Transformative Potential of Next-Generation Digital Twins in the AECO Industry

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Abstract
The Architecture, Engineering, Construction, and Operation (AECO) industry is beginning to explore the potential of Digital Twins. These applications range from prototyping to simulations, incorporating technologies like Building Information Modeling (BIM), the Internet of Things (IoT), and Artificial Intelligence (AI). The industry is at an early stage of Digital Twins maturity, focusing on integrating dynamic, predictive, or simulated data. However, there's ambiguity regarding advanced Digital Twins, with terms like cognitive, prescriptive, autonomous and intelligent Digital Twins used inconsistently. This research aims to clarify and standardize terminology and understanding of next-generation Digital Twins, focusing on the last two maturity levels. This research will provide AECO practitioners with a comprehensive understanding of these advanced Digital Twins, guiding their selection based on specific needs and advancing research for more accessible and cost-effective Digital Twins while maintaining functionality. Ultimately, this research aims to unlock the full potential of Digital Twins in the AECO industry.

Keywords: AECO; next-generation Digital Twins; Digital Twins' maturity; Cognitive; Prescriptive; Autonomous; Intelligent.

1 Introduction
The concept of Digital Twins has gained significant traction in several industries, including aerospace and defense, agriculture, food and beverage, fintech, healthcare and life sciences, manufacturing, mobility and transportation, natural resources, telecommunication, and the architectural, engineering, construction and operations (AECO) industry. For the AECO industry, Digital Twins are of key interest because of their significant contribution to maximizing the efficiency of every stage of construction. This includes prioritizing safety and managing costs effectively; evaluating intelligent building analytics and predictive data from completed structures to guarantee optimal performance; analyzing the effects on sustainable practices, such as circular economy principles and reducing carbon emissions; providing precise design and documentation for seamless coordination across various domains; and implementing streamlined and automated operational procedures to enhance overall workflow (Digital Twin Consortium 2024).

Several researchers investigated the definition of Digital Twins, their applications in the built environment, and the associated challenges (Boje *et al.* 2020; Sacks *et al.* 2020; Camposano *et al.* 2021; Agrawal *et al.* 2022; Ammar *et al.* 2022; Shahzad *et al.* 2022). Recently, AlBalkhy *et al.*

(2024) conducted a systematic literature review of the published research and industry reports on Digital Twins in the built environment. The authors reviewed 228 publications, among which 82 papers were published in 2023, and 78 papers were published in 2022, indicating a noticeable interest increase in the concept despite the late adoption compared to other industries. They were able to identify 38 definitions. However, this lack of clarity and consistency on a common definition poses a risk, as an inadequate or ambiguous definition and elucidation of a Digital Twin and its implementation might lead individuals to dismiss it as mere hype (Wright & Davidson 2020). Consequently, once the hype subsides and the inevitable backlash ensues, the ultimate level of interest and utilization—the "plateau of productivity"—may fall significantly short of the technology's maximum potential (Wright & Davidson 2020).

Although there's growing interest in digital transformation in the AECO industry, the extent of implementation of Digital Twins is largely undisclosed and possibly limited. Many existing studies focus on conceptual frameworks or propose Digital Twin solutions rather than assessing real-world implementation. This indicates that while there's enthusiasm for Digital Twins, tangible applications and widespread adoption are lacking, hindering its dissemination (AlBalkhy *et al.* 2024). The applications of Digital Twins in the AECO industry are still in their early stages, and this could pertain to an array of challenges. Among these challenges is the lack of awareness of the concept's full potential and understanding of the different levels of the Digital Twin ecosystem (Ammar *et al.* 2022; AlBalkhy *et al.* 2024). This ambiguity makes it difficult for stakeholders to compare and evaluate alternative Digital Twins solutions, potentially resulting in inconsistencies and inaccuracies in representing actual assets. Therefore, to establish a higher level of Digital Twins readiness in the AECO industry, it is important to improve the maturity of Digital Twins in the sector and clearly distinguish between the different functionalities, enabling technologies, and capabilities.

2 Research Objectives and Approach

This research investigates the current awareness of Digital Twins' full potential and captures next-generation Digital Twins' functional and technical requirements in the AECO industry. The research methodology adopted is presented in Figure 1 and discussed in the following sections and sub-sections.

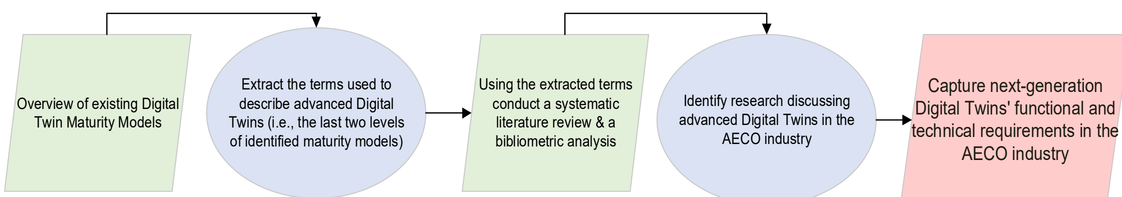

Figure 1. Research Methodology Overview

3 Overview of Existing Digital Twin Maturity Models

A Digital Twins maturity model serves as a valuable instrument for gauging the evolving benefits garnered from a Digital Twin's capabilities (Eirinakis *et al.* 2020). Following identifying these benefits, the subsequent vital phase in crafting a maturity model entail delineating the attributes, parameters, and functionalities of Digital Twins. These attributes, parameters, and functionalities can be conceptualized across multiple dimensions and rubrics within the maturity model to differentiate their growing system capability and capacity along a specified trajectory (Chen *et al.* 2021; Scheibmeir & Malaiya 2022). The maturity stage of a specific technology is evaluated by measuring the technology readiness level (TRL). Each technology project undergoes assessment based on predefined parameters for each level of technological advancement, leading to the assignment of a TRL rating reflecting the project's progress (Manning 2023). The existing maturity models for Industry 4.0 can inform the development of a maturity model for Digital Twins (Agostini & Filippini 2019). These models often encompass dimensions that address overarching aspects such as people and culture, which encompass skills, organizational structures, and processes alongside technology (Cognet *et al.* 2019).

Among the most cited Industry 4.0 maturity index studies is the one developed by (Zeller *et al.* 2018), which defined six stages in the Industry 4.0 development path. These stages are: 1) computerization, 2) connectivity, 3) visibility, 4) transparency, 5) predictive capacity, and 6) adaptability. Following suit, several scholars, researchers, and industry pioneers developed maturity levels for Digital Twins. We identified thirteen Digital Twin Maturity models to understand how industries classify Digital Twin maturity. These sources came from industries including system engineering (Madni *et al.* 2019; Scheibmeir & Malaiya 2022), electronics and telecommunications (Kim 2020), information systems and automation (Kharche 2022), data science (Rao 2022), software technology development (Haziyev *et al.* 2022; Deleu 2023), energy (Nhede 2018), manufacturing (Hu *et al.* 2023), and the AECO industry (Chen *et al.* 2021; Mêda *et al.* 2021; Autodesk 2024; buildingSMART International 2024)

The maturity level names and their descriptions were extracted from each maturity model. It was noticed that industries used different terminology to describe Digital Twin maturity levels. Based on the given descriptions and to facilitate analysis, these descriptions were used to group the various terminologies, regardless of their specific names. Each group was then assigned a common maturity level name that best matched the described functionality of the group. For instance, for a Level 5 Digital Twin, Rao (2022) defined "Adaptive Autonomous Twins" as a twin capable of understanding and learning changes in behavior and response to environmental uncertainties. Conversely, Mêda *et al.* (2021) defined Level 5 as an "Intelligent twin," a self-learning and self-regulating twin capable of taking corrective and preventive actions to increase building performance. Since both these twins focused on self-learning to automate response to environmental changes, they were clustered as "Adaptive Autonomous Twins." Figure 2 presents the relationship between the Digital Twin maturity level and the denoted level description.

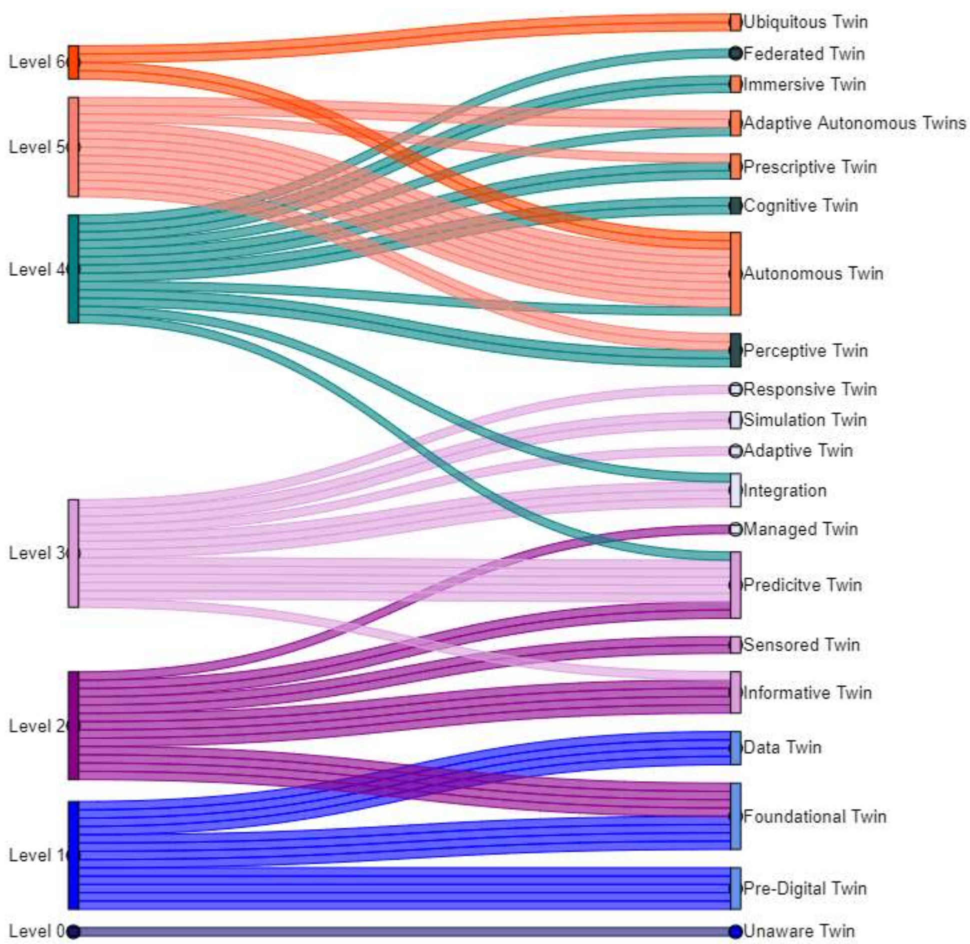

Figure 2. Existing Digital Twin Maturity Levels and the used level naming

The developed Sankey diagram (Figure 2) shows the discrepancy in the terminology used by different investigated maturity models to describe a Digital Twin and the inconsistency in terminology associated with each maturity level. For instance, when considering Digital Twins with maturity at levels 0, 1, and 2, fewer branches are observed in the figure, showcasing a consensus in naming and understanding of the functionality of such Digital Twins. This can be attributed to the extensive research on these Digital Twins, which has led to a common understanding of their utility, enabling technology, and functionality. However, more branches are observed at the advanced stages of Digital Twins (i.e., levels 4, 5 , and 6) leading to an ambiguity in understanding where the utility of these twins exists, what their functionality should be, and what enabling technologies should be used. This ambiguity reflects an initial understanding of these levels due to developing research along the development path of Digital Twins.

4 Advanced Digital Twins Systematic Literature Review

To develop a comprehensive understanding of advanced Digital Twins, a systematic literature review was conducted using the Scopus database. The review focused on papers published between 2018 and 2024, in English, encompassing journal and conference papers. The search string used was “Digital twin” AND “keywords” AND (“AECO” OR “Architecture” OR “Engineering” OR “Construction” OR “Operation”). Keywords included adaptive, autonomous, cognitive, intelligent, and prescriptive since these terms were mainly used to describe advanced Digital Twins (Figure 2). Approximately 900 papers were identified. Abstracts were reviewed, and 106 relevant papers were selected and managed using Mendeley software. After removing duplicates, 99 unique papers were analyzed. VOSviewer software was used for qualitative analysis to map relationships between terminologies, using a thesaurus file to standardize terms and binary counting for reliable data analysis. The analysis results are presented in Figure 3.

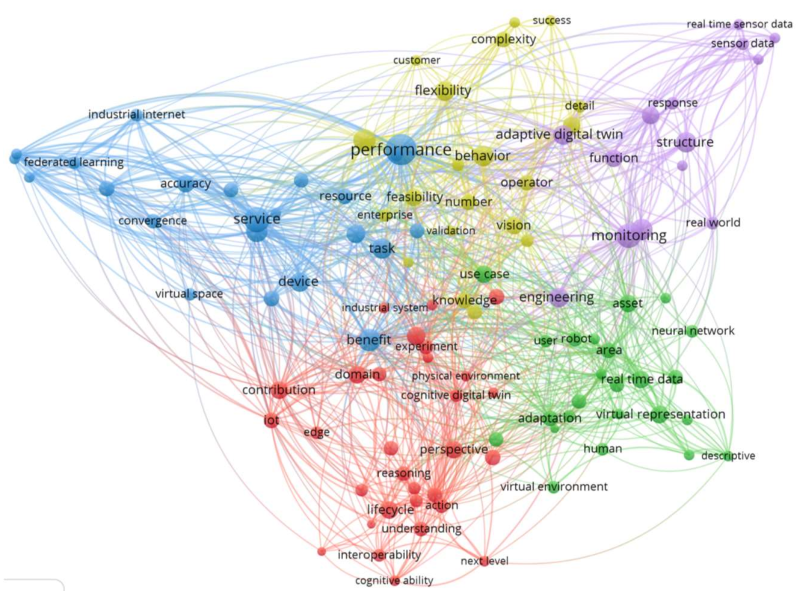

Figure 3. Keywords co-occurrences analysis

The analysis showed that the 111 keywords can be gathered in five clusters with 1640 links. The first cluster (in purple) encompassed terms linked to “adaptive digital twins,” such as “real-time sensors data,” “monitoring,” “maintenance,” and “prescriptive maintenance.” The second cluster (in green) is related to human/user adaptation, including keywords such as “virtual environment,” “virtual representation,” “virtual reality,” “situation,” and “decision-making process.” The third cluster (in red) is linked to the “cognitive digital twin” with keywords including “understanding,” “lifecycle,” “interoperability,” “cognitive ability,” “IoT,” and “perspective.” The fourth cluster (in blue) is related to “federated learning,” “deep reinforcement learning," "processing," "performance," and "industrial internet." The fifth cluster (in yellow) is linked to "autonomous decision making" and "automation" with keywords such as "enterprise," "complex systems," "operator," "behavior" and "validation." These clusters showcase an overlap between the functionalities of advanced Digital Twins, requiring a more detailed overview of their use cases and enabling technologies.

5 Advanced Digital Twins in the AECO Industry

Among the 99 reviewed papers, 38% were sourced from manufacturing and industrial engineering, followed by computer science (36%), while research related to the AECO industry and advanced Digital Twins accounted for 26% of the published papers. A detailed review of the identified papers related to the AECO industry was conducted, and the type of research, research contribution, and enabling technologies are summarized in Table 1. Each category of advanced Digital Twins sorted alphabetically is further discussed in the following sub-sections.

Table 1. Advanced Digital Twins applications in the AECO industry

Advanced Digital Twin	Type of Research	Research contribution & enabling technologies	Ref.
Adaptive Digital Twin	Development & pilot study	They integrated a physics-based structural model and sensor data to adapt to changes in the environment and member properties.	(Miao et al. 2022)
Autonomous Digital Twin	Applied research	They developed a Digital Twin & human-robot collaboration to optimize the assembly process of complex-shaped architectural structures.	(Ye et al. 2022)
	Simulation-based research	They used Digital Twins to reassign multiskilled workers in offsite construction to facilitate the implementation of automated reassignment strategies and provide a platform for evaluating the impact of operation interventions in offsite construction settings.	(Barkokebas et al. 2022)
	Framework & applied research	They integrated AI in an audio-based Digital Twin for autonomous monitoring, optimization, and management of roadway construction.	(Deria et al. 2022)
	Conceptual framework	They proposed a six-layer Digital Twin model for mining processes by leveraging big data technologies and machine learning for predictive maintenance.	(Mostafa et al. 2021)
	Case Study	They utilized IoT sensors, crowd simulations, and agent-based simulations to study and manage the behavior of building occupants and effectively communicate provisions to end-users.	(Bolpagni et al. 2023)
Cognitive Digital Twin	Conceptual framework	They integrated deep learning to support real-time interpretations & decision-making support of complex buildings based on Digital Twin cognitive abilities.	(Kor 2021; Kor et al. 2023)
	Conceptual framework	They integrated machine learning & analytical tools throughout the project lifecycle to facilitate the implementation & evaluation of consistent cognitive Digital Twins for building lifecycle management.	(Yitmen et al. 2021)
	Framework and pilot study	They developed a BIM-GIS web-based platform as an asset management system app to provide real-time visualization of the asset in 3D maps connected to analytical dashboards for management support.	(Meschini et al. 2022)
	Conceptual framework	They investigated the potential of integrating Digital Twins with AI & IoT into modular production systems. Also, they investigated combining knowledge graphs & cognitive modular production to systems with	(Jaryani et al. 2023)

		perception & decision-making capabilities to enable autonomous operations.	
Intelligent Digital Twin	Framework, implementation & case study	They integrated BIM, data collected by sensors and IoT devices, to create a cyber-physical production system for precast concrete elements.	(Kosse et al. 2022)
	Implementation & case study	They used RFIDs to collect mechanical parameters at every step of the excavation process, according to which the geometric model of the pit is updated. Using FLAC3D interface and FISH language, risks during foundation pit excavation are captured and analyzed.	(Sun et al. 2023)
	Framework & implementation	They utilized virtual space defined by Digital Twin models using long-range radio and IoT to carry out hoisting path planning using Dijkstra's algorithm for prefabricated components.	(Zhao et al. 2022a)
	Framework & implementation	They collected and analyzed field data from the backpropagation neural network-based Digital Twin to safely assess structural components.	(Zhu & Wang 2022)
	Framework & case study	They integrated BIM, IoT, & smart construction platforms to improve construction and management efficiency, energy consumption control, and other aspects of steel structure construction.	(López-Almansa et al. 2024)
	Framework & case study	They developed a Digital Twin that utilized IoT, sensor networks, & long-range networks to offer a unified implementation to optimize space management applications and services.	(Hossein Motlagh et al. 2024)
	Framework & case study	They used powerful computing and analysis capabilities of 3D GIS, big data, & BIM to develop a Digital Twin that can simulate and predict production activities in the physical twins.	(Zhou et al. 2021)
	Framework	They developed a Digital Twin to collect, process, and analyze data, then output diagnostic and predictive results using an artificial neural network to support the decision-making of related work.	(Zhao et al. 2022b)
Prescriptive Digital Twin	Conceptual framework	They developed computer-aided engineering (CAE) simulation strategies and deep learning during the structure's life span.	(Malek et al. 2021)
	Conceptual framework	They integrated big data, cloud computing, AI, augmented reality (AR), & IoT to develop a Digital Twin prescriptive model for physical workspaces.	(Latifah et al. 2022)
	Conceptual framework	They integrated sensor data to facilitate dynamic recalibration of deterioration and maintenance models for enhanced decision-making processes.	(Momber et al. 2022)
	Framework & pilot study	They utilized BIM, 3D scanning, image processing, finite element method, weigh-in-motion, fiber bragging sensors, and physics-informed machine learning.	(Jeon et al. 2024)

5.1 Adaptive Digital Twins

Industry 4.0 maturity index identifies adaptability as the key goal of digital transformation, emphasizing the importance of predictive capabilities for automated actions and decision-making. Adaptability is achieved when companies use data from digital shadows to make optimal decisions quickly and implement automatic responses. This continuous adaptation allows companies to delegate specific decisions to IT systems, enabling rapid responses to changing business conditions based on the complexity of decisions and cost-benefit analysis (Zeller et al.

2018). In the AECO industry, adaptive Digital Twin integrates sensor data and models to reflect the current status of buildings, adjusting to changes in the environment and member properties. This approach offers a superior solution to challenges faced in traditional structural simulation models (Miao et al. 2022).

5.2 Autonomous Digital Twins

In the AECO industry, autonomous Digital Twins have been defined for managing construction activities in work zones, offering significant benefits such as reducing delays, material wastage, and rework due to human errors. These systems facilitate real-time data sharing among stakeholders, save manual labor, minimize the need for on-site supervision, and optimize resources through systematic planning, thereby cutting project costs (Deria *et al.* 2022). While these advantages are substantial, it is important to note that the autonomous phase of the Digital Twin involves implementing interfaces connected back to its physical twin, enabling self-diagnosing and self-repairing functionalities (Mostafa *et al.* 2021). However, this technology is often categorized as "semi-autonomous," as it incorporates some autonomous functionalities but is not yet fully autonomous (Bolpagni *et al.* 2023). The Digital Twin system, a novel concept in the construction field, is integrated with deep reinforcement learning to autonomously optimize construction activities and forecast construction logistics, aiming to reduce delays and enhance productivity (Deria *et al.* 2022). One intriguing aspect of this system is its ability to continuously monitor human movements and architectural geometries during the assembly process, updating the digital assembly model and automatically providing the assembly robot with feedback to make synchronous adjustments (Ye *et al.* 2022).

5.3 Cognitive Digital Twins

From a computer science perspective, cognitive Digital Twins can exhibit advanced intelligence, mimic human cognitive processes, and perform autonomous actions with minimal or no human intervention (Zhang et al. 2022). These capabilities are facilitated by cognitive science, machine learning, and artificial intelligence, enabling Digital Twins to selectively focus, interpret data, and retrieve information and knowledge (Al Faruque et al. 2021). In manufacturing and system engineering, Digital Twins with cognitive abilities are viewed as advanced dynamic models that use AI-powered human-like cognition and estimation-based methods to predict and enhance performance (Sicard et al. 2023). In the AECO industry, cognitive Digital Twins possess abilities to detect complex actions and optimize dynamic processes, aiding decision-making. However, awareness of the impact of integrating technologies like cognitive Digital Twins, machine learning, cyber-physical systems, big data, AI, and IoT is limited. These technologies form self-learning hybrid models with proactive cognitive capabilities throughout various project phases (Kor 2021; Yitmen et al. 2021; Kor et al. 2023). Additionally, integrating knowledge graphs, which structure and interlink entities and their relationships, can enhance decision-making and autonomous operations (Jaryani et al. 2023). Furthermore, combining BIM-GIS with cognitive Digital Twins improves the management of complex systems like university building portfolios and smart cities, enabling buildings to act autonomously and respond dynamically to environmental changes, facilitating timely decisions based on real-time conditions (Meschini et al. 2022).

5.4 Intelligent Digital Twin

Intelligent digital twins are autonomous platforms integrating physical and virtual twins bidirectionally (Mêda et al. 2021). In the AECO industry, these twins enhance construction safety and accuracy when developed without errors and biases. They operate independently using self-learning and self-regulating algorithms. They leverage IoT, machine learning, optimization algorithms, RFIDs, and big data to optimize construction processes, facility maintenance, space management, quality assurance, and energy-efficient controls. These twins, also known as decision-making Digital Twins, incorporate feedback loops from production into BIM, aiding in quality assurance by comparing actual geometry to design elements (Kosse et al. 2022). However, implementing these Digital Twins involves high costs due to the extensive resources required for sensor installation and data monitoring, and their effectiveness is limited by the need for realistic and accurate training data (Sun et al. 2023).

5.5 Prescriptive Digital Twins

From a manufacturing perspective, prescriptive Digital Twins use bidirectional communication to adjust the physical environment for dynamic optimization. Unlike traditional descriptive and diagnostic analytics, prescriptive analytics predict future outcomes and recommend actions to achieve desired results (Reisch et al. 2023). In the AECO industry, prescriptive Digital Twins go beyond monitoring and predicting by making autonomous decisions through digital representations and decision support models, completing a full control loop without human involvement (Latifah et al. 2022). This concept evolved into the LIVE Digital Twin, which supports modeling, inspection, and maintenance phases, enhancing operational excellence and predictive maintenance (Malek et al. 2021). The prescriptive Digital Twin framework aims to streamline maintenance operations with predefined action plans, optimization strategies, and self-diagnostic capabilities. It also introduces an advanced information system and data schema to improve data management and reduce human intervention, enhancing operational efficiency and reliability (Jeon et al. 2024).

6 Conclusion, Limitations, and Future Studies

The AECO industry is progressively exploring the potential of Digital Twins, leveraging technologies like BIM, IoT, and AI for various applications from prototyping to simulations. However, the industry is still in the early stages of Digital Twin maturity, primarily focusing on integrating dynamic, predictive, or simulated data. This research aimed to clarify and standardize the terminology and understanding of advanced Digital Twins, specifically adaptive, autonomous, cognitive, intelligent, and prescriptive Digital Twins. By providing a comprehensive overview of existing Digital Twins maturity models and research in the AECO industry and other industries, this study guides AECO practitioners in selecting appropriate Digital Twin technologies based on their specific needs, thereby advancing the adoption and functionality of Digital Twins in the industry. The insights gained are expected to enhance the accessibility and cost-effectiveness of Digital Twins, ultimately unlocking their full potential in the AECO sector. Further studies should also investigate these technologies' practical implementation challenges and benefits in real-world AECO projects. Longitudinal studies examining the evolution and impact of Digital Twins over time would provide valuable insights into their effectiveness and areas for improvement. Additionally, exploring the integration of emerging technologies with Digital Twins could reveal new opportunities for innovation in the AECO industry.

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