

An investigation for integration of deep learning and digital twins towards Construction 4.0

Construction
4.0

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Received 26 August 2021
Revised 15 November 2021
20 December 2021
Accepted 20 December 2021

Abstract

Purpose – The purpose of this paper is to investigate the potential integration of deep learning (DL) and digital twins (DT), referred to as (DDT), to facilitate Construction 4.0 through an exploratory analysis.

Design/methodology/approach – A mixed approach involving qualitative and quantitative analysis was applied to collect data from global industry experts via interviews, focus groups and a questionnaire survey, with an emphasis on the practicality and interoperability of DDT with decision-support capabilities for process optimization.

Findings – Based on the analysis of results, a conceptual model of the framework has been developed. The research findings validate that DL integrated DT model facilitating Construction 4.0 will incorporate cognitive abilities to detect complex and unpredictable actions and reasoning about dynamic process optimization strategies to support decision-making.

Practical implications – The DL integrated DT model will establish an interoperable functionality and develop typologies of models described for autonomous real-time interpretation and decision-making support of complex building systems development based on cognitive capabilities of DT.

Originality/value – The research explores how the technologies work collaboratively to integrate data from different environments in real-time through the interplay of the optimization and simulation during planning and construction. The framework model is a step for the next level of DT involving process automation and control towards Construction 4.0 to be implemented for different phases of the project lifecycle (design-planning-construction).

Keywords Digital twins, Deep learning, Artificial intelligence, Internet of things, Simulation, Optimization, Construction 4.0

Paper type Research paper

1. Introduction

The architecture, engineering and construction (AEC) sector is notorious for its resource planning, risk management and logistic issues, which frequently lead to design flaws, project delays, cost overruns and contractual conflicts. Building information modeling (BIM) has been used to increase the efficiency of the construction process, eliminate waste during construction and enhance the quality of AEC projects throughout the last several decades. BIM enables the

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It is the authors' pleasure to express gratitude to all participants, including all design managers, design coordinators, project managers, construction managers, digitalization specialists, BIM manager, BIM coordinator, product manager and platform developer for their contributions to and participation in this research.



early identification and correction of possible issues before they reach the construction site. BIM is beneficial but insufficient, and the AEC sector needs something more substantial (Bakhshi *et al.*, 2022; Rahimian *et al.*, 2021). The existing constraints have prompted research into the use of powerful machine learning (ML) techniques, such as deep learning (DL), to diagnose and predict causes and preventive measures. Over the last few years, the AEC industry has demonstrated an unprecedented level of resiliency. Because of their willingness to take advantage of and adapt to new technologies, enterprises who embrace the latest technology, particularly during the pandemic phase, will place themselves ahead of the competition (Cardno, 2020; Wang *et al.*, 2021). Companies have been encouraged in recent years to adapt to new technologies, techniques, procedures and ways of working to maintain or improve the performance of their projects. As a result of the present epidemic forcing AEC businesses to plan, design, monitor and manage their projects remotely, the transition to digital transformation has been more rapid than most had anticipated (Alizadehsalehi *et al.*, 2020).

Industry 4.0 is a concept that refers to the current trend of technology automation and data exchange, which includes cyber-physical systems (CPSs), the Internet of things (IoT), cloud computing, cognitive computing and developing smart businesses in the AEC industry (Sawhney *et al.*, 2020). In this environment, construction engineering and management are constantly evolving toward digitalization and more intelligent systems to achieve significant automation, productivity and dependability (Pan and Zhang, 2021b; Rahimian *et al.*, 2019). CPSs are defined as systems that work by using various sensors to understand physical components, automatically transferring captured data to cyber components, analyzing the data, and then converting the data into required information via cyber processes that can be used to make required decisions and actions. Intelligent building systems are one of the examples of CPSs. The physical resources in such a system are components and elements of the building and air conditions, and data are received through sensors of these resources, which make up the cyber part of the system. Data used to monitor and control physical resources are frequently transmitted across a communication channel. On the cyber side, calculations are performed to optimal resource use, and a suitable decision is made, based on which physical resources are further managed. CPS, which consists of networked and integrated smart technology, can revolutionize the AEC industry and aid in the development of Construction 4.0. Construction projects that are planned, managed, developed and connected to other autonomous systems are expected to benefit greatly from CPS applications (Yitmen and Alizadehsalehi, 2021a). Currently, design, construction and operation processes are increasingly affected by technologies including value-added monitoring of sensor network data, data management in secure and resilient storage systems based on semantic models, and engineering system simulation and optimization (Boje *et al.*, 2020).

CPS describes how multiple physical systems might work together to incorporate sensors, communication, processing and control in a large-scale cyberinfrastructure. Digital twin (DT) construction, on the other hand, is a new engineering model for controlling construction production that uses data streaming and unique capabilities from multiple site-monitoring systems (Sacks *et al.*, 2020). In the AEC sector, a DT performs artificially intelligent tasks such as providing correct status information, proactively analyzing and optimizing ongoing design and planning, and developing new services to maximize its value. Researchers in the AEC industry have made tremendous advances and significant progress in order to keep pace with the rate at which DL is being applied (Galanos and Chronis, 2021; Hou *et al.*, 2021a; Ma *et al.*, 2020; Zhong *et al.*, 2020b). The adoption of DLs in the AEC industry has been aided by the rapid growth of graphics processing unit (GPU)-accelerated computation techniques and structured and labeled data availability (Akinosho *et al.*, 2020).

With current enabling technologies and cutting-edge applications and implementations of DT in the AEC industry, there are still various significant knowledge gaps that must be addressed through continuing study to make DT more capable, dependable and practical in

real-world applications (Alizadehsalehi and Yitmen, 2021; Yitmen and Alizadehsalehi, 2021b). The cost of having technologies, software and hardware, as well as acquiring and training expert workers, are some of these problems. Others include a lack of completely automated systems, codes, computation, storage, network bandwidth, and a lack of regulations, policies, security and procedures (Alizadehsalehi and Yitmen, 2021). Despite mature IoT techniques, data loss during the transfer process (“Process” might imply as (1) the data are not received by the target recipient, (2) the data are not being sent from the sender or (3) the data are being received but the recipient’s processor trims the data, and the recipient chooses not to store all the received data) is still a problem due to various reasons such as software incompatibility and data fading (the gradual degradation of the bits on storage media that are not in constant use). The current simulation methodologies for the built environment are generally not correlated with the real-time environmental data (ur Rehman *et al.*, 2019; Wang *et al.*, 2020). Not only does the next generation of DT allows real-time visualization and prediction to aid decision-making, but it also provides autonomous feedback and management of the built environment (Deng *et al.*, 2021).

Following up on previous research, there is still a lack of knowledge about the true potential impact of DT integration, DL and IoT, which are all connected to self-learning hybrid models with proactive cognitive capabilities for smart planning, design and construction. In this research, the goal is to investigate the potential integration of DT and DL (DDT) to facilitate smart planning and construction by performing an explorative analysis in order to discover and close this gap. In alignment with the study’s purpose, mainly three research questions are posed:

- RQ1. What constitutes technically justifiable (components, characteristics and requirements) for a digital platform integrating DT and DL to facilitate smart planning and construction?
- RQ2. How can capacity be developed in order to seize opportunities and overcome constraints on implementing DL integrated DT applications to simulate and optimize planning and construction processes autonomously and collaboratively?
- RQ3. How can this DDT become successful in addressing the potential values to be created for construction companies, engineering consulting firms, facility operators, real estate agents and owners (clients) when utilizing such a DT model?

The main contribution to the knowledge domain is an insight into the DL integrated DT model that will establish an interoperable functionality and develop typologies of models described for autonomous real-time interpretation and decision-making support for complex building systems development, based on the cognitive capabilities of DT. Section 2 of this article begins with a review of prior work on the concepts of Construction 4.0, DT, DL and IoT in the AEC industry, as illustrated in Figure 1. The applied research method, which includes a hybrid approach of quantitative and qualitative assessments, is discussed in Section three. The observations and analysis of the data are presented in Section 4. Decision support capabilities, integrability enablement and practical consequences are discussed in Section 5. Finally, this article presents conclusions, recommendations and future directions for DT/DL integration in various construction management sectors in Section six.

2. Literature review

This section outlines the key-related works in five main areas relevant to this paper: (1) Construction 4.0; (2) DT in AEC industry; (3) DL; (4) IoT and (5) process optimization.

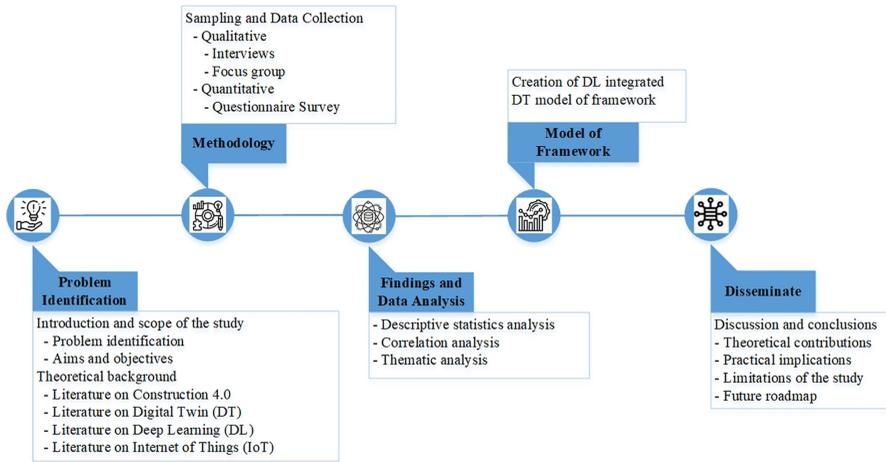


Figure 1. Research framework

2.1 Construction 4.0

Construction 4.0 is the construction industry's equivalent of Industry 4.0, and it is the process of deploying CPSs to encourage the digitization of the construction industry to achieve maximum performance. To promote maximum project performance, Construction 4.0 incorporates technology that supports smart construction sites, simulation and virtualization. Prefabrication, 3D printing, automation, extended reality (XR), unmanned aerial vehicles (UAVs), various types of sensors, robots and big data utilized to improve real-time decision-making processes are just a few examples. Construction 4.0 is primarily divided into three scenarios:

Physical domain/automation, which refers to digital end-to-end engineering integration and technologies for the automation of the physical construction environment.

- (1) Simulations and modeling, which refers to modeling and simulation tools for the design, construction and operation of buildings and infrastructures
- (2) Digitalization, which refers to digital end-to-end engineering integration and technologies for the automation of the physical construction environment.

Construction 4.0 will allow firms to increase productivity, reduce project delays and costs, manage complexity, and improve safety, quality and resource economy (Craveiroa *et al.*, 2019).

AEC projects are increasingly becoming more attractive, energy-efficient, comfortable, affordable, safe and sustainable as innovative technology and materials are developed. Construction has reached a new era, recent advancements in materials and cutting-edge technologies (such as AI, robotics, nanotechnology, 3D printing and biotech) (Qi *et al.*, 2018). The opportunities afforded by big data and the IoT, as well as technological advancements driving down the cost of sensors, data storage and computer services are causing massive shifts.

Advanced technology, tools and materials for the digital transformation of the construction industry provides a comprehensive overview of developments in materials, emerging trends, cutting-edge technologies, and strategies in the fields of smart building design, construction and operation, providing the reader with a comprehensive guideline on how to take advantage of the new opportunities provided by the digital transformation. All of these factors, as indicated in Figure 2, contribute to the development of Construction 4.0.

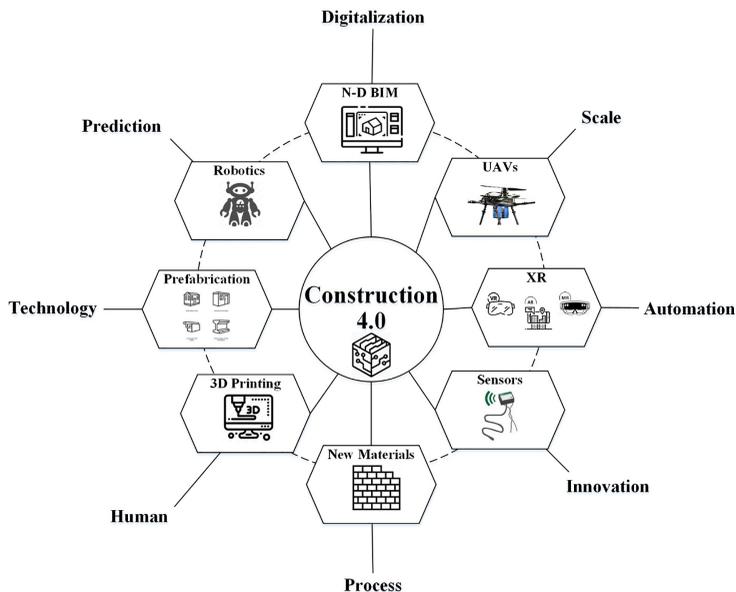


Figure 2.
Different aspects of
Construction 4.0

2.2 Digital twin (DT)

The CPS for visualization, modeling, simulation, analysis, prediction and optimization is realized in DT (Tao *et al.*, 2019; Yitmen *et al.*, 2021). A practical loop comprises three primary components: a physical entity, a virtual entity and a data link. In the DT, there are commonly two approaches for dynamic mapping. Inspection data are collected in the actual world and then transferred to the simulated environment for further assessment (Aheleroff *et al.*, 2021; Dawood *et al.*, 2020; Pan and Zhang, 2021a; Qi *et al.*, 2018). The virtual model runs simulations to obtain optimum predictions, allowing it to provide quick solutions that adapt natural processes to changing conditions (Pan and Zhang, 2021b). DT combines real-time and historical data from physics-based models, physical systems and advanced analytics to produce digital equivalents with high integrity, awareness and adaptability, allowing planning and construction entities to receive predictive services. It facilitates real-time monitoring, simulation, optimization and control of CPSs. In order to provide on-demand prediction services to users in the physical and virtual worlds, DT-based CPS must continuously acquire, integrate, analyze, simulate and synchronize data. Ubiquitous connection and smart objects, enhanced analytics, cooperative decision-making, autonomous and rapid model construction and updates, and autonomous disturbance handling and resilience control are the major characteristics and requirements for DT integration in CPS (Lee *et al.*, 2020). Deng *et al.* (2021) created a five-level ladder taxonomy to capture the transition from BIM to DT. BIM Level 1, BIM Level 2, supported simulations, BIM Level 3 integrated with IoT, BIM Level 4 integrated with AI approaches for forecasts and level 5—optimal DT are the levels. Each level of the ladder taxonomy was separated into several sub-categories focused on separate research fields assigned to the design, construction, operation and demolition phases based on the building life cycle (Yitmen *et al.*, 2021). As a result, BIM Level 4+AI exemplifies the use of BIM and AI techniques to improve decision-making and database predictions, while level 5 ideal DTs exemplifies interaction and optimization (Deng *et al.*, 2021).

To discover discrepancies to create and describe “Digital twin construction (CDT),” [Boje et al. \(2020\)](#) analyzed BIM literature on construction applications and examined DT uses in adjacent fields. They proposed that a CDT can be developed over three generations. The first generation is represented as an up-to-date version of BIM on construction sites; the second generation includes semantics, defining CDTs as “enhanced restricted intelligence monitoring platforms where a common web-language system is deployed to represent the DT with all its integrated IoT devices, thus forming a knowledge base”; and the third generation, “To build a self-reliant, self-updatable, and self-learning DT, ML, DL, data mining and analysis capabilities are required.” [Rausch et al. \(2020\)](#) show how computational methods may aid in the production of DTs, and how these workflows can be utilized to find optimum and heuristic solutions to difficult situations. [Table 1](#) shows a variety of DT applications based on the most recent research.

2.3 Deep learning (DL)

DL is a subset of ML, which is a subset of artificial intelligence (AI) that uses neural networks to learn unsupervised from unstructured or unlabeled data. AI is a technique that allows a machine to replicate human behavior ([Liu et al., 2021](#); [Wu et al., 2019](#)). ML is a method of achieving AI through data-driven algorithms with a key role in making construction “smart” ([Feng and Chen, 2021](#); [Xu et al., 2021](#)). Finally, DL is a sort of ML that is inspired by the structure of the human brain, and this structure is referred to as an artificial neural network in DL ([Xiao and Kang, 2021](#)). DL algorithms can be used to teach systems how to think like a human brain ([Yitmen and Alizadehsalehi, 2021a](#)). DL is part of a larger family of ML approaches that can take raw data and automatically generate the representations needed for tasks like classification, regression, clustering and pattern recognition. In high-dimensional data, DL is extremely effective in detecting complicated structures. It allows for higher levels of abstraction without the need for time-consuming feature engineering, and it performs well in a wide range of applications. However, with the exception of some image classification and language processing tools, feature engineering is almost always required in ML projects. Even with DL, there are limitations ([Lee et al., 2020](#)). DL has a wide range of applications, particularly in the AEC in areas like site planning and management ([Abdelkader, 2021](#)). [Kung et al. \(2021\)](#) suggested a model based on convolutional neural networks (CNNs) for automatic identification and localization of critical construction defects using images (efflorescence, spalling, cracking and defacement). The findings of this study indicate that combining DL and UAV may effectively detect a variety of external wall defects and enhance detection efficiency. In another research, [Ogunseiju et al.](#) investigated the effectiveness of a variation of deep CNNs for recognizing construction worker activities from images of signals from time-series data using large datasets for training and testing DL algorithms ([Ogunseiju et al., 2021](#)). Even though DL is good at handling this type of data, the level of efficiency feasible with the available unlabeled data remains unknown ([Akinosho et al., 2020](#)). Based on the most recent research, [Table 2](#) demonstrates a variety of DL uses.

2.4 Internet of things (IoT)

The International Organization for Standardization (ISO 2018) defines IoT as “an infrastructure of interconnected objects, people, systems and information resources, coupled with intelligent services that allow them to handle and react to information from the real and virtual environment.” As a result, IoT is a hybrid of physical and virtual states that carries physical elements like sensors, actuators, cloud services, communication and protocols with a variety of designs to provide a framework and explanation for IoT systems. The emergence of IoT has been aided by a remarkable expansion in sensor and contemporary communications in recent years. In the construction and industrial sectors, such as

<i>n</i>	References	Year	References
1	Alizadehsalehi and Yitmen (2021)	2021	Develop a generic framework called DRX that can be used for anything from automated construction progress monitoring to extended reality. It is based on DT and can be used for anything
2	Alonso et al. (2019)	2019	SPHERE platform was investigated for its potential to improve the energy performance of buildings
3	Alshammari et al. (2021)	2021	The topic of cybersecurity for DTs in the built environment was presented and investigated
4	Boje et al. (2020)	2020	Examined the many-faceted applications and limitations of BIM, as well as the necessity of construction DT in the construction industry
5	Bosch-Sijtsema et al. (2021)	2021	The applications of digital technologies in the AEC industry were discussed
6	Camposano et al. (2021)	2021	The manner in which AEC/FM practitioners describe DTs of built assets was investigated
7	Cureton and Dunn (2021)	2021	It conducted research on decentralized cities and evasive futures
8	Dawood et al. (2020)	2020	AECO's DT, VR, AR and BIM technologies were reviewed, developed and implemented
9	Del Giudice and Osello (2021)	2021	The development of smart cities was the subject of investigation. DTs serve as the foundation
10	Deng et al. (2021)	2021	It conducted research on the progression of BIM to DTs in built environment applications
11	Götz et al. (2020)	2020	It looked into the asset life cycle management system
12	Hasan et al. (2021)	2021	AR and DT were used to investigate the operation of construction machinery and the tracking of work
13	Hou et al. (2021b)	2021	The applications and challenges of DTs in the construction industry were discussed
14	Ozturk (2021)	2021	There has been a discussion of current patterns, gaps and trends in DT research in the AECO-FM industry as well as future directions for stakeholders in this industry
15	Kaewunruen and Lian (2019)	2019	DT was evaluated for its ability to provide sustainable lifecycle management for railway turnout systems
16	Khajavi et al. (2019)	2019	The topic of DT for building life cycle management was discussed
17	Lu et al. (2019)	2019	The proposed smart asset management framework is based on distributed ledger technology
18	Liu et al. (2020)	2020	The investigation into the building's indoor safety management was conducted
19	Mathot et al. (2019)	2019	Packhunt.io, the next generation parametric system, was developed and discussed in conjunction with BIM, DT and mixed reality (XR) technologies
20	Menassa (2021)	2021	It was necessary to conduct a systematic review in order to identify developments in emerging technologies that would facilitate the transition from BIM to DTs in built environment applications
21	Pan and Zhang (2021a)	2021	In order to facilitate advanced project management, we developed a data-driven design framework based on BIM, IoT and data mining
22	Quaye (2021)		A systematic literature review was conducted in conjunction with interviews with key industry players
23	Rausch et al. (2020)	2020	The application of a computational algorithm to assist DTs in the construction process
24	Villa and Chiaia (2021)	2021	It demonstrated the current state of the art, as well as challenges and opportunities
25	Yitmen et al. (2021)	2021	A study was conducted to determine the applicability, interoperability and integrability of an adapted cognitive digital twin (CDT) model for use in building lifecycle management (BLM)

Table 1.
Diverse applications of DT, based on the latest research in AEC industry

<i>n</i>	References	Year	Applications
1	Alawadhi and Yan (2021)	2021	Presented a concept for a hybrid system that uses BIM and hyperrealistic rendering for DL to synthesize data sets for training a neural network for object recognition in photographs, with the goal of building object recognition in photographs
2	Chang et al. (2019)	2019	By applying DL and BIM to indoor positioning, we were able to develop a sound-based method
3	Chen and Demachi (2021)	2021	The combination of DL-based object detection and individual detection using geometric relationships analysis resulted in a novel solution for identifying improper use of personal protective equipment
4	Hou et al. (2021a)	2021	Identified relevant gaps, challenges and future work on DL-based applications for safety management in the AEC industry
5	Kim and Lee (2020)	2020	With reference images and a deep-learning model, this paper describes a stochastic approach for identifying and appending interior design style information to a design document
6	Marzouk and Zaher (2020)	2020	DL was used to present a methodology for exploitation of artificial intelligence in facility management using DL
7	Ma et al. (2020)	2020	With DL, a methodology for generating synthetic point clouds from 3D BIM models was demonstrated and discussed
8	Perez-Perez et al. (2021)	2021	Presented an end-to-end DL method, Scan2BIM-NET, for semantically segmenting the structural, architectural and mechanical components present in point cloud data, as well as experimental results demonstrating the method's effectiveness
9	Wu et al. (2020)	2020	DL and NLP techniques were used to develop a method for screening patents related to information and communications technology (ICT) in construction
10	Xue and Zhang (2021)	2021	It was proposed that a part-of-speech (POS) tagger tailored to building codes be developed, which would be empowered by DL and transformative rules
11	Zhong et al. (2020a)	2020	In order to improve the efficiency and effectiveness of retrieving queries pertaining to building regulations, a robust end-to-end methodology was developed that integrates information retrieval with a DL model of natural language processing (NLP) (NLP)

Table 2.
Diverse applications of DL, based on the latest research in AEC industry

transportation, security, health, smart building and automotive, an increasing number of devices and sensors are being implemented. The IoTs' objective is to make everything smarter and more connected. Therefore, a number of technologies are being utilized to improve management efficiency in both the virtual and physical worlds ([Lin and Cheung, 2020](#)). Based on the most recent study, [Table 3](#) depicts a variety of IoT applications.

2.5 Process optimization

Optimization is a decision-making process for pursuing and delivering feasible, long-term construction solutions. Optimization may make a process completely follow a set of criteria and restrictions by maximizing the expected impacts. During the period of carrying out construction activities on a complicated site, optimization aids in better resource allocation, crew organization, facility layout determination, and making consistent alterations in a reasonable and timely manner ([Akanbi et al., 2020](#); [Matar et al., 2013](#); [Oprach et al., 2019](#)). DT entails simulation, prediction and optimization in a virtual model, which can provide fast solutions to manage a realistic process and make it adapt to a changing environment by learning data from many sources ([Pan and Zhang, 2021b](#)). Optimization tools will enable process optimization through real-time data and CDT models in the CDT and analytics for the process simulation phase. The outcome of this optimization is used to make judgments for regulating physical entities ([Yitmen et al., 2021](#)).

<i>n</i>	References	Year	Applications
1	Alavi et al. (2018)	2018	The current state-of-the-art and future trends in the IoTs are discussed in detail here
2	Arthur et al. (2018)	2018	The topic of emulation and simulation of IoT-based devices for BIM was discussed
3	Atazadeh et al. (2019)	2019	The use of a BIM environment to communicate the legal ownership of IoT-generated data in multi-owned buildings has been successful in several cases
4	Ding et al. (2018)	2018	The use of BIM and the IoTs to construct smart steel bridges was discussed
5	Ghosh et al. (2020)	2020	By utilizing a scientific mapping tool, we were able to identify and rank the perceived importance level of the principal research areas associated with the IoTs and the construction industry
6	Lin and Cheung (2020)	2020	The advantages and challenges of integrating IoT technology and Internet-enabled physical devices in the construction industry were investigated and identified
7	Linares et al. (2019)	2019	The technologies for implementing CPSs in the AEC industry were evaluated
8	Lokshina et al. (2019)	2019	Design of a proposed system that makes use of blockchain technology as a means to secure and control a framework that incorporates integrated IoT and BIM technologies is considered. Despite the fact that this paper examines system design as it is applied in a smart museum, the authors assume that the design is generic and can be applied to other building types
9	Malagnino et al. (2021)	2021	BIM and IoT for smart and sustainable environments have been reviewed
10	Pasini et al. (2016)	2016	The proposed IoTs and BIM framework for managing cognitive buildings
11	Sarkar et al. (2020)	2020	The development of an integrated cloud-based IoTs platform for asset management of elevated metro rail projects was completed
12	Siountri et al. (2020)	2020	Research was conducted on the development of smart buildings through the use of BIM, IoT and blockchain
13	Tang et al. (2019)	2019	An in-depth examination of the integration of BIM and IoTs devices in the AEC industry was presented
14	Zhong et al. (2017)	2017	By incorporating IoTs-enabled tools for prefabricated construction, 3D BIM has been transformed into nD BIM

Table 3. Diverse applications of IoT, based on the latest research in AEC industry

3. Research methodology

The research methodology for this paper is comprised of five steps: a systematic literature review, a quantitative and qualitative digital survey, descriptive statistics and covariance analyses, a thematic analysis and a model of framework development. The systematic literature review is the first step. To acquire information from worldwide industry experts on the applicability and interoperability of DL integrated DT with decision-support capabilities for process optimization, a mixed approach comprising interviews, focus groups and a questionnaire survey was employed. A conceptual model of the framework has been built based on the results of quantitative and qualitative analyses.

3.1 Sampling and data collection

3.1.1 Survey. Professionals from design companies, project management consulting firms, contracting firms and IT companies in North America, South America, Europe, Scandinavia, Asia–Pacific and the Middle East made up the survey population. Large (>250 employees), medium (50–250 employees) and small (50 employees) firms are all represented in the sample. A total of 150 companies were contacted via LinkedIn, with one representative from each being requested to take part in the computerized self-administered questionnaire (CSAQ). The research objectives were explained to the participants, as well as the confidentiality and

anonymity of their responses. A total of 53 completed surveys were received, giving in a 35% response rate. The participants were asked to discuss their present role, expertise, experiences and the firm they work for. On a five-point Likert scale of 1 (strongly disagree) to 5 (strongly agree), they have indicated how much they agree with the items representing their organization's opinion on the DDT for promoting smart planning and construction statements (strongly agree). Table 4 shows the proportions of firm roles, experiences, sizes and geographies.

3.1.2 Thematic analysis is a method of analyzing data. The interview replies and focus group meeting data were examined thematically, identifying patterns of themes, using the qualitative data analysis program NVivo using a grounded theory coding approach. From chaotic data to a map of the most relevant themes in the data, an iterative method was used. Table 5 shows the characteristics of interviewees as well as interview details. To describe the content, preliminary codes were assigned to the data. Themes were found in the interviews and focus group talks by searching the codes. Themes were then examined, defined and titled. In interviews, the following themes were identified:

- (1) Implementation of BIM Level 2 (BIM-supported simulations and collaboration) has a number of advantages.
- (2) Implementation challenges for BIM Level 3 (BIM integrated with IoT).
- (3) Through semantic models, IoT and AI agents (data analytics, ML and DL) can be integrated.
- (4) DT promises to move forward with Construction 4.0 AI's role in DT realization prediction and optimization.
- (5) Challenges in DT's ability to optimize construction processes.
- (6) Interoperability between DT and DL at a reasonable level for Construction 4.0 added value of DT and DT for construction process optimization.

A focus group meeting was held digitally at House of DTs, hosted by Christina Savian, founder of DTs Club on ClubHouse (www.houseofdigitaltwins.club), to discuss an achievable level of interoperability between DT and DL in the context of Construction 4.0, as well as the potential added value of integrating DT and DL for construction process optimization. Table 6 illustrates this. Professionals from both the manufacturing and construction industries were among the attendees at the gathering.

3.1.3 Model of framework development. The information collected from the literature research, where use cases were identified, and the responses gathered from the questionnaire, which reported on the dynamics of technological ecosystems and current asset life cycle management practices, served as the foundation for the model development. One of the most essential principles of the model architecture is represented by the integrability enablers. As a consequence, the thematic NVivo® analysis of the open-ended questions section, where industry professionals were asked to freely discuss their current and planned digitization initiatives, including DL, DT and IoT projects, was the primary source of insights. The application cases of the DDT, as well as their functional interoperability with current practice and technological ecosystems, are emphasized in the framework model. It also outlines the degree to which it will be able to achieve its main objective of providing "live" and information-rich management applications and decision support tools.

4. Findings and analysis of results

The findings are divided into three sections, and a model of the framework is provided in each section. The survey results are presented in the first two sections, while the third piece

Firm type	Design firm	Project management firm	Contracting firm	IT firm
Role	Design Manager Design Coordinator Project Manager	BIM Manager BIM Coordinator Digitalization Specialist	Project Manager Construction Manager BIM Manager	Product Manager Platform Developer
Experience	>5 years 5 > x > 10 years 20<years	15% 21% 10%	19% 8% 23%	4% 8% 6%
Company size	8% 4% 8% 11% 2% 2% 19% 2% 0%	21% 10% 21% 13% 15% 15% 2% 4% 10%	0% 2% 17% 6% 10% 2% 0% 4% 6% 2% 2%	0% 0% 10% 0% 4% 6% 0% 2% 0% 0% 2% 6%
Region	Large (>250 employees) Medium (50–250 employees) Small (<50 employees) USA and Canada UK Asia Europe except Sweden			

Table 4.
Company region, size
and role in percentage

Table 5.
Profiles of interviewees
and interview details

ID	Position	Organization	Location	Interview type	Interview duration
1	BIM specialist	IT firm	California, USA	CSAQ	20 min
2	BIM specialist	Project management firm	Dubai, UAE	CSAQ	20 min
3	BIM manager	Design firm	Vancouver, Canada	CSAQ	20 min
4	BIM manager	Project management firm	Sydney, Australia	Online meeting	55 min
5	BIM specialist	IT firm	Stockholm, Sweden	CSAQ	25 min
6	Project manager	Project management firm	Stockholm, Sweden	CSAQ	20 min
7	Construction manager	Contracting firm	Gothenburg, Sweden	CSAQ	30 min
8	Digitalization specialist	Design firm	Gothenburg, Sweden	CSAQ	20 min
9	Digitalization specialist	Design firm	Gothenburg, Sweden	CSAQ	25 min
10	Digitalization specialist	Design firm	Malmö, Sweden	CSAQ	20 min
11	BIM manager	Contracting firm	Malmö, Sweden	CSAQ	25 min
12	Construction manager	Contracting firm	Gothenburg, Sweden	CSAQ	30 min

Table 6.
Profiles of focus group
meeting and
participants' details

ID	Position	Organization	Location	Interview type	Interview duration
1	BIM specialist	IT firm	California, USA	Online meeting	75 min
2	BIM specialist	IT firm	SJ, Costa Rica	Online meeting	75 min
3	Design manager	Design firm	Sydney, Australia	Online meeting	75 min
4	BIM manager	Project management firm	Sydney, Australia	Online meeting	75 min
5	BIM manager	IT firm	DC, USA	Online meeting	75 min
6	BIM specialist	IT firm	DC, USA	Online meeting	75 min

concentrates on the results of interviews and focus group meetings. The framework for a DL integrated DT model is discussed in the fourth part.

4.1 Descriptive statistics

Table 7 presents descriptive statistics for questionnaire responses, including mean values and standard deviations. The questionnaire responses were divided into two groups. As an overview of the perception of the concepts by industry professionals, the summarized statistics reveal some noteworthy understandings. It was discovered that the mean scores for 22 out of a total of 32 questions were higher than 4.00 out of a possible 5.00. The overall mean rating for the proposed model was 4.064, indicating that industry professionals support approaching DL integrated DT development for process optimization and decision-making purposes, and that integrability enablers confirm the progression towards Construction 4.0 as a result.

It was discovered that "DT can support visualizations, simulations and scenario generation applications" from DT has a mean value of 4.13. According to the relative

Factors/References	Questionnaire statement	Mean	SD	Rank
Construction 4.0 (Hong <i>et al.</i> , 2021; Kumar, 2018; Li <i>et al.</i> , 2020; Wu, 2018)	BIM Level 2 “BIM supported simulations and collaboration” is implemented as collaborative working and information exchange methods	4.15	0.894	9
	Cloud-based common data environment is one of the main challenges for the full implementation of BIM Level 3 “BIM integrated with IoT”	3.88	1.060	14
	BIM clash detection and resolution reduce rework and delayed schedules	4.25	0.947	5
	4D BIM planning and scheduling are used for progress monitoring	3.71	1.289	18
	Reality capture technologies are used for automated data collection from site	3.71	1.073	18
	From 3D point clouds to as-built models are used to revise design and update the progress of construction	3.88	1.215	14
	Digital reality improves efficiencies by making smart and informed decisions	4.37	0.841	3
	DT helps to formulate a data-centric mode of smart planning and construction	4.21	0.848	6
	DT facilitates generative design process by using AI	3.79	1.073	16
	DT helps to optimize creativity in design process	3.85	1.073	15
Digital twin (Alizadehsalehi and Yitmen, 2021; Deng <i>et al.</i> , 2021; Meža <i>et al.</i> , 2021; Yitmen and Alizadehsalehi, 2021a, b; Yitmen <i>et al.</i> , 2021)	DT helps support visualizations, simulations and scenario generations applications	4.42	0.801	1
	DT leverages the data streaming from a variety of site monitoring technologies and artificially intelligent functions	4.13	0.950	10
	DT provides accurate status information to proactively analyze and optimize ongoing design, planning and construction	4.13	0.971	10
	A DT provides real-time and effective decisions based on well-informed and reliable what-if scenario assessments	4.27	0.910	4
	DT provides long-term feedback for design and planning	4.23	0.942	6
	IoT is included in DT as connecting the physical and virtual worlds	4.17	1.004	8
	IoT facilitate to integrate and share data by a network of interconnected physical devices	4.19	0.841	7
	IoT promote the efficiency of the data collection, data transmission, data processing based on cloud computing	4.38	0.771	2
	IoT solution support real-time data transformation and instantaneous data analysis	4.25	0.860	5
	IoT-based sensing systems help feasibly track the progress and monitor the worksite	3.96	1.102	13
Internet of things (Gamil <i>et al.</i> , 2020; Mahmud <i>et al.</i> , 2018; Oke and Arowoiya, 2021; Woodhead <i>et al.</i> , 2018)	IoT help to automate the real-time decision making	4.19	0.886	8

(continued)

Table 7.
Descriptive statistics
analysis

Factors/References	Questionnaire statement	Mean	SD	Rank	
Deep learning (Akanbi <i>et al.</i> , 2020; Darko <i>et al.</i> , 2020; Hou <i>et al.</i> , 2021a; Zhang <i>et al.</i> , 2019)	Current challenges promote exploiting the use of DL in tackling construction problems	3.87	0.950	13	
	DL facilitate the huge amount of recorded data to analyzed and offer actual insights for better supervision and decision-making	4.02	0.918	8	
	DL is required to construct a self-reliant, self-updatable and self-learning DT	3.96	0.928	13	
	DL enables autonomous DT that generates predictive insights and foster continuous optimization processes	4.10	0.934	11	
	DL facilitate to automate generative design process	3.79	0.997	16	
	DL support to solve cash flow prediction, onsite safety and project risk mitigated analysis in construction	4.06	0.873	10	
	Process Optimization (Akanbi <i>et al.</i> , 2020; Matar <i>et al.</i> , 2013; Oprach <i>et al.</i> , 2019)	The simulation, prediction and optimization abilities of a DT are inter-dependent and act in unison in solving the problems in planning, design and construction	4.02	0.874	12
		DT facilitates dynamic optimization technologies that enable real-time system reflections and automatic model evolvement with updated data feed	4.13	0.841	10
		Optimization process depends on the simulated prediction (“what will happen?”) applied for planning, or various other construction management objectives	4.25	0.813	5
		DT enables pro-active modeling, tracking and optimization of construction processes and their associated off- and on-site resources	4.02	0.939	12
Optimization would be fully entrusted to the DT’s goals and learning patterns in agent-driven socio/technical platforms		3.73	0.931	17	
	OM	4.064			

Table 7.

importance of the variables, the statement “IoT promote the efficiency of data collection, data transmission and data processing based on cloud computing” from IoT had the highest mean of $x = 4.38$ in terms of relative importance. “DT facilitates generative design process by using AI” from DT had the second highest mean of $x = 4.32$, behind only “DT facilitates generative design process by using AI.” In the study, the statement “Digital reality improves efficiencies by allowing people to make smart and informed decisions” from DT received the third-highest mean of $x = 4.37$. Regarding smart planning and construction, most respondents believed that the DL integrated DT model will encompass cognitive abilities to identify complicated and unpredictable activities, reasoning about dynamic process optimization techniques and decision-making.

4.2 Correlation analysis

Table 8 shows the results of a correlation analysis of respondents’ perceptions of the decision support capabilities of DL integrated DTs based on their perceptions of DL integration. It is a statistical method that is used to determine whether or not there is a relationship between two variables or data sets, as well as how strong that relationship might be.

The correlation matrix is examined, and it is discovered that the significant values of the correlation are greater than 0.5, indicating that the matrix is suitable for factorization. As shown in Table 9, the Bartlett sphericity test is also significant, and the Kaiser–Meyer–Olkin sampling adequacy ratio is greater than 0.6, indicating that the sample is sufficiently representative. According to the calculations, the strongest correlation between DL and smart planning and construction was calculated to be $r = 0.812$. In the second strongest correlation, calculated as $r = 0.743$, the relationship between DL and DT was found to be the most significant. In the case of IoT and DT, the weakest correlation was calculated to be $r = 0.558$. It is a statistical method that is used to determine whether or not there is a relationship between two variables or data sets, as well as how strong that relationship might be.

4.3 Thematic analysis

The thematic analysis stage of the research process is the final step in the process. Based on the responses from the interviews and group focus meetings, NVivo 12 was used to create thematic analysis in Table 10. NVivo is a qualitative and mixed-methods research software program that is used in many different types of research. In particular, it examines interviews, focus groups, surveys, social media and journal publications. It is a statistical method that is used to determine whether or not there is a relationship between two variables or data sets, as well as how strong that relationship might be.

4.4 Model of framework

In order to develop a management system for any practical purpose, it is necessary to first gain an understanding of the process details. A schematic representation of the integrated DL model at various stages of planning, design and construction is depicted schematically in Figure 3. The framework model is a step towards the next level of DT, which will involve process automation and control in the direction of Construction 4.0, which will be implemented for different phases of the project lifecycle (design–planning–construction). For smart planning and construction, IoT, ML and big data integration are all linked to

Spearman's rank correlation coefficient matrix		Digital twin	Internet of things	Deep learning	Process optimization
	Smart planning and construction				
Smart Planning and Construction	1.000				
Digital twin	0.654*	1.000			
Internet of things	0.617*	0.558*	1.000		
Deep learning	0.812*	0.743*	0.609*	1.000	
Process Optimization	0.640*	0.661*	0.627*	0.664	1.000

Note(s): $N = 52$; All correlations had a 2-tailed Sig. < 0.000; *Correlation is significant at the 0.01 level (2-tailed)

Table 8. Correlation analysis of respondents' perception on DL integrated DTs' decision support capabilities

Kaiser–Meyer–Olkin measure of sampling adequacy		0.768
Bartlett's test of sphericity	Approx. Chi-square	1136.094
	df	496
	Sig	0.000

Table 9. Kaiser–Meyer–Olkin and Bartlett's test

Coded themes	Thematic answer summary analysis
Benefits of BIM Level 2 (BIM-supported simulations and collaboration) implementation	BIM-supported simulations help in project planning and on-site trade coordination for critical construction areas. It saves time and reduces cost. BIM collaboration helps in real-time clash checks and coordination with the stakeholders, saves onsite wastage and reduces coordination time. Digitization first as it assumes no paper model anymore. Collaboration is easier, but reconciling each party's model can certainly be a challenge
Challenges for the implementation of BIM Level 3 (BIM integrated with IoT)	Gives the full perspective of the process and brings all the disciplines on the same round. It helps a lot in reducing the clashes that might happen during the construction process
Integration of IoT and AI agents (data analytics, ML, DL) through semantic models	Specifications or dimensions are set for each object and standards are set for the production, exchange and archiving of information in one package
DT promises progressing towards Construction 4.0	Involves developing building information in a collaborative 3D environment with data attached, but created in separate discipline models
Role of AI for prediction and optimization in DT realization	Improving processes and increasing the efficiency of the construction industry in an intelligent environment
Challenges in construction process optimization abilities of DT	Integrating data in a smart environment
Achievable level of interoperability between DT and DL towards Construction 4.0	Implementing, improving processes and increasing the efficiency of the construction industry. Discipline in the building design environment
Added value of DT and DT for process optimization in construction	Managing the data with related parts and optimizing the conclusion

Table 10. Thematic analysis of the interviews and group focus meeting responses

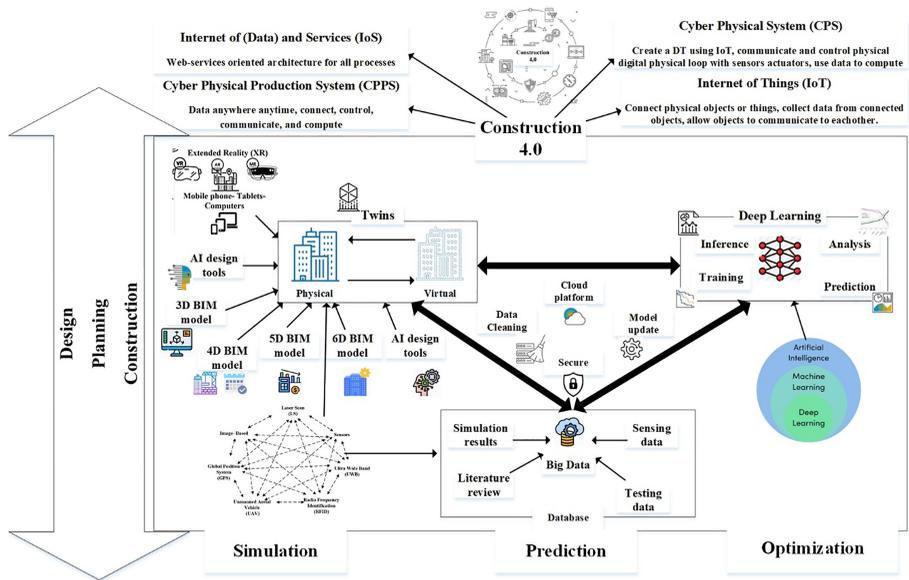


Figure 3. DL integrated DT (DDT) model of framework

self-learning hybrid models with proactive cognitive capabilities. The DL integrated DT model will help decision-making better judgments in real-time through the interplay of optimization and simulation by incorporating cognitive ability to recognize complicated and unpredictable activities, as well as reasoning about dynamic process optimization techniques. It is a statistical method that is used to determine whether or not there is a relationship between two variables or data sets, as well as how strong that relationship might be. Project data to be used in design, planning and construction stages has increased almost exponentially since BIM adoption, experiencing what is termed “data-based drawings.”

As shown in [Figure 3](#), DDT in the proposed framework can now be applied throughout the full building lifecycle from design to construction and is effective in terms of 4D, 5D and 6D BIM models as traditionally utilized at the simple BIM models. Decision-making has been automated through the use of DL to reduce reliance on humans and to provide autonomous functionalities that are repeatable and consistent in their outcomes. With the use of DDT, it is hoped that transparency will be improved throughout the entire operating network. By integrating real-time and historical data from machines and inventory, as well as information from suppliers, customers and maintenance technicians into DT models, the proposed DDT model of framework helps simulate and optimize predictive maintenance strategies for the components. Various historical data as the main database with the help of various AI design tools will generate the best 3D BIM model scenarios accessible to use in XR devices.

DT enables building stakeholders to harness nD BIM data throughout the design process and ultimately improve operations in the construction stage. These processes help the visualization to be clear and specific to user’s needs and to support collaborative and coordination meetings, from a functional as well as from an ergonomic perspective. DDT is dynamic, and it is more than just a collection of 3D models starting from the design phase of a project. DDT from the construction stage incorporates sensors, IoT technologies and AI, feeding real-time data back into the digital nD-models. It evolves with input and gives stakeholders new insights. In this stage, when the optimized plan is ready, it is sent back to the physical system, along with supplementary visual information to be implemented. All models work independently and collaboratively to build a closed-loop predictive framework, which is achieved by iteratively repeating this process in a semi-real-time environment.

5. Discussion and implications

5.1 Theoretical contributions

When it comes to construction, the novelty of the next-generation design-thinking concept, which can be integrated with digital learning and leveraged in the same way that it has been in other industries, was the driving force behind this study. When compared to the applications of other digital technologies such as BIM and other ML algorithms, there are currently insufficient DL applications in the DT industry at this time ([Akinoshio et al., 2020](#); [Braun and Borrmann, 2019](#)). What constitutes a technically justifiable DT platform integrating DT and DL to facilitate smart planning and construction is the subject of this study. It also investigates how capacity can be developed in order to seize opportunities and overcome constraints associated with the implementation of DL integrated DT applications to simulate and optimize planning and construction processes are the subject of this study.

DL integrated DT model facilitating smart planning and construction will incorporate cognitive abilities to detect complex and unpredictable actions, as well as reasoning about dynamic process optimization strategies to support decision-making, as revealed by the quantitative and qualitative analyses of the data collected from the surveys, interviews and group focus meetings ([Yitmen et al., 2021](#)). When used in conjunction with other data sources, such as physical counterparts and sensors from all aspects of an industrial system’s

operational conditions, the semantic-driven detection, learning, prediction, inference, estimation and decision capabilities of the DL integrated DT model will be enhanced. In addition to cognitive abilities such as anomaly detection and behavioral learning during the construction process, the DL integrated DT model will provide the capability to decide on the actions of the physical twin to improve the measures defining its state or function (Eirinakis *et al.*, 2020).

DT makes use of real-time data streaming from a variety of site monitoring technologies, as well as artificially intelligent features. The IoTs improve the efficiency of data collection, data transmission and data processing through the use of cloud computing. DT is assisting in the formulation of a data-centric model for smart planning and construction (see Figure 1). By utilizing AI, DT makes the generative design process more efficient. The IoTs' solutions enable real-time data transformation and instantaneous data analytics. Construction processes and their associated off- and on-site resources can be modeled, tracked and optimized in real-time using digital technology. In agent-driven socio-technical platforms, optimization would be completely delegated to the DT's goals and learning patterns, with no human intervention (Turner *et al.*, 2020).

Planning, designing and delivering built assets more effectively and efficiently are all made possible by Construction 4.0, with a particular emphasis on the physical-to-digital transition and subsequently the digital-to-physical transformation. DDT allows for tighter connections between computer models and physical entities, bridging the existing gap and therefore being termed the "heart" of Construction 4.0 (Akanmu *et al.*, 2021; Begić and Galić, 2021).

The dependability and interoperability of BIM-based data transmission is critical in such applications. Further, machine-aided rule interpretation might lead to complicated disputes. The accuracy of BIM models impacts the performance of DDTs. When imported into reality simulation platforms, the models can be used to perform what-if scenarios and make decisions in real-time (Karmakar and Delhi, 2021).

Sensors and data communication technologies enable resource networks to connect and exchange data. Such data are vital for establishing relationships between processes, operations and resources, creating models that can predict physical system behavior and managing the physical world (Akanmu *et al.*, 2021).

The IoT is a network of interconnected physical devices that makes integration and data sharing easier (Turner *et al.*, 2020). Due to real-time data analytics, IoT in construction offers various possibilities and advantages. Moreover, IoT applications and technology can improve user comfort, security and energy efficiency throughout construction, maintenance and operation. Utilizing IoT, real-time data from a construction site drives BIM models to track progress. Current IoT solutions in construction are regarded to be isolated for specific applications but lack coordination throughout the entire construction process (Begić and Galić, 2021). The use of DT in the built environment may be considerably enhanced by providing real-time automated control with the potential to expand the number of scenarios examined in order to improve the efficiency and reliability of the control systems via DDT system.

The DT has limited intelligence, depending on inherent knowledge rules as well as independent AI-enabled simulations and forecasts to make decisions and make predictions. This generation needs a large amount of human intervention in order to carry out DT optimization and operation (Deng *et al.*, 2021). One of the most important tasks that may be accomplished with a DT is connection and data fusion, which mostly relates to preparing large amounts of data, data mining and real-time optimization. Physical entities and several related applications may create data, which can make determining the appropriate data format and type, as well as ensuring reliable communication across all of the relevant devices and entities, challenging. Connectivity is a vital component of smart systems, such as smart

construction, and it should be increased as a fundamental demand of DT to achieve greater efficiency (Sepasgozar, 2021).

The potential benefits of ML in construction are increasingly well known through predictive analytics applications and ML capabilities have continued to grow, especially in areas such as DL (Venkatasubramanian, 2021). The predictive model to predict failures is based on a DL model and can be reused on similar installations in different facilities by using transfer learning, which can allow one to cut the development cost and reduce the implementation time (Bouabdallaoui *et al.*, 2021). There are DL approaches to create solutions to construction problems like generative design, cash flow prediction and project risk analysis. However, the availability of data, due to the widespread use of predictive analytics applications, the potential advantages of DL in construction are becoming more widely recognized, and the capability of DL has continued to develop, particularly in areas such as DT. By utilizing learning algorithm, the predictive model to forecast failures may be reused on identical installations in multiple facilities, providing for a reduction in development costs and a decrease in implementation time (Bouabdallaoui *et al.*, 2021). For construction challenges such as generative design, cash flow prediction and project risk analysis, there are DL techniques that may be used to generate solutions. In the AEC industry, however, some of the current hurdles include data availability, data privacy and ethics, as well as a lack of in-house capabilities for DL and adversarial ML.

5.2 Practical implications

The DDT system developed in this study automates and speeds up the time-consuming management task. To construct 3D models and produce XR models, DDT in the design stage helps AI technologies to extract knowledge and learn from obtained raw data. As part of the planning stage, DDT creates 4D models that optimize the construction process and resource allocation, properly estimating budgetary requirements and analyzing economic and operational elements throughout the lifecycle. Using CPSs and technology to understand and regulate progress, DDT automatically learns from collected data, and facilitates workflow optimization of the construction process to make better judgments. As the opportunities, DDT uses cognitive algorithms to improve design procedures, while XR's immersive nature helps visualize and evaluate designs. With real-time cost display and communication of changes in expenses, DDT ensures accurate energy consumption forecasting and early conflict detection in the planning stage. In the construction stage, it uses cognitive analytics to increase construction accuracy by combining reasoning and optimization.

However, the DDT model involves challenges of lacking historical data availability and validation, complicated environment modeling and skilled human resources. Also, experienced crew, adequate IT infrastructure in the planning stage, and lack of complete modeling language, scalability and large-scale computation in the construction stage are other challenges of the proposed model. Table 11 presents a sample of the DDT model processes, opportunities and challenges for design, planning and construction.

5.3 Future work

The purpose of this study was to investigate and debate the possibility and ways of combining ML with decision-making DT technology. At the present, the research and application of DT technology are still in the early stages of development and refinement, and a significant amount of time and effort is required. The findings of this research were limited in its insight due to the limited number of professionals from various industrial sectors who participated in it. An increased number of samples on a larger scale and response rate are recommended to improve the future study's reliability. Future research on this topic needs to be undertaken as follows: (1) to enhance the DT models at each stage and accumulate,

	Process	Opportunities	Challenges
Design	Facilitating AI tools to extract knowledge and learn from collected raw data, applying generative design to create 3D models and develop XR models	Implementing intelligent-based algorithms to improve design practices, and with immersive nature of XR visualizing and evaluating designs more effectively	Lack of historical data availability and validation of data, complex environment modeling and competent human resources
Planning	Developing 4D models with scheduling optimization construction process and resource allocation, accurately predicting the budgetary requirements along with the changes in scope, material, manpower or equipment requirements, and analyzing economic and operational aspects over the entire lifecycle	Helping in early conflict detection by seamlessly managing information related to site status and visualizing the impact of changes undertaken during the entire lifecycle, real-time cost visualization with notification on changes in costs, and ensuring accurate prediction of energy consumption requirements	Lack of fully automated digital platform, experienced staff, and IT infrastructure
Construction	Sensing and capturing real-time data using CPSs and technologies (drone, WSN, AR etc.) to comprehend and control the progress, automatically learning from collected data and workflow optimization of the construction process to make better decisions	Applying cognitive analytics through data-enriched simulations and combining reasoning and optimization for improved accuracy of construction schemes	IoT network in terms of scalability, integration of transfer learning algorithms, lack of comprehensive modeling language and large-scale computation

Table 11. Sample of DDT model processes, opportunities and challenges for design, planning and construction

integrate and apply life cycle information; (2) to develop a synchronous and efficient mapping mechanism between physical and virtual data to fulfill the needs of real-time analysis and dynamic decision-making; (3) to build the system structure and workflow of a DL, IoT and integrated DT model that can assist in automating real-time decision making at an operational level to remotely manage the construction worksite, optimize project performance and anticipate future circumstances.

6. Conclusions

It was discovered that DDTs play an important role in the AEC industry, and it was presented as a model of a framework called DDT framework. There are a number of processes that describe how these technologies collaborate to manage data and information in AEC projects, which are listed above. The findings demonstrate unequivocally that there is widespread awareness of the real-world implications of DT integration with DL and IoT in order to efficiently resolve previously unknown situations. When this model of the framework is implemented, it will allow for better real-time decision-making through the interaction of optimization and simulation during the planning and construction phases of the project.

Despite the fact that this study identifies a number of promising research areas for the future, it also contains some significant limitations. The findings of this study were limited in their insight due to the small number of specialists from various industry sectors who participated in it. It is recommended that the number of samples be increased on a larger scale, as well as the response rate, in order to improve the reliability of future studies.

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