A RISK ASSESSMENT MODEL FOR THE IMPLEMENTATION OF DIGITAL TWIN TECHNOLOGY IN CHINA’S CONSTRUCTION INDUSTRY

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by

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LIST OF ABBREVIATIONS

AECO	Architecture, Engineering, Construction, and Operation
AHP	Analytical Hierarchy Process
AI	Artificial Intelligence
AM	Asset Management
ANP	Analytic Network Process
AR	Augmented Reality
BCDT	Blockchain-based Digital Twin
BIM	Building Information Modelling
BWM	Best-Worst Method
CAD	Computer-aided design
CDT	Construction Digital Twin
DT	Digital Twin
DTC	Digital Twin Construction
FDM	Fuzzy Delphi Method
FGD	Focus Group Discussion
FM	Facility Management
GBWM	General Best-Worst Method
G-Cy-BWM	General-Cybernetic- Best-Worst Method
ICT	Information and Communication Technology
IoT	Internet of Things
ML	Machine Learning
O&M	Operation and Monitoring
RAM	Risk Assessment Model
RF	Risk Factor
SHM	Structural Health Monitoring
SLR	Systematic Literature Review
VDC	Virtual design and construction
VR	Virtual Reality

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MODEL PENILAIAN RISIKO UNTUK PELAKSANAAN TEKNOLOGI DIGITAL TWIN DALAM INDUSTRI PEMBINAAN CHINA

ABSTRAK

Industri pembinaan di China telah dikritik kerana kadar penggunaan pendigitalan yang perlahan, sementara teknologi Digital Twin (DT) diiktiraf sebagai penyelesaian yang berpotensi. Namun, pelaksanaan DT hadir dengan pelbagai risiko yang melibatkan peluang dan ancaman. Selain itu, terdapat jurang ketara dalam penilaian risiko khususnya untuk pelaksanaan DT dalam sektor pembinaan di China. Untuk mengisi jurang ini, penyelidikan ini bertujuan untuk membangunkan model penilaian risiko (RAM) yang berkesan untuk menilai risiko yang berkaitan, dengan matlamat untuk meningkatkan kejayaan pelaksanaan DT dalam pembinaan. Pertama, penyelidikan ini menjalankan kajian literatur yang komprehensif untuk mengenal pasti potensi risiko yang berkaitan dengan amalan DT dalam industri pembinaan. Kedua, temu bual separa berstruktur dan Kaedah Fuzzy Delphi dijalankan untuk memperhalusi risiko-risiko tersebut. Ketiga, bagi menilai risiko ini dengan lebih baik, penyelidikan ini membangunkan RAM General Cybernetic Best-Worst Method (G-Cy-BWM) untuk mengenal pasti dan menilai faktor risiko penting (RF) yang berkaitan dengan amalan DT dalam sektor pembinaan. Kaedah membuat keputusan multikriteria (MCDM) digunakan, melibatkan 36 pakar yang berkelayakan dalam pelbagai fasa penyelidikan ini. Hasilnya, sejumlah 32 RF kritikal, termasuk 23 peluang dan 9 ancaman, telah dikenal pasti dan diutamakan berdasarkan wajaran saling bergantung yang dikira menggunakan RAM yang dibangunkan. Secara khusus, peluang-peluang ini dikategorikan kepada empat kumpulan: Ekonomi (4), Teknikal(3), Pemantauan & Keselamatan (7), dan Pengurusan (8). Begitu juga, ancaman dikategorikan kepada:

Ekonomi (3), Teknikal (3), Dasar & Pengurusan (3). Peluang dan ancaman yang paling ketara ialah 'Peningkatan dalam pemboleh digital utama' dan 'Peningkatan kos sumber manusia' masing-masing. Sebagai tambahan, kategori Ekononi di kenal pasti sebagai yang paling penting untuk kedua-dua peluang dan ancaman, menekankan keperluan untuk perancangan ekonomi strategik bagi memanfaatkan peluang dan mengurangkan potensi ancaman dalam konteks RAM yang dibangunkan. Walau bagaimanapun, RAM yang dibangunkan tidak termaasuk strategi mitigasi untuk risiko ketara yang dikenal pasti. Oleh itu, terdapat keperluan untuk mencadangkan strategi rawatan terhadap risiko yang ketara dalam penyelidikan masa depan. Analisis sensitiviti mengesahkan kekukuhan RAM yang dibangunkan dan kebolehgunaannya disahkan melalui perbincangan kumpulan fokus. RAM yang dibangunkan dalam penyelidikan ini dapat memudahkan pihak berkepentingan projek pembinaan dalam melaksanakan DT dengan kadar kejayaan yang lebih tinggi dan membolehkan pengamal menilai risiko yang disesuaikan dalam bidang masing-masing.

A RISK ASSESSMENT MODEL FOR THE IMPLEMENTATION OF DIGITAL TWIN TECHNOLOGY IN CHINA's CONSTRUCTION INDUSTRY

ABSTRACT

The Chinese construction industry has been criticized for its slow adoption of digitization, while Digital Twin (DT) technology is recognized as a potential solution. However, the implementation of DT comes with various risks, encompassing both opportunities and threats. Moreover, there is a notable gap in risk assessment specific to DT implementation within the Chinese construction sector. To fill this gap, this research is aiming at developing an effective risk assessment model (RAM) for evaluating associated risks, with the goal of enhancing the successful implementation of DT in construction. First, this research conducted a comprehensive literature review to identify potential risks associated with the practice of DT in the construction industry. Second, semi-structured interviews and the Fuzzy Delphi Method are carried out to refine the risks. Third, to better evaluate these risks, this research develops a General Cybernetic Best-Worst Method (G-Cy-BWM) RAM to identify and assess the significant risk factors (RFs) associated with the practice of DT within the construction sector. The multicriteria decision-making (MCDM) methods are adopted and a total of 36 qualified experts are involved in different phases of this research. As a result, a total of 32 critical RFs, including 23 opportunities and 9 threats, are identified and prioritized based on their interdependent weights calculated using the developed RAM. Specifically, opportunities are categorized into four groups: Economic (4), Technical(3), Monitoring & Safety (7), and Management (8). Similarly, threats are categorized into: Economic (3), Technical (3), Policy &Management (3). Consequently, the most significant opportunity and threat are 'Enhancement in key

digital enablers' and 'Increase of cost on human resource' respectively. Moreover, for both opportunities and threats, Economic is the most significant category. This highlights the necessity for strategic economic planning to effectively capitalize on opportunities and mitigate potential threats in the context of the developed RAM. However, The developed RAM lacks mitigation strategies for the identified notable risks. In this case, there is a need for the proposal of treatment suggestions towards the significant risks in the RAM in future research. A sensitivity analysis validates the solidity of the developed RAM and its applicability is validated through a focus group discussion. The developed RAM in this research facilitates construction project stakeholders in implementing DT with a higher success rate and enables practitioners to analyze customized risks in their respective fields.

CHAPTER 1

INTRODUCTION

1.1 Introduction

The construction industry plays a significant role in contributing to the economic growth of countries around the globe. According to Nnaemeka et al. (2021), the global construction market is anticipated to grow by 85%, reaching $15.5 trillion by 2030. However, this industry has long been plagued by fragmentation issues, such as information silos, isolated stakeholders, and decentralized on-site labor, due to the slow adoption of digitization (Kor et al., 2022; Lee et al., 2021; Rampini & Re Cecconi, 2022; Teisserenc & Sepasgozar, 2022; Zhao & Taib, 2022). Nonetheless, the advent of various technologies is reshaping the execution of construction projects. One notable technology in this regard is Building Information Modelling (BIM), which has improved collaboration by providing a centralized platform for information sharing, change management, and conflict resolution (Durdyev et al., 2022; Han et al., 2022).

However, it should be noted that BIM has limitations in offering dynamic data of the physical objects and handling large volumes of data (Tuhaise et al., 2023). In contrast, Digital Twin (DT) technology enables dynamic bidirectional data exchange, thereby representing the dynamic status and characteristics of construction sites during the project lifespan (Opoku et al., 2022; Tuhaise et al., 2023). Specifically, this real-time bidirectional data exchange of DT offers significant benefits to the construction industry, including enhanced safety monitoring, improved productivity, reduced costs, and timely decision-making (Malhotra & Mehta, 2022). Therefore, DT has received and is expected to get more attention within the construction sector.

There are multiple definitions of DT across different contexts. In 2003, Michael

Grieves initially defined DT as a virtual model that represents the physical products (Madubuike et al., 2022a). National Aeronautics and Space Administration (NASA) proposed a more comprehensive definition in 2012, which involves integrating multi-physics, multiscale, and probabilistic simulation to create an objective representation using the best available physical models (Angjeliu et al., 2020). Subsequently, to develop a more widely applicable DT concept in other fields, Tao et al. (2019) proposed a DT model with five-dimension, which includes physical objects, virtual representations, connections, data, and services.

Within the construction industry, the definition of DT lacks a universally accepted definition. However, numerous researchers are actively working towards proposing a definition of DT specifically tailored to the construction field (Sacks, Brilakis, et al., 2020). To illustrate, Kor et al. (2021) put forth a definition for DT in construction as a comprehensive engineering model capable of monitoring construction products through multi-site monitoring systems, utilizing data flow and unique capabilities. Similarly, Inrahim Yitman et al. (2021) extended the DT concept to define Construction Digital Twin (CDT) as a system that monitors complex construction procedures based on the DT functions. This includes anomaly detection, and behavioral learning, and predicts the actions and functions of the physical twin.

According to Jiang et al. (2021) and Tao et al. (2019), it is significant for DT to deliver a specific service. In this case, a comprehensive five-level taxonomy to encompass the diverse levels of services that DT can provide is proposed including descriptive, informative, predictive, comprehensive, and autonomous twin (Hertz, 2023; Seaton et al., 2022). In level 1 (descriptive), the DT is a digital representation that, using computer-aided engineering (CAE), incorporates simulation of the physical entities and serves as a descriptive DT for further development. In level 2 (informative), the DT evolves by incorporating predictions from CAE-based simulations and time-series analysis. This level emphasizes the integration of data-driven insights into the DT framework for generating insights.

In level 3 (predictive), the DT encompasses a digital representation that enables the fusion of the sensor data and a comprehensive data model. This integration enables real-time monitoring and analysis, facilitating a more accurate understanding of the asset's behavior. Level 4 (comprehensive) DT represents an advanced stage where sensor data and human knowledge are encoded and integrated within the DT. By leveraging various sources of information, level 4 DT offers enhanced predictive capabilities and a deeper understanding of the performance of the assets. Finally, at level 5 (autonomous), the DT achieves its highest level of sophistication with digital technologies to reduce its reliance on human intervention. In general, the five-level DT complexity concept serves as a guiding paradigm, offering valuable directions for the progressive evolution of DT practice from level 1 (descriptive) to level 5 (autonomous).

1.2 Background

Given the persistent challenges in China's construction industry, such as low productivity, fragmentation, poor industry image, and low predictability (Opoku et al., 2021), DT has garnered significant attention as one of the most potential technologies applicable throughout the entire lifespan of construction projects (Boje et al., 2020). Research focusing on how DT addresses these issues in the construction sector has gained momentum recently (Ozturk, 2021; Ryzhakova et al., 2022; Sacks et al., 2020). Concurrently, the capabilities of DT have evolved alongside the development of enabling technologies like Artificial Intelligence (AI), machine learning (ML), blockchain, and the Internet of Things (IoT) (Opoku et al., 2022). For instance, Zhao et al. (2022) proposed that integrating DT with ML algorithms offers a viable approach to predicting building status during the Operation and Maintenance (O&M) phase. Opoku et al. (2021) also emphasized that DT has a high potential to transform the construction industry but highlighted the scarcity of practical implementations. Specifically, DT is potentially capable of delivering significant opportunities to the construction industry, including improved visualization, enhanced collaboration, cost reduction, increased safety, enhanced quality control, and accelerated construction process (Madubuike et al., 2022b; Radzi et al., 2019; Visartsakul & Damrianant, 2023). Therefore, as supposed by Ammar et al. (2022), further improvement and broad adoption of DT within China's construction industry are crucial.

1.3 Problem Statement

Although DT is a promising technology offering numerous benefits to the construction industry, its application in this field brings inherent risks because of the complexity of the construction projects (Madubuike et al., 2022b; Pham et al., 2023). The risks of implementing DT throughout the lifespan of construction projects are expected to be interconnected (Lei et al., 2023), for example, the seamless data integration in DTs from various sources could also lead to inconsistencies and inaccuracies that affect decision-making. Also, for instance, the ability to modify DT models in response to the dynamic information can introduce variability in project planning and execution, potentially leading to discrepancies between the digital visualization and its physical correspondence. Therefore, the flexible functions of DT notably amplify uncertainty during its practical implementation. Moreover, construction projects are prone to long lifespans, complex sites, multiple stakeholders, and numerous engineering risks (Alaloul et al., 2020).

Furthermore, once risks are identified, they should undergo an assessment (Tabatabaee, et al., 2022). Proactive risk assessment aids construction project managers in gaining a deeper understanding of the risks, facilitating the successful adoption of DT technology. On one hand, risk assessment can effectively alleviate the threats in the practice of DT in the construction industry. On the other hand, risk assessment allows industry professionals to take advantage of DT to its full potential, thus maximizing the opportunities associated with DT. Given various risks, inappropriate risk assessment may lead to many negative outcomes or even project failure – consequences that would trigger a series of problems like cost overruns, prolonged timelines, and compromised quality and safety standards (Sunil et al., 2017).

Currently, there is lack of studies comprehensively exploring the risks related to DT practice in the construction industry. Hence, a deficiency in awareness among construction practitioners regarding the existence and importance of risks in DT implementation leads to reduced effectiveness in achieving objectives within construction projects. At the same time, in China, construction companies lack dedicated risk management teams, and risk assessment is always absent in construction projects(Leung et al., 2024). Therefore, RAM is required in China's construction industry.

Three gaps exist in the literature that this research tends to fill are: (1) there is a lack of a comprehensive study, to the best of the author's knowledge (Wang et al., 2024), that has examined the risks—both opportunities and threats—involved in adopting DT in the construction industry. (2) risk factors (RFs) are interrelated, while there is no study focused on the priority of risks in implementing DT considering both the interrelations and their intensity among the risk factors. (3) There is no RAM capable of evaluating the risks of DT practice within China's construction industry. In this case, it is quite necessary to construct a RAM that can identify and assess the risks of the practice of DT to enhance the probability of implementing DT in the construction industry successfully.

1.4 Research Questions

To fill the abovementioned gaps and address the stated problem, the main research questions are put forward:

1: What are the risks related to DT implementation in China's construction industry?

2: What are the most critical risks related to the practice of DT in China's construction industry?

3: Given the interrelations among risks, how can practitioners effectively assess such risks in their real-life projects?

4: Is the developed RAM for DT implementation valid and practical in China's construction industry?

1.5 Research Aim and Objectives

The aim of this research is to provide a holistic understanding and a practical approach for the assessment of the risks related to DT practice in the China's construction industry and to develop a RAM for evaluating the risks of implementing DT. To achieve the aim of this research, subsequent objectives have been determined:

1. To investigate the risks affecting the implementation of DT in China's construction industry.
2. To identify the most significant risks of implementing DT in China's construction industry.
3. To develop a RAM capable of considering the interdependencies and intensities of

the risks affecting the implementation of DT in China's construction industry.

4. To evaluate the application of the developed RAM in China's construction industry.

1.6 Research Scope

According to the Project Management Institute (PMI), risk management comprises: identify risks, analyze risks, response to risks, and monitor and control risks (PMBOK, 2021). This research specifically targets the risk assessment phase, which is comprised with risk identification and risk analysis, of the PMI risk management approach, aiming at evaluating risks associated with the practice of DT within the Chinese construction industry. Acknowledging the scarcity of DT implementation in the China's construction industry, this study extends beyond traditional building engineering to encompass infrastructure engineering sectors such as bridge engineering and tunnel engineering. This broader scope ensures a more comprehensive data collection, facilitating a more thorough understanding of the risks across various parts of the construction industry (as suggested by Gieskes et al. (2000)). Therefore, not only the RFs, but also the involved experts for this study consist of qualified practitioners from the abovementioned industries. Because DT is an emerging technology, urban centers are more prone to hosting DT-related projects. In this case, the targeted geographical regions are the most developed cities in China, namely Beijing, Shanghai, Shenzhen, and Guangzhou (Yin & Song, 2023). Furthermore, this research specifically concentrates on the implementation risks associated with DT in China's construction projects throughout the whole lifecycle. Notably, the identified risks include both positive (opportunity) and negative (threat) aspects.

1.7 Research Significance

The practice of DT in China's construction industry has a high potential to improve the efficiency of projects in the construction industry. However, the intricacy of the construction projects may lead to numerous risks in the practice of DT. Therefore, the successful implementation of DT in China's construction industry demands a thorough comprehension of the associated risks and the development of an effective RAM. This research holds great significance in addressing the critical need for several aspects. Firstly, through thoroughly identifying and assessing the risks associated with DT implementation, this study fills the existing gap in literature and is able to provide invaluable insights and practical guidance to industry stakeholders. Secondly, by focusing on the identified critical RFs, stakeholders can adopt effective measures to address the specific risks posed by DT practice. Thirdly, the development of a robust RAM capable of considering the interdependencies and intensities of risks associated with DT implementation represents a significant methodological contribution. Therefore, this RAM enhances the accuracy and reliability of risk evaluations in the implementation of DT in China's construction industry. Finally, the evaluation of the developed RAM in China's construction industry provides practical validation of its effectiveness and applicability. The validation not only demonstrates the utility of the proposed model but also offers valuable insights into its implementation in real case, facilitating its adoption by industry practitioners and decision-makers.

1.8 Thesis Outline

The subsequent chapters are structured in the following manner: **Chapter 2** illustrates a comprehensive literature review of construction industry in China, DT's concept and implementation, risk management in the construction industry, and RFs of DT practice in the literature. **Chapter 3** explains the whole framework and core methods of the thesis, including literature review, semi-structured interview, fuzzy Delphi method, a general cybernetic Best-worst method. It also discusses the novelty of the developed G-Cy-BWM risk assessment model. To fulfill research questions, **Chapter 4** shows the results and discussions of the literature review, semi-structured interview, and fuzzy Delphi method. First, it illustrates the identified risk factors from the literature review. Subsequently, the refined critical risk factors using semi-structured interviews and the fuzzy Delphi method are also reported. Also, this chapter illustrates the prioritization of the core RFs using the general cybernetic Best-worst method, which involves the interdependencies and their strength among the RFs. A risk assessment model is developed based on the above methods. **Chapter 5** mainly talks about the conclusions, limitations, implications, and recommendations for the research that could be done in the future.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter provides an in-depth exploration of Digital Twin in the construction industry through comprehensive literature review. Information and Communication Technology (ICT) encompasses technologies that enable access to information via telecommunications (Clutterbuck, 2013). It has rapidly evolved with advancements in communication technologies, such as computer technology, wireless networks, cell phones, and other types of communication (Osterrieder et al., 2020). As a result, ICT has emerged as the main driver for the development of the modern economy, revolutionizing various fields (Du et al., 2020). The construction industry, being an indispensable component of the economy, is no exception to this influence. ICT introduces numerous opportunities for improving the construction process (Lu et al., 2015). DT technology, which can realize dynamic convergence and cyber-physical interoperation, is regarded as one of the key enablers of the ICT revolution (Jiang et al., 2022).

The construction industry, in accordance with the manufacturing industry's exploration of ICT-enabled technologies in Industry 4.0, is also striving to identify and leverage the benefits, known as Construction 4.0 (Schönbeck et al., 2020). It focuses on improving the quality of "digital building" throughout all stages, including planning, design, construction, operation, and maintenance stages (Walter, 2020). By digitizing the entire project management process, virtual reality and real-time interaction can be combined, increasing the efficiency of construction processes and ensuring the quality of building products. To embrace Construction 4.0, construction enterprises must leverage advanced digital technologies to manage key aspects of construction projects, including the construction process, construction site work cooperation, and building lifecycle.

Digital twin (DT), recognized as the fourth wave of technological advancements in Industry 4.0, is recognized as one of the key enablers of the ICT revolution. (Madubuike et al., 2022b; Teisserenc & Sepasgozar, 2021). DT culminates in the development of a digital model that mirrors the physical entity (Liu et al., 2021). The opportunities of digitalization are vast, including improved project management efficiency, enhanced product quality, reduced safety risks at construction sites, and overall progress for the construction industry. However, despite being a key industry in China's economy, the construction industry is often considered outdated due to its technological lag (Forcael et al., 2020; Kor et al., 2022). While the technical systems in construction have improved over the past several industrial revolutions, they still trail behind other industries. This has resulted in a growing technological gap between the construction industry and other fields.

2.2 Digital Twin in the Construction Industry

The construction industry develops sluggishly due to poor digitization (Teisserenc & Sepasgozar, 2021). According to Tahmasebinia et al. (2023), digitization involves data management in digital format using the internet and software. Also, Ammar et al. (2022) proposed that construction projects rely heavily on large volumes of data originating from diverse sources. Therefore, data is crucial for the development of the whole industry. With the emergence of innovative technologies such as IoT, big data analytics, cloud computing, and AI, the concept of data and data-centric decision-making is increasingly prevalent (Qi et al., 2021). Specifically, to make valued decisions, the data quality is significant for decision-makers. Therefore, DT is regarded as a key facilitator for the digital revolution of the construction industry, enhancing the digitization performance of the whole industry (Ammar et al., 2022). Therefore, DT's implementation in the construction industry should be further explored.

2.2.1 Definitions of DT in the Construction Industry

The definition of 'twin' was first mentioned by the National Aeronautics and Space Administration (NASA) in the aerospace industry, specifically during the Apollo project in the 1960s (Negri et al., 2017). NASA developed a model of space vehicles on Earth that could simulate their conditions, essentially serving as replicas of the prototypes (Rosen et al., 2015). Professor Michael Grieves first proposed the term "digital twin" in 2003 within the field of product lifecycle management (Grieves, 2014). In 2012, NASA successfully utilized DT technology to create dynamic models mirroring the real-time status of flying physical twins. These digital twins had access to historical information and data, allowing them to make predictions regarding the health and remaining lifespan of the vehicles (Glaessgen & Stargel, 2012). Siemens applied DT technology in 2016, marking its integration into the development of the manufacturing industry as the rise of Industry 4.0 (Qi et al., 2021). According to Tao et al. (2019), DT has emerged as a core intelligent technology that can achieve smart manufacturing and Industry 4.0. Academic research has also extensively addressed on DT. In 2017, Tao Fei et al. (2017) proposed a 5-dimension Digital twin shop-floor model, building upon the previous 3-dimension DT model. Figure 2.1 below depicts some notable milestones related to DT.

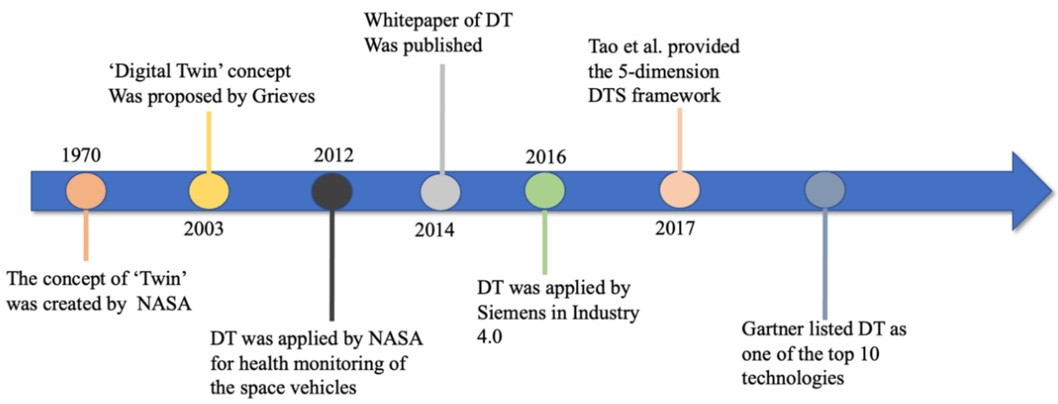

Figure 2.1. Timeline of DT history (designed by the author, adopted from (Qi et al., 2021))

Over the years, numerous definitions of DT have emerged with the continuous evolution of DT-enabling technologies. These technologies encompass various aspects such as sensing, data acquisition, modeling, data management methods, DT services, and data connectivity since the 2000s (Hu et al., 2021; Qi et al., 2021). The initial definition of DT was put forth by Michael Grieves in 2003, describing it as a *"virtual digital representation equivalent to physical products"* (Grieves, 2014). However, the concept of DT did not see significant development until 2012 when NASA proposed a more comprehensive definition (Glaessgen & Stargel, 2012). In general, the definition highlights DT as the integration of multi-physics, multiscale, probabilistic simulation of an as-built object, employing the best available physical models to create its corresponding twin (Angjeliu et al., 2020). This makes DT a popular research topic in the aerospace field. Following NASA's definition, Rios et al. (2015) expanded the concept of DT to encompass other domains. Similarly, Rosen et al. (2015) put forward a definition that DT is the mirroring of physical and virtual objects to assess the behavior of the physical counterpart. During this phase, the definition of DT primarily focused on explaining its purpose and the components involved (Madubuike et al., 2022a).

Thereafter, the definitions of DT were improved in the manufacturing industry. Boschert & Rosen (2016) proposed a more concise definition, stating that DT encompasses all useful data related to a physical product. However, this definition lacked comprehensiveness as it did not address the purpose and components of DT. In 2017, Grieves and Vickers provided a more detailed definition, considering DT as a system of digital information that represents a physical product. It can be seen as the virtual counterpart of the manufactured object. This definition emphasizes how DT enables researchers to gain a better understanding of their designs and enhances control over end-product quality (Grieves & Vickers, 2016). Although this definition is more specific to the product lifecycle management industry, it offers great detail. Zhuang et al. (2018) defined DT within the field of smart manufacturing. They described it as a virtual model in the virtual world that accurately maps its corresponding physical counterpart and dynamically changes along with it in every aspect. In product design engineering, Tao et al. (2019) defined DT as a complete correspondence between physical objects and their digital representations, incorporating physical, virtual, and interactive data between them.

The concept of DT is ill-defined in the AEC industry, lacking a universal definition (Sacks, Brilakis, et al., 2020). However, several researchers have made efforts to propose comprehensive definitions of DT specifically tailored to the construction industry. Madni et al. (2019) defined DT as a virtual model of its physical twin that continually evolves throughout its lifecycle to simulate maintenance, performance, and health status. Building upon these concepts, Kor et al. (2021) put forward a definition for DT in construction, characterizing it as a comprehensive engineering model that utilizes multi-site monitoring systems, data flow, and unique capabilities to monitor construction projects. Similarly, Alizadehsalehi & Yitmen (2021) extended the

DT concept to a Construction Digital Twin, which encompasses real-time monitoring, anomaly detection, behavioral learning, and the ability to predict the actions and functions of the physical twin. These definitions primarily address the real-time monitoring function of DT, which is particularly relevant for predictive maintenance in construction projects. Notably, there is no general definition of DT applicable to all industries since each industry has its own specific purposes and requirements when utilizing DT technology. Table 2.1 illustrates several significant DT definitions within the construction industry.

Table 2.1. Main concepts of DT within construction industry

Reference	Definitions	Applied field
Madni et al. (2019)	A virtual instance of its physical corresponding, and it is continually changing during its lifecycle to simulate the physical one in maintenance, performance, and health status	Construction
Kor et al. (2022)	A comprehensive engineering model that can monitor the construction product from multi-site-monitoring systems with the help of data flow and unique abilities	Construction
Yitmen et al. (2021)	Construction digital twin (CDT) is the evolution of the DT concept, and it is able to monitor complicated construction procedures based on the basic functions of DT. A CDT is not only a DT, it also has the ability to conduct anomaly detection and behavioral learning. Most importantly, it can predict the actions and functions of the physical twin	Construction
Sacks et al. (2020)	An innovative approach to managing construction products. It utilizes data streams from diverse monitoring technologies and employs AI to deliver precise information. This enables proactive analysis and optimization of continuous processes related to design, planning, and production.	Construction
Sepasgozar (2021)	Current definitions of DTs emphasize: (1) the necessity for precise digital representations that encompass the geometric features and attributes of physical objects, (2) DTs should also incorporate the logic and rules dictating the behavior of these physical entities, (3) DTs are anticipated to encode data, encompassing historical records, current states, and predictions related to the corresponding physical entities.	Construction
Jasiński et al. (2023)	A concept applied across various fields, defined by the development of a virtual copy for an existing object. This virtual representation is typically based on a digital model and enables dynamic monitoring of the real-world counterpart.	Civil and Bridge Engineering
Britain (2022)	Lifelike digital representations of physical assets, serving the purpose of monitoring and forecasting performance, providing valuable insights, and facilitating interventions.	Built Environment
Boje et al. (2020)	The conception of DT is developed based on BIM, enhanced by incorporating sensing capabilities, big data, and IoT from site to building operation	Buildings and Infrastructure
Jiang et al. (2021)	Characterized by virtual representations mirroring their physical counterparts. Data transfer between the physical and	Civil Engineering

	virtual worlds is necessary.	
Naderi & Shojaei (2023a)	A virtual replica of a physical asset with bidirectional data flow.	Infrastructure

In summary, from the definitions of DT in Table 2.1, DT establishes a twin relationship between the virtual and physical worlds, characterized by its capacity for dynamic bidirectional data exchange (Jiang et al., 2021; Opoku et al., 2022). DT is capable of creating digital representations that can be regularly updated using multiple data sources, enabling predictions, optimization, monitoring, and improved decision-making (Opoku et al., 2023). Based on the literature, this study proposed a definition of DT tailored to the construction industry: *A digital twin is a digital replica that simulates and mirrors real-world entities or processes in a virtual environment. This virtual representation is synchronized in real-time to maintain alignment with its physical counterpart, capturing a high level of fidelity to enable comprehensive analysis, monitoring, and optimization.* Notably, the real-world entities could be both entities (e.g., construction equipment and products, workers, construction sites, and assets) and processes (e.g., design, construction, operation & management, and demolition) in the construction projects. Virtual representation is a digital duplicate of construction objects and processes, which includes various linked digital assets (e.g., digital models, images, documents, and videos) and supporting data (Seaton et al., 2022). Synchronization, which enables the status of the DTs to be consistent with their physical counterparts (McKee, 2023), is a key element that differentiates a digital twin from other digital models. At the same time, synchronization is affected by both frequency and fidelity, which determines the timing of updates and precision of the virtual representation, respectively.

2.2.2 Digital Twin Maturity Model in the Construction Industry

Several DT maturity models have been proposed in different domains. In the manufacturing industry, Kritzinger et al. (2018) outlined three hierarchical tiers of DTs based on the degree of data integration: digital model, digital shadow, and digital twin. Building upon this framework, Liu et al. (2024) introduced two additional levels: Cognitive DT and Federated DT. Another model specific to manufacturing was developed by Hu et al. (2023), including Basic, Connection, Integration, Perception, Interaction, and Autonomy. In the field of systems engineering, Madni et al. (2019) proposed a 4-level model based on the sophistication of the virtual model: Pre-digital Digital Twin, Digital twin, Adaptive Digital Twin, and Intelligent Digital Twin. Similarly, Kumar et al. (2022) proposed a more comprehensive model including Digital model, Digital twin, Adaptive digital twin, Technical and functional DT, and Autonomous DT. In the Aerospace area, Medina et al. (2021) introduced a 4-level maturity model comprising Monitoring, Diagnostic, Prediction, and Prescription.

In the construction industry, there are also several maturity models have been developed. ARUP (2019) proposed a 5-level evolution model based on four metrics: autonomy, intelligence, learning, and fidelity, which are expected to increase as the DT progresses. According to the characteristics of each level, the five levels are named: Linked, Feedback & Control, Predictive & Analytic, Learning, and Autonomous. Chen et al. (2021) developed their 6-level model grounded in asset management maturity stages: Unaware, Identifiable, Aware, Communicative, Interactive, Instructive & Intelligent. Furthermore, models by Boje et al. (2020) and Naderi et al. (2023b) emphasize technical advancements, while some models focus on functional completeness. For instance, Wagg et al. (2020) proposed a 5-level model for asset management: Supervisory, Operational, Simulation, Intelligent, and Autonomous

Management. Similarly, Autodesk (2021) introduced a tailored 5-level model for the Architecture, Engineering, and Construction (AEC) industry: Descriptive twin, Informative twin, Predictive twin, Comprehensive twin, and Autonomous twin, which was also adopted by Seaton et al. (2022). The different DT maturity models are listed in Table 2.2.

Table 2.2. Digital twin maturity model in the literature.

Domain	Reference	Levels	Name of the Levels
General	Liu et al. (2024)	0~4	Digital model, Digital shadow, Digital twin, Cognitive DT, Federated DT
	Kumar et al. (2022)	1~5	Digital model, Digital twin, Adaptive digital twin, Technical and functional DT, Autonomous DT
Manufacturing	Hu et al. (2023)	1~6	Basic, Connection, Integration, Perception, Interaction, Autonomy
	Kritzinger et al. (2018)	1~3	Digital model, Digital shadow, Digital twin
Systems engineering	Madni et al. (2019)	1~4	Pre-digital twin, Digital Twin, Adaptive Digital Twin, Intelligent Digital Twin
Aerospace	Medina et al. (2021)	1~4	Monitoring, Diagnostic, Prediction, Prescription
Construction	ARUP (2019)	1~5	Linked, Feedback and Control, Predictive and Analytic, Learning and Autonomous
	Wagg et al. (2020)	1~5	Supervisory, Operational, Simulation, Intelligent, Autonomous management
	Boje et al. (2020)	1~3	Monitoring Platform, Intelligent Semantic Platform, Agent-driven socio-technical platform
	Autodesk (2021)	1~5	Descriptive twin, Informative twin, Predictive twin, Comprehensive twin, Autonomous twin
	Seaton et al. (2022)	1~5	Descriptive twin, Informative twin, Predictive twin, Comprehensive twin, Autonomous twin
	Chen et al. (2021)	1~6	Unaware, Identifiable, Aware, Communicative, Interactive, Instructive and Intelligent
	Naderi et al. (2023b)	0~4	BIM, Digital twin, enhanced DT, Metaverse

Given the relevance and comprehensiveness of the 5-level model proposed by Autodesk (Autodesk, 2021) and Seaton *et al.* (Seaton et al., 2022) as shown in Figure. 2.2, it is adopted in this review paper. At the Descriptive level (level 1), DTs represent the digital model connected to real-world systems but lack intelligence, learning, and autonomy (Ghorbani et al., 2024). While the Informative level (level 2) involves converting data into actionable information. This is achieved with computer vision techniques, which are supported by deep learning technologies (Pan & Zhang, 2021b). The Predictive level (level 3) employs operational data for prediction. Specifically, with artificial intelligence (AI)-based technologies (e.g., process mining), DTs can utilize large volumes of data to make valuable analytics and predictions (Pan & Zhang, 2021b; van der Aalst, 2016). In the Comprehensive level (level 4), DTs learn from diverse data sources within the surrounding environment, and it is able to conduct real-time analytics through what-if simulations. By utilizing AI techniques such as machine learning, DTs can analyze historical data and real-time information to simulate various scenarios. Finally, at the Autonomous level (level 5), with the help of AI, DTs can learn and minimize reliance on human inventions through automatic analytics and decision-making. Obviously, AI and AI-based technologies play a significant role throughout the DT levels.

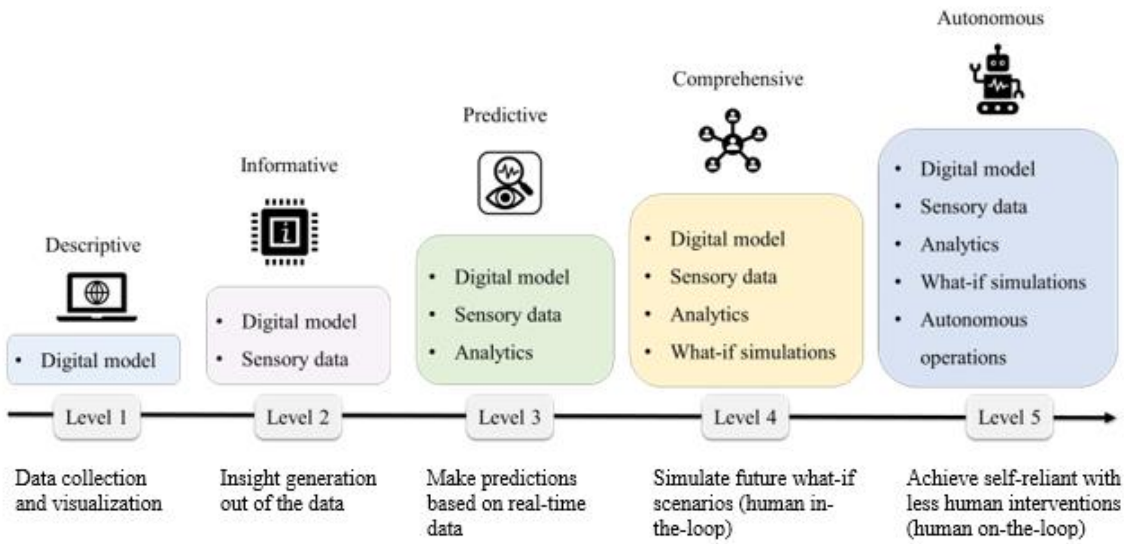

Figure 2.2. DT maturity model (adopted from (Autodesk, 2021; Seaton et al., 2022)).

2.2.3 Review Articles of Digital Twin Applications within the Construction Sector

In this section, a comprehensive literature review is conducted to explore the conceptions and applications of DT. During this process, the potential risk factors (RFs) are also extracted from the literature. This section aims to provide a thorough overview of the previous *literature reviews* pertaining to the practice of DT in the construction industry and a total of 45 published reviews within the last decade are explored. The reviews can be categorized into four clusters based on their scope, including exploration of DT enabling technologies (e.g., AR, AI, and IoT), differentiation of DT from other similar concepts (e.g., digital shadow, BIM, and Cyber-Physical Systems, identification of barriers or challenges associated with DT adoption, and investigation of DT's applications in the construction industry (e.g., sustainability, fault detection, and monitoring). The cluster distribution is illustrated in Figure 2.3.

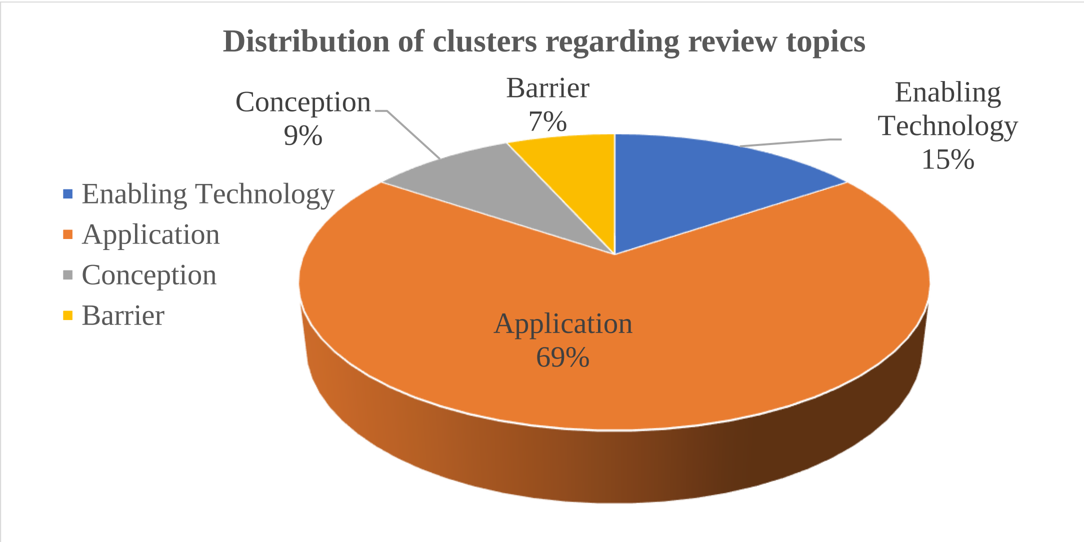

Figure 2.3. Distribution of clusters regarding review topics

In terms of DT enabling technologies, Tuhaise, et al. (2023) conducted a systematic review using demonstrative case studies to identify the emerging key enabling technologies for DT implementation in the literature, such as IoT sensors, vision and component-based sensing devices. They (*ibid*) highlighted research gaps in area such as data transmission, data processing, and visualization. These areas also represent the future directions for technological development. Similarly, Hosamo et al.

(2022) systematically reviewed the development and practice of DT technologies in construction. They (*ibid*) identified four technological drivers for digitization: big data, IoT, and cloud-based access. In a review conducted by Naderi & Shojaei (2023a), 85 studies related to infrastructure DT between 2012 and 2022 were analyzed. The authors (*ibid*) categorized DT technologies into three groups: information model technologies, data acquisition technologies, and data processing technologies.

Moreover, Deng et al. (2021) conducted a comprehensive review to investigate the current state of DT technologies in built environment applications. Baghalzadeh et al. (2022) concluded that DT, BIM, and IoT are trending technologies across various fields within the construction industry based on their analysis. Sadri et al. (2023) examined 86 academic articles to investigate DT-enabling technologies, challenges, scope, and integration possibilities. Their findings revealed the potential benefits of integrating technologies (e.g., blockchain and IoT) in addressing implementation challenges individually. Opoku et al. (2021) adopted a systematic literature review method to comprehensively explores the concept, technologies, and applications of DT in construction industry. They (*ibid*) highlighted that DT can be applied throughout all stages of a construction project's lifecycle. Although plenty of advanced DT-enabling technologies have been recognized by researchers, considerable knowledge gaps remain to be addressed. Resolving these gaps is imperative to enhance the capabilities, reliability and applicability of DT in real-world scenarios (Deng et al., 2021).

In terms of DT definitions and concepts, Boje et al. (2020) reviewed numerous applications of BIM in the construction industry as a foundation for developing the concept of construction DT. They (*ibid*) highlighted that the benefits of DT extend beyond real-time data to include profound impacts such as economic and sustainable benefits for smart construction. In distinguishing the DT concept from digital shadow, Sepasgozar (2021) emphasized that DT not only provides a digital representation but also facilitates bidirectional data flow and real-time self-management. Radzi et al. (2023) analyzed 54 studies and identified four different DT-BIM relationships: BIM is a part of DT, DT is a part of BIM, BIM is equivalent to DT, and no connection between the two. They also found that the previous research on DT and BIM focuses on areas of planning, design, construction, O&M, and decommissioning. For different purposes, Jiang et al. (2021) distinguish DT from BIM and CPS based on the physical and digital aspects, connections, and twin relationships. Mêda et al. (2021) conducted a review to enhance our understanding of DT and concluded that digital data templates and digital building logbooks are key factors for the development of digital twin construction (DTC), which was proposed by Sacks et al. (2020), within the construction process.

In terms of DT implementation barriers and challenges, Opoku et al. (2023) identified the barriers to DT implementation in construction. Similarly, Lei et al. (2023) identify the challenges related to urban DTs through a systematic review and an expert survey. Consequently, they identified nine non-technical and 14 technical challenges, and the most significant challenges were interoperability and practice value. In the context of sustainable structural design, Zhang et al. (2020) reviewed current research to explore the implementation of DT. They also provided suggestions for future improvements based on their findings. Farouk et al. (2023) identified and categorized 45 barriers into six groups, determining that the most significant obstacles to DT are related to "performance" and "security". In general, researchers aim to make DT more adaptable and practical to construction industry by addressing these barriers.

In terms of DT's application, most of the review articles have examined the application of DT in asset management (AM) and facility management (FM). For instance, Xie et al. (2023) conducted a review using clustering, knowledge mapping, and network analysis methods. They (*ibid*) generated a knowledge map that depicted three stages of construction DT for AM and fault prediction. Similarly, Hosamo et al. (2022) employed qualitative research methods to explore DT's capabilities in fault detection. They (*ibid*) concluded that DT requires further development in scanner hardware and software, prediction and detection algorithms, and modeling to achieve effective fault detection and prediction. Zhong et al. (2023) proposed a predictive maintenance method based on DT, which offers three key advantages: real-time perception, high-fidelity models, and accurate simulation predictions. Arisekola & Madson (2023) utilized social network analysis to examine DT's application in assessment management. Their findings revealed that topics real-time data and decision-making were important topics in the literature.

Furthermore, Saback et al. (2022) took a systematic approach to review DT's application in asset management, and several gaps were addressed, including a lack of unified DT definition, complex data flow, and software compatibility for DT development. Coupry et al. (2021) highlighted the potential utilization of DT in conjunction with extended reality technologies to improve maintenance operations in smart buildings. Hakimi et al. (2023) reviewed 248 documents related to DT in FM, and concluded that the current literature focuses on BIM-based FM, AI-based predictive maintenance, dynamic cyber-physical system data integration, and lifecycle FM. Meanwhile, Hou et al. (2023) investigated DT's application in heritage facilities management and found that DT could support decision-making, monitor and predict performance, design maintenance strategies, and evaluate and manage energy in heritage facilities.

Several studies have highlighted DT's potential through the lifespan of construction projects. In a study by Visartsakul and Damrianant (2023), DT is shown to have applications in various stages of construction. Another systematic review conducted by Khallaf et al. (2022) analyzed the applications of DTs in construction through content analysis. They categorized the applications into nine areas: lifecycle analysis, FM, energy, education, disaster, structural health monitoring(SHM), smart cities, infrastructure management, and miscellaneous purposes.

Furthermore, Hu et al. (2022) reviewed 182 papers on DT in construction and proposed six key applications. The study concluded that the majority of literature focuses on improving the method, milieu, and measurement aspects of construction processes, while the machine, manpower, and material parts receive less emphasis. Through a comprehensive bibliometric analysis on 77 articles about DT application in the AEC-FM industry, Deng et al. (2021) drew a conclusion that information standardization is the most significant obstacle that hindering the application of DT in the construction sector. In general, the dynamic data flow enables a DT to mirror physical entities by consistently adapting to operational changes and alterations predicated on informational inputs and online data aggregation (Tuhaise et al., 2023). Consequently, this empowers the lifecycle management and predictive capabilities of DT within construction projects.

DT has shown potential to enhance the sustainability of buildings. Sepasgozar et al. (2021) highlighted the combination of BIM and IoT as a means to achieve sustainable construction. Megahed & Hassan (2022) emphasized its contribution towards sustainable development goals. In the energy efficiency field, Bortolini et al. (2022) conducted a comprehensive review of DT's application in buildings, categorizing the literature into four areas: design optimization, occupants' comfort, building operation and maintenance, and energy consumption simulation. Furthermore,