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Review

Digital Twins in Construction: Architecture, Applications, Trends and Challenges

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Abstract: The construction field currently suffers from low productivity, a lack of expertise among practitioners, weak innovation, and lack of predictability. The digital twin, an advanced digital technology, empowers the construction sector to advance towards intelligent construction and digital transformation. It ultimately aims for highly accurate digital simulation to achieve comprehensive optimization of all phases of a construction project. Currently, the process of digital twin applications is facing challenges such as poor data quality, the inability to harmonize types that are difficult to integrate, and insufficient data security. Further research on the application of digital twins in the construction domain is still needed to accelerate the development of digital twins and promote their practical application. This paper analyzes the commonly used architectures for digital twins in the construction domain in the literature and summarizes the commonly used technologies to implement the architectures, including artificial intelligence, machine learning, data mining, cyber–physical systems, internet of things, virtual reality, augmented reality applications, and considers their advantages and limitations. The focus of this paper is centered on the application of digital twins in the entire lifecycle of a construction project, which includes the design, construction, operation, maintenance, demolition and restoration phases. Digital twins are mainly moving towards the integration of data and information, model automation, intelligent system control, and data security and privacy. Digital twins present data management and integration challenges, privacy and security protection, technical manpower development, and transformation needs. Future research should address these challenges by improving data quality, developing robust integration methodologies, and strengthening data security measures.

Keywords: digital twin; BIM; construction industry; AEC; construction project lifecycle

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1. Introduction

With the continuous progress of technology and digital transformation, digital twins have shown immense vitality and unlimited potential in various fields. Among them, the field of architecture, which is crucial to people's living, working, and residential environments, is currently addressing core challenges such as low productivity, a shortage of professional knowledge, a lack of innovation, and poor predictability that have persisted in the field for a long time [1]. These challenges severely limit the development of digital technologies in the field of architecture, making the application of digital transformation complex and challenging [2–6].

With the introduction of BIM and other digital tools [7,8], the industry has begun to move toward greater efficiency and intelligence [9–11]. The emergence of the digital twin has further fueled this transformation, providing a full lifecycle solution for construction projects from conceptual design to facility management [12–15]. The emergence of digital twins has transformed the construction sector, which has been characterized by low levels of digitization and informatization and a slow pace of innovation [16].

The digital twin offers vital support throughout the construction project lifecycle [4,17–20]. It enhances design precision, construction efficiency, and operational sustainability by creating accurate virtual replicas to simulate and optimize each phase. It can enhance the visibility and manageability of the construction project lifecycle [21]. Therefore, the development of digital twins has become an important task in developing the construction field. In the construction sector, digital twin technology has a wide range of applications, including but not limited to the visualization of building design, simulation of the construction process, real-time monitoring of building performance, optimization of energy consumption, and planning of maintenance and rehabilitation strategies [22–25]. By integrating IoT devices, AI algorithms, and ML models, digital twins are able to process and analyze large amounts of data, bringing greater efficiency and sustainability to building operations [26–33].

The digital twin was first introduced by M. W. Grieves [34] in 2002 and defined as the "digital equivalent to a physical product". Since then, researchers have gradually clarified the characteristics of digital twins and how they differ from other related concepts. In 2010, NASA made the first application of digital twins in the field of aviation [35]. Since then, digital twins have been gradually applied to manufacturing [36], automobiles [37], medicine [38], energy [39] and other fields. The construction field applied digital twins for the first time in 2017 [40]; this application aimed to create a building entity presented in digital form.

Digital twins provide comprehensive and accurate information to support the whole lifecycle of construction projects by interconnecting the building in the physical world with the data in the digital model [41]. This comprehensive information support provides architects, designers, construction teams, and operations managers with opportunities for deeper and more comprehensive collaboration and analysis [42]. With the digital twin during the design phase, simulations and tests can be performed using the digital twin model to predict the execution effectiveness of the construction project, optimize the design, and reduce the construction cost [43]. During the construction phase, the digital twin allows the construction team to better understand all aspects of the construction project, including the structure, materials, and construction processes [44]. During the operations and maintenance phase, digital twins can also support decision-making by providing data and visual analyses when selecting materials, technologies and systems, leading to more informed and reliable decisions [45].

This paper specifically examines the extensive array of uses and possible advantages of digital twins in architecture. Prior research has mostly examined the implementation of digital twin architecture in the various stages of construction projects, but with a narrow focus on individual phases or specific scenarios. On the other hand, there have been six comprehensive evaluations of the use of digital twins in the construction industry. These evaluations offer a summary of the research on digital twins in the AECO-FM business using bibliometric analysis [4,21,41,42,46–48].

The majority of the assessments in these studies primarily concentrate on technology; however, the associated reviews fail to offer a comprehensive examination of the entire lifecycle. This paper stands out for its comprehensive coverage of digital twins across all phases of construction projects. This paper forecasts the potential future advancements of digital twins in building restoration and demolition stages and advocates for their increased adoption in actual construction projects. A comprehensive building project should encompass the design, construction, operation, demolition, and restoration stages. This thoroughness enables practitioners to fully exploit the potential of digital twins in building projects. The main tasks of this paper can be summarized as follows:

(1) To provide a concise overview and examination of digital twin architecture and frequently used technologies, as well as the merits, drawbacks, and practical uses of each.
(2) This article explores the full lifecycle of a building project and underscores the advantages of utilizing digital twin applications.
(3) The paper examines the challenges and solutions associated with creating digital replicas in the construction industry, while also analyzing emerging prospects and trends.

The rest of the paper is organized as follows: Section 2 describes the methodology used in this paper. In Section 3, the digital twin architecture and the technologies that comprise it are presented. Sections 4.1–4.4 discuss in detail the application of digital twins in design, construction, operation, and maintenance, respectively. Section 5 summarizes the current trends and major challenges in applying digital twins in the construction domain.

2. Methodology

2.1. Research Methodology

This paper adopts a systematic literature review, assessed through a systematic and organized approach that follows a clearly defined process to identify, evaluate, and synthesize previously published research on digital twins in architecture. This approach enhances the transparency and integrity of the research. The systematic evaluation was conducted using multiple quantitative and qualitative studies and followed the Preferred Reporting Items for Systematic Evaluation and Meta-Analysis (PRISMA) statement. Figure 1 represents the step-by-step process of retrieving the literature from popular scientific research databases.

Web of Science, ScienceDirect, and Scopus were used for literature search and screening, and publications between January 2015 and September 2023 were used for this paper. This timeframe was chosen because there was less research on digital twins in the construction field prior to 2015. However, given the significant changes in the construction industry in recent years, this systematic evaluation aims to review the most recent applications of digital twins in the field, ensuring the results are sufficiently relevant to today's construction industry.

Web of Science was used as the initial literature search tool for this paper. Search terms included "digital twin" OR "virtual twin" OR "cyber–physical system" OR "digital replica" OR "virtual twin" OR "framework" OR "digital solutions" OR "construction" OR "construction industry" OR "AEC" OR "construction management" OR "lifecycle." Compared with other search engines, Web of Science can retrieve papers before 1900, covering a more comprehensive range of publications, while Scopus can retrieve the latest published research, ensuring that the articles are state-of-the-art, and ScienceDirect covers a wider range of scientific and technical literature in the subject area. Therefore, using a combination of these search engines can help us access information from different perspectives and fields, thus helping us to understand the research topic in greater depth. The literature reviewed was categorized into two main categories: articles and reviews. This categorization helps to ensure a comprehensive understanding of the use of digital twins in architecture from different perspectives and viewpoints. Similarly, a total of 1031 articles were collected through Web of Science, ScienceDirect, and Scopus.

Initially, research not related to the field of construction was first screened out by reviewing article titles and abstracts. If the article studied digital twins and their related technologies and was based on the field of construction, it was included in the review. If the research was not based on digital twins and related technologies or the manuscript was not in English, the research was excluded. In the second step of reviewing the remaining articles, we excluded 46 articles that did not use the appropriate technology for the construction project lifecycle, 51 articles that did not provide enough information about the implementation of the technical digital twin, 33 articles that focused on only one technology or lacked compatibility between different technologies, and 55 articles that had limited examples of how the digital twin can be applied to the construction project lifecycle. The criteria included the remaining 106 studies. We further reviewed the remaining content of the articles by examining the constituent technologies of the digital twin application framework, their connectivity, the use of digital twins in various construction project lifecycles, and the trends and challenges associated with digital twins.

The literature collected through these methods was used to outline and summarize the information related to the application of digital twins throughout the lifecycle of a construction project. This process ensured that our literature selection was conducted based on the architectural domain, digital twins, and rigorous evaluation criteria to ensure the quality and relevance of the study. This paper, while detailing the state-of-the-art applications of digital twins in the architectural domain, pays special attention to their practical use throughout the architectural project lifecycle. This focus aims to highlight the comprehensive nature and broad applicability of digital twins. Figure 1 illustrates the sequential procedure for accessing literature from widely used scientific research resources.

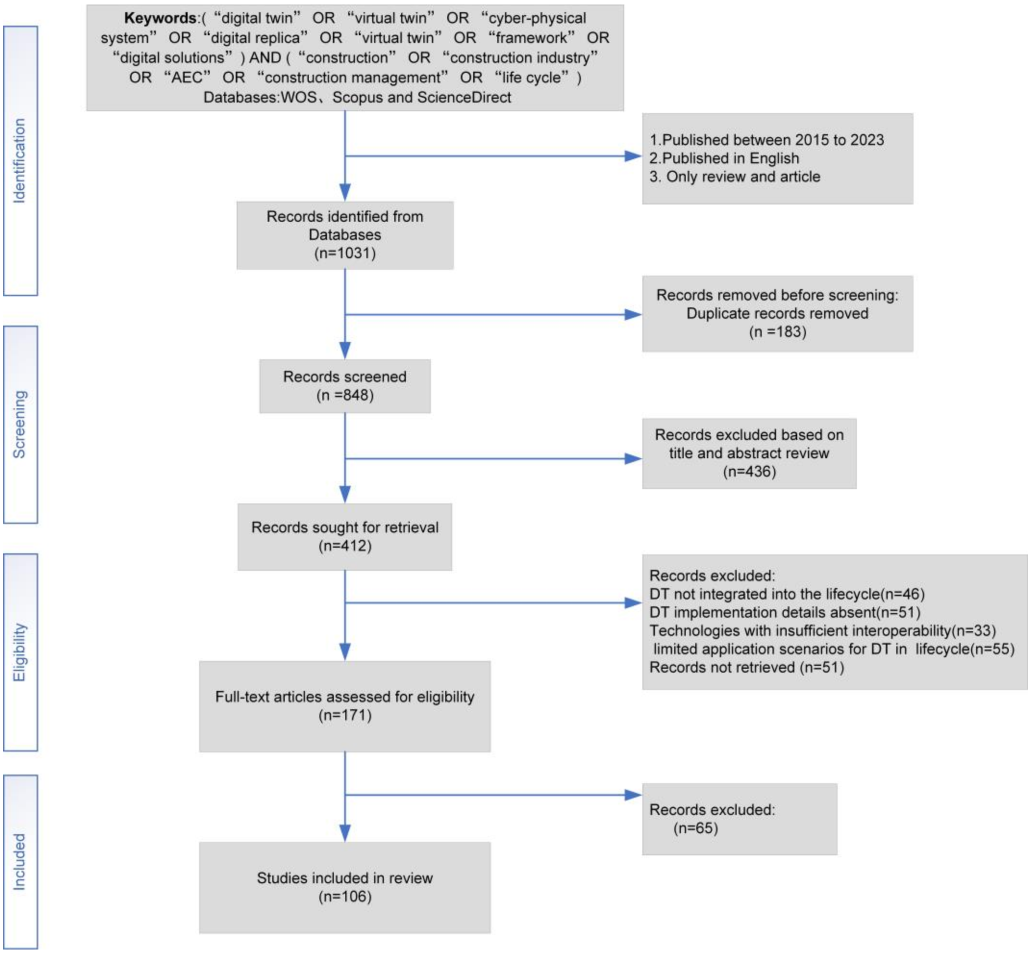


Figure 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 flow chart for determining the studies included in the paired meta-analysis.

2.2. Data Analysis

As can be seen from Figure 2, there were fewer publications on “Digital Twins in Construction” from 2015 to 2018. However, the number of publications increased in 2019, reaching 93.85% of the total between 2020 and 2023. In addition, Web of Science categorized these publications into different areas of application based on their content. Table 1 shows the results of the categorization.

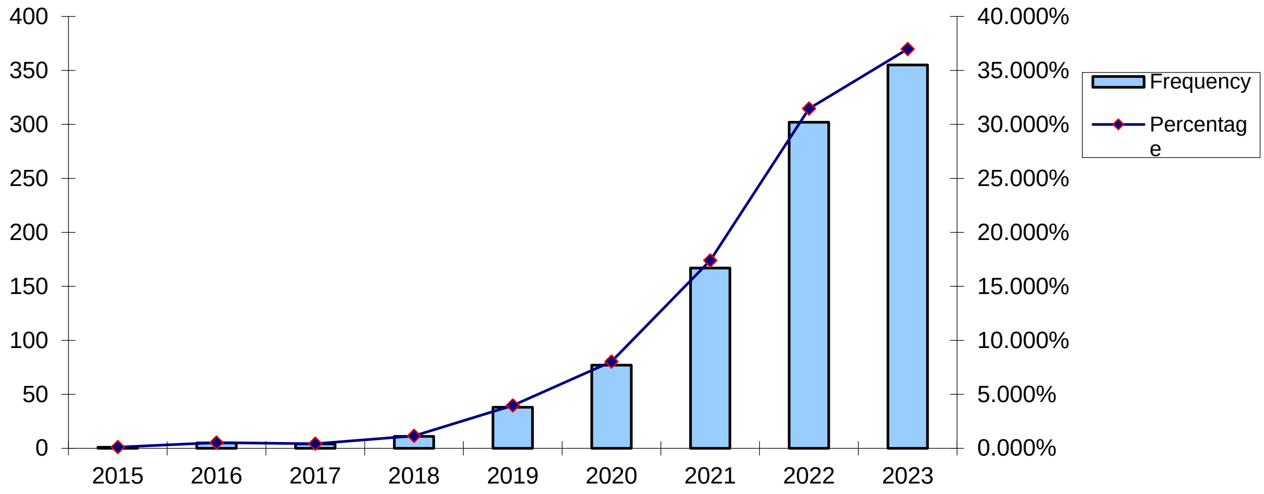


Figure 2. Summary results of publications.

Table 1. Categories of publications in search results (Web of Science, ScienceDirect, and Scopus).

Categories	Frequency	Percentage
Engineering civil	273	29.35%
Construction building technology	206	22.15%
Engineering electrical electronic	144	15.48%
Engineering manufacturing	81	8.71%
Computer science interdisciplinary applications	74	7.96%
Engineering multidisciplinary	100	10.75%
Computer science information systems	93	10.00%
Green sustainable science technology	58	6.24%
Materials science multidisciplinary	62	6.67%
Total	960	100%

Engineering civil, construction building technology, and engineering electrical electronic were more frequent in past publications, reaching 66.98% of the total, followed by engineering multidisciplinary, and computer science information systems. Web of Science's classification of publications deals with identifying the various fields to which a publication belongs based on its content.

3. Architecture and Technology in Digital Twinning

3.1. Digital Twin Architecture

Digital twin architecture is a complex construct that integrates information technology in order to create and manage a digital twin system. The construction of a specific architecture typically consists of four basic phases: (1) collecting data and information about a particular building's geometry, materials, and equipment characteristics, (2) collecting real-time measurements from IoT sensors and information-gathering devices installed in the building to monitor its real-time operating conditions, (3) incorporating model-based modeling to simulate the building's real-time conditions, and (4) developing a software platform to integrate the first three phases [49].

Using the corresponding concepts, one can propose a corresponding architecture. At its core, this architecture consists of three basic elements: the physical space, the virtual space, and the connectivity model [50,51] (as shown in Figure 3). The key to the development of the digital twin lies in the establishment of a bi-directional data connection between the physical entity and the corresponding equivalent virtual model. IoT sensors collect data in real time from physical building projects [52]. These data are not only used to create accurate numerical representations but also to simulate the behavior of physical entities under different conditions. Ongoing data collection and analysis drives the evolution of these models, ensuring that the digital twin is always able to accurately replicate its physical counterpart. Digital twin architectures use simulation models, also known as data models, to accurately replicate real-world physical entities. These let us accurately reflect on and study how physical systems work [49]. The process requires technologies such as AI, ML, DM, etc., to process these data. Ultimately, these data are interacted with by the user through visualization techniques [53].

These techniques have been conceptualized as digital twin system architecture with five development layers: data collection, data transfer, data integration, data visualization, and services. In the data collection layer, we focus on the data collection techniques and the accumulated datasets. The transmission layer, on the other hand, covers network technologies, communication protocols, and data transfer mechanisms. The digital modeling layer focuses on techniques for quantifying the properties of physical entities and methods for constructing virtual models. The data integration layer integrates a variety of technologies that support data storage, data and model integration, processing and analysis, visualization, and the application of artificial intelligence, machine learning, and simulation engines [50,51,54,55].

At the same time, these data serve as the basis for building digital models of the system, whether simulation models based on physical laws or data models based on big data and machine learning algorithms [56]. It is important to emphasize that these models are not static; they evolve as the data are continuously acquired and analyzed, ensuring that the digital twin is always a true representation of its physical counterpart.

A simulation model anchors the architecture, providing users with an intuitive visualization interface. This interface is vital for presenting the state and outcomes of the digital twin system in various formats, such as web-based user interfaces or immersive reality interaction interfaces, including VR and AR [57]. This capability allows engineers and decision-makers to monitor the physical systems in real time, enabling proactive troubleshooting and performance optimization [58].

A pivotal aspect of DT architecture is its ability to connect real-world physical systems with their digital representations, facilitating real-time bi-directional data transfer and information sharing [58]. This connectivity is underpinned by data transfer protocols, network connectivity, and data storage solutions that ensure secure and efficient data management [25].

Moreover, the digital twin architecture includes provisions for data analytics and algorithms that are integral to processing data collected from physical systems and sensors [40]. The application of ML, artificial intelligence, and pattern recognition techniques allows for the extraction of insights and information regarding the performance, operational status, and predictive analytics of the physical system [18]. This real-time data model updating capability is crucial for providing up-to-date decision support [59].

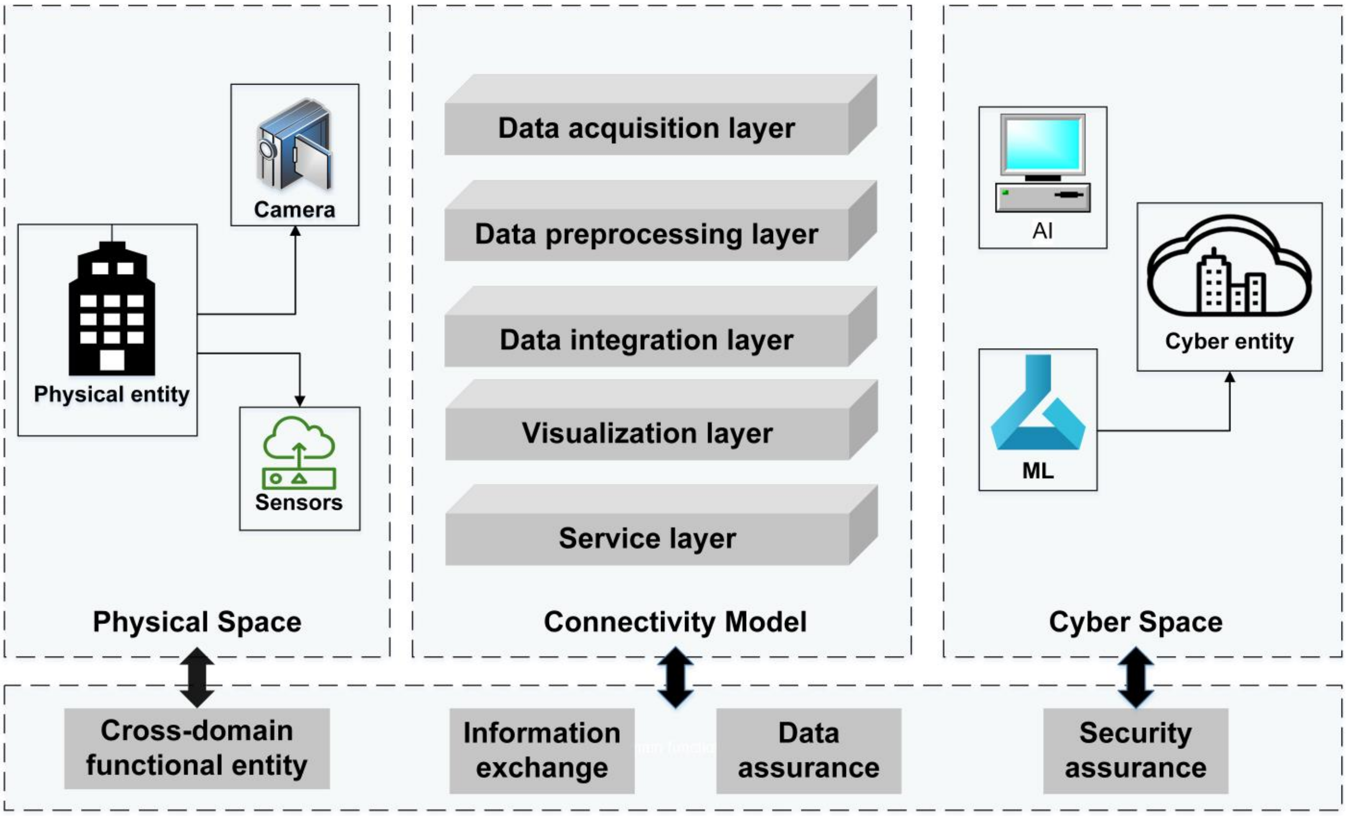


Figure 3. Digital twin architecture schematic.

3.2. Digital Twin Components

Different digital twin architectures use different techniques. This section summarizes the seven digital technologies commonly used for the composition of digital twin architectures (1) AI [60]; (2) ML [61]; (3) CPS [44]; (4) IoT [62]; (5) DM [45]; (6) VR [63]; (7) AR [64]. These technologies are the pillars of the digital twin architecture, and together they provide the basis for creating accurate, real-time, and interactive digital copies. In contrast, technologies such as blockchain, cloud computing, big data, simulation and emulation are seen as complements and extensions to the digital twin architecture, which provide additional functionality and capabilities to the digital twin system [50,65,66]. The technologies are also analyzed for their application in the construction field, as well as the advantages and limitations of their application (the applications associated with the discussed concept are detailed in Figure 4, showcasing their practical implications).

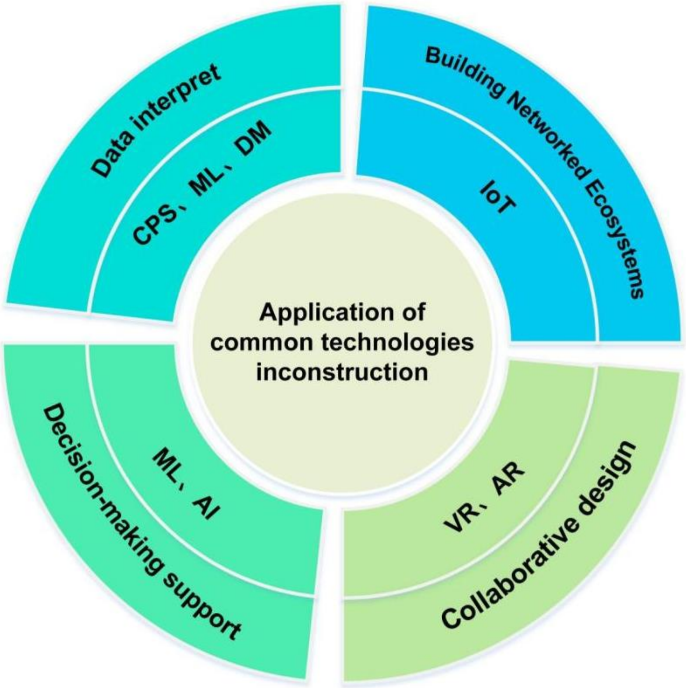


Figure 4. Application of digital twin in construction project lifecycle.

3.2.1. AI

Artificial intelligence, as a branch of computer science, is designed to create systems capable of emulating intelligent human behavior. The Royal Society [67] defines AI as "an umbrella term for the science of making machines smart" and, in general, as efforts that create "systems that think like humans, act like humans, think rationally, or act rationally". AI systems are designed to perform a range of tasks that would normally require the thinking and decision-making capabilities of human intelligence. The definition of AI includes making computer systems have some degree of intelligence in order to perform a variety of tasks that may cover language comprehension, image recognition, decision making, problem solving, etc., (strengths and limitations of AI in the construction field, as shown in Table 2).

In the construction field, AI can take advantage of the large-scale data generated during a construction project, which can then be analyzed over the entire lifecycle of the construction project and the huge data [60]. The main applications include the following: (1) automated building modeling [68], (2) risk mitigation [60], (3) construction progress tracking and analysis [24], (4) predictive maintenance [69], and (5) computer vision [70]. AI technologies can cut across multiple layers, especially where intelligent decision-making and automated processing are required, such as providing intelligent analytics and forecasting at the service layer [60].

AI still faces several limitations in construction project applications. (1) Multifaceted complexity: construction projects involve multiple aspects such as engineering, people management, supply chain coordination, etc., so fully modeling this complexity is an extremely challenging task; (2) technical and hardware requirements: AI places relatively high demands on technical and hardware aspects to ensure the reliability and effectiveness of the implementation. Current technologies may struggle to meet the demands of complex computation and data processing; (3) interpretability issues: in current research and applications, the interpretability of AI systems poses a challenge. Despite the advances in AI technology, understanding the decision-making process and reasoning basis within the model is still difficult in many cases. This lack of interpretability has important implications for practical applications; (4) quantity and quality of data: an important challenge in AI applications is the lack of quantity and the quality of available data. The size and quality of available data often limit the performance of models, despite significant advancements in AI technology. Here are some comprehensive solutions to these challenges:

(1) Addressing complexity: because of the complexity of construction projects, AI systems must be able to handle multifaceted information. Solutions include developing integrated and modular AI models, as well as collaborating with domain experts to ensure models can adapt to the specific needs of construction projects. (2) Technical and hardware upgrades: to meet the computational demands of AI, it is recommended to invest in high-performance computing hardware, leverage cloud computing services, and optimize algorithms to improve efficiency. (3) Enhancing AI interpretability: to increase the transparency of AI decision-making processes, use explainable AI technologies, visualization tools, and training for users to help them understand the logic behind AI decisions. (4) Improving data quantity and quality: establish standardized data collection processes, apply data augmentation technologies, and explore cross-domain data integration to increase and improve the quality and diversity of training datasets. (5) Interdisciplinary collaboration: form interdisciplinary teams composed of data scientists, software engineers, and construction industry experts to jointly develop AI solutions and create a shared knowledge platform to facilitate communication. (6) Policy and standard setting: cooperate with industry associations to establish industry standards and best practices for AI applications, and promote policy support to encourage the application of AI technology.

These comprehensive measures can overcome the challenges of AI in the construction industry, enabling its effective application and sustainable development in the field. These solutions require not only technological progress but also industry cooperation, policy support, and ongoing innovative efforts.

Table 2. Strengths and limitations of AI applications in construction projects.

AI Strengths	AI Limitations
Personalized and automated design [71]	Multifaceted complexity [70]
Processing information quickly and efficiently [72]	High technical and hardware requirements [45]
More efficient decision support [68]	Insufficient interpretability [73]
Automated environmental monitoring [74]	Lack of data quantity and quality [75]

3.2.2. ML

ML is a branch of the field of computer science and artificial intelligence that was founded by The Royal Society [67]. It defines ML as "a set of rules that allows systems to learn directly from examples, data and experience". This involves the development of algorithms and models that allow computer systems to learn from data, extract models, and apply those models to make decisions or make predictions without explicit programming [76] (strengths and limitations of ML in the construction field, as shown in Table 3).

In the construction domain, a large amount of high-quality images and the data collected through sensors during construction projects provide a wealth of information for ML to perform a variety of tasks with higher accuracy and lower cost [77]. This includes (1) historical building reconstruction for analyzing information (geometric, radiometric, and intensity features) and semantic annotation according to task requirements [78], (2) intelligent building management for monitoring ventilation systems, daylighting, and green building features, thus improving the efficiency of decision-making and prediction [61], (3) bridge-damage detection and assessment for analyzing the structural state of bridges and detecting and assessing bridge damage [79]. ML techniques are very useful in data preprocessing, such as data cleaning, feature selection, and data transformation [76].

ML still faces certain limitations in applications related to construction projects. (1) The specificity of the construction domain requires ML models to be able to adapt to new environments and contexts in a timely manner. However, the training and updating of models require a lot of computational resources and time. It is difficult to address how to balance the accuracy and real-time performance of construction models in construction project applications. (2) The application of ML models in the construction domain often relies on a large amount of data. However, obtaining high-quality and diverse data can be a challenging task. If the data are of poor quality or not sufficiently representative of the actual situation, the performance of the ML model may be limited. (3) The complexity and uncertainty of construction projects are a challenge for ML applications. The lifecycle of a construction project involves multiple phases, including design, construction, and operation, and each phase has its own unique characteristics and variables. In addition, construction projects are usually affected by external factors (weather, supply chain changes, etc.), increasing the uncertainty of the system. ML models may struggle to accurately predict and optimize when dealing with complex and uncertain construction environments. Particularly during the construction process, the interaction of various variables (e.g., worker productivity and on-time delivery of materials) complicates the modeling of the model. (4) A construction project is a dynamic process that needs to respond to changing conditions at any time. ML models may face challenges in terms of real-time and dynamic adjustment, especially when timely changes to schedules and resource allocation are required. If ML models are unable to respond in real-time or near real-time environments, their usefulness in construction projects will be compromised. When dealing with unexpected events or changes, models need to be able to adapt quickly to new situations.

Table 3. Strengths and limitations of ML applications in construction projects.

ML Strengths	ML Limitations
Data analysis and prediction [80]	Model training and updating [44]
Quality control [75]	Data dependency [80]
Design optimization [44]	Complexity and uncertainty [80]
Smart building management [78]	Dynamic and real-time adjustments [81]

3.2.3. CPS

CPS is a system that integrates physical entities, sensors, communications, and computing technologies to achieve a variety of goals through data acquisition, processing, and communication in the physical world. Typically, these systems connect to entities in the physical world to monitor, control, coordinate, and optimize processes and activities. According to the National Science Foundation, cyber–physical systems are defined as "engineered systems built from and dependent upon the seamless integration of computation and physical components.

Such systems combine the physical world with computation and communication technologies to enable smarter and more efficient data acquisition, control, and collaboration [40] (strengths and limitations of ML in the construction field, as shown in Table 4).

CPS tightly integrates the physical world with computer systems to create smarter, more efficient, and more sustainable buildings. The main applications are as follows: (1) physical assets can be transformed into physical networked systems by integrating CPS technology with BIM, so that the acquired and integrated data can be better utilized for improved design, construction, operations, and maintenance [18]; (2) CPS can help building managers monitor equipment performance in real-time through sensors and real-time data analysis. Through predictive maintenance, the system can detect abnormal equipment behavior and take action in advance, thereby reducing maintenance costs and downtime; (3) CPS can support indoor positioning and, through navigation systems, it can achieve automatic navigation within the building, and by integrating CPS with AI, IoT, and other technologies, so as to automatically generate emergency evacuation routes in the event of emergencies so as to achieve more stable and efficient pedestrian evacuation [82]. CPS technology can be used in the service layer to provide intelligent services by integrating computational, cyber, and physical processes [83].

However, there are still some limitations to CPS in construction projects. (1) High investment costs limit the diffusion of CPS in construction. Establishing a digital twin system requires a large investment in hardware and software, as well as the cost of training personnel. (2) Digital twin systems collect and process large amounts of sensitive data, making data privacy and security issues a key limitation in their application. Data that are not properly protected may be subject to malicious attacks or misuse, so a robust data security system is needed when promoting CPS. (3) The construction field involves multiple domains and multiple stakeholders. Thus, digital twins need to be able to interoperate with a variety of different hardware and software systems. A lack of unified technical standards leads to integration challenges between different systems and limits the complete application of CPS in the construction domain. (4) CPS requires rapid data processing and immediate decision-making to function effectively in real-time environments. The need for speed is critical in feedback-controlled settings like robotics, where lag can result in system failure. To achieve this, CPS relies on fast computation and latency-optimized algorithms, along with a system design that prioritizes efficient data management and task scheduling to uphold system integrity and performance.

Table 4. Strengths and limitations of CPS in construction project applications.

CPS Strengths	CPS Limitations
Real-time monitoring and feedback [84]	High investment costs [85]
Intelligent decision support [86]	Data privacy and security [85]
Resource optimization and sustainability [87]	Technical standards and interoperability [88]
Teamwork and information sharing [89]	Real-time processing demands [90]

3.2.4. IoT

IoT is a networked ecosystem of physical devices, sensors, objects, and systems linked together through Internet connectivity and interoperability to enable data collection, remote control, and intelligent decision-making. The use of technologies such as wireless communication technologies, cloud computing, big data analytics, and artificial intelligence enables objects to sense their surroundings, collect data and communicate and collaborate with other objects [91] (strengths and limitations of ML in the construction field, as shown in Table 5).

In the construction sector, IoT has a wide range of applications. During the design phase, IoT uses IoT sensors to collect real-time data and perform real-time data analysis to understand changes in the building environment. This can include data on temperature, humidity, lighting levels, etc., helping designers make more accurate design decisions [92]. During the construction phase, IoT integrates sensors and data analytics to monitor building progress in real time. By analyzing the data, potential schedule delays can be identified and acted upon [93]. During the operation and maintenance phase, IoT enables real-time data collection by installing sensors on building equipment (lifts, fans, pumps, and HVAC systems) to monitor their performance and operating status. With these sensors, potential problems can be identified and equipment failures can be predicted, allowing maintenance teams to adjust equipment in advance, avoiding unnecessary downtime and repair costs [92]. In addition, IoT technology can have a significant impact on the sustainability of buildings by monitoring the performance of renewable energy systems and helping building managers optimize energy use, reduce carbon footprints, and comply with green building standards. IoT technology is ideal for data collection because it can connect multiple devices and sensors to collect data from the environment [94].

However, there are still some challenges and limitations to using IoT ML in construction projects: (1) the sheer volume and complexity of IoT networks increases security risks, and it becomes more difficult to effectively manage and monitor connected devices; (2) large-scale data transmission and processing requirements place higher demands on power infrastructure, which needs to be continuously upgraded in terms of scalability and reliability; (3) IoT involves a wide range of devices from different manufacturers, and the lack of uniform standards and interoperability may lead to difficulties in integrating devices; (4) construction projects involve multiple contractors and different technologies, and the introduction of IoT may increase the complexity of the system, and the effective integration of the different systems may be challenging.

Table 5. Advantages and limitations of IoT in construction project applications.

IoT Strengths	IoT Limitations
Real-time monitoring and data collection [95]	Security risk [21]
Smartness and automation [62]	Dependency on electricity [94]
Predictive maintenance [93]	Standardization and interoperability [96]
Space utilization optimization [92]	Complexity and integration challenges [95]

3.2.5. DM

Data mining is a complex and sophisticated process of extracting unknown but potentially valuable information and knowledge from massive amounts of data. The process encompasses several fields, including statistics, ML, artificial intelligence, and database management. Data mining technology, with the help of various algorithms and models, helps analysts discover patterns, trends, correlations, and anomalies in data, providing powerful support for decision-making (strengths and limitations of DM in the construction field, as shown in Table 6).

Table 6. Advantages and limitations of DM in construction project applications.

DM Strengths	DM Limitations
High quality visuals [97]	Requires large amounts of labelled data [44]
Promoting retention of information [21]	Data imbalance [97]
Predictive maintenance [68]	Dimensional disaster [97]

In the construction field, data mining can help practitioners gain insights into the details and correlations across the entire lifecycle of a construction project. In the design phase, by deeply analyzing historical construction project data, practitioners are able to identify which design elements perform best in a given context, thus providing directions for improvement in the design of new projects [68]. These design elements include structural design, ventilation systems, daylighting, and green building features. During the construction phase, data mining technologies can optimize the construction process. Monitoring sensor data on the construction site allows for real-time tracking of construction progress and resource usage, thereby enhancing overall efficiency. In addition, data mining can assist in managing risk by analyzing historical data and risk scenarios to predict potential problems and delays, thus reducing uncertainty in construction projects [97]. Data mining technologies significantly contribute to the operations and maintenance phases by monitoring energy usage. With energy data captured by sensors and intelligent control systems, data mining analysis can identify opportunities for energy-saving improvements, including adjustments to lighting and air conditioning systems and optimization of heating systems, with the aim of reducing energy costs and carbon footprints [59]. DM technology is suitable for data integration and can help integrate data from different sources to ensure data consistency and availability [97].

However, despite the remarkable achievements of data mining in construction projects, its application is still subject to some limitations: (1) constructing data mining models necessitates a substantial amount of labeled training data, but obtaining large-scale labeled data in construction projects can be challenging and costly, creating a bottleneck that restricts its widespread application. Insufficiently labeled data may affect model performance; (2) the number of samples of certain categories in a construction project's data may be uneven, which may also affect model performance; (3) when faced with large-scale datasets, data mining technologies still encounter challenges related to dimensionality. In construction projects, the data involved may include a large number of features and variables, increasing the complexity of training and inferring models in high-dimensional spaces. Future research and development must overcome these limitations.

3.2.6. VR

VR refers to a technology that allows users to immerse themselves in a digitally created environment that is experienced through sensory stimuli such as sight, sound, and touch [98]. In the construction field, VR has a wide range of applications throughout the construction project lifecycle. In the design phase, through virtual reality technology, architects and designers can experience immersively the architectural design and examine the spatial layout, material selection, and lighting effects, so as to better understand and evaluate the design scheme. In the construction phase, virtual reality can also be used to simulate the building construction process, train construction personnel, and provide support for safety training and risk management [48]. The use of virtual reality in construction provides project teams with a more intuitive and comprehensive working tool that can help improve efficiency and quality [48,57,63,83,99] (strengths and limitations of VR in the construction field, as shown in Table 7).VR can provide immersive and interactive applications by integrating BIM, IoT, and other technologies. This is mainly reflected in the following aspects: (1) by providing designers with a more intuitive and interactive design environment, developers can simulate architectural spaces, view architectural models in real time, and roam virtually through virtual reality to better understand design solutions. In addition, VR can be used for collaborative design, where multiple designers can work together in a virtual environment to improve design accuracy and efficiency [100]; (2) by helping construction teams to plan, collaborate, train, and manage engineering projects through visualization and supervision, task planning and execution, and two-way communication capabilities to enable collaborative construction between humans and robots, thereby improving project quality, safety, and efficiency [57]; (3) by helping operators better manage and maintain building facilities; by combining building information modeling with IoT sensors, operators can monitor the status of construction projects in real time [101], perform remote maintenance, improve energy efficiency, optimize maintenance schedules, and provide a better user experience [102]. In addition, VR can be used to train operations staff to improve their operational skills [63]. VR is suitable for data visualization and presenting complex data and information through immersive experiences [63].

There are some limitations to VR in the construction industry that affect its widespread use and maximization of benefits: (1) the use of virtual reality technology requires some training and adaptation time. Staff in the construction field may need time to get used to the virtual environment, which may affect their productivity in the initial stage; (2) VR technology has some limitations in terms of realism and perception, and the difference between the tactile sensation of objects in the virtual environment and the real environment may affect the user's immersion in the virtual environment; (3) interoperability issues between different design and construction software may hinder effective information sharing and collaboration in virtual environments; (4) virtual reality systems usually require high-performance computers and specialized equipment, such as head-mounted displays and tracking devices. These hardware requirements are a major limitation for the widespread adoption of VR technology.

Table 7. Advantages and limitations of VR applications in construction projects.

VR Strengths	VR Limitations
High quality visuals [103]	Time course [20]
Promoting retention of information [101]	Realism and perception [57]
Project marketing and presentation [63]	Compatibility issues with software [70]
Flexibility testing	Limited range of applications [63]

3.2.7. AR

AR refers to a technology that enhances the user's real-world experience by overlaying virtual information or objects onto the real environment [104]. Users can use AR by sensing and tracking real-world environments, then overlaying virtual objects, images, or information onto the perceived real-world scene. This makes AR valuable in the construction field in the long term, especially when integrated with technologies for visualizing and detecting environmental anomalies in construction projects [105] (strengths and limitations of AR in the construction field, as shown in Table 8).

The integration of AR with AI, ML, and other technologies during the design phase of a construction project enables visual monitoring of anomalies and helps to reduce unnecessary dismantling for maintenance purposes [81]. In addition, during the construction phase, AR enables the visualization of the construction process and progress by integrating with IoT technologies, providing the construction management team with the ability to plan better and coordinate the works [47]. In the operation and maintenance phases, AR is also able to monitor factors affecting the indoor environment, such as temperature, humidity, and carbon dioxide concentration, which improves the efficiency of the operator's decision-making on anomalous data [64]. The visualization layer can use augmented reality to overlay digital information onto the real world, resulting in a more intuitive data presentation and interactive experience [106].

However, AR in the construction industry faces a number of challenges that limit its widespread use and maximize its benefits. (1) Despite the continuous development of AR technology, the system may require higher accuracy and stability in complex construction environments, which may affect its reliability and effectiveness at real construction sites. Errors and delays may prevent construction workers from working together in virtual and actual spaces. (2) AR systems typically require special hardware devices, such as AR glasses or headgear, which limits their widespread use and increases the cost of training and adoption. In addition, some environments may not be suitable for wearing these devices, such as construction sites that require safety helmets. (3) AR systems require high levels of accurate environmental perception and localization. In complex environments such as construction sites, there may be perception and localization challenges that can lead to discrepancies between virtual elements and actual buildings or structures. (4) AR devices are typically energy-intensive and have a limited battery life, which may pose a significant limitation in scenarios like construction sites that demand extended operation. Frequent charging or battery changes may disrupt the workflow of construction workers, adding to the complexity of device management.

Table 8. Advantages and limitations of AR in construction project applications.

AR Strengths	AR Limitations
High quality visual [85]	Technology maturity [64]
Promoting retention of information [99]	Hardware device dependencies [107]
Visualization design and presentation [108]	Environmental perception and localization issues [83]
Constructability analysis [106]	Energy intensive [99]

4. Digital Twin Lifecycle and Its Functions

4.1. Applications in the Design Phase

Digital twins are used in construction projects to build virtual models, primarily facilitated by BIM technology. BIM serves as an intelligent and adaptive digital twin modeling technology, enabling the construction of digital twins that offer deeper insights and optimization solutions throughout the entire lifecycle of construction projects [109].

BIM integrates the 3D models and data information of a construction project through digital technology, thereby providing data integration and comprehensive visualization, as well as enhancing collaboration and decision support [110]. Unlike conventional virtual models or software, BIM allows for the creation of models with specific semantics, which leads to more efficient and comprehensive information exchange and collaboration during the design and construction phases of a project [111]. BIM offers a digital collaboration space that empowers designers and engineers to collect, manage, and share information in a unified digital format throughout the project lifecycle

Recent studies have further expanded on the application of BIM in the context of digital twins. Bolshakov et al. highlight the role of BIM in asset management within the architecture, engineering, construction, and owner-operated (AECO) sectors, emphasizing its potential to reduce the discrepancies between as-built and as-designed facilities through the use of digital twins [112]. Furthermore, they discuss the integration of BIM with other digital technologies to form a holistic lifecycle management approach that minimizes trial operation time and operational costs.

In addition, the work of Boje et al. provides a comprehensive review of the multifaceted applications of BIM during the construction stage, underscoring its limitations and requirements for the development of a construction digital twin (CDT) [4]. They suggest a semantically improved CDT that takes advantage of the synchronicity of cyber–physical data flows to provide a more process-oriented understanding of complex building materials.

Through the application of BIM, the digital twin not only enables the optimization of design solutions for construction projects but also leads to more comprehensive planning, more economical construction, and enhanced fluidity and accuracy in engineering [17]. BIM can be integrated with other technologies such as DT, DL, and mixed reality to create a real-time visual warning system, ensuring that engineers can collect real-time information from the site during the engineering phase [113]. Moreover, the integration of BIM with AI is utilized for automated project design and drafting through a rule-based automated building information modeling methodology [114]. Digital twins in construction projects enable automated design and modeling, which can minimize material waste and reduce the potential for additional costs during reworking [115].

4.2. Applications in the Construction Phase

In the lifecycle of a construction project, the construction phase represents not only the translation of design and plans into an actual physical structure but also involves a high degree of management of resources, time, and costs to ensure the successful delivery of the project [116]. The success of the construction phase will have a direct impact on the quality, safety, schedule, and cost-effectiveness of the project. Therefore, the application of digital twins can be more efficient, smarter, and safer in completing the construction phase of a construction project [117].

Digital twins can change the current situation of insufficient information exchange during the construction phase, weak global awareness of construction personnel, and outdated safety monitoring technology [118]. Digital twins can be used to capture images or videos of the physical site by combining AR and VR devices with sensors to achieve safety monitoring, risk warning, and remote guidance during the construction phase [100]. Construction project participants are able to simulate, monitor, and analyze the state of the building at different points in time, leading to a better understanding of the building system functionality, performance, and interaction effects during the construction phase [119]. In addition, it is also possible to transform 3D BIM into 4D/5D BIM by incorporating schedule and cost into the dimensions of the visual building model provided by BIM to form an organic correlation between the design and construction phases [21].

Digital twins can enhance the digitalization and intelligence of the construction phase by providing participants with more efficient and comprehensive information exchange and collaboration [120]. Researchers can integrate technologies such as BIM and IoT so as to achieve real-time monitoring of construction projects [17]. (1) A step-by-step approach for capturing accurate, as-built conditions and predicting potential assembly clashes through the use of "Dyna-BIM" to reduce errors between BIM and as-built conditions [121]; (2) an evolutionary modeling approach and mass data-association modeling in the assembly building construction process to enhance the digitalization and intelligence of the prefabricated assembly lifting process [122]; (3) automatic interpretation and decision support can be optimized in the design and construction phases through deep learning-based digital twin architecture [123].

4.3. Applications in the Operation and Maintenance Phase

Digital twins are at the heart of the future construction project lifecycle's operations and maintenance phase, which separates the builder from the operations and maintenance phase, preventing direct collaboration and decision-making. Digital twins are changing the way buildings are managed and operated in their lifecycle [124].

The digital twin can provide operators and maintainers with a clear idea of operations and maintenance. The digital twin collects construction project performance information through physical sensors, which are then integrated through BIM and IoT to visualize the performance of the buildings [95]. Digital twins can change the current problem of the low availability of construction project performance information [55]. A digital twin-based operations management architecture provides efficient and automated decision analysis support for construction projects [125]. Digital twins can collect real-time data to ensure that operators and maintainers are able to make informed decisions [126].

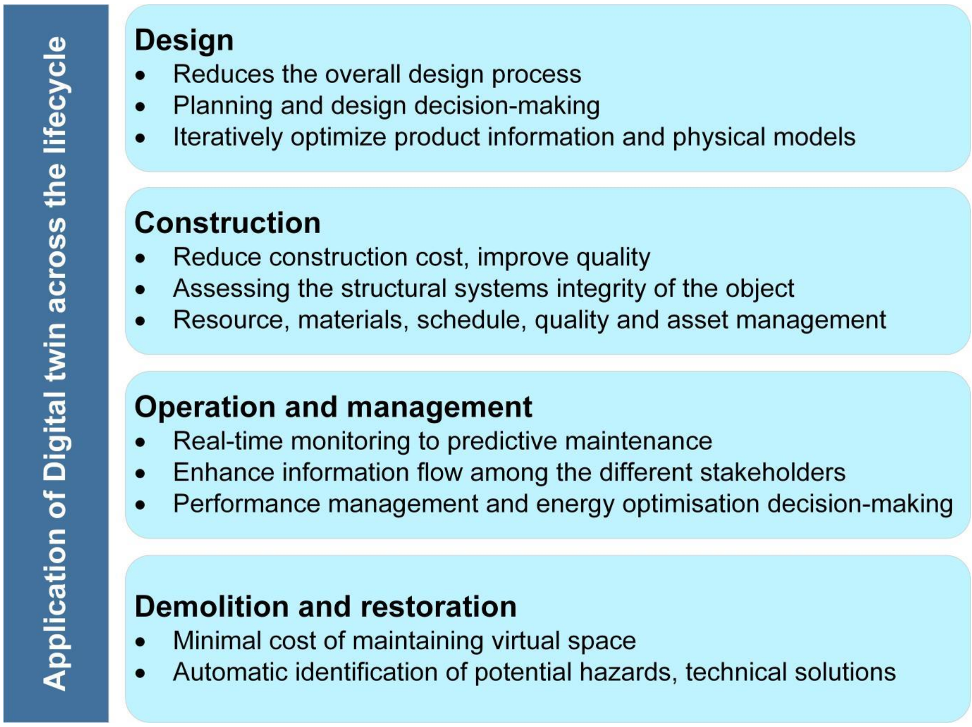
By collecting real-time data on the performance, environment, and structure of the construction project, digital twins enable real-time monitoring and predictive maintenance. A digital twin can be used to monitor the building performance of the heating system, temperature, energy consumption, and other building performance in the construction project through IoT and physical sensors, so as to monitor the operation of various equipment [127]. The presence of DT allows operators to make equipment adjustments in advance, avoiding unnecessary downtime and maintenance costs [128]. In addition, DT can automatically fit 3D shapes to point clusters using a slice-based object fitting method, allowing for better maintenance of existing construction projects [129].

Ancient architecture offers a plethora of opportunities for the operation and maintenance of digital twins in construction projects [130], with technologies like IoT, laser scanning, and BIM finding widespread application in ancient building maintenance [131]. The main use of terrestrial laser scanning is for measurement so as to generate a digital point cloud, then modeling through BIM, and finally the use of digital twin and other technologies to analyze and operate the historical buildings [132]. These technologies do not require physical contact and help preservationists more accurately understand the state of the building in order to better plan conservation measures and avoid damage to heritage buildings [133]. In addition, digital twins can be used to prevent building damage (cracking, blistering, scaling, chipping, and peeling of wall surfaces) by monitoring the environment of ancient buildings (temperature, relative humidity, and air pollutants such as sulfur dioxide) according to [134].

4.4. Applications in the of Demolition and Restoration Phrase

The application of digital twins to the demolition and restoration phases of construction projects does have significant potential. Although no specific application to the demolition phase has been identified in the current research, some studies have applied digital twins to the renovation of historic buildings, suggesting the potential application of digital twins to project restoration and alteration [135].

The development of a BIM management system linked to an operational multifunctional toolkit for different AEC stakeholders [136], integrating a set of tools for the improvement of BIM applications in refurbishment environments based on interoperable information flows [137] would provide an integrated approach to integrating digital twins. The formation of a chronology is used to document and survey historic buildings for later restoration and replication through a variety of methods such as laser scanning, oblique photogrammetry, and BIM. The role of the digital twin in the design, construction, operation, maintenance, destruction, and restoration phases is shown in Figure 5.



Design
- Reduces the overall design process
- Planning and design decision-making
- Iteratively optimize product information and physical models

Construction
- Reduce construction cost, improve quality
- Assessing the structural systems integrity of the object
- Resource, materials, schedule, quality and asset management

Operation and management
- Real-time monitoring to predictive maintenance
- Enhance information flow among the different stakeholders
- Performance management and energy optimisation decision-making

Demolition and restoration
- Minimal cost of maintaining virtual space
- Automatic identification of potential hazards, technical solutions

Figure 5. Application of digital twin in design, construction, operation, maintenance, dismantling and restoration phases.

5. Trends and Challenges for the Digital Twin

5.1. Trends in Digital Twin Technology and Applications

5.1.1. Model Automation

Automatic model building means that, based on a dual data driver, architects and designers can create digital twin models that simulate the appearance, structure, and performance of a building to better understand the potential impact of design decisions. This can help reduce design errors and costs and improve the sustainability of buildings [49]. The effectiveness of automated model building technologies in construction projects is mainly in the areas of planning, clash detection, and construction management, bringing significant benefits to the construction field.

On the planning side, automated model building technology provides more detailed and comprehensive data support for construction project planning. Utilizing automatically constructed digital twin models, project planners gain precise insights into the building's structure, equipment arrangement, and spatial utilization [138].

In terms of the intelligence of construction management, the digital twin model automatic construction technology introduces intelligent elements to construction management. With the real-time updated digital twin model, construction managers can monitor the gap between the actual progress of the building and the planned progress, identify potential problems and make adjustments in a timely manner. This helps to increase transparency in the construction process and reduce project risks [139].

5.1.2. System Intelligent Control

Using digital twin technology and intelligent control algorithms together allows for fine-grained, automated management of construction projects based on the system's models and goals. This allows the system to be accurately mapped and modeled in a virtual environment, reflecting the state and performance of the physical system in real time. Intelligent control algorithms based on this model achieve real-time decision-making and improve the stability, efficiency, and reliability of the system by continuously learning and adapting to changes in the system [140]. This provides architects and engineers with the ability to create realistic, highly accurate virtual modeling, which helps to make better decisions during the design and planning stages, optimize space utilization, improve building performance, and identify potential design problems in advance [141]. In addition, by detecting potential conflicts, such as pipeline and cable crossings, through real-time virtual simulation, the system's intelligent control can help to solve problems in advance, reduce errors in construction, and lower repair costs [142].

Systematic intelligent control is also widely used in intelligent construction and monitoring [134]. Several construction sites have practiced "learning from demonstration" to teach robots to perform construction-related tasks [143]. In the future, digital twins will be combined with the development of smart cities to achieve seamless integration between buildings, infrastructure, and urban systems [144].

5.1.3. Emergency Response

Conducting safety evacuation drills is critical for increasing the safety consciousness of building occupants as well as their ability to save themselves and provide assistance to others. Thanks to the advancement of digital twin technology, it is now feasible to create more accurate simulations and assessments of safety evacuation situations. Digital twin technology enables the secure modeling of complex real-world environments by creating a virtual replica of the physical setting. Safety evacuation drills, like those for fires and earthquakes, can use this technology to simulate disaster dynamics, crowd behavior, and building characteristics. As a result, it aids in the safety assessment [145].

The assessment of safety conditions is a key component of evacuation drills. Through digital twin modeling, the dynamic changes in fire development and crowd evacuation can be updated in real time to provide decision support for emergency managers. For example, scholars optimized the evacuation route of an offshore drilling platform through a dynamic optimization model by combining geographic information systems (GIS) and fire-dynamics simulation (FDS) [146]. Evacuation-route optimization is critical for improving evacuation efficiency and safety. Researchers have come up with a real-time fire evacuation system that uses the ant colony optimization algorithm (RFES-ACO) to plan the best routes for multiple scenarios [147].

The researchers also looked at the average system throughput, the time it took to evacuate, and the delay before evacuation by building a performance model of an intelligent emergency evacuation system using a stochastic Petri net [148]. The digital twin technology not only enables simulation and evaluation, but also visualizes the evacuation process through 3D models and provides user interaction. This allows the public to participate in fire evacuation drills via mobile Web3D devices, which improves the drills' participation and educational effect [146]. The application of digital twin technology in disaster evacuation drills demonstrates its enormous potential for improving evacuation efficiency and safety. Future research should further explore how to incorporate technologies such as artificial intelligence and big data analytics to achieve more intelligent and automated safety assessments.

5.2. Challenges of the Digital Twin

5.2.1. Integration of Data and Information

Data fusion in digital twin construction projects is a sophisticated process that integrates key data from both virtual models and physical entities to create a comprehensive data-aware structure that spans the entire lifecycle of a construction project, encompassing design, construction, operation, and maintenance phases [149]. To improve the digital twin model, this integration is necessary. It involves combining different types of data, such as sensor data, IoT data, historical records, and CAD models, which may have different formats, protocols, and levels of accuracy [150].

To address the challenges of data quality, such as noise, incompleteness, and inaccuracy, future advancements in data fusion necessitate the development of robust data quality control and cleansing technologies [151]. Making sure that digital twins work in real time is very important. Setting up a reliable real-time data synchronization system is necessary to achieve this. Combining cloud computing, edge computing, and IoT technologies can simplify this process [59]. Additionally, the large volumes of data generated by digital twins demand effective big data management and storage solutions, with potential future developments including the use of distributed databases, data lakes, and high-performance computing resources [96].

The collaborative nature of digital twins, often involving multiple stakeholders in construction projects or industrial operations, underscores the need for collaborative tools and platforms to share information, data, and models across different organizations and teams. The current lack of harmonized standards in digital twin technology leads to interoperability and data-sharing challenges [152]. There is a need to promote standards in the future to facilitate better collaboration between different systems and organizations. In the future, researchers will be able to use AI and ML technologies to automate the process of data analysis and model building to extract valuable information from multi-source data [21].

The absence of a unified set of data standards [153] complicates the integration of various data types in the construction domain, including architectural design drawings, sensor data, supply chain information, and maintenance records [154]. Current attempts to develop workflows for digital twins in existing construction projects, as well as their real-world experimentation, have yet to fully address these issues [155]. Moreover, the efficient management and storage of large-scale data, such as CAD models, construction progress, and quality inspection reports, remain a challenge due to the lack of a complete system for integrating data from physical entities and virtual models [156].

It is harder to combine data from the different software tools used in construction projects, like architectural design software, project management tools, and ERP systems, because they do not work with each other and there is no interface or middleware to make them work together [94]. Interoperable systems and unified data standards are essential for the advancement of digital twin technology in the construction industry.

5.2.2. Privacy and Security Protection

Digital twins in construction projects are integral in capturing and sharing sensitive data, which underscores the importance of robust data privacy and security measures [157]. These data often encompass a range of sensitive information, including design drawings, safety records, and maintenance schedules, which may contain personally identifiable information, trade secrets, and intellectual property. The critical need for a secure data collection and storage system is paramount to safeguarding against misuse and leaks. To ensure data integrity, we employ advanced encryption technologies and access control policies. Moreover, regular data cleansing and archiving act as effective strategies to safeguard sensitive information, preventing misuse or leakage of no longer required data [158].

In scenarios where multiple users or teams collaborate using digital twins, the risk of data misuse or inappropriate access increases. To counter this, establishing effective permission management and access control mechanisms is essential. Adhering to the principle of least privilege, each user or team should be granted access rights that allow them to access only the data and functionality necessary to them, thereby reducing the likelihood of unauthorized access [159]. In the context of digital twin research, data security and privacy are pressing issues, particularly in construction projects that handle a substantial amount of sensitive information [160]. Future applications of digital twins necessitate enhanced data security measures that include data encryption [80], authentication, access control, and privacy protection to prevent data leakage and unauthorized access. Researchers are exploring the use of blockchain-based digital twins to address these concerns, offering a promising approach to improve trust, collaboration, data sharing, information security, and sustainability. This innovative method has the potential to reduce fragmentation, improve communication quality during the construction phase, and ultimately enhance data security within the construction sector [17]. This provides a new way of thinking to address security issues in the construction sector [161].

5.2.3. Technical Manpower Development and Transformation Needs

The widespread use of digital twins in construction presents unprecedented opportunities. However, it also brings with it a range of challenges related to manpower development and transformation requirements. Firstly, digital twins incorporate knowledge from a wide range of fields, including construction engineering, information technology, data science, and artificial intelligence. Existing engineers and construction professionals will need to relearn or add new skills to master the use of digital twins. This includes learning new modeling and simulation tools, data analysis skills, and the ability to collaborate with other departments [162]. At the same time, the cost and time of training are also a challenge, as construction companies need to ensure that their employees are able to transition seamlessly into the digital twin workflow.

Attracting and retaining new hires with digital twin expertise is also a challenge, and demand in this area is growing and competition is fierce. In addition, digital twins rely on large-scale data capture and analysis. The construction field requires professionals with skills in data management, big data analytics, and data visualization to effectively process and utilize digital twin data. This involves not only training at the technical level, but also establishing appropriate talent recruitment and retention strategies to ensure that digital twin-literate professionals in the field are fully utilized.

6. Discussion

This section discusses in detail the results of applying digital twins to the construction domain.

Firstly, digital twins provide the construction domain with more accurate, real-time, and comprehensive building models [163]. This not only includes the geometry of the building structure but also incorporates sensor data, real-time monitoring, and simulation analysis, making the digital model a more realistic representation of the building's behavior. This provides better decision support to designers, builders, and operators, enabling them to better predict, identify, and solve problems in the building process [164]. It is important to note that most of the studies have focused mainly on the construction, operation, and maintenance phases due to the structural fragmentation and inadequate application of technological levels in the design and engineering phases of construction projects [17].

Second, a look at how digital twins are used in construction projects right now shows that they are quickly changing in the field towards data–information fusion, automatic model building, intelligent system control, data security, and privacy. These trends have impacted different participants in construction projects, including designers, operators, and builders. However, a number of challenges accompany this development, including data management and integration, privacy and security protection, and technical manpower development and transformation needs.

In order to solve these difficulties, the primary objective of the digital twin is to establish a cohesive framework, representation, and repository for data. This will lead to a better uptake of the digital twin by the construction field, enabling it to address a variety of issues. In addition, the development and transformation of technical staff is another serious challenge that digital twins are currently facing. The late start of digital twins compared to other technologies, as well as the relatively small number of digital twin researchers in the construction field, may have contributed to slower overall development. Future research should focus on improving the efficiency and safety of the demolition phase of construction projects while controlling costs.

This paper aims to provide a clearer research direction and practical guidance for the application of digital twins in the construction field, based on in-depth research. Digital twinning is a complex and collaborative system engineering process that entails the development and high degree of integration of multiple new technologies, as well as the comprehensive application of interdisciplinary knowledge. In this field, key technological approaches include modeling, big data analysis, ML, simulation, and so on.

This study enables professionals in the construction industry, such as engineers, architects, project managers, and construction teams, to comprehend the industry's needs and how DTs can fulfill them, e.g., enhancing design accuracy, reducing errors, and optimizing resource allocation.

It also aids various stakeholders, including owners, contractors, designers, and regulators, in grasping the potential benefits of digital twin technology. Owners can obtain a comprehensive view of their projects for better cost control and risk management via digital twins. The real-time data and simulation results help evaluate different design options. Contractors can optimize construction plans and resource allocation with digital twins. They can predict potential problems and develop countermeasures. Digital twins enhance safety management on construction sites. Regulators have the ability to improve supervision efficiency and quality, detect violations and hazards, and develop construction standards and policies.

7. Conclusions

This paper systematically reviews the emerging role of digital twins in the construction industry, emphasizing their transformative impact on decision-making and automation. Through a literature search on the Web of Science, this study synthesizes recent advances in the field, identifies future challenges, and predicts trends. Its main contributions are as follows:

(1) A variety of applications for digital twin architectures are catalogued, including system integration, data visualization, and service delivery. These frameworks are often underpinned by cutting-edge technologies such as AI, ML, CPS, IoT, DM, VR and AR. Their application in buildings facilitates real-time monitoring, secure data exchange and enhanced decision-making processes.

(2) The review also reveals the lifecycle applications of digital twins in construction, from design and planning to maintenance and asset management. Notably, the demolition and restoration phases were identified as areas with emerging potential, mainly explored through modeling and case studies. This observation emphasizes the need for further research to deepen the understanding of digital twins in these areas.

(3) This paper depicts the trends of digital twins in construction, emphasizing model automation, intelligent system control, and emergency response capabilities. At the same time, it reveals the challenges associated with data management, privacy issues,

and practitioner engagement. Addressing these issues is imperative for advancing the digital transformation of the construction industry and improving project efficiency and sustainability.

This paper has limitations due to its reliance on specific databases (Scopus, Web of Science, and ScienceDirect) and a narrow search filter (English, journal articles, and reviews). This approach may have overlooked significant literature in other languages or formats, potentially biasing the construction analysis of digital twins. To address this, future research should expand the dataset and consider a wider range of literature sources for a more comprehensive evaluation of digital twins' role in construction.

This study suggests that future research should explore the detailed applications of digital twins in construction, particularly in restoration and demolition. Integration with artificial intelligence and ML could enhance design environments, enabling real-time building model visualization and optimization. Additionally, digital twins could be instrumental in emergency response, with real-time monitoring and early warning systems to pre-emptively alert personnel and simulate safety risks.

Expanding the literature review to include diverse datasets and multilingual publications is crucial for a more holistic understanding of digital twins' impact in the construction industry. This broader scope would aid in developing more effective strategies and technologies in construction management and safety.

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Abbreviations

AEC	Architecture, engineering, and construction
BIM	Building information modeling
AI	Artificial intelligence
ML	Machine learning
DM	Data mining
CPS	Cyber–physical systems
IoT	Internet of things
VR	Virtual reality
AR	Augmented reality
DL	Deep learning

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