. Svennevig, K. Svidt, D. Han, H.K. Nielsen, A digital twin predictive maintenance framework of air handling units based on automatic fault detection and diagnostics, *Energy Build.* 261 (2022) 111988, <https://doi.org/10.1016/j.enbuild.2022.111988>.
- [5] H.H. Hosamo, M.H. Hosamo, Digital twin technology for bridge maintenance using 3D laser scanning: a review, *Adv. Civ. Eng.* 2022 (2022), <https://doi.org/10.1155/2022/2194949>.
- [6] H.H. Hosamo, H.K. Nielsen, A.N. Alnmr, P.R. Svennevig, K. Svidt, A review of the digital twin technology in the AEC-FM industry, *Front. Built. Environ.* 8 (2022), <https://doi.org/10.3389/fbuil.2022.1013196>.
- [7] W. Hu, X. Wang, K. Tan, Y. Cai, Digital twin-enhanced predictive maintenance for indoor climate: a parallel LSTM-autoencoder failure prediction approach, *Energy Build.* 301 (2023) 113738, <https://doi.org/10.1016/j.enbuild.2023.113738>.
- [8] F. Longo, L. Nicoletti, A. Padovano, Ubiquitous knowledge empowers the smart factory: the impacts of a service-oriented digital twin on enterprises' performance, *Annu. Rev. Control* 47 (2019) 221–236, <https://doi.org/10.1016/j.arcontrol.2019.01.001>.
- [9] C.J. Roberts, D.J. Edwards, M.R. Hosseini, M. Mateo-Garcia, D.G. Owusu-Manu, Post-occupancy evaluation: a review of literature, *Eng. Constr. Archit. Manag.* 26 (2019) 2084–2106, <https://doi.org/10.1108/ECAM-09-2018-0390>.
- [10] C. Chang, F. Di Maio, R. Bheemireddy, P. Posthoorn, A.T. Gebremariam, P. Rem, Enhancing quality inspection efficiency and reliability of unscreened recycled coarse aggregates (RCA) streams using innovative mobile sensor-based technology, *Dev. Built Environ.* 21 (2025) 100611, <https://doi.org/10.1016/J.DIBE.2025.100611>.
- [11] D.J. Cook, N.L. Greengold, A.G. Ellrodt, S.R. Weingarten, *The Relation between Systematic Reviews and Practice Guidelines*, (2016).

- [12] The PRISMA2020 statement: An updated guideline for reporting systematic reviews, (2025). <https://www.equator-network.org/reporting-guideline/s/prisma/>.
- [13] M.F. Jahangir, C.P.L. Schultz, A. Kamari, A review of drivers and barriers of digital twin adoption in building project development processes, 2024. [10.36680/j.itcon.2024.008](https://doi.org/10.36680/j.itcon.2024.008).
- [14] H.H. Hosamo, H.K. Nielsen, A.N. Alnmr, P.R. Svennevig, K. Svidt, A review of the digital twin technology for fault detection in buildings, *Front. Built. Environ.* 8 (2022) 1–23, <https://doi.org/10.3389/fbuil.2022.1013196>.
- [15] C. Coupriy, S. Noblecourt, P. Richard, D. Baudry, D. Bigaud, BIM-Based digital twin and XR devices to improve maintenance procedures in smart buildings: A literature review, *Appl. Sci.* 11 (2021), <https://doi.org/10.3390/app11156810> (Switzerland).
- [16] F. Hodavand, I.J. Ramaji, N. Sadeghi, Digital twin for fault detection and diagnosis of building operations: a systematic review, *Buildings* 13 (2023), <https://doi.org/10.3390/buildings13061426>.
- [17] O. Hakimi, H. Liu, O. Abudayyeh, Digital twin-enabled smart facility management: a bibliometric review, *Front. Eng. Manag.* 11 (2024) 32–49, <https://doi.org/10.1007/s42524-023-0254-4>.
- [18] K. Chen, M. Eskandari Torbaghan, M. Chu, L. Zhang, A. Garcia-Hernández, Identifying the most suitable machine learning approach for a road digital twin, *Proc. Inst. Civ. Eng. Smart Infrastruct. Constr.* 174 (2022) 88–101, <https://doi.org/10.1680/jsmic.22.00003>.
- [19] S.M. Hallaji, Y. Fang, B.K. Winfrey, Predictive maintenance of pumps in civil infrastructure: state-of-the-art, challenges and future directions, *Autom. Constr.* 134 (2022) 104049, <https://doi.org/10.1016/j.autcon.2021.104049>.
- [20] Y. Mousavi, Z. Gharineiat, A.A. Karimi, K. McDougall, A. Rossi, S.G. Barsanti, Digital twin technology in built environment: a review of applications, capabilities and challenges, *Smart Cities* 7 (2024) 2594–2615, <https://doi.org/10.3390/smartcities7050101>.
- [21] A. Adhikari, T. Karunaratne, N. Sumanaratna, Machine learning techniques for predictive maintenance of building services: a comprehensive review and research outlook, *Facilities* 43 (2025) 803–817, <https://doi.org/10.1108/F-02-2025-0032>.
- [22] T. Karunaratne, I.R. Ajiero, R. Joseph, E. Farr, P. Piroozfar, Evaluating the economic impact of digital twinning in the AEC industry: a systematic review, *Buildings* 15 (2025), <https://doi.org/10.3390/buildings15142583>.
- [23] O.O. Lawal, N.O. Nawari, O. Lawal, AI-enabled cognitive predictive maintenance of urban assets using city information modeling—systematic review, *Buildings* 15 (2025), <https://doi.org/10.3390/buildings15050690>.
- [24] Y. Mousavi, Z. Gharineiat, A.A. Karimi, K. McDougall, A. Rossi, S.G. Barsanti, Digital twin technology in built environment: a review of applications, capabilities and challenges, *Smart Cities* 7 (2024) 2594–2615, <https://doi.org/10.3390/smartcities7050101>.
- [25] A. Alhadi, B. Dr Tom, R. Yacine, Enhancing asset management: integrating digital twins for continuous permitting and compliance - a systematic literature review, *J. Build. Eng.* 99 (2025), <https://doi.org/10.1016/j.jobbe.2024.111515>.
- [26] E. Zio, Prognostics and Health Management (PHM): where are we and where do we (need to) go in theory and practice, *Reliab. Eng. Syst. Saf.* 218 (2022) 108119, <https://doi.org/10.1016/j.res.2021.108119>.
- [27] M.M. Futai, T.N. Bittencourt, H. Carvalho, D.M. Ribeiro, Challenges in the application of digital transformation to inspection and maintenance of bridges, *Struct. Infrastruct. Eng.* 18 (2022) 1581–1600, <https://doi.org/10.1080/15732479.2022.2063908>.
- [28] J. Mehta, Y. Hooda, Y. Aggarwal, Emerging application of digital twin technology toward development of smart infrastructure, 2025. [10.1201/9781003582489-13](https://doi.org/10.1201/9781003582489-13).
- [29] M.F.M. Kamal, I. Yin, A.A.S. Muthuveeran, H.M. Affandi, N.M. Nasir, Barriers in the integration of digital twins (DTs) and building information modelling (BIM) for predictive maintenance in facility management, *J. Des. Built Environ.* 2025 (2025) 112–125.
- [30] S. Rashidian, S.T. Hossain, K. Volz, M. Teo, Enabling circularity in construction: a technology-phase alignment of construction 4.0 and circular economy principles, *Sustain. Prod. Consum.* 60 (2025) 245–259, <https://doi.org/10.1016/j.spc.2025.10.004>.
- [31] D. Davletshina, V.K. Reja, I. Brilakis, Constructing and maintaining road geometric digital twins, *J. Comput. Civ. Eng.* 40 (2026), <https://doi.org/10.1061/JCCEES.CPENG-6239>.
- [32] H.H. Hosamo, H.K. Nielsen, D. Kraniotis, P.R. Svennevig, K. Svidt, Digital Twin framework for automated fault source detection and prediction for comfort performance evaluation of existing non-residential Norwegian buildings, *Energy Build.* 281 (2023) 112732, <https://doi.org/10.1016/j.enbuild.2022.112732>.
- [33] Q. Lu, X. Xie, A.K. Parlikad, J.M. Schooling, Digital twin-enabled anomaly detection for built asset monitoring in operation and maintenance, *Autom. Constr.* 118 (2020) 103277, <https://doi.org/10.1016/j.autcon.2020.103277>.
- [34] H. Sadri, I. Yitmen, L.C. Tagliabue, F. Westphal, A conceptual framework for blockchain and ai-driven digital twins for predictive operation and maintenance, in: *Proceedings of the European Conference on Computing in Construction*, 2023, <https://doi.org/10.35490/EC3.2023.219>.
- [35] S.M. Hallaji, Y. Fang, B.K. Winfrey, A digital twin framework for enhancing predictive maintenance of pumps in wastewater treatment plants, in: *Proceedings of the International Symposium on Automation and Robotics in Construction*, 2021, pp. 88–93, <https://doi.org/10.22260/isarc2021/0014>, 2021-Novem.
- [36] S. Agostinelli, Actionable framework for city digital twin-enabled predictive maintenance and security management systems, *WIT Trans. Built Environ.* 205 (2021) 223–233, <https://doi.org/10.2495/BIM210191>.
- [37] O. Hakimi, H. Liu, O. Abudayyeh, A. Houshyar, M. Almatared, A. Alhawiti, Data fusion for smart civil infrastructure management: a conceptual digital twin framework, *Buildings* 13 (2023), <https://doi.org/10.3390/buildings13112725>.
- [38] J. Wong, P. Hoong, E. Teo, A. Lin, Digital twin: a conceptualization of the task-technology fit for individual users in the building maintenance sector, *IOP Conf. Ser. Earth Environ. Sci.* 1101 (2022), <https://doi.org/10.1088/1755-1315/1101/9/092041>.
- [39] M. Kherbache, M. Maimour, E. Rondeau, Digital twin network for the IIoT using Eclipse Ditto and Hono, *IFAC-PapersOnLine* 55 (2022) 37–42, <https://doi.org/10.1016/j.ifacol.2022.08.007>.
- [40] J.H. Chan, C.Y. Lau, Enhancement of Jaibot: developing safety and monitoring features for Jaibot using IoT technologies, *Int. J. Technol.* 14 (2023) 1309–1319, <https://doi.org/10.14716/ijtech.v14i6.6627>.
- [41] C.S. Wickramasinghe, K. Amarasinghe, D.L. Marino, C. Rieger, M. Manic, Explainable unsupervised machine learning for cyber-physical systems, *IEEE Access* 9 (2021) 131824–131843, <https://doi.org/10.1109/ACCESS.2021.3112397>.
- [42] V. Weerapura, R. Sugathadasa, M.M. De Silva, I. Nielsen, A. Thibbotuwawa, Feasibility of digital twins to manage the operational risks in the production of a ready-mix concrete plant, *Buildings* 13 (2023), <https://doi.org/10.3390/buildings13020447>.
- [43] R.P. Fischer, F. Schnicke, B. Beggel, P. Oliveira Antonino, Historical data storage architecture blueprints for the asset administration shell, in: *Proceedings of the IEEE International Conference on Emerging Technologies and Factory Automation, ETFA*, 2022, pp. 1–8, <https://doi.org/10.1109/ETFA52439.2022.9921613>, 2022-Sept.
- [44] L. Makama, A. Telukdarie, Improving maintenance management of reservoir structures using smart systems, in: *Proceedings of the 2022 IEEE 28th International Conference on Engineering, Technology and Innovation, ICE/ITMC*, 2022, pp. 1–5, <https://doi.org/10.1109/ICE/ITMC-IAMOT55089.2022.10033213>, 2022 and 31st International Association for Management of Technology, IAMOT 2022 Joint Conference.
- [45] H. Pruvost, F. Forns-Samsø, O. Gnepper, O. Enge-Rosenblatt, Integrating energy system monitoring and maintenance services into a BIM-based digital twin, in: *Proceedings of the IECON Proceedings (Industrial Electronics Conference)*, 2023, pp. 1–6, <https://doi.org/10.1109/IECON51785.2023.10311659>.
- [46] V. Villa, B. Naticchia, G. Bruno, K. Aliiev, P. Piantanida, D. Antonelli, Iot open-source architecture for the maintenance of building facilities, *Appl. Sci.* (2021) 11, <https://doi.org/10.3390/app1125374> (Switzerland).
- [47] A. Costantini, G. Di Modica, J.C. Ahouangonou, D.C. Duma, B. Martelli, M. Galletti, M. Antonacci, D. Nehls, P. Bellavista, C. Delamarre, D. Cesini, IoT Twins: toward implementation of distributed digital twins in industry 4.0 settings, *Computers* 11 (2022) 1–18, <https://doi.org/10.3390/computers11050067>.
- [48] V.V. Krishna, Q. Wu, S. Hossein-Nia, M. Spiraygin, S. Stichel, Long freight trains & long-term rail surface damage—a systems perspective, *Veh. Syst. Dyn.* 61 (2023) 1500–1523, <https://doi.org/10.1080/00423114.2022.2085584>.
- [49] Z.A. Bukhsh, I. Stanovic, Predictive maintenance for infrastructure asset management, *IT. Prof.* 22 (2020) 40–45, <https://doi.org/10.1109/MITP.2020.2975736>.
- [50] A. Haghshenas, A. Hasan, O. Osen, E.T. Mikalsen, Predictive digital twin for offshore wind farms, *Energy Inform.* 6 (2023) 1–26, <https://doi.org/10.1186/s42162-023-00257-4>.
- [51] Q.L. Vиви, A.K. Parlikad, P. Woodall, G.D. Ranasinghe, J. Heaton, Developing a dynamic digital twin at a building level: using Cambridge campus as case study, in: *Proceedings of the International Conference on Smart Infrastructure and Construction* 2019, 2019, pp. 67–75, <https://doi.org/10.1680/icsic.64669.067>. ICSIC 2019: Driving Data-Informed Decision-Making 2019.
- [52] X. Kestelyn, G. Denis, V. Champaney, N. Hascoet, C. Ghatios, F. Chinesta, Towards a hybrid twin for infrastructure asset management : investigation on power transformer asset maintenance management, in: *Proceedings of the 2022 7th International Advanced Research Workshop on Transformers (ARWtr)*, 2022, pp. 109–114, <https://doi.org/10.23919/ARWtr54586.2022.9959914>.
- [53] N.N.M. Cross-functionally, Track Geometry Prediction Using Three-Dimensional Recurrent Neural Network-Based Models Cross-Functionally Co-Simulated with BIM, (2023).
- [54] J. Wimmer, T. Braml, Digital twins for engineering structures—an industry 4.0 perspective, *Struct. Concr.* 25 (2024) 4202–4218, <https://doi.org/10.1002/suco.202400683>.
- [55] P. Vrachnos, C. Ramonell, I. Koulalis, K. Ioannidis, I. Stanovic, S. Vrochidis, A framework for vision-based 3d inspections for maintenance activities and digital twin integration, in: *Proceedings of the International Workshop on Content-Based Multimedia Indexing*, 2024, <https://doi.org/10.1109/CBIMI62980.2024.10859253>.
- [56] B. Karunanidhi, L. Ramasamy, A. Alexander Stonier, C.R. Sathiasamuel, Development of a digital twin framework for a PV system to resolve partial shading, *Math. Probl. Eng.* 2024 (2024), <https://doi.org/10.1155/2024/8374487>.
- [57] E. Filippova, S. Hedayat, T. Ziarati, M. Manganelli, Artificial intelligence and digital twins for bioclimatic building design: innovations in sustainability and efficiency, *Energies* 18 (2025), <https://doi.org/10.3390/en18195230> (Basel).
- [58] J. Zhou, Multi-dimensional model and interactive simulation of intelligent construction based on digital twins, *Sci. Rep.* 15 (2025), <https://doi.org/10.1038/s41598-025-17100-3>.

- [59] I. Yitmen, A. Almusaed, M. Hussein, A. Almssad, AI-driven digital twins for enhancing indoor environmental quality and energy efficiency in smart building systems, *Buildings* 15 (2025), <https://doi.org/10.3390/buildings15071030>.
- [60] T. Hielscher, S. Khalil, N. Virgona, S.A. Hadigheh, A neural network based digital twin model for the structural health monitoring of reinforced concrete bridges, *Structures* 57 (2023) 105248, <https://doi.org/10.1016/j.istruc.2023.105248>.
- [61] H. Vassilev, M. Laska, J. Blankenbach, Uncertainty-aware point cloud segmentation for infrastructure projects using Bayesian deep learning, *Autom. Constr.* 164 (2024), <https://doi.org/10.1016/j.autcon.2024.105419>.
- [62] Y.M. Hsieh, J. Wilch, C.Y. Lin, B. Vogel-Heuser, F.T. Cheng, Analysis of process data for remote health prediction in distributed automation systems, in: *Proceedings of the IEEE International Conference on Automation Science and Engineering* 2022–August, 2022, pp. 1289–1294, <https://doi.org/10.1109/CASE49997.2022.9926576>.
- [63] K. Xing, K.P. Kim, D. Ness, Cloud-BIM enabled cyber-physical data and service platforms for building component reuse, *Sustainability* 12 (2020) 1–22, <https://doi.org/10.3390/su122410329> (Switzerland).
- [64] C.C. Lin, D.J. Deng, C.H. Kuo, L. Chen, Concept drift detection and adaption in big imbalance industrial IoT data using an ensemble learning method of offline classifiers, *IEEE Access* 7 (2019) 56198–56207, <https://doi.org/10.1109/ACCESS.2019.2912631>.
- [65] W. Hu, X. Wang, K. Tan, Y. Cai, Digital twin-enhanced predictive maintenance for indoor climate: a parallel LSTM-autoencoder failure prediction approach, *Energy Build.* 301 (2023) 113738, <https://doi.org/10.1016/j.enbuild.2023.113738>.
- [66] M. Milasinić, D. Ivetić, M. Stojković, D. Savić, Failure conditions assessment of complex water systems using fuzzy logic, *Water Resour. Manag.* 37 (2023) 1153–1182, <https://doi.org/10.1007/s11269-022-03420-w>.
- [67] R. Carotenuto, M. Merenda, F.G.D. Corte, D. Iero, Online black-box modeling for the IoT digital twins through machine learning, *IEEE Access* 11 (2023) 48158–48168, <https://doi.org/10.1109/ACCESS.2023.3275447>.
- [68] M.C. De Simone, A. Lorusso, D. Santaniello, Predictive maintenance and structural health monitoring via IoT system, in: *Proceedings of the 2022 IEEE Workshop on Complexity in Engineering, COMPENG*, 2022, pp. 1–4, <https://doi.org/10.1109/COMPENG50184.2022.9905441>, 2022.
- [69] J. Sresakoolchai, S. Kaewunruen, Railway infrastructure maintenance efficiency improvement using deep reinforcement learning integrated with digital twin based on track geometry and component defects, *Sci. Rep.* 13 (2023) 1–16, <https://doi.org/10.1038/s41598-023-29526-8>.
- [70] F. Zonzini, C. Aguzzi, L. Gigli, L. Sciuolo, N. Testoni, L. De Marchi, M. Di Felice, T. S. Ciotto, C. Mennuti, A. Marzani, Structural health monitoring and prognostic of industrial plants and civil structures: a sensor to cloud architecture, *IEEE Instrum. Meas. Mag.* 23 (2020) 21–27, <https://doi.org/10.1109/MIM.2020.9289069>.
- [71] R. Nasimi, S. Atcity, D. Thompson, J. Murillo, M. Ball, J. Stormont, F. Moreu, Use of Remote Structural Tap Testing Devices Deployed via Ground Vehicle for Health Monitoring of Transportation Infrastructure, (2022) 1–11.
- [72] B. Skobie, A. Niemi, Validation of copula based weather generator for maintenance model of offshore wind farm, *WMU J. Marit. Aff.* (2022) 73–87, <https://doi.org/10.1007/s13437-021-00255-x>.
- [73] K.A.B. Asare, R. Liu, C.J. Anumba, R.R.A. Issa, Real-world prototyping and evaluation of digital twins for predictive facility maintenance, *J. Build. Eng.* 97 (2024), <https://doi.org/10.1016/j.jobte.2024.110890>.
- [74] G. Morgenthal, M. von Butler-Helmrich, Cloud-based asset management for image-based inspections of infrastructures, bridge maintenance, safety, management, digitalization and sustainability, in: *Proceedings of the 12th International Conference on Bridge Maintenance, Safety and Management, IABMAS 2024*, 2024, pp. 2040–2047, <https://doi.org/10.1201/9781003483755-240>.
- [75] S. Das, S.S. Maraju, J. Lewis, J. Arantes, Application of digitalization and digital twins to mooring integrity assessment of floaters, in: *Proceedings of the International Conference on Offshore Mechanics and Arctic Engineering - OMAE* 1, 2024, <https://doi.org/10.1115/OMAE2024-135728>.
- [76] K.A.B. Asare, R. Liu, C.J. Anumba, R.R.A. Issa, Real-world prototyping and evaluation of digital twins for predictive facility maintenance, *J. Build. Eng.* 97 (2024), <https://doi.org/10.1016/j.jobte.2024.110890>.
- [77] D.E. Gispert, I. Yitmen, H. Sadri, A. Taheri, Development of an ontology-based asset information model for predictive maintenance in building facilities, *Smart Sustain. Built Environ.* 14 (2025) 740–757, <https://doi.org/10.1108/SASBE-07-2023-0170>.
- [78] M. Buhaievskiy, Y. Petrenko, Simulation of production and logistics for concrete plants, *Radioelectron. Comput. Syst.* 2024 (2024) 190–204, <https://doi.org/10.32620/REKS.2024.3.13>.
- [79] H. Sadri, AI-driven integration of digital twins and blockchain for smart building management systems: a multi-stage empirical study, *J. Build. Eng.* 105 (2025), <https://doi.org/10.1016/j.jobte.2025.112439>.
- [80] M.B. Maru, Y. Wang, H. Kim, H. Yoon, S. Park, Improved building facade segmentation through digital twin-enabled RandLA-Net with empirical intensity correction model, *J. Build. Eng.* 78 (2023) 107520, <https://doi.org/10.1016/j.jobte.2023.107520>.
- [81] H.H. Hosamo, H.K. Nielsen, D. Kraniotis, P.R. Svennevig, K. Svdt, Improving building occupant comfort through a digital twin approach: a Bayesian network model and predictive maintenance method, *Energy Build.* 288 (2023) 112992, <https://doi.org/10.1016/j.enbuild.2023.112992>.
- [82] F. D'Amico, L. Bertolini, A. Napolitano, V. Gagliardi, L. Bianchini Ciampoli, A novel BIM approach for supporting technical decision-making process in transport infrastructure management, 11863 (2021) 19, [10.1117/12.2600140](https://doi.org/10.1117/12.2600140).
- [83] An AR-based inspection system for monitoring temperature abnormalities in daily O&M management, in: *Proceedings of the Construction Research Congress*, 2020, pp. 162–171.
- [84] P. Tavakoli, I. Yitmen, H. Sadri, A. Taheri, Blockchain-based digital twin data provenance for predictive asset management in building facilities, *Smart Sustain. Built Environ.* 13 (2024) 4–21, <https://doi.org/10.1108/SASBE-07-2023-0169>.
- [85] I. Conference, Challenges of 360° Inspection of Bridge Infrastructure Using Unmanned Aerial Vehicles (UAVs), in: 2022: pp. 96–108.
- [86] M. Granzner, A. Strauss, M. Reiterer, M. Cao, D. Novák, Data-driven condition assessment and life cycle analysis methods for dynamically and fatigue-loaded railway infrastructure components, *Infrastructures* 8 (2023), <https://doi.org/10.3390/infrastructures8110162> (Basel).
- [87] L. Zhou, C. An, J. Shi, Z. Lv, H. Liang, Design and construction integration technology based on digital twin, in: *Proceedings of the 2021 Power System and Green Energy Conference, PSPEG* 2021, 2021, pp. 7–11, <https://doi.org/10.1109/PSPEG51302.2021.9541682>.
- [88] W.J.V.D.M. Steyn, A. Broekman, Development of a digital twin of a local road network: a case study, *J. Test. Eval.* 50 (2022) 2901–2915, <https://doi.org/10.1520/JTE20210043>.
- [89] B.C. Fialho, R. Codinhoto, M.M. Fabricio, J.C. Estrella, C.M. Neves Ribeiro, J. M. Dos Santos Bueno, J.P. Doimo Torrezan, Development of a BIM and IoT-based smart lighting maintenance system prototype for universities' FM sector, *Buildings* 12 (2022), <https://doi.org/10.3390/buildings12020099>.
- [90] M. Mahmoodian, F. Shahrivar, S. Setunge, S. Mazaheri, Development of digital twin for intelligent maintenance of civil infrastructure, *Sustainability* 14 (2022), <https://doi.org/10.3390/su14148664> (Switzerland).
- [91] S. Kaewunruen, J. Sresakoolchai, W. Ma, O. Phil-Ebosie, Digital twin aided vulnerability assessment and risk-based maintenance planning of bridge infrastructures exposed to extreme conditions, *Sustainability* 13 (2021) 1–19, <https://doi.org/10.3390/su13042051> (Switzerland).
- [92] S. Kaewunruen, J. Sresakoolchai, Y. Lin, Digital twins for managing railway maintenance and resilience, *Open Res. Eur.* 1 (2021) 91, <https://doi.org/10.12688/openreseurope.13806.1>.
- [93] S.H. Khajavi, N.H. Motlagh, A. Jaribon, L.C. Werner, J. Holmstrom, Digital twin: vision, benefits, boundaries, and creation for buildings, *IEEE Access* 7 (2019) 147406–147419, <https://doi.org/10.1109/ACCESS.2019.2946515>.
- [94] M. Signorini, N. Moretti, J. Merino, B. Daniotti, A. Parlikad, Digital-twin based data modelling for digital building logbook implementation, *IET Conf. Proc.* 2023 (2023) 130–137, <https://doi.org/10.1049/icp.2023.1744>.
- [95] F. Cumo, Digital twin for critical infrastructures: the Ventotene island port case study, Italy, *WIT Trans. Built Environ.* 205 (2021) 217–222, <https://doi.org/10.2495/BIM210181>.
- [96] C. Sassanelli, T. Arriga, S. Zanin, I.D. Adamo, S. Terzi, P. Bari, V. Orabona, E. Srl, Industry 4.0 Driven Result-oriented PSS: An Assessment in the Energy Management, 12 (2022) 186–203.
- [97] S. Agostinelli, F. Cumo, Machine learning approach for predictive maintenance in an advanced building management system, *WIT Trans. Ecol. Environ.* 255 (2022) 131–138, <https://doi.org/10.2495/EPM220111>.
- [98] H. Sofia, E. Anas, O. Faiz, Mobile mapping, machine learning and digital twin for road infrastructure monitoring and maintenance: case study of Mohammed VI bridge in Morocco, in: *Proceedings of the 2020 IEEE International Conference of Moroccan Geomatics 2020, MORGE0*, 2020, <https://doi.org/10.1109/Morgeo49228.2020.9121882>.
- [99] A. Consilvio, J.S. Hernández, W. Chen, I. Brilakis, L. Bartocchini, F. Di Gennaro, M. van Welie, Towards a digital twin-based intelligent decision support for road maintenance, *Transp. Res. Procedia* 69 (2023) 791–798, <https://doi.org/10.1016/j.trpro.2023.02.237>.
- [100] V. Saback, J. Eliasson, C. Daescu, J. Gonzalez-Liberos, C. Popescu, T. Blanksvärd, B. Täljsten, G. Sas, Digital twins for asset management: case study of snow galleries in Northern Sweden, *Struct. Infrastruct. Eng.* (2025), <https://doi.org/10.1080/15732479.2025.2483913>.
- [101] M. Držek, U. Klanšek, T. Hartner Zupančič, R. Cajzek, Improving concrete plant operations and maintenance with digital twin technology, in: H. Glavaš, M. Hadzima-Nyarko, N. Ademović, T. Hanák (Eds.), *Proceedings of the 33rd International Conference on Organization and Technology of Maintenance (OTO 2024)*, Cham, Springer Nature Switzerland, 2025, pp. 166–179.
- [102] M. Grieves, J. Vickers, Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems, *Transdiscipl. Perspect. Complex Syst. New Find. Approaches* (2016) 85–113, https://doi.org/10.1007/978-3-319-38756-7_4.
- [103] W. HU, K.Y.H. Lim, Y. Cai, Digital twin and industry 4.0 enablers in building and construction: a survey, *Buildings* (2022) 1–27.
- [104] W. Kritzing, M. Karner, G. Traar, J. Henjes, W. Sihn, Digital twin in manufacturing: a categorical literature review and classification, *IFAC-PapersOnLine* 51 (2018) 1016–1022, <https://doi.org/10.1016/j.ifacol.2018.08.474>.
- [105] M. Balla, O. Haffner, E. Kučera, J. Cigánek, Educational case studies: creating a digital twin of the production line in TIA Portal, Unity, and Game4automation framework, *Sensors* 23 (2023) 4977, <https://doi.org/10.3390/S23104977>, 2023, Vol. 23, Page 4977.
- [106] Z. Turk, R. Kline, A social-product-process framework for construction, *Build. Res. Inf.* 48 (2020) 747–762, <https://doi.org/10.1080/09613218.2019.1691487>.
- [107] B. Yang, Z. Lv, F. Wang, Digital twins for intelligent green buildings, *Buildings* 12 (2022), <https://doi.org/10.3390/buildings12060856>.

- [108] M. Jasilewicz-Kaczmarek, S. Legutko, P. Kluk, Maintenance 4.0 technologies - new opportunities for sustainability driven maintenance, *Manag. Prod. Eng. Rev.* 11 (2020) 74–87, <https://doi.org/10.24425/MPER.2020.133730>.
- [109] M. Jasilewicz-Kaczmarek, A. Gola, Maintenance 4.0 technologies for sustainable manufacturing - an overview, *IFAC-PapersOnLine* 52 (2019) 91–96, <https://doi.org/10.1016/j.ifacol.2019.10.005>.
- [110] W. Hu, Y. Cai, A semi-supervised method for digital twin-enabled predictive maintenance in the building industry, *Neural Comput. Appl.* 1 (2024), <https://doi.org/10.1007/s00521-024-09926-1>.
- [111] C. Chang, F. Di Maio, R. Bheemireddy, P. Posthoorn, A.T. Gebremariam, P. Rem, Intelligent optimization of particle size distribution in unscreened recycled coarse aggregates using 3D surface analysis, *J. Ind. Inf. Integr.* 46 (2025) 100864, <https://doi.org/10.1016/j.jiit.2025.100864>.
- [112] K.Y.H. Lim, P. Zheng, C.H. Chen, A state-of-the-art survey of digital twin: techniques, engineering product lifecycle management and business innovation perspectives, *J. Intell. Manuf.* 31 (2020) 1313–1337, <https://doi.org/10.1007/s10845-019-01512-w>.
- [113] L. Huang, S. Dutta, Y. Cai, Laser scanned real environment for intelligent virtualization of crane lifting, *Virtual Real. Intell. Hardw.* 2 (2020) 87–103, <https://doi.org/10.1016/j.vrih.2020.04.003>.
- [114] J.Y. Khan, Introduction to IoT Systems, *Internet of Things (IoT)* (2019) 1–24, <https://doi.org/10.1201/9780429399084-1>.
- [115] Q. Lu, X. Xie, A.K. Parlikad, J.M. Schooling, Digital twin-enabled anomaly detection for built asset monitoring in operation and maintenance, *Autom. Constr.* 118 (2020) 103277, <https://doi.org/10.1016/j.autcon.2020.103277>.
- [116] C. Chang, F. Di Maio, P. Rem, Real-time sensor-based characterization of recycled coarse aggregates (RCA): advancing sustainable construction through automated quality assessment, in: *Proceedings of The 6th International Conference, 2025*, pp. 656–667.
- [117] C. Chang, F. Di Maio, P. Rem, A.T. Gebremariam, F. Mehari, H. Xia, Cluster-based identification algorithm for in-line recycled concrete aggregates characterization using laser-induced breakdown spectroscopy (LIBS), *Resour. Conserv. Recycl.* 185 (2022) 106507, <https://doi.org/10.1016/j.resconrec.2022.106507>.
- [118] H. Vassilev, M. Laska, J. Blankenbach, Uncertainty-aware point cloud segmentation for infrastructure projects using Bayesian deep learning, *Autom. Constr.* 164 (2024), <https://doi.org/10.1016/j.autcon.2024.105419>.
- [119] M. Silion, G. Suciu, L. Luminariu, C. Beceanu, C. Alexandru, S. Stefanescu, M. L. Rosu, I. Taranu, F.V. Panaitescu, M. Panaitescu, I. Voicu, A.A. Scupi, L.C. Stan, G. Raicu, L. Necula, Complex system for monitoring environmental factors at the galata platform in the black sea, proceedings of the 16th international conference on electronics, *Comput. Artif. Intell. ECAI 2024* (2024), <https://doi.org/10.1109/ECAI61503.2024.10607460>.
- [120] W. Hu, Y. Cai, A semi-supervised method for digital twin-enabled predictive maintenance in the building industry, *Neural Comput. Appl.* 36 (2024) 15759–15775, <https://doi.org/10.1007/s00521-024-09926-1>.
- [121] P. Tavakoli, I. Yitmen, H. Sadri, A. Taheri, Blockchain-based digital twin data provenance for predictive asset management in building facilities, *Smart Sustain. Built Environ.* 13 (2024) 4–21, <https://doi.org/10.1108/SASBE-07-2023-0169>.
- [122] J. Kodikara, A. Sounthararajah, L. Chen, Reimagining unbound road pavement technology: integrating testing, design, construction and performance in the post-digital era, *Transp. Geotech.* 47 (2024), <https://doi.org/10.1016/j.trgeo.2024.101274>.
- [123] M. Riggio, M. Mrissa, M. Krész, J. Včelák, J. Sandak, A. Sandak, Leveraging structural health monitoring data through avatars to extend the service life of mass timber buildings, *Front. Built. Environ.* 8 (2022) 1–7, <https://doi.org/10.3389/fbuil.2022.887593>.
- [124] C. Chang, Quality assessment & monitoring of recycled coarse aggregates, (2025).
- [125] C. Yang, Q. Chen, W. Shen, B. Gunay, Toward failure mode and effect analysis for heating, ventilation and air-conditioning, in: *Proceedings of the 2017 IEEE 21st International Conference on Computer Supported Cooperative Work in Design 2017, CSCWD, 2017*, pp. 408–413, <https://doi.org/10.1109/CSCWD.2017.8066729>.
- [126] V. Srinivasan, An integration framework for product lifecycle management, *CAD Comput. Aided Des.* 43 (2011) 464–478, <https://doi.org/10.1016/j.cad.2008.12.001>.
- [127] V. Villa, B. Naticchia, G. Bruno, K. Aliev, P. Piantanida, D. Antonelli, Iot open-source architecture for the maintenance of building facilities, *Appl. Sci.* 11 (2021), <https://doi.org/10.3390/app11125374> (Switzerland).
- [128] S.M.E. Sepasgozar, Differentiating digital twin from digital shadow: elucidating a paradigm shift to expedite a smart, sustainable built environment, *Buildings* 11 (2021), <https://doi.org/10.3390/buildings11040151>.
- [129] W. Hu, Z. Xie, Y. Cai, A network analysis-based approach for as-built BIM generation and inspection, *Appl. Sci.* 14 (2024) 6587, <https://doi.org/10.3390/app14156587>.
- [130] Y. Xie, S. Li, T. Liu, Y. Cai, As-built BIM reconstruction of piping systems using PipeNet, *Autom. Constr.* 147 (2023) 104735, <https://doi.org/10.1016/j.autcon.2022.104735>.
- [131] T. Czerniawski, F. Leite, Automated digital modeling of existing buildings: a review of visual object recognition methods, *Autom. Constr.* 113 (2020) 103131, <https://doi.org/10.1016/j.autcon.2020.103131>.
- [132] Y.-C. Lin, W.-F. Cheung, Developing WSN/BIM-based environmental monitoring management system for parking garages in smart cities, *J. Manag. Eng.* 36 (2020) 04020012, [https://doi.org/10.1061/\(asce\)jme.1943-5479.0000760](https://doi.org/10.1061/(asce)jme.1943-5479.0000760).
- [133] C. Chang, F. Di Maio, R. Bheemireddy, P. Posthoorn, A.T. Gebremariam, P. Rem, Rapid quality control for recycled coarse aggregates (RCA) streams: Multi-sensor integration for advanced contaminant detection, *Comput. Ind. Ind.* 164 (2025) 104196, <https://doi.org/10.1016/j.compind.2024.104196>.
- [134] F. Shalabi, Y. Turkan, Bim-energy simulation approach for detecting building spaces with faults and problematic behavior, *J. Inf. Technol. Constr.* 25 (2020) 342–360, <https://doi.org/10.36680/JITCON.2020.020>.
- [135] A. Anderson, A. Marsters, C.S. Dossick, G. Neff, Construction to operations exchange: challenges of implementing COBIE and BIM in a large owner organization, construction research congress 2012: construction challenges in a flat world, in: *Proceedings of the 2012 Construction Research Congress, 2012*, pp. 688–697, <https://doi.org/10.1061/9780784412329.070>.
- [136] P. Bourhis, J.L. Reutter, F. Suárez, D. Vrgoč, JSON: data model, query languages and Schema specification, in: *Proceedings of the ACM SIGACT-SIGMOD-SIGART Symposium on Principles of Database Systems, 2017*, pp. 123–135, <https://doi.org/10.1145/3034786.3056120>.
- [137] A. Gouda Mohamed, M.R. Abdallah, M. Marzouk, BIM and semantic web-based maintenance information for existing buildings, *Autom. Constr.* 116 (2020) 103209, <https://doi.org/10.1016/j.autcon.2020.103209>.
- [138] C. Martinie, P. Palanque, R. Fahssi, J.P. Blanquart, C. Fayollas, C. Seguin, Task model-based systematic analysis of both system failures and human errors, *IEEE Trans. Hum. Mach. Syst.* 46 (2016) 243–254, <https://doi.org/10.1109/THMS.2014.2365956>.
- [139] N. Es-sakali, M. Cherkaoui, M.O. Mghazli, Z. Naimi, Review of predictive maintenance algorithms applied to HVAC systems, *Energy Rep.* 8 (2022) 1003–1012, <https://doi.org/10.1016/j.egy.2022.07.130>.
- [140] N. Kikuchi, T. Fukuda, N. Yabuki, Future landscape visualization using a city digital twin: integration of augmented reality and drones with implementation of 3D model-based occlusion handling, *J. Comput. Des. Eng.* 9 (2022) 837–856, <https://doi.org/10.1093/jcde/qwac032>.
- [141] M. Rahmani Asl, S. Zarrinmehr, M. Bergin, W. Yan, BPOpt: a framework for BIM-based performance optimization, *Energy Build.* 108 (2015) 401–412, <https://doi.org/10.1016/j.enbuild.2015.09.011>.
- [142] H. Hamledari, E.R. Azar, B. McCabe, IFC-based development of as-built and as-Is BIMs using construction and facility inspection data: site-to-BIM data transfer automation, *J. Comput. Civ. Eng.* 32 (2018) 1–15, [https://doi.org/10.1061/\(asce\)cp.1943-5487.0000727](https://doi.org/10.1061/(asce)cp.1943-5487.0000727).
- [143] F. Shalabi, Y. Turkan, Bim-energy simulation approach for detecting building spaces with faults and problematic behavior, *J. Inf. Technol. Constr.* 25 (2020) 342–360, <https://doi.org/10.36680/JITCON.2020.020>.
- [144] V. Villa, B. Naticchia, G. Bruno, K. Aliev, P. Piantanida, D. Antonelli, Iot open-source architecture for the maintenance of building facilities, *Appl. Sci.* 11 (2021), <https://doi.org/10.3390/app11125374> (Switzerland).
- [145] ISCAN2BIM | A/P Cai Yiyu (MAE) - YouTube, (2025). https://www.youtube.com/watch?v=RE-vNYs_i_w (accessed October 19, 2025).
- [146] Y. Fan, J. Yang, J. Chen, P. Hu, X. Wang, J. Xu, B. Zhou, A digital-twin visualized architecture for flexible manufacturing system, *J. Manuf. Syst.* 60 (2021) 176–201, <https://doi.org/10.1016/j.jmsy.2021.05.010>.
- [147] P. Maheshwari, S. Kamble, S. Kumar, A. Belhadi, S. Gupta, Digital twin-based warehouse management system: a theoretical toolbox for future research and applications, *Int. J. Logist. Manag.* (2023), <https://doi.org/10.1108/IJLM-01-2023-0030>.
- [148] S. Process, M. Live, I.B. Comfort, Digital Twin and Cloud BIM-XR Platform Development : From, (2022).
- [149] S.K.M. Ataelmanan, M.A.H. Ali, Developing a framework for data communication in a wireless network using machine learning technique, *Int. J. Adv. Comput. Sci. Appl.* 12 (2021) 333–342, <https://doi.org/10.14569/IJACSA.2021.0120341>.
- [150] K. Xing, K.P. Kim, D. Ness, Cloud-BIM enabled cyber-physical data and service platforms for building component reuse, *Sustainability* 12 (2020) 1–22, <https://doi.org/10.3390/su122410329> (Switzerland).
- [151] G. Piras, S. Agostinelli, F. Muzi, Digital twin framework for built environment: a review of key enablers, *Energies* 17 (2024), <https://doi.org/10.3390/en17020436> (Basel).
- [152] Y. Zhou, Y. Su, Z. Xu, X. Wang, J. Wu, X. Guan, A hybrid physics-based/data-driven model for personalized dynamic thermal comfort in ordinary office environment, *Energy Build.* 238 (2021) 110790, <https://doi.org/10.1016/j.enbuild.2021.110790>.
- [153] C. Rausch, C. Haas, Automated shape and pose updating of building information model elements from 3D point clouds, *Autom. Constr.* 124 (2021) 103561, <https://doi.org/10.1016/j.autcon.2021.103561>.