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DIGITAL TWINS IN THE CONSTRUCTION INDUSTRY: A SYSTEMATIC REVIEW OF CURRENT PRACTICES AND FUTURE DIRECTIONS

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SUMMARY: *As part of Industry 4.0 initiatives, the construction industry is increasingly adopting Digital Twin (DT) to enhance asset lifecycle management, predictive maintenance, and data-driven decision-making. However, DT implementation remains fragmented and uneven across lifecycle phases, application domains, and organisational contexts. This study aims to address these gaps through a comprehensive review of current DT practices in construction. A two-stage systematic literature review, following PRISMA guidelines, was conducted. The first stage analysed 122 DT review articles to map thematic trends, research focuses, and overlooked areas. The second stage synthesised 297 empirical studies to examine practical application distribution, technology integration frameworks, deployment barriers, and mitigation strategies. Current DT research is heavily concentrated on the operation and maintenance phase, with limited attention to early design or end-of-life activities. Key challenges include data fragmentation, interoperability issues, high initial costs, limited stakeholder engagement, and insufficient regulatory and organisational support. A range of technical and institutional strategies has been identified to address these barriers. Crucially, the study translates these findings into actionable roadmaps for key stakeholders, offering role-specific strategies to bridge the gap between theory and practice. This study presents a comprehensive synthesis of over 400 publications from 2019 to 2024, systematically mapping DT applications across lifecycle stages, categorising key barriers, and evaluating targeted strategies for each. By identifying critical knowledge gaps and limitations within the current body of DT research, it offers valuable insights to inform future investigations and support more scalable and integrated implementation in practice.*

KEYWORDS: *digital twin (DT), construction industry, life cycle, built environment, systematic review, barriers and strategies.*

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1. INTRODUCTION

Industries are increasingly adopting digital and intelligent technologies to address their complexities with the advent of Industry 4.0 (Adu-Amankwa et al., 2023). The construction industry is trending towards leveraging the approach of DTs to manage, plan, predict, and present buildings and infrastructure (Lu et al., 2020). The concept of Digital Twin (DT), originating from Michael Grieves' presentation on Product Lifecycle Management in 2002, outlined the basic elements of it: the physical entity, the virtual equivalent, and the bi-directional flow of data between the two (Grieves and Vickers, 2017). It has evolved and proliferated in a variety of domains, flourishing not only in product manufacturing and aerospace, but more recently gaining attraction in construction and smart cities (Boje et al., 2020). Since there is no universally accepted definition of DT, many studies and organisations have attempted to define it in terms of its characteristics and functions. Schluse and Rossmann (2016) defined DT as a virtual representation of a real-world subject or object including data, functionality and communication interfaces, while Madni et al. (2019) described DT as consisting of connected products and a digital thread which collects data from the physical twin to update the virtual models. In civil engineering, Jiang *et al.* (2021) defined DT as an integration of Building Information Modelling (BIM) and the Internet of Things (IoT). Unlike the static, one-way data flow of BIM, DTs facilitate dynamic, real-time interaction through continuous, bidirectional data exchange (Tao et al., 2019). Specifically in the built environment, the Centre for Digital Built Britain defined DTs as "a realistic digital representation of assets, processes or systems in the built or natural environment" (Bolton et al., 2018) while Opoku *et al.* (2022) describe it as a real-time representation of a building or structure that reflects the state and features of its physical counterpart. Despite field-specific variations, most definitions focus on three key components: the physical entity, the virtual model, and the data flow between them (Tao et al., 2019).

Given the increasing digitalisation needs of industry, it is evident that DT, with its advanced digital features, offers significant advantages and application potential (Jiang et al., 2021). Although DT has proven to be a valuable contributor in construction projects and throughout the lifecycle, the application of DTs in construction is still underexplored, particularly in the early lifecycle phases (Long et al., 2024). Current research focuses more on theoretical frameworks than practical deployment (Zhao et al., 2022b, Madubuike et al., 2022) with studies often limited to specific areas such as heritage facilities (Hou et al., 2024), bridges (Jiménez Rios et al., 2023), construction safety (Hou et al., 2021), etc. or discussing the relationship between DT and other concepts such as BIM (Radzi et al., 2024) and blockchain (Adu-Amankwa et al., 2023).

However, despite this rapid growth, the synthesis of existing knowledge remains fragmented. Most existing reviews focus on specific technologies, application domains or isolated lifecycle phases, often neglecting a holistic analysis across technical, operational, and strategic dimensions and lack an integrated perspective on how enabling technologies are effectively operationalised within construction DTs. Furthermore, because existing studies focus primarily on original research rather than evaluating the review literature itself, their limitations and research gaps are often unrecognised. This absence of a systematic "review-of-reviews" obscures the broader research landscape, making it difficult to define targeted directions for future study. To address these gaps, this study introduces a two-stage research design that distinguishes it from previous single-layer reviews. First, it utilises a "review-of-reviews" to identify how the field has been framed and to assess what has been well explored or insufficiently addressed. Second, it synthesises empirical studies to explore the application of DTs in different domains, examine key barriers, and assess technology integration. Crucially, this synthesis is translated into actionable, stakeholder-specific strategies aimed at overcoming challenges of DT deployment. This dual approach is essential to move beyond broad overviews and construct a solid, multi-dimensional roadmap for future research and implementation.

Accordingly, this paper aims to systematically assess the current practice and emerging trends in the development and implementation of DTs in construction, identify key knowledge gaps, and address the following research questions (RQs):

RQ1: What key thematic trends emerge from existing DT research in construction?

RQ2: What are the main barriers to the DT implementation and what strategies have been proposed?

RQ3: What enabling technologies are used and how are they integrated into the construction DT ecosystem?

This paper begins with an introduction to the DT concept and the rationale for the study, followed by a two-stage systematic literature review methodology. The findings are presented in three parts: an overview of the literature distribution and keyword co-occurrence networks; an analysis of review articles to identify thematic trends and research gaps; and a synthesis of empirical studies focusing on application areas, technology integration, implementation barriers, and mitigation strategies. This is followed by a discussion of key findings, directions for future research and limitations. The paper concludes with a summary of the research process and results. By highlighting best practices, challenges, and future trends, this review provides valuable insights for stakeholders and supports strategic decision-making for the effective adoption of DT in the construction industry.

2. METHODOLOGY AND DATA COLLECTION

This study employed a systematic literature review (SLR) method, conducting comprehensive searches and reviews of relevant literature within the defined research scope. The SLR method typically follows a rigorous and explicit procedure (Su et al., 2023) , applying clearly defined search and selection criteria (Hou et al., 2024). The review was conducted in three main phases: planning, implementation and literature synthesis.

2.1 Stage1: Planning

The process began with the formulation of clear research questions and objectives, aligned with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework. As outlined in the introduction, this study aims to evaluate the current status and future trends of DTs in the construction industry. Specifically, the review addresses three core research objectives:

(1) to identify thematic trends in existing DT research in construction.

(2) to explore a comprehensive framework and roadmap for enabling DT technologies and their integration, and

(3) to examine the main barriers to DT implementation and related solutions.

These objectives informed the design of the review protocol, inclusion and exclusion criteria, and synthesis framework. The databases Scopus, the Web of Science and ScienceDirect were chosen for the initial search of the literature due to their extensive coverage of construction research (Naderi and Shojaei, 2023, Opoku et al., 2021, Deng et al., 2021). To ensure a broad and inclusive search, keywords were extended to cover related terms such as “built environment”, “AEC”, “building” and “infrastructure”. The final search string was:

(“digital twin”) AND (“construction” OR “AEC” OR “built environment” OR “building” OR “infrastructure”).

The search was limited to English-language journal articles published up to the end of 2024, to ensure quality, consistency, and relevance for comparative analysis.

Inclusion criteria were applied to studies that: Explicitly focused on DTs within the construction industry; Presented empirical findings, theoretical frameworks, or structured reviews.

Exclusion criteria included studies that: Did not engage directly with DTs; Were outside the construction or built environment domains; Mentioned DTs only as a future research direction without substantial focus.

2.2 Stage 2: Implementation

The defined search strategy was applied to the three databases. The initial search retrieved 3292 articles from Scopus, 2892 from Web of Science, and 994 from ScienceDirect. After removing 3076 duplicates, 4102 articles remained for screening.

The initial screening of titles, abstracts, and keywords reduced the corpus to 859 articles for full-text assessment. Subsequently, a detailed full-text review against the inclusion and exclusion criteria yielded a final dataset of 419 articles for synthesis. The full review workflow is illustrated in Figure 1.

2.3 Stage 3: Synthesis

The final pool of articles underwent a qualitative content analysis. Key bibliographic and thematic data were extracted and coded to facilitate thematic clustering. This process enabled a structured synthesis of research trends, application areas, technology integration pathways, implementation challenges, and proposed solutions. The findings directly address the research objectives and provide a critical knowledge base to inform future research directions and practical DT deployment in construction.

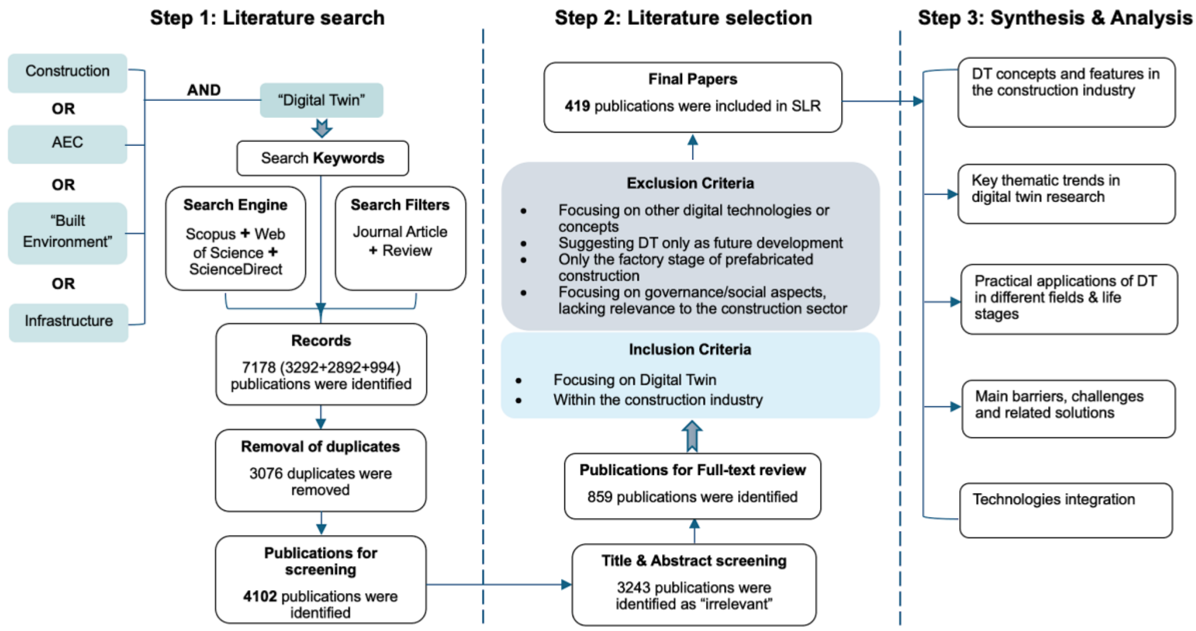

Figure 1: The systematic literature review process workflow.

3. RESULTS AND FINDINGS

3.1 Overview of selected samples

A total of 419 relevant articles from 135 international journals were included in the final dataset. Table 1 presents the distribution of articles among journals with five or more publications, distinguishing between research and review articles. Although these 22 journals represent only 16.3% of all sources, they account for 278 articles (66.3% of the total dataset), highlighting their centrality in shaping the DT research landscape in construction.

The most prolific outlets were *Buildings* and *Automation in Construction*, contributing 10.7% and 10.5% of the total publications respectively. Together, they make up over one-fifth of the entire dataset, highlighting their dominant influence. A second tier includes *Sustainability* (5.0%), *Journal of Building Engineering* (4.3%), and *Applied Sciences* (4.1%), reflecting the interdisciplinary scope and applicability of DT. Notably, journals such as *Buildings* and *Automation in Construction* show a balanced mix of research and review articles, supporting both empirical inquiry and knowledge synthesis. Others, including *Engineering, Construction and Architectural Management* and *Journal of Information Technology in Construction*, lean more towards review articles, indicating a focus on conceptual exploration. In contrast, technically oriented journals such as *Tunnelling and Underground Space Technology* and *Building and Environment* predominantly published original research, highlighting their emphasis on applied studies and implementation

Figure 2 shows the annual distribution of reviewed articles from 2019 to 2024, segmented into original research and review articles. The total number of publications has increased significantly over the past six years, reflecting the rapidly growing interest in research on DTs in the field of construction. In 2019-2020, at an early stage of concept development, a limited number of publications were published, mainly research articles. In 2021-2022, the number of publications increased significantly, both articles and reviews. The growth rate slowed slightly in 2023, but the largest increase was in 2024, with a total of 179 articles (114 research articles and 65 reviews). This trend points to both sustained interest in empirical research and an increasing demand for integrative reviews that consolidate existing knowledge and guide future developments.

Table 1: Journal source and type distribution.

Rank	Journal Name	Count	Proportion	Article	Review
1	Buildings	45	10.7%	26	19
2	Automation in Construction	44	10.5%	30	14
3	Sustainability	21	5.0%	13	8
4	Journal of Building Engineering	18	4.3%	12	6
5	Applied Sciences	17	4.1%	14	3
6	Sensors	13	3.1%	12	1
7	Frontiers in Built Environment	10	2.4%	9	1
8	Advanced Engineering Informatics	10	2.4%	7	3
9	Energies	9	2.1%	6	3
10	Energy and Buildings	9	2.1%	8	1
11	IEEE Access	9	2.1%	7	2
12	Engineering, Construction and Architectural Management	9	2.1%	4	5
13	Advances in Civil Engineering	8	1.9%	7	1
14	Smart and Sustainable Built Environment	8	1.9%	4	4
15	Journal of Information Technology in Construction	7	1.7%	2	5
16	Tunnelling and Underground Space Technology	7	1.7%	7	0
17	Building and Environment	6	1.4%	6	0
18	Journal of Computing in Civil Engineering	6	1.4%	6	0
19	Structure and Infrastructure Engineering	6	1.4%	6	0
20	International Journal of Construction Management	6	1.4%	5	1
21	Developments in the Built Environment	5	1.2%	4	1
22	Sustainable Cities and Society	5	1.2%	3	2
Total		278	66.3%	198	80

3.1.1 Keywords Co-occurrence Network

To explore the thematic structure of DT research in construction, a keyword co-occurrence analysis was conducted using VOSviewer. Author keywords were selected over index terms as they better capture the core focus of the articles (Opoku et al., 2021). Synonyms such as “digital twin”, “DT”, and “digital twins”, as well as variations of “BIM” and “IoT”, were merged for analytical consistency.

Finally, out of a total of 1159 keywords, 42 keywords with a frequency of five or more occurrences were identified and formed eight clusters. Figure 3 presents the co-occurrence network, with node size indicating keyword frequency and proximity reflecting thematic correlation (Hosamo et al., 2022).

Figure 4 shows the corresponding cluster dendrogram. Cluster 1 illustrates the DT lifecycle, with a focus on infrastructure applications such as bridges. It includes sensor-based data acquisition, point cloud modelling, simulation, and structural health monitoring (SHM). This cluster overlaps with Cluster 2, which incorporates machine learning (ML), reflecting the integration of real-time data with predictive analytics for intelligent asset management. Clusters 2, 3, and 7 centre on core DT functions, including construction management, facility management, smart buildings, and intelligent construction. Cluster 4 highlights advanced digital integrations such as deep learning, AI, and blockchain, indicating an increasing emphasis on automation, diagnostics, and data security. Cluster 6 reflects the link between DT and sustainability, including operational carbon reduction and energy efficiency, where simulation tools are used to enhance building performance and support low-carbon transitions. Clusters 5 and 3 capture conceptual development and implementation challenges, including theory building, framework development, and assessments of industry readiness.

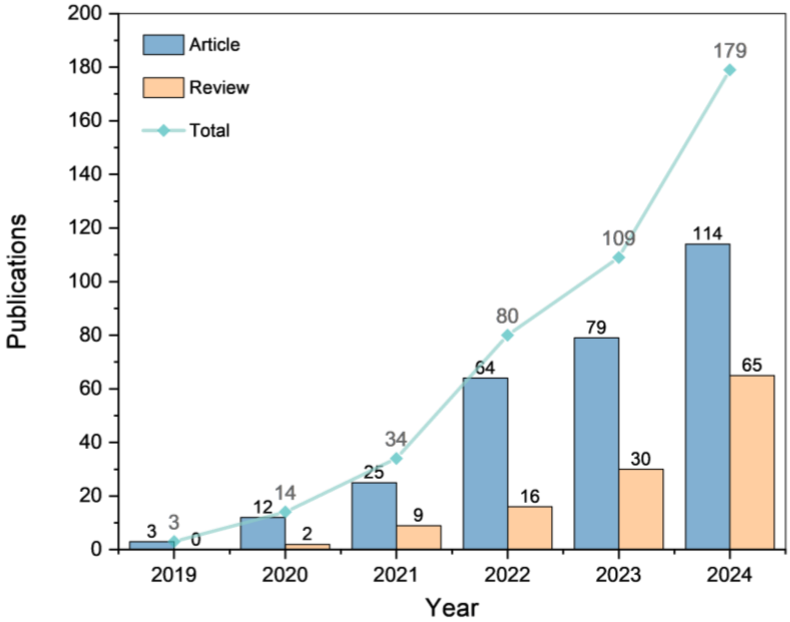

Figure 2: Annual distribution of the reviewed articles.

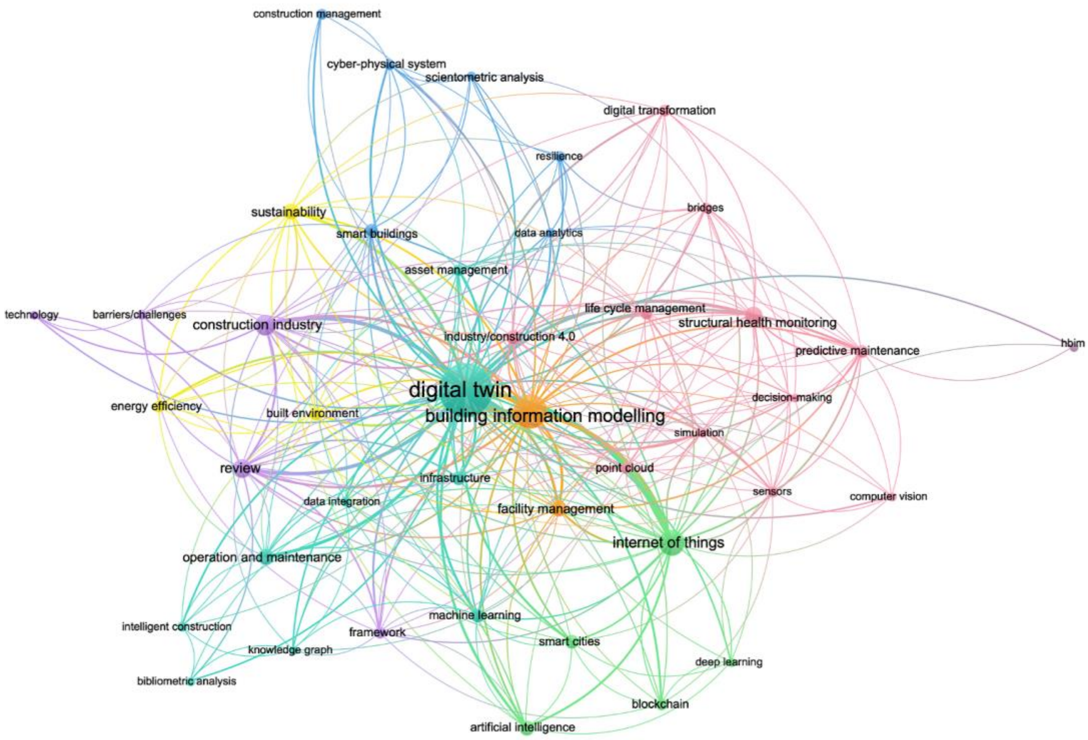

Figure 3: Keyword co-occurrence network.

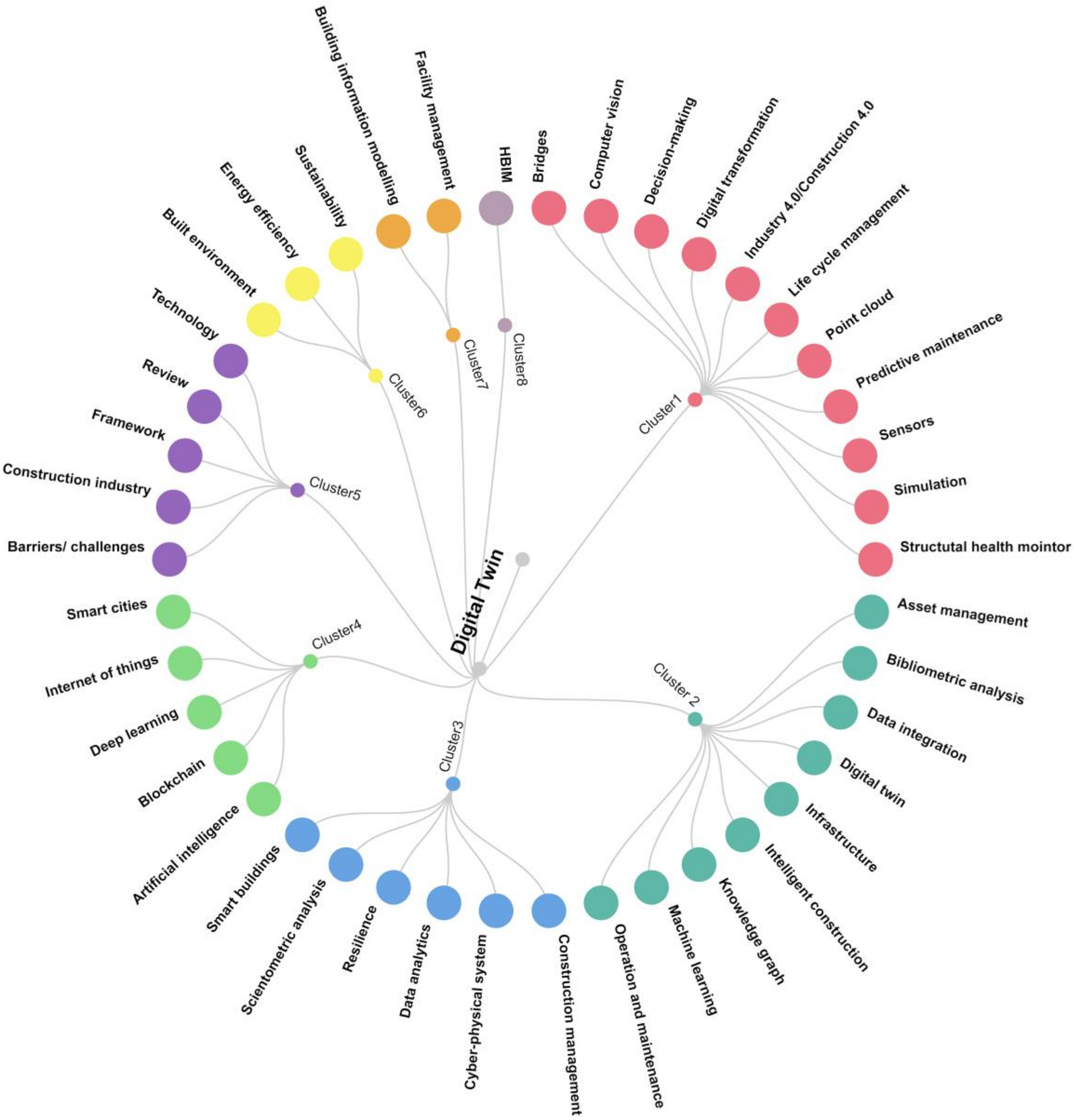

Figure 4: Keyword cluster dendrogram.

Overall, the co-occurrence analysis reveals a technically robust and thematically expanding research landscape. DT research in construction is evolving beyond foundational technologies such as BIM and IoT, toward intelligent systems, data-driven decision-making, and sustainable asset development.

3.2 Synthesis of rview papers

Table 2 presents a summary of review papers on DTs according to both lifecycle phases and application domains. The lifecycle phases are categorised into Construction, Operation and Maintenance (O&M), and Cross lifecycle. The application domains include Facilities management (FM), Building, Cultural heritage, Infrastructure, Urban Digital Twins (UDTs)/Smart cities, and Broad conceptual and industry-wide studies.

From a lifecycle perspective, most review studies (90 out of 122) take a cross-lifecycle approach, highlighting overarching frameworks and integrated DT applications that span multiple phases. The O&M phase is the next most frequently addressed, while construction-focused reviews are comparatively fewer, and the design phase remains substantially underexplored. Despite advancements in lifecycle integration, current reviews predominantly emphasise theoretical contributions rather than phase-specific implementation strategies. In terms of domains, the most substantial group of reviews was broad conceptual studies. This is followed by reviews focusing on infrastructure and buildings, reflecting current DT adoption trends. Conversely, domains such as cultural heritage, FM, and UDTs remain relatively underrepresented in the literature.

Table 2: Research domains and life cycle distribution for review papers.

Domain \ Phase	Construction	O&M	Cross lifecycle	Total
FM	0	0	2	2
Building	1	12	8	21
Cultural heritage	0	2	2	4
Infrastructure	1	5	22	28
UDTs / smart cities	0	0	5	5
Broad conceptual and industry-wide studies*	6	5	51	62
Total	8	24	90	122

** This category includes studies that address DTs at a broad or conceptual level within the domain such as the Construction Industry; Civil Engineering; Built Environment; Architecture, Engineering and Construction (AEC); and Architecture, Engineering, Construction, and Operations (AECO).*

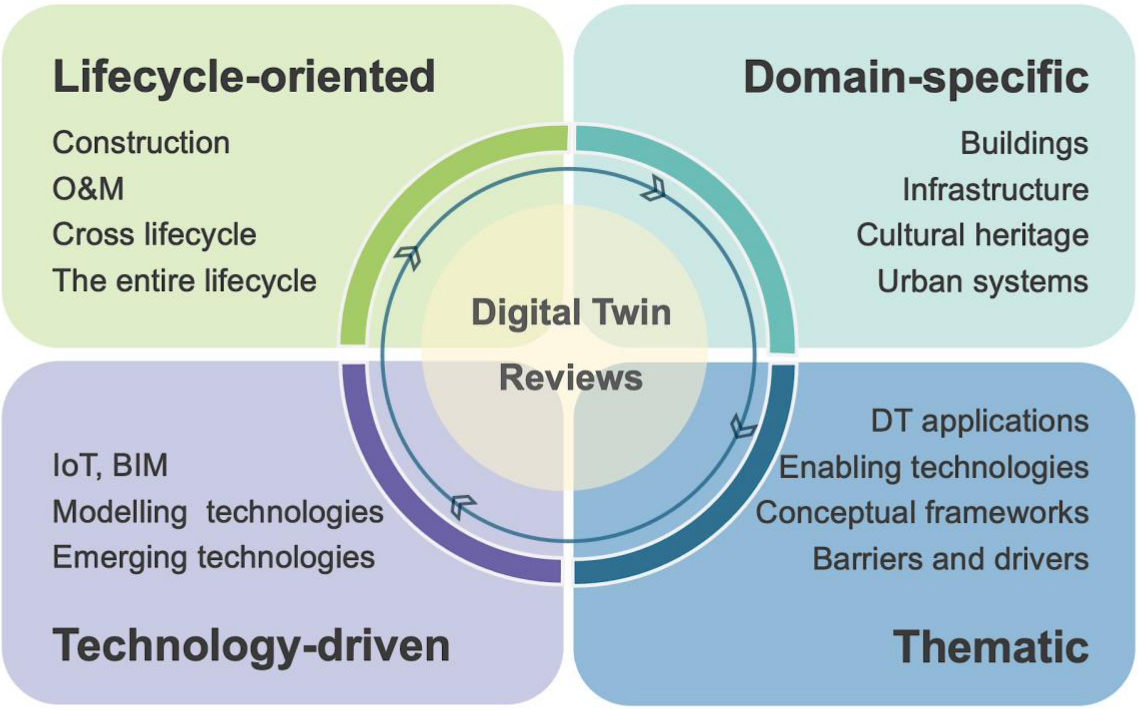

Figure 5: Dimension matrix for review papers.

Combining both dimensions, cross-lifecycle research dominates, particularly in infrastructure and conceptual studies, highlighting a system-level focus over phase-specific detail. In contrast, building-related reviews emphasise O&M, aligning with asset management needs. Construction-phase reviews remain limited, likely due to the ongoing challenges in DT integration during early project stages.

Overall, existing review literature can be grouped into four main categories, as illustrated in Figure 5:

(1) Life-cycle oriented studies that examine DT across construction, O&M, or the entire asset lifecycle.

(2) Domain specific reviews that target particular sectors such as buildings (Lauria and Azzalin, 2024b), infrastructure (Lampropoulos et al., 2024) or urban systems (Therias and Rafiee, 2023);

(3) Technology driven studies that focus on the enabling technologies (Tuhaise et al., 2023, Yan et al., 2025) and frameworks (Mousavi et al., 2024) that support DT development; and

(4) Thematic studies that span applications, enabling technologies, conceptual frameworks, barriers and drivers, and emerging research trends.

Technological analyses in the literature primarily emphasise BIM (Nguyen and Adhikari, 2023) and IoT (Siccardi and Villa, 2023), with significantly less attention given to AI, ML, blockchain, and other digital technologies, despite their increasing importance in recent DT systems.

Despite the growing literature, key gaps remain. There is limited systematic analysis of barriers to DT adoption and few strategies for overcoming them. While emerging technologies are acknowledged, in-depth studies on their deployment and integration, particularly AI, blockchain, and the semantic web are scarce. Additionally, there is no comprehensive review on evaluating DT success. Performance metrics and validation methods are either missing or fragmented. This highlights a maturing but still fragmented field, where conceptual clarity is improving, but practical and evaluative research is lacking. Bridging these gaps is crucial for moving DTs toward scalable implementation in construction.

3.3 Synthesis of research articles

Current DT research in construction is highly multidimensional, with broad, intersecting topics. To address core research questions, this section provides a critical analysis along four dimensions: (1) distribution of DT applications across lifecycle phases and domains; (2) integrated technology frameworks from data collection to decision-making; (3) key barriers to industry adoption; and (4) a multidimensional strategy matrix for response.

3.3.1 DT applications distribution across domains and lifecycle

Table 3 classifies 297 DT-related articles by lifecycle phases and domains.

Among all domains, infrastructure has attracted the widest academic attention (n = 94) with a strong focus on the O&M phase (n = 59) where DTs enable risk management and decision support. Given the great importance of infrastructure safety, the DT function in existing studies focuses on two core activities: (1) inspection and monitoring, which significantly reduces operational costs and safety risks by improving safety management effectiveness and automating inspections to replace high-risk manual work; and (2) decision response, through the fusion and analysis of data from multiple sources, to provide data-driven support for decision-making, predictive maintenance and performance optimisation. DTs integrate emerging wireless communication technologies, predictive maintenance approaches, IoT, structural reliability analysis, and other advanced tools to enhance the understanding of structural behaviour and integrity, thereby enabling real-time monitoring of the behavioural evolution of infrastructure assets (Futai et al., 2022). Feng et al. (2024a) developed an integrated DT model including both the physical components and operational processes of a pump station, achieving a 100% automatic detection rate in case studies and realising cost savings of 2.25 million RMB (approximately US$310,000). Hagen and Andersen (2024) proposed the integration of DT with ML to improve the detection and diagnosis of bridge damage, while Heng et al. (2024) incorporated predictive models, monitoring data, and detection outcomes into DTs to support proactive and sustainable maintenance of ageing infrastructure and to optimise resource allocation. In the construction phase, DT is mainly applied to dynamic control of construction quality, process optimisation and real-time risk monitoring. The DT model delivers real-time feedback on over-excavation and under-excavation data during tunnel construction, facilitating accurate assessment of geotechnical conditions and enabling dual control of construction quality and cost (Fang et al., 2024). DT has demonstrated considerable value in the safety management of tunnel construction. It was confirmed that DT systems can detect tunnel deformation and generate early warnings alongside responsive action plans (Feng et al., 2024b). Zhao et al. (2022a) reported that the prediction accuracy of settlement values using DT meets the requirements for dynamic safety assessment. Building on this, He et al. (2024) enhanced the accuracy and reliability of water inrush disaster simulations by integrating

ML with finite element analysis. In a case study, Ye et al. (2023) developed an intelligent early warning platform based on multi-source information, which successfully predicted a collapse at the tunnel excavation face and safeguarded construction personnel through timely emergency intervention. However, research in the planning and design phases is still limited, with existing results focusing on improving design efficiency and accuracy. By creating highly detailed 3D models, DTs can provide stakeholders with a comprehensive visual representation, which can contribute to better understanding and communication between stakeholders (Li et al., 2023). While technologies like BIM already support these capabilities, DTs go further by integrating real-time data and advanced analytics, making them powerful decision-making tools. DT provides effective decision support for the design process of complex infrastructure engineering systems by quantitatively and conveniently predicting and managing design changes (Chen and Whyte, 2022).

Table 3: Research domains and lifecycle distribution of research articles.

Phase / Field	Design & Planning	Construction	O&M	The entire lifecycle/not limited
Building (n = 85)	2	8	60	15
	Building energy efficiency analysis. Energy consumption.	Decision analysis. Site safety management. Construction project performance. Construction site management. Information pipelines.	FM: sensing and monitoring; fault detection and diagnosis; damage detection; early warning; SHM. Energy: energy consumption monitoring, predictions and efficiency optimisation. Occupancy: monitoring, visualising, assessment; human-building interactions; space management. Emergency and safety: fire protection or emergency; danger warning and positioning; seismic behaviour monitoring and post-earthquake safety prediction. Smart buildings. Predictive maintenance. Carbon emissions control & reduction. Building performance. Renovation: renovation strategies assessment. Model upgrade: in situ model fusion; enriching geometric digital twins. Building collapse accident investigation.	Sustainability assessment. Building environment monitoring. Energy performance. FM. Embodied carbon estimation. Smart buildings.
Construction project (n = 20)	0	15	0	5
		Construction management: optimise the process; safety management. Automated construction. Progress monitoring. Modular integrated construction: real-time monitoring and dynamic control; supply chain management.		Accountable information sharing in projects. Decision support. Maturity measurement.

Field \ Phase	Design & Planning	Construction	O&M	The entire lifecycle/not limited
		Prefabricated construction: intelligent safety risk prediction. Smart construction. Robotic construction.		Optimal construction project management: performance management; project data categorisation.
Construction site (n = 20)	0	20	0	0
		Tower cranes: Predicting degraded lifting capacity; Stability analysis. On-site assembly: real-time synchronisation for planning, scheduling, and execution Quality assessment/error control. Safety risk analysis/threat assessment. Construction efficiency: cable structure demolition optimisation. Collaborative human-robot. Construction management.		
Structure & materials (n = 8)	1	5	2	0
	Quality control (precast concrete elements).	Construction material: construction material provenance tracing and tracking. Construction element: remote real-time concrete compressive strength monitoring. Continuous monitoring of temperature & humidity in construction elements. Structural safety analysis: intelligent safety assessment method of prestressed steel structures.	Crack monitoring (concrete). Structural performance and damage prediction (earthquake-affected pinched structures).	
Cultural heritage (n = 19)	0	0	19	0
			Predictive maintenance. Preventive maintenance. SHM: structural stress analysis; structural integrity after earthquake (cracks). Indoor environment: IAQ; humidity; temperature. Risk/threat detection.	
	3	14	59	18

Field \ Phase	Design & Planning	Construction	O&M	The entire lifecycle/not limited
Infrastructure (n = 94)	To predict and manage design changes. Clearance check for underpass roads in road widening design. Just-in-time design of rock tunnel: improve efficiency and accuracy.	Safety management & hazard prevention: health, safety, and real-time monitoring. Quality assurance & process optimisation: quality control and precision construction. Structural performance & risk mitigation: deformation prediction and structural integrity. Data integration & operational efficiency: data-driven decision support.	SHM & predictive maintenance. Energy and carbon management. Safety and emergency management. Automated inspections and asset management. Data integration and decision support. Performance optimisation.	Enhancing decision-making and management. Sustainability assessment and risk management. Maintaining structural sustainability. Comprehensive lifecycle monitoring and management.
UDT (n = 8)	1	1	4	2
	Urban road planning: facilitating the evaluation and comparison of road development proposals.	Urban excavation safety: to proactively monitor urban excavation, dynamically assess collision risk, and timely warn against unsafe behaviours.	Environmental monitoring management. Sustainable comfort monitoring. Predictions, and what-if analysis for assessing impact of changes: enabling stakeholder and citizen participation.	Theory building: framework; urban dynamics (cases).
Broad conceptual and industry-wide studies (n = 41)	0	3	10	28
		Automated progress monitoring. Intelligent dispatching System. Human-robot collaborative system.	FM: indoor air quality; emergency; asset health. Human-robot teaming: compatibility of the environment with robots. Model upgrade: federated data modelling to improve interoperability. Carbon reduction (residential area). Experience improvement	Workforce development: engineering education; safety training. Theory building: awareness; DT readiness assessment; barriers; contractor's perspective. Deep learning integration. Circular economy integration.
Total	6	66	156	69
Proportion	2%	22%	53%	23%

Similarly, studies related to buildings (n = 85) also exhibit strong attention to the O&M phase (n = 60), with DTs enhancing facility management, energy efficiency, comfort, and disaster response. By deeply integrating AI and big data analytics, DT achieves high-precision modelling and real-time mapping of a building's physical state and drives a fundamental shift from static management to dynamic prediction and intelligent decision-making (Tan et al., 2022). Research shows that DT demonstrates significant advantages in thermal comfort control (ElArwady et al., 2024), energy consumption prediction (Henzel et al., 2022), carbon emissions monitoring (Arsiwala et al., 2023), predictive maintenance (Hosamo et al., 2023b), structural health assessment (Longman et al., 2023), and disaster response (Lauria and Azzalin, 2024a). Some case studies have successfully applied it to complex scenarios like healthcare facilities, using multi-objective optimisation algorithms, ML models, and model predictive control to effectively enhance the response efficiency and energy performance of building systems (Hosamo et al., 2023a, Harode et al., 2023). Fewer studies focus explicitly on construction and design phases, indicating that building-oriented DT research predominantly targets post-construction operational efficiencies and occupant-centred applications. However, recent research indicates that DT is gradually emerging as one of the key technologies for intelligent construction of buildings, enabling real-time monitoring and dynamic response to construction progress, site safety, equipment utilisation, and performance and quality management (Chacón et al., 2024, Posada et al., 2024, Torres et al., 2024). Lifecycle-spanning studies highlight emerging interests in sustainability assessment (Boje et al., 2023), embodied carbon estimation (Chen et al., 2021), and integrated smart building systems (Eneyew et al., 2022).

The domains of construction projects (n = 20) and construction sites (n = 20) mainly target the construction phase, where DTs' real-time data transmission capabilities shine. Research on construction projects focuses largely on optimising management processes, modular construction, automated progress monitoring, and intelligent risk prediction. Similarly, construction-site studies emphasise safety management, equipment monitoring, on-site assembly optimisation, and collaborative human–robot systems. DTs enable real-time site monitoring, which supports efficient site management by providing dynamic updates on construction progress (Deng et al., 2021). Automated site monitoring with DTs improves logistics, progress control, site safety, quality assessment and management, ultimately reducing long-term costs (Boje et al., 2020). From a management perspective, Jiang et al. (2022b) utilised the real-time resource status and construction progress information obtained from DT to facilitate planning, scheduling and execution of construction projects, thereby improving efficiency and productivity. DTs accurately predict worker behaviours in risky situations (Jiao et al., 2024) and analyse the information collected through ML, thus effectively contributing to the improvement of construction safety and risk control (Zhao et al., 2022b). Moreover, some experiments have confirmed that DTs enable human-robot collaboration by integrating visualisation and supervision of the planning and execution of tasks as well as bi-directional communication, which greatly improves efficiency (Wang et al., 2021). In contrast, studies focusing on cultural heritage (n = 19) are entirely oriented towards the O&M, emphasising condition monitoring (Vila-Chã et al., 2023), structural integrity (Sivori et al., 2023), preventive maintenance (Galiano-Garrigós et al., 2024) and indoor environment control (Zhang et al., 2023). The exclusive focus on O&M in this domain aligns with the distinctive preservation and risk mitigation needs associated with heritage assets.

Structures and materials domain (n = 8) displays research activity across multiple lifecycle phases, which typically address real-time monitoring of the conditions of structures(Liu and Bao, 2023) and materials like concrete (Iqbal et al., 2024), structural safety analysis (Liu et al., 2022), and material tracing (Xu et al., 2023), reflecting an interest in lifecycle-integrated material and structural performance monitoring. Also, the emerging area of UDTs (n = 8) shows a relatively balanced distribution across lifecycle phases. Research in this domain addresses diverse issues, from urban planning and excavation safety to environmental monitoring and stakeholder participation, demonstrating an integrated and systemic approach at the urban scale (la Riccia et al., 2024, Afif Supianto et al., 2024).

Finally, extensive conceptual and industry-specific studies (n = 41) mostly adopted a full lifecycle or non-specific phase perspective (n = 28), covering foundational theoretical issues such as theoretical framework building, technology readiness assessment (Alnaser et al., 2024), workforce capability development (Hazrat et al., 2023), and the integration of DT with sustainability strategies like circular economy (Meng et al., 2023). These studies reflect scholars' shared focus on integrating fragmented knowledge, overcoming adoption barriers, and advancing the maturity of DT technology.

Overall, current DT research exhibits significant phase-based imbalances: the O&M phase dominates (53%), construction phase research is relatively scarce (22%), and research on the design and planning phase is severely lacking (2%). Additionally, Long et al. (2024) highlighted the insufficient research on DT applications in the demolition phase. DT has the potential to enhance demolition operations by enabling precise planning and simulation of demolition activities through detailed virtual models, improving safety by identifying and mitigating hazards (Borjigin, 2022). It can also assess environmental impacts, promote effective waste management and resource recovery, and optimise cost and time schedules. In contrast, the number of studies on the entire life cycle (23%) is relatively substantial, indicating that academia is deepening its understanding of DT from a lifecycle perspective and in terms of integration. However, future research should focus on DT application in the early and late phases of the lifecycle to drive the construction sector toward achieving true lifecycle digital asset management.

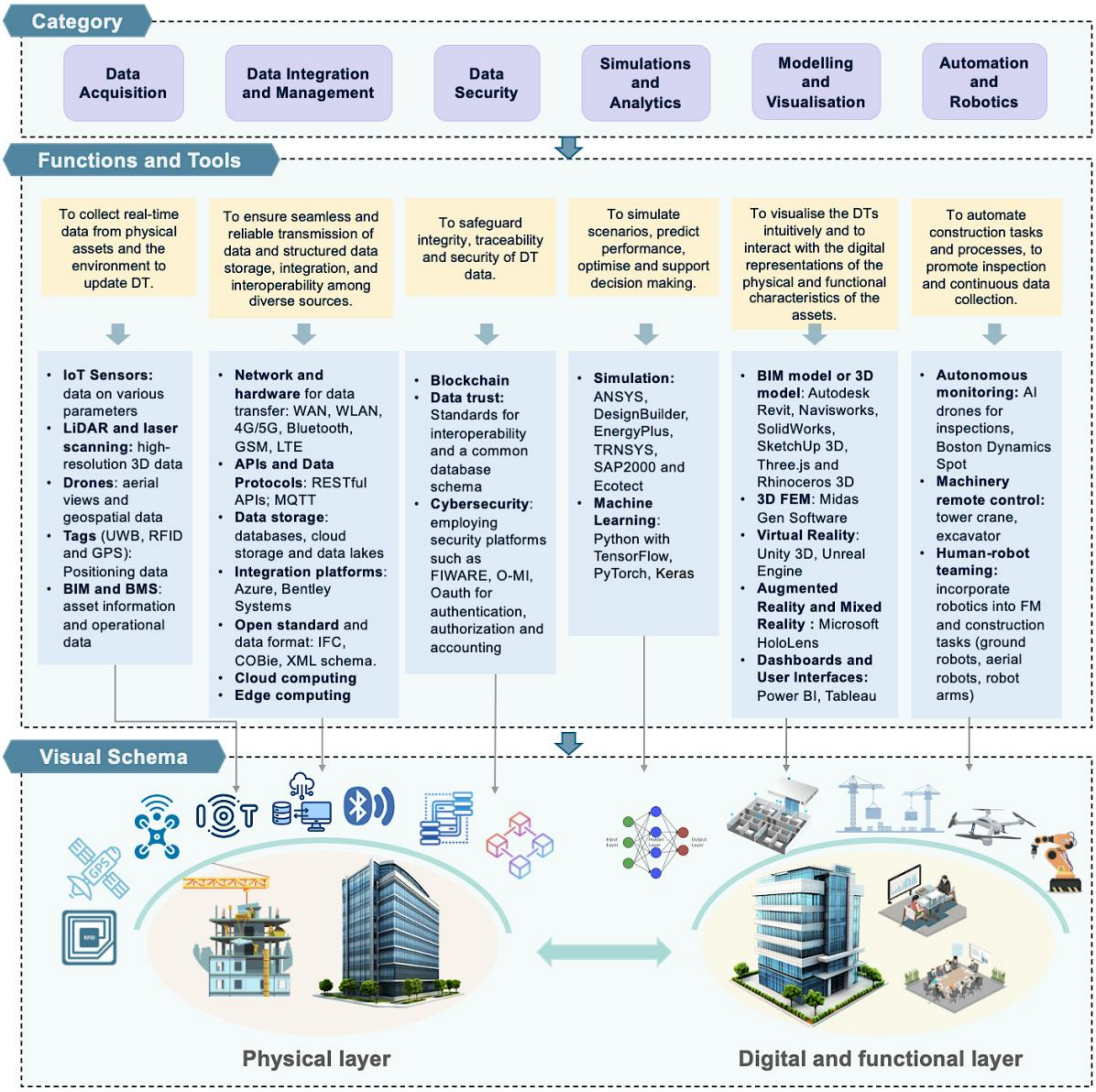

Figure 6: Framework of DT technologies.

3.3.2 DT technology framework

As an evolving concept, DTs face notable technical challenges (Rasheed et al., 2020) with insufficient research on enabling technologies. Core technologies for data acquisition, modelling, and processing are essential to achieving DTs' key features. However, supporting technologies that enhance DT performance, such as data integration, security, and automation, remain underexplored and fragmented.

Therefore, a structured DT technology framework was developed (Figure 6) and organised into six primary categories: Data Acquisition, Data Integration and Management, Data Security, Simulations and Analytics, Modelling and Visualisation, and Automation and Robotics. These categories collectively support the comprehensive lifecycle management and functionalities of DT systems. The framework differentiates between two fundamental layers: the Physical layer, comprising real-world assets and environments, and the Digital and Functional layer, involving digital replicas and analytical functionalities. The Physical layer includes real-time data acquisition through advanced sensing technologies such as IoT sensors, LiDAR, drones, and Radio Frequency Identification (RFID) tags (Shi et al., 2024, Chen et al., 2021) as well as other system sources such as BIM and Building management system (Hosamo et al., 2023b). These instruments facilitate the accurate collection of geospatial data, environmental parameters, asset information, and operational metrics crucial for maintaining the fidelity of digital twins.

The Digital Layer begins with data integration and management. Network and hardware infrastructure employing protocols such as Representational State Transfer Application Programming Interface (RESTful APIs) and Message Queuing Telemetry Transport (MQTT) ensure seamless data transfer and interoperability across diverse platforms (Banfi et al., 2022, Gao et al., 2023). Additionally, edge computing and cloud-based integration platforms (e.g., Azure and Bentley Systems) support real-time processing and storage, maintaining continuous and effective DT operation (Harode et al., 2023) . Central to the DT framework's security strategy is blockchain technology, which provides enhanced integrity, transparency, and traceability of the data streams (Figueiredo et al., 2024, Naderi and Shojaei, 2024). Cybersecurity protocols further ensure secure interactions and compliance with international standards for authentication and authorisation (Liu et al., 2024).

Simulations and analytics form the analytical core of the Digital layer, where tools such as ANSYS, EnergyPlus, and SAP2000 (Galiano-Garrigós et al., 2024, Dang et al., 2022), coupled with ML libraries such as TensorFlow and PyTorch (Tan et al., 2022, Peng et al., 2020), enable predictive analysis, scenario testing, and informed decision-making. These computational tools offer extensive analytical capacity, underpinning proactive asset management and operational optimisation. Furthermore, modelling and visualisation technologies including BIM and 3D Finite element models, augmented reality (Microsoft HoloLens), virtual reality platforms (Unity 3D, Unreal Engine), and business intelligence dashboards (Power BI, Tableau), facilitate intuitive user interactions (Futai et al., 2022, Asare et al., 2024, El Mokhtari et al., 2022, Harode et al., 2023). They provide visually rich and interactive environments, enabling stakeholders to explore, interpret, and manage the physical assets effectively.

Lastly, the Automation and Robotics category addresses the integration of AI-driven autonomous systems, such as robotic inspection platforms, remote-controlled machinery, and collaborative human-robot operations (Gao et al., 2023, Ye et al., 2022). These technologies enhance operational efficiency, precision, and safety across construction, maintenance, and facility management tasks.

In sum, the framework provides a holistic and layered view of DT technologies, linking physical assets to digital intelligence and enabling data-driven decision-making across the built environment lifecycle.

3.3.3 Barriers and challenges for DT implementation

Despite the transformative potential of DT in construction, adoption remains limited due to a complex set of barriers. Table 4 categorises 26 identified barriers into four key domains: technological, organisational, industry and market, and regulatory. Ranked by frequency in the literature, these barriers reveal the multi-dimensional challenges constraining DT implementation.

Technological challenges were the most frequently cited category across the reviewed articles. A recurring issue involves sensor installations and the volume of data generated by advanced sensing networks, which place significant strain on existing digital infrastructures (Adeagbo et al., 2024). Massive data processing reduces system agility and operational efficiency, triggering huge computing demands (Piras et al., 2024). Agostinelli et al. (2021) reported that network capacity, device battery life, and maintenance costs often make real-time monitoring systems impractical, particularly in projects with complex site conditions. Moreover, the potential heterogeneity of DT architectures due to a lack of unified design, tools, approaches and platforms introduces further complexity (Adeagbo et al., 2024). This heterogeneity, combined with disparate information systems, results in data fragmentation which remains a critical challenge. Without a shared framework and detailed maintenance procedure for ensuring data integrity and synchronisation, the value and quality of data updated in DTs is compromised (Mahmoodian et al., 2022). Additionally, data privacy and security concerns persist, especially in critical infrastructure or sensitive information (Piras et al., 2024, Xiao et al., 2024).

Organisational barriers primarily originate from cultures and strategies resistant to change and a lack of strategic vision among practitioners and decision-makers (Agrawal et al., 2022). Literature highlights the difficulty many organisations face in making suitable decisions and investments regarding enabling technologies, particularly where the benefits of DTs are not well understood. In several studies, lack of structured project pathways was identified as a critical barrier, leading to uncertainty around how to initiate or scale DT implementations (Agrawal et al., 2022, Yang and Ng, 2024). The absence of clear value propositions also featured prominently in findings. Without demonstrable application cases or benchmarks, stakeholders are hesitant to commit resources to DT systems perceived as experimental (Vieira et al., 2024). Skill and knowledge gaps further hinder progress. For instance, Asare et al. (2024) reported low levels of knowledge on the design and implementation of DT-based projects, making it difficult to select appropriate platforms and benchmarks.

Table 4: Barriers for DT implementation.

Barrier category	**Code**	**Sub-barriers**	**Barrier description**	**Frequency**
Technological barriers	T1	Data integration and processing complexity	Disparate data sources leading to processing and integration challenges.	32
	T2	Interoperability issues	Incompatibility between DT platforms, legacy systems, or tools.	29
	T3	Technical challenges	Practical issues with sensors or IoT devices, platforms, models and hardware deployments.	23
	T4	Difficulty in real-time communication	Real-time communication is difficult due to lack of performance.	14
	T5	Computational demand	High resource requirements for real-time processing or large-scale simulations.	8
	T6	Cybersecurity, data security and privacy concerns	Risks of data breaches, unauthorised access, and uncertainty over privacy policies. Data security and privacy issues raise concerns in the areas of intellectual property, privacy and asset security.	8
	T7	Data management and governance	Large volumes of data are difficult to collect, store, process, and analyse.	5
	T8	Lack of standards and frameworks	Lack of unified DT development standards, models or interoperability protocols.	5
Organisational factors	O1	Resistance to change	Cultural inertia or scepticism toward adopting DT workflows.	12
	O2	Lack of skilled workforce	Shortage of personnel trained in DT technologies.	11
	O3	Cultural barriers and collaboration issues	The difficulty for effective collaboration and teamwork among DT practitioners to addressing the variety, complexity, and scale.	9
	O4	Knowledge and awareness gaps	The lack of knowledge and awareness of DT capabilities or implementation among owners and contractors.	5
	O5	Resource constraints	Limited budget for pilot studies, training and other resources input.	3
	O6	Unclear value proposition	The absence of clear value propositions for DTs results in weak stakeholder engagement.	2
	O7	Trust and reliability concerns	Low confidence in the fidelity of DT outputs and decision support.	2
Industry and market environment	I1	Return uncertainty	The return on investment of DT projects and the benefits are unclear and uncertain.	8
	I2	High initial investment and cost concerns	Significant upfront costs for DT projects.	7
	I3	Risk aversion and innovation resistance	The industry is more cautious about taking risks and adopting innovation.	5

Barrier category	Code	Sub-barriers	Barrier description	Frequency
	I4	Economic pressures	Competitive pressures, tight schedules, and minimal profitability hinder investment and changes in conventional workflows.	3
	I5	Fragmentation and structural rigidity	The sector's fragmented nature (transient subcontracting networks) poses a barrier to process innovation.	3
	I6	Lack of scalability or implementation scale	Most DT applications are specific-use cases and lack scalability, resulting in high costs.	3
	I7	Market confusion	Software vendors' promotion simplifies the concept of DT into a mere technology or product, which confuses the market.	1
Regulatory constraints	R1	Policy and government support gaps	Absence of relevant policies, standards and government incentives.	7
	R2	Lack of standards and regulations for DT	Lack of standards and regulations leads to inconsistencies in implementations.	5
	R3	Data privacy and ethical concerns	Ownership, ethical and copyright concerns arise when dealing with the vast amount of data, especially personal data.	3
	R4	Regulatory and compliance issues	Uncertainty around approvals, data governance rules, IP ownership and legal processes.	2

Structural characteristics of the industry increase the challenges above. The sector is widely described as fragmented, with a generally conservative approach to innovation (Sacks et al., 2020). These conditions create an ecosystem that is digitally hesitant and often lacks clarity on return on investment, discouraging experimentation with novel technologies (Pregnolato et al., 2022). High initial costs and uncertainties surrounding long-term financial benefits remain dominant deterrents (Torres et al., 2024). Moreover, the lack of consistent communication from technology vendors has resulted in conceptual ambiguity, where terms like DT are interpreted inconsistently across stakeholders (Camposano et al., 2021). This conceptual misalignment, combined with practical challenges in procurement, hinders the scaling of DT applications beyond demonstration-level initiatives. As a result, industry adoption remains slow, often limited to large, innovation-led projects or university-affiliated demonstrators.

Although less frequently reported, regulatory issues pose long-term risks. Issues of data ownership, ethics, and intellectual property are particularly problematic in multi-stakeholder, high-volume data environments (Adeagbo et al., 2024). The absence of supportive policies and legal clarity contributes to compliance uncertainty (Pregnolato et al., 2022). Additionally, limited government incentives restrict adoption, especially given the substantial initial investment required (Yang and Ng, 2024).

In sum, DT implementation is hindered by a highly interdependent web of constraints. Technological readiness alone cannot ensure success without organisational capacity, regulatory clarity, and market confidence. A coordinated, cross-sectoral response is essential to overcoming these multifaceted challenges.

3.3.4 Multidimensional Strategies for DT Implementation

Table 5 maps the categorised barriers to DT implementation against a comprehensive set of strategies proposed in the reviewed literature. The strategies fall into four interdependent domains: Technical solutions, Organisational measures, Industry collaboration, and Policy support. The table offers an integrated framework for overcoming adoption challenges.

Technical strategies focus on modular and decentralised DT architectures to enhance interoperability and scalability (Adeagbo et al., 2024, Niccolucci et al., 2022), which mitigates scalability challenges and allows systems to evolve incrementally across stakeholders and project phases which directly responds to interoperability concerns (T2) and the heterogeneity of digital platforms (T7). The increasing reliance on real-time data from distributed environments introduces vulnerabilities in communication architecture. In this context, AI-enhanced

IoT (AIoT) and edge computing architectures (Gao et al., 2023) offer improved resilience by reducing dependency on centralised processing and enabling real-time decision-making at the network edge, particularly relevant for barriers related to communication stability and performance (T4, T5). Data governance and privacy, central to regulatory and technical concerns, are addressed through secure data-sharing mechanisms such as blockchain and multilevel access control systems (Figueiredo et al., 2024). These solutions enhance trust across DT ecosystem by establishing clear protocols for ownership, protection, and role-based access, tackling barriers T6 and R3. Efforts to simplify sensing and modelling technologies are gaining traction as a response to the high complexity and cost of current DT systems (Kang and Mo, 2024). Lightweight solutions enable real-time data handling without compromising performance, thus targeting barriers related to hardware complexity (T1), system modelling (T3), and overall integration difficulty (T7). Simultaneously, the development of user-friendly interfaces (Banfi et al., 2022) is emerging to reduce technical entry barriers for non-specialist users (O2, O4), which often impede wider adoption.

Table 5: Strategies for DT implementation.

Strategy category	Strategy	Description	Addressed barriers	References
Technical solutions	Modularisation and decentralisation of DT systems	Breaking down DT systems into modular, decentralised units improves scalability, resilience, and adaptability across different project phases and stakeholders.	T1, T2, T7	(Adeagbo et al., 2024, Niccolucci et al., 2022, Teisserenc and Sepasgozar, 2021)
	Development of secure data-sharing mechanisms	Utilising blockchain or trusted data-sharing frameworks to ensure the secure exchange, ownership control, and privacy of DT data across multiple systems and stakeholders.	T6, R3	(Figueiredo et al., 2024, Naderi and Shojaei, 2024, Xiao et al., 2024)
	AIoT and edge computing for communication resilience	Deploying AI-enhanced IoT and edge computing architectures minimises reliance on centralised systems, enabling real-time decision-making even under network disruptions.	T4, T5, T7	(Gao et al., 2023, Armijo and Zamora-Sánchez, 2024)
	Lightweight sensing, modelling and analysing	Utilizing lightweight sensors and simplified modelling approaches to minimise data complexity, optimise system performance, and facilitate real-time data integration and analysis.	T1, T3, T7	(Kang and Mo, 2024, Shlash Mohammad et al., 2024, Dan et al., 2022)
	Multilevel security and access control	Implementing hierarchical security protocols ensures that only authorised users can access specific DT datasets, protecting sensitive data.	T6, R3	(Piras et al., 2024, Shahzad et al., 2022, Ellul et al., 2024)
	Development of user-friendly interfaces	Developing intuitive DT interfaces that lower the technical barrier for users, facilitating broader adoption among non-specialist stakeholders.	T3, O2, O4	(Naderi and Shojaei, 2024, Banfi et al., 2022)
Organisational measures	Internal training program for digital skills	Providing training and skill development opportunities to close digital skill gaps and prepare employees for DT-related tasks and workflows.	O2	(Piras et al., 2024, Broo and Schooling, 2023, Naderi and Shojaei, 2024)
	Fostering a culture of openness and innovation	Promoting an organisational culture of openness, knowledge sharing, and digital innovation that encourages the workforce to learn and experiment with DT tasks.	O1, O3	(Broo and Schooling, 2023, Piras et al., 2024)
	Development and comparative evaluation of DT prototypes	Developing prototypes of alternative DT solutions and presenting detailed comparisons of their advantages and limitations to stakeholders, facilitating informed decision-making and stakeholder confidence in DT implementation.	O3, O4, O6, O7	(Asare et al., 2024)

Strategy category	Strategy	Description	Addressed barriers	References
	Promoting collaborative governance	Setting clear and measurable objectives, emphasising transparency and accountability, and fostering cooperation between stakeholders during DT project.	O3, O4	(Broo and Schooling, 2023, Haraguchi et al., 2024)
Industry collaboration	Establishment of industry-wide standards	Establishing industry-wide standards and common protocols for DT implementation. Defining open, non-proprietary standards for data formats, communication protocols, and system interfaces to facilitate integration.	T2, T8, I5, I6, R2	(Adeagbo et al., 2024, Callcut et al., 2021, Camposano et al., 2021, Shahzad et al., 2022, Vieira et al., 2024)
	Promotion of non-proprietary tools and ecosystem cooperation	Encouraging the development and adoption of tools that work across platforms to improve interoperability and promote cross-sector cooperation.	T1, T2, O4, I7	(Casillo et al., 2024)
	Development of DT pilot projects	Launching pilot DT projects to validate concepts, refine designs, and reduce concerns. Documenting and publishing open DT case studies to provide relatable, evidence-based examples.	O1, O4, I1, I6, I7	(Karatzas et al., 2024, Yang and Ng, 2024)
	Mapping the business value of DT	Assessing the expected business value and returns of DT projects early to support strategic decision-making and resource allocation.	O6, O7, I1, I2	(Torres et al., 2024, Vieira et al., 2024, Yang and Ng, 2024, Mahmoodian et al., 2022)
Policy and regulatory support	Development of regulatory frameworks	Developing legal guidelines to address data ownership, protection, and sharing issues specific to DT deployments.	R2, R3, R4	(Camposano et al., 2021, Naderi and Shojaei, 2024, Ohueri et al., 2025)
	Government support and incentives	Providing support, financial incentives and subsidies for early DT projects to lower adoption risks and subsidies costs.	I2, R1	(Yang and Ng, 2024, Xiao et al., 2024, Ohueri et al., 2025)

A core theme across the organisational domain is the gap between technological readiness and institutional capacity. Internal training programs (Broo and Schooling, 2023) are essential for closing digital skill gaps, directly addressing the frequent lack of DT knowledge reported among project teams and managers (O2). However, training alone may not be sufficient without structural support. Studies emphasise the importance of fostering a culture of openness and innovation (Piras et al., 2024). Another promising strategy is the development and comparative evaluation of DT prototypes (Asare et al., 2024). By assessing multiple DT implementation options, stakeholders can better understand trade-offs in performance, cost, and integration, thereby addressing value ambiguity (O6), technical trust (O7), and cross-stakeholder collaboration (O3, O4). Closely related is the notion of collaborative governance, which frames DT adoption not just as a technological upgrade but as an inter-organisational process requiring shared objectives, transparency, and accountability (Haraguchi et al., 2024). It helps overcome relational and procedural barriers that often appear as fragmented knowledge flows or stakeholder disengagement (O3, O4).

Barriers associated with market structure and fragmented supply chains can be addressed through collaborative initiatives. The establishment of industry-wide standards (Shahzad et al., 2022) has emerged as a foundational enabler for DT implementation, targeting systemic issues like data format inconsistency (T2), integration across project phases (I5, I6), and regulatory uncertainty (R2). In parallel, efforts to promote non-proprietary tools and ecosystem cooperation (Casillo et al., 2024) counteract vendor lock-in and platform incompatibility (T1, I7). Cross-sector cooperation enables DTs to remain adaptable and interoperable across application cases, thus supporting long-term scalability. Pilot projects have also proven to be an effective means of reducing adoption risk. These small-scale experiments allow organisations to demonstrate feasibility, resolve technical barriers incrementally, and generate stakeholder confidence through case-based learning (Yang and Ng, 2024). Mapping DT business value can justify investment and align implementation with corporate objectives (Torres et al., 2024).

Although underrepresented, policy support is vital. Regulatory frameworks are essential for managing legal ambiguity and supporting ethical data practices (Camposano et al., 2021), directly targeting barriers related to data ownership, security, and ethical governance (R2, R3, R4). Government support and financial incentives were identified as a catalyst for early adoption (Ohueri et al., 2025). By offsetting high upfront costs (I2) and reducing perceived investment risk, such support mechanisms can trigger adoption among smaller firms and encourage broader diffusion.

These integrated strategies provide a practical roadmap to overcome the multifaceted barriers to DT implementation, enabling sustainable and scalable adoption in the construction industry.

4. DISCUSSION, FUTURE DIRECTIONS AND LIMITATIONS

DTs offer stakeholders a unique opportunity to smoothly integrate the physical world with the digital domain, significantly enhancing the construction industry's capacity to address long-term challenges (Su et al., 2023). While notable progress has been made, the effective application and widespread adoption of digital technologies remain limited, requiring further strategic, technical, and institutional efforts (Opoku et al., 2023).

4.1 Lifecycle

Recent research increasingly underscores the importance of viewing Digital Twins (DTs) through a whole-lifecycle lens, particularly for enhancing cross-phase coordination and improving asset management. However, current DT implementations tend to remain siloed within individual project stages. Cross-phase data continuity, particularly from construction to O&M, is essential to enable proactive decision-making and enhance downstream efficiencies (Long et al., 2024).

A major impediment is the heterogeneity of data formats and schemas used across lifecycle phases, which often lack standardisation and semantic consistency (Piras et al., 2024, Mahmoodian et al., 2022). This challenge is exacerbated by stakeholder fragmentation, disparities in digital maturity, and ongoing concerns regarding data security, ownership, and interoperability (Sacks et al., 2020). The increasing volume of data (Adeagbo et al., 2024), the incompatibility between proprietary technology platforms (Banfi et al., 2022), and persistent concerns around data security and privacy (Piras et al., 2024) also hinder efforts to establish seamless lifecycle integration.

Additionally, there is a tendency in existing literature to focus on transitions between adjacent phases while neglecting incorporating early-stage (design) and end-of-life (demolition) stages (Long et al., 2024), despite their relevance to project traceability, feedback loops, and cross-project knowledge transfer. Future research should focus on unlocking the latent potential of DTs in underrepresented lifecycle phases. For instance, studies could explore deploying IoT and material tagging technologies during early phases to support long-term component tracking and reuse at end-of-life (Iqbal et al., 2024). Furthermore, there is a critical need to design interoperable DT platforms capable of evolving across lifecycle stages while preserving data integrity, and to investigate feedback mechanisms from late-stage demolition to inform future design standards and material choices.

4.2 Technology integration and Human-AI interactions

Despite growing interest, the construction industry continues to face substantial technological barriers in adopting DTs, particularly due to its traditionally low digital maturity and the complexity of project environments (Rasheed et al., 2020, Naderi and Shojaei, 2022). Construction projects generate vast and highly heterogeneous datasets drawn from diverse sources, ranging from BIM and IoT sensors to maintenance records and BMS systems (Adeagbo et al., 2024). However, a significant portion of this data remains unstructured, limiting its utility. For instance, quality assurance processes often rely on text-based inspection logs, which traditional geometric DTs fail to capture. Recent efforts, such as the development of semantic datasets for fire door defects (Wang et al., 2025), demonstrate how converting unstructured construction records into structured data through automatic methods is essential for maintaining a seamless digital thread from construction into operations. These data are frequently stored in isolated, incompatible formats. The resulting lack of interoperability not only hinders data processing and integrated analytics but also undermines the accuracy and reliability of AI-driven insights (Banfi et al., 2022). As such, the development of standardised data protocols and integration frameworks remains an urgent research priority.

In recent years, the role of AI, including ML and DL, in DT applications for the built environment has gained substantial traction. However, the successful deployment of these data-driven models is frequently hampered by the lack of high-quality training data. To address this, a growing body of research has focused on bridging the gap between theoretical algorithms and real-world data availability. For instance, Wang (2025b) established comprehensive labelled operational datasets for Air Handling Units across diverse facilities, including offices, auditoriums, and hospitals, offering essential benchmarks for model training. Further research has tackled the challenge of class imbalance, where fault data is inherently rare. Hybrid generative models, such as SMOTE and Trans-CWGAN, have been successfully employed to synthesise realistic fault patterns (Wang, 2025a). Beyond data limitations, the progress of AI has also raised concerns about the trustworthiness of AI-enabled decision-making (Callcut et al., 2021). Due to the non-transparent nature of many AI algorithms, particularly in DL, human users often struggle to interpret or verify the internal logic of such systems. This "black box" characteristic poses a serious barrier to trust (Zhang et al., 2024), especially among construction professionals such as site managers and facility managers, who are hesitant to rely on decisions that lack transparency or verifiability. To address this, studies proposed a shift of human roles from passive task executors to active supervisors of autonomous systems (Wang et al., 2021). Through targeted training and task reallocation, users can be empowered to participate in collaborative decision-making processes, thereby improving both trust and the effectiveness of human–robot collaboration, especially on construction sites (Wang et al., 2021, Lee et al., 2023). Moreover, the advancement of explainable AI (XAI) techniques offers a promising path forward. By enabling the reasoning processes behind automated decisions to be more transparent and interpretable, XAI bridges the trust gap between human users and AI systems (Riggio and Nasir, 2024). Such developments are vital not only for enhancing the accountability of AI systems in safety-critical environments, but also for enabling more effective human–AI collaboration in the construction DT projects.

4.3 Cost, value, and maturity considerations in DT adoption

While many DT case studies have demonstrated compelling benefits, these successes are often context-specific and difficult to replicate across varying project types and scales(Camposano et al., 2021). The lack of systematic frameworks for evaluating the DT value in a standardised, consistent, evidence-based manner limits both the comparability of outcomes and the strategic confidence of stakeholders, particularly in early decision-making stages (Pregnolato et al., 2022).

The adoption of DT typically requires substantial upfront investment, including hardware acquisition (e.g., LiDAR scanners, high-fidelity sensors), software development, integration platforms, and workforce training (Sacks et al., 2020, Broo and Schooling, 2023). These costs present significant barriers to adoption, especially for small and medium-sized enterprises, which often lack the capital and technical capacity to support the resources required for DT deployment (Piras et al., 2024). To address this, there is a growing need for comprehensive cost and benefit analyses that assess the economic viability of DTs across diverse project scales and lifecycle phases. Such evaluations should consider both direct financial outcomes such as reductions in operational costs and time savings and indirect or intangible benefits (e.g., risk mitigation, enhanced decision-making and sustainability). In parallel, research should explore strategies to reduce implementation costs, including the adoption of modular DT architectures, the use of open-source platforms, the deployment of cloud-based solutions and crowdsourcing (Casillo et al., 2024) to lower technical entry barriers. Furthermore, when evaluating the value proposition of DTs in the construction industry, a recurring concern in the literature is the limited involvement of key stakeholders and organisations in both the development and assessment processes (Agrawal et al., 2022). Existing studies tend to underrepresent the perspectives of those directly responsible for project delivery, asset operation, and long-term strategic planning. It is therefore crucial to investigate DT value from a stakeholder-centric viewpoint, encompassing not only cost-saving efficiencies but also broader opportunities for revenue creation and competitive advantage (Zhu et al., 2024). This includes exploring how DTs can support new business models, enhance service offerings, and improve client satisfaction, thereby positioning their adoption as a strategic investment rather than a purely technical or operational upgrade.

Additionally, the maturity of DTs is increasingly recognised as a critical factor influencing both adoption and value realisation. Maturity models help assess the organisational, technical, and operational readiness for DT deployment. Chen et al. (2024) introduced an expert-driven evaluation framework to assess DT maturity in building projects, offering a useful foundation but lacking sufficient granularity and differentiation for diverse DT applications. Similarly, Li et al. (2024) proposed a five-level hierarchical maturity model for infrastructure DT adoption. However, it lacks quantitative indicators such as data volume thresholds and system response latency that would affect precision in evaluating specific DT implementations. Further, the model missed collaborative and systemic dimensions, such as cross-disciplinary coordination or stakeholder integration, which are essential for lifecycle-wide deployment. Thus, establishing a more comprehensive and adaptable DT maturity model which incorporates both qualitative and quantitative metrics and aligns with distinct characteristics could be a promising future research direction. Such a maturity framework would enable practitioners to benchmark progress, identify capability gaps, and prioritise adoption strategies in line with organisational goals.

Overall, these efforts can contribute to a more inclusive, economically sustainable, and scalable DT ecosystem, which can operate beyond isolated case success and support widespread, long-term value creation in the construction industry.

4.4 Practical implications for stakeholders

Building on the previously identified barriers and strategies, this section converts the findings into concrete actions for key stakeholder groups, thereby bridging the gap between theoretical potential and practical deployment.

For asset owners, the priority is to recognise the strategic value of the digital twin and to articulate a digital vision aligned with organisational key performance indicators (Callcut et al., 2021). DTs should not be understood as static deliverables but rather as evolving systems whose long-term utility depends on robust data governance frameworks and standardised information structures. Moreover, asset owners must invest in comprehensive internal training to improve staff awareness, technical competency, and acceptance of DT, thereby bridging the divide between organisational IT capabilities and operational requirements (Piras et al., 2024, Broo and Schooling, 2023).

For designers, considering the principle of "digital twin readiness” is essential for the subsequent construction, integration, and operational performance of the DT system. Design activities should account for sensor deployment strategies, data acquisition pathways, and the scalability of information models, while also conforming to established modelling specifications and semantic standards to minimise downstream integration costs (Chen and Whyte, 2022). The adoption of parametric and modular modelling methodologies further enhances the efficiency, reproducibility, and analytical value of simulation processes and DT construction (Adeagbo et al., 2024). Given that DTs span the full lifecycle of an asset, version traceability and cross-phase interoperability of design models are crucial.

Contractors continue to face a fundamental challenge arising from the disparity between static design BIM models and the dynamic conditions of construction sites. This discrepancy frequently results in scheduling and resource decisions being based on outdated or incomplete information, thereby constraining construction efficiency (Esmaeili and Simeone, 2023). Continuous capture of the “as-built” environment through a construction digital twin provides a mechanism for generating real-time semantic updates, reducing dependency on static models. From an implementation perspective, it is necessary to prioritise high-value scenarios such as progress monitoring, equipment utilisation analytics, and safety risk detection, rather than attempting to create a comprehensive twin of the entire project at the outset. Furthermore, by adopting standardised business process models and integrating service-oriented interfaces, contractors can embed DTs directly into operational workflows, alleviating cost pressures while enhancing progress visibility, resource optimisation, and overall site productivity (Torres et al., 2024).

Technology vendors typically undertake the critical tasks of constructing the technical framework for DT systems and enabling cross-system integration. As industry expectations shift towards enhanced real-time analytics and predictive intelligence, providers must reinforce interoperable system architectures (Naderi and Shojaei, 2024). Sustainable operation of DTs further requires providers to establish long-term support mechanisms, including model updating, sensor calibration, and periodic algorithmic retraining to ensure continuous synchronisation between the digital and physical systems.

Given that DT systems involve cross-departmental and cross-system data flows, their effective application heavily relies on unified standards. For policymakers and regulators, establishing industry-level standards and clarifying data security requirements can mitigate interoperability risks stemming from system fragmentation while ensuring data security and privacy compliance (Camposano et al., 2021, Naderi and Shojaei, 2024, Ohueri et al., 2025). Additionally, policy interventions such as fiscal incentives, targeted R&D funding, and performance-based subsidies can significantly reduce organisational barriers to adoption and stimulate innovation within the wider ecosystem (Ohueri et al., 2025).

Facility managers and O&M teams are most closely engaged with physical assets throughout the DT lifecycle, having direct influence over the fidelity and validity of twin models. To unlock the long-term value of DTs, these systems must be integrated into daily operational routines. Continuous calibration, achieved through real-time data feeds, equipment health diagnostics, and systematic annotation of anomalies, enables the DT to maintain an accurate representation of the physical system (Hosamo et al., 2022). Cross-phase collaboration between O&M teams, designers, and contractors further strengthens data continuity and lifecycle coherence. With the growing adoption of predictive maintenance and risk-informed decision-making, operations personnel must increasingly cultivate digital literacy, analytical capability, and interpretive skills, supporting a transition from reactive operational behaviour to proactive, data-driven asset management (Almatared et al., 2024).

Regarding end users, while DTs offer technical advantages such as visualisation, real-time feedback, and intelligent decision support, their practical value is often influenced by user experience and operational complexity. System design must therefore prioritise usability and interpretability, ensuring users can comprehend state changes reflected by the twin model through intuitive interfaces and receive clear decision support prompts when necessary (Lee et al., 2023). Furthermore, user participation plays a vital role in the continuous optimisation of twin systems. Feedback data not only assists developers in refining interfaces and interaction logic but also serves as a crucial data source for training models, enabling dynamic optimisation of DT systems (Asare et al., 2024).

4.5 Limitations

This study provides a macro-level synthesis of recent developments in DT research, offering a clear and systematic overview of current trends and future directions, particularly for readers less familiar with the concept. While this broad perspective improves accessibility, it involves certain trade-offs. Due to space constraints, areas such as technological frameworks and domain-specific applications are not explored in depth and require focused attention in future research. The methodology, centred on a systematic literature review, is inherently influenced by the selection bias. Specifically, the search string prioritised the full term “Digital Twin” to ensure high relevance. While this decision was necessary to avoid significant noise, as the abbreviation “DT” is widely used for unrelated concepts such as “Decision Trees” or “Data Transmission”, it may have inadvertently excluded studies that rely solely on the abbreviation or alternative terminologies in their metadata. Although the snowballing technique was used to expand the literature base during the discussion, the overall scope may remain limited. In addition, the review emphasises conceptual and thematic synthesis rather than empirical validation. Future research would benefit from more in-depth studies, case analyses, and comparative evaluations to build on the foundations established here.

5. CONCLUSIONS

This study has conducted a comprehensive two-stage systematic literature review to assess the development, implementation, and integration of Digital Twins (DTs) in the construction industry. The review first synthesised 122 existing review articles to map thematic trends and lifecycle focus areas, followed by an in-depth analysis of 297 original research articles to identify domain applications, enabling technologies, barriers, and response strategies. This dual approach enabled a multidimensional understanding of both the conceptual evolution and practical realities of DT adoption in construction.

Findings indicate that despite the growing research volume, the DT landscape remains fragmented and thematically skewed. A substantial majority of studies are clustered around the operation and maintenance (O&M) phase, while early-stage design and end-of-life phases remain critically underexplored. This gap not only limits the strategic potential of DTs but also hinders the development of circular and data-driven asset management practices. The review also identifies technological, organisational, industrial, and regulatory barriers that hinder DT implementation. These include data heterogeneity, platform incompatibility, unclear value propositions, limited stakeholder participation, and a lack of policy guidance. A range of multidimensional strategies, such as modular architecture, blockchain integration, and collaborative governance, have been proposed and mapped with barriers.

To address these challenges, the study formulates actionable strategies for key stakeholders. Asset owners are urged to shift from passive procurement to active data governance and internal competency building. For contractors and designers, the adoption of hybrid human-digital workflows and "Twin-Ready" design standards is essential to ensure verifiable "as-built" data. Furthermore, policymakers and regulators need to collaborate to establish applicable standards and fiscal incentives to de-risk adoption.

Additionally, the study highlights limitations in trust in AI systems and value realisation. The lack of standardised data protocols and the limited use of explainable AI hinder effective integration and stakeholder trust. Moreover, high implementation costs and the absence of consistent, stakeholder-informed value assessment frameworks restrict broader adoption. Existing maturity models often lack practical metrics and overlook collaborative dimensions, limiting their applicability.

Overall, this review contributes to a more integrated understanding of DT research in construction, clarifying its current limitations and identifying actionable directions. Addressing the gaps identified, particularly in lifecycle coverage, value definition, stakeholder engagement, and maturity evaluation, will be essential to transforming DTs from isolated technological pilots into scalable, trustworthy, and strategic systems in the construction sector.

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