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Digital Twins for the built environment: learning from conceptual and process models in manufacturing

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ABSTRACT

The overall aim of this paper is to contribute to a better understanding of the Digital Twin (DT) paradigm in the built environment by drawing inspiration from existing DT research in manufacturing. The DT is a Product Life Management information construct that has migrated to the built environment while research on the subject has grown intensely in recent years. Common to early research phases, DT research in the built environment has developed organically, setting the basis for mature definitions and robust research frameworks. As DT research in manufacturing is the most developed, this paper seeks to advance the understanding of DTs in the built environment by analysing how the DT systems reported in manufacturing literature are structured and how they function. Firstly, this paper presents a thorough review and a comparison of DT, cyber-physical systems (CPS), and building information modelling (BIM). Then, the results of the review and categorisation of DT structural and functional descriptions are presented. Fifty-four academic publications and industry reports were reviewed, and their structural and functional descriptions were analysed in detail. Three types of structural models (i.e. conceptual models, system architectures, and data models) and three types of functional models (process and communication models) were identified. DT maturity models were reviewed as well. From the reviewed descriptions, four categories of DT conceptual models (prototypical, model-based, interface-oriented, and service-based) and six categories of DT process models (DT creation, DT synchronisation, asset monitoring, prognosis and simulation, optimal operations, and optimised design) were defined and its applicability to the AECO assessed. While model-based and service-based models are the most applicable to the built environment, amendments are still required. Prognosis and simulation process models are the most widely applicable for AECO use-cases. The main contribution to knowledge of this study is that it compiles the DT's structural and functional descriptions used in manufacturing and it provides the basis to develop DT conceptual and process models specific to requirements of the built environment sectors.

1. Introduction

The Digital Twin (DT) paradigm is an information construct that consists of a physical asset, its identical digital representation, a digital asset, and a data connection between them. The DT paradigm and its implications for the built environment have been discussed intensely in the Architecture, Engineering, Construction, and Operations (AECO) academic and industrial sectors. It has been a topical theme in the last few years, as demonstrated by the massive increase in the number of academic publications on the subject. For example, only two documents are listed in Scopus for 2016 when searching for the terms "Digital Twin" and "building"; while, 178 documents are listed for 2020. Nevertheless, DT research within the AECO sectors is still at an early stage compared to other fields such as aerospace and manufacturing. Research at early stages, when a new paradigm is introduced, is characterised by an intense organic development with limited structure and vague definitions; followed by a period of homogenisation in which definitions and scopes are agreed upon. For instance, a similar process occurred with the development of Building Information Modelling (BIM), in which the initial key definitions and scope evolved significantly since its inception in the mid-70 s (see Section 3.4). This type of early research is useful to broaden the potential application scope of the new paradigm and to set the foundations to develop more mature definitions and robust research frameworks. However, it can also lead to

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misunderstandings of capabilities and complexities, which could limit the full potential of the technology [1].

The majority of fundamental and applied research on DT has been carried out in the manufacturing sector. Regarding fundamental research, notable efforts have been done to map the multitude of existing definitions contributing to a more structured knowledge, e.g. [2]. More importantly, besides reviewing definitions, the DT characteristics and potential use-cases have been analysed for aerospace and manufacturing [3]. These are examples of very valuable research efforts that have provided a clearer conceptualisation of the DT paradigm and have set the basis for other practical research studies on DT for manufacturing. In contrast, the DT definitions and scopes for the built environment are not as developed; and, the key conceptual and functional characteristics of the DT paradigm in the AECO context have not been sufficiently defined. There have been valuable efforts to advance the understanding of DTs in the built environment in academia, e.g. [4,5] and in industry, e.g. [6–8]. However, fundamental research for the understanding and application of DTs in the built environment is still required.

Thus, the motivation of this study is to learn from existing knowledge on DT in manufacturing literature; and, to translate that knowledge into the AECO context. More concretely, the main objectives are

(1) to analyse how the DT systems reported in the manufacturing literature are structured and how they function, and

(2) to assess its potential applicability to AECO use-cases.

In this sense, a broad-scope literature review was carried out, including not only journal articles and conference papers, but also industry reports from relevant companies and organisations (i.e. Arup, Atkins, Siemens, The Institution of Engineering Technology, Centre for Digital Built Britain, the High Value Manufacturing Catapult, and the Technical University of Munich).

This paper is structured as follows: firstly, the research method used is explained in detail. Secondly, a brief explanation of the DT concept and a comparison with cyber-physical systems (CPS) and BIM concepts are presented to frame the scope of the study. Then, DT system descriptions referred to as "structural models" (i.e. conceptual models, system architectures, and data models) and functional descriptions referred to as "functional models" (i.e. process models and communication models) compiled and derived from DT literature are presented, categorised, and explained in the AECO context. Conceptual models and process models are analysed in more detail and are presented in sections five and six, respectively; while, the rest are presented in section seven. Lastly, discussion topics and conclusions are provided in the last two sections.

2. Research method

In this section, the method employed for the review is described. The approach for data collection was partly based on existing methods for systematic academic literature reviews, e.g. [9]. However, a broader scope was used due to the limited amount of publications on DT concepts in the AECO area; thus, other related fields were considered as well. Industry reports were also surveyed. The research method consists of six phases, as follows (Fig. 1):

(1) Conceptual Review. The first phase was to investigate the original DT notions and compare them with cyber-physical systems (CPS), and BIM concepts. The intention was to outline differences and coincidences among the terms to provide a robust theoretical background that guided the subsequent research steps. The following research question was formulated.

Q1: What are the main differences between the DT, CPS, and BIM concepts?

A literature review of seminal publications on DT, CPS, and BIM was performed to obtain the information required to carry out the comparisons. Regarding the comparison between DT and CPS, relevant research already exists and results from several publications were compiled. However, for the comparison between DT and BIM, no systematic comparisons were found in literature. So, in this case, the essential capabilities, use-cases, and enabling technologies for DT and BIM were identified and compared. For this purpose, seminal literature on BIM, DT, and DT in the built environment context were used as the basis for the comparison. The results of this step are reported in Section 3.

(2) Scope Definition. Drawing inspiration from software engineering approaches to software system development and analysis [10], an investigation was carried out into the structural and functional

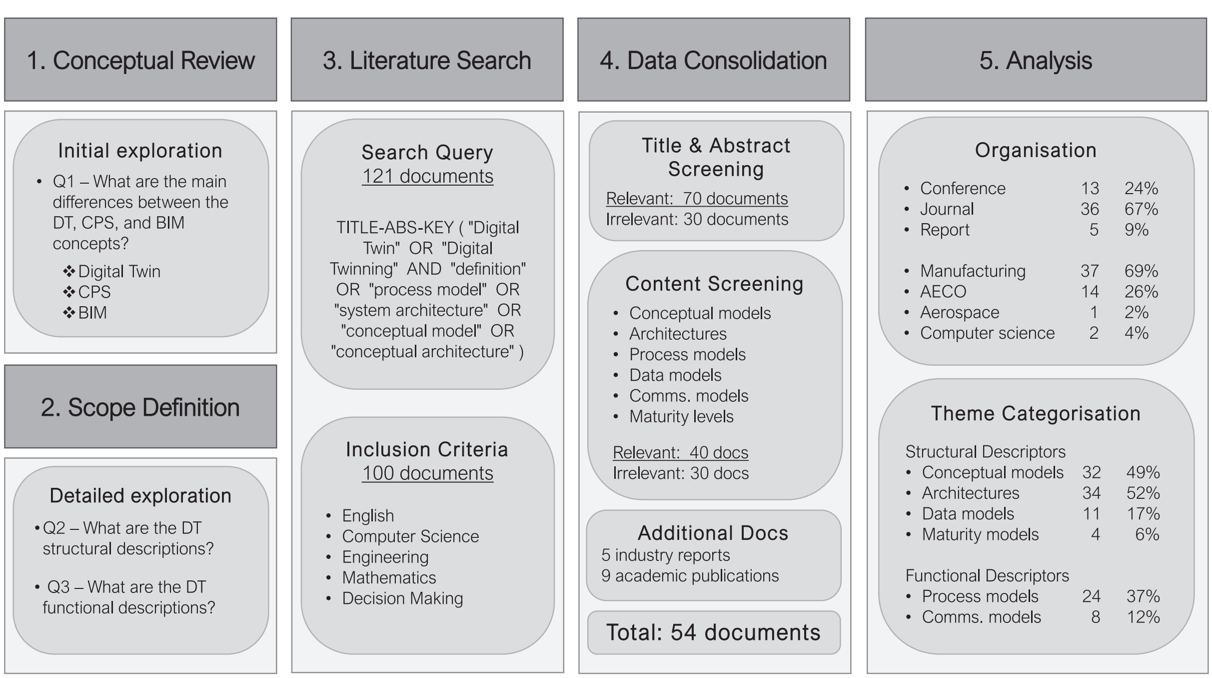

Fig. 1. The six phases followed in the research method.

descriptions of DT systems reported in the literature. The intention was to gain a better understanding of how DT systems are structured and how they function, which in turn could provide valuable insights for their potential applicability into the AECO sectors. Therefore, the following two research questions were selected:

Q2: What are the DT structural descriptions reported in the literature?

Q3: What are the DT functional descriptions reported in the literature?

In order to answer the questions above, a literature review was conducted to find academic and industry publications that contained information on the definition, conceptualisation, and function of DTs. The approach followed for the review is detailed in the following three steps.

(3) Literature Search. The Scopus database was used to search the academic literature from August to December 2020. Note that additional references were included during the peer-review process until March 2021. The terms "Digital Twin" and "Digital Twinning" were searched, within the title, abstract and keywords, in combination with the terms "definition", "process model", "system architecture", "conceptual model", and "conceptual architecture". One hundred and twenty-one documents were retrieved using the following search string:

TITLE-ABS-KEY ("Digital twin" OR "digital twinning" AND "definition" OR "process model" OR "system architecture" OR "conceptual model" OR "conceptual architecture")

Then, all the papers that were not written in English, and that did not belong to closely related fields (e.g. Medicine and Healthcare) were discarded, resulting in 100 documents. The definitive search string used was:

TITLE-ABS-KEY ("Digital Twin" OR "Digital Twinning" AND "definition" OR "process model" OR "system architecture" OR "conceptual model" OR "conceptual architecture") AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (SUBJAREA, "COMP") OR LIMIT-TO (SUBJAREA, "ENGI") OR LIMIT-TO (SUBJAREA, "MATH") OR LIMIT-TO (SUBJAREA, "DECI"))

(4) Data Consolidation. The first part of this phase was to screen the title and abstracts of the 100 retrieved documents to discard documents that were not relevant to the study and that were not correctly discriminated by the initial filters. The inclusion criterion was that the document focused primarily on DT in the fields of engineering and computer science. For example, studies related to social and medical sciences or project management were discarded. Seventy documents remained after this initial screening. Then, the entire content of the remaining documents was screened to identify the papers that included descriptions of the structure or function of the DT systems. Also, a quality evaluation of the selected papers was carried out, identifying whether the document included a clear methodology and results. After this second screening, 40 documents remained. Lastly, an online survey of industry reports and white papers was carried out to complement the review. The same overall strategy as the review of academic works was employed, but in this case, the search was carried out using the Google search engine. The same search terms were used as well as discrimination criteria, namely, only reports focused on the engineering and built environment fields and that included DT structural and functional descriptions. Five industry reports and nine additional papers were included in the selection of documents to be analysed. The final set for analysis consists of 54 documents.

(5) Analysis. The analysis phase consisted of five major steps, as follows: (i) Theme identification, five themes were identified that relate to structural and functional descriptions of the DT systems surveyed. The structural models are conceptual models, system architectures, and data models; the functional models are process models and communication models. Note that maturity models were identified and analysed as well. (ii) Paper categorisation, the papers were categorised based on whether one of the above models were addressed explicitly. (iii) Overall theme analysis, a general analysis of the publications was carried out identifying the type of publication, the area of application, and the specific use-case. (iv) Detailed analysis, the publications describing conceptual and process models were analysed in more detail because they provide the most relevant information regarding how the DT systems are structured and how they function. The structural and functional descriptions were condensed, and a categorisation was defined consisting of four types of DT conceptual models and six types of process models, which are discussed in sections five and six, respectively. Lastly, (v) the applicability of the conceptual and process models to AECO use-cases was assessed and the main conceptual and functional DT characteristics relevant for the built environment identified and discussed.

3. Digital Twins, BIM, and Cyber-Physical Systems

3.1. The original definition of the DT paradigm

The term "digital twin" (DT) was first used in two papers in 2011 and 2012 published by NASA experts. The first paper presented a conceptual model of a DT that could be used for predicting the life of an aircraft structure and assuring its structural integrity [11]. The second paper proposed a DT as a way to integrate simulations with the aircraft's health management system, maintenance history, and all historical fleet data to mirror the life of the physical aircraft and greatly increase safety and reliability levels [12]. However, the ideas behind the DT term have been explored many years before in PLM, and similar terms were proposed such as Mirrored Spaces Model [13] and Information Mirroring Model [14]. The most up-to-date concepts defining the DT paradigm are presented by Grieves (2019); in which the DT is defined as an information construct, depicted in Fig. 2, that consists of a physical asset, a digital asset and a connection between the two assets. The main objective of the DT is to enable remote and real-time monitoring and control of a physical asset. The data incorporated into the digital asset is employed to identify anomalies, run simulations, and predict potential failures. This information is then used to control the asset operations in an optimal manner.

Note that while initially the DT was considered to support primarily real-time monitoring, now it is being considered as well as a way to build and test products in virtual environments and to support design and manufacturing. In this alternative conceptual model, the DT can be divided into three components [16], i.e.: (1) the DT Prototype ("DTP"), (2) the DT Instance ("DTI"), and (3) the DT Aggregate ("DTA") as shown in Fig. 3. The DTP consists of the designs, analyses, and processes necessary to manufacture a physical asset. The DTI is the DT of each individual instance of the asset once it is manufactured. The DTA agglutinates all the DTIs, and its aggregated data can be used for predictive maintenance of the DTIs and for improving future designs through "lessons learned" feedback.

3.2. Evolving DT definitions

Even though there is a clear definition of the DT paradigm as presented by Grieves (2019), in practice, there is no agreed definition, and multiple definitions are commonly used. A few research efforts have been made to identify and map all these definitions. For example, Negri et al. (2017) compiled 16 different definitions for DTs. Most notably,

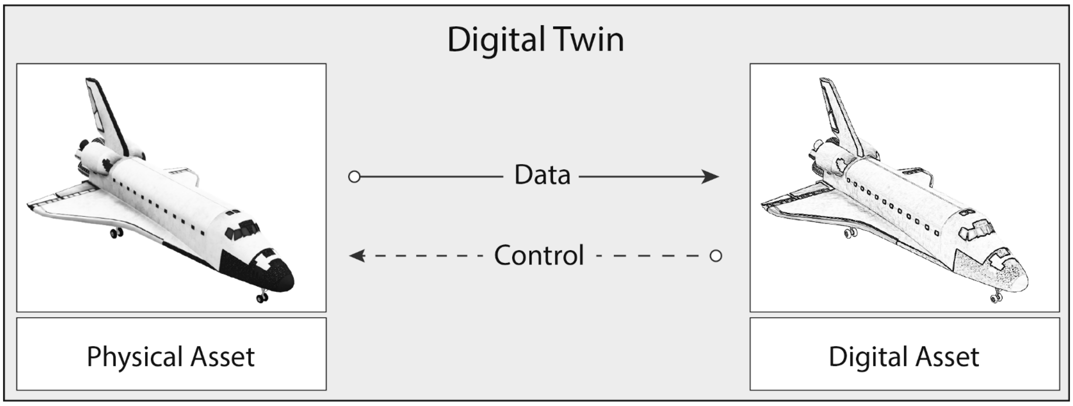

Fig. 2. Conceptual diagram of the three elements of a DT [15].

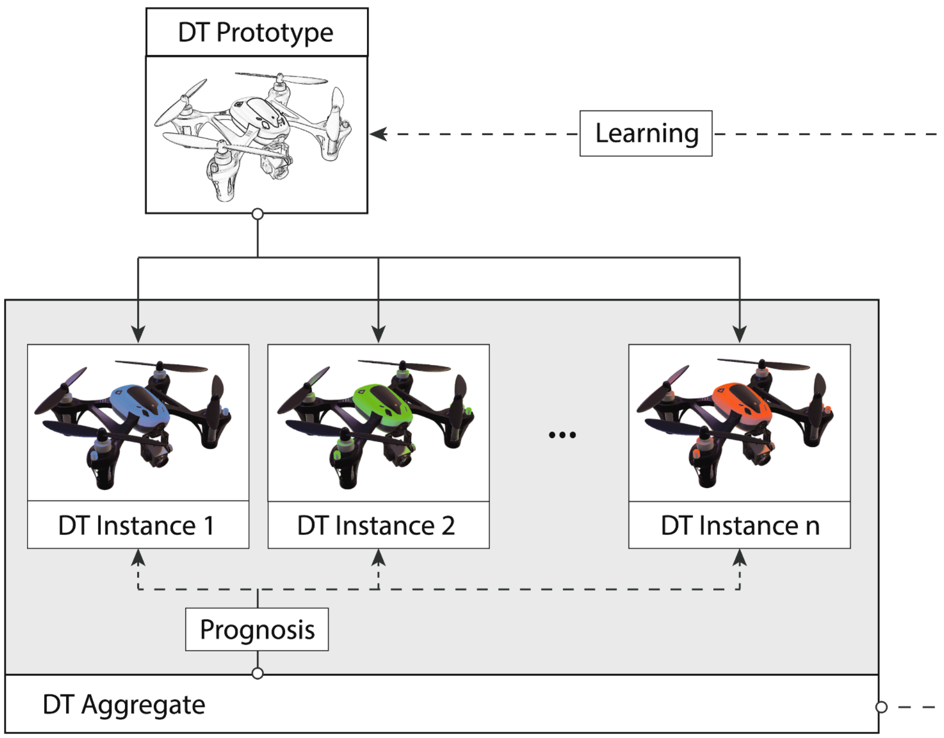

Fig. 3. Conceptual diagram of the DT prototype, instance, and aggregate [16].

Barricelli et al. (2019) presented a literature review on DT's definitions, which found that about half of the publications on DT do not provide a definition and that the definitions provided vary widely. Around 30 distinct definitions were analysed and grouped into six categories based on structural and functional descriptions, i.e.: (i) integrated system, (ii) clone or counterpart (iii) data links and control, (iv) information construct, (v) simulation and prediction, and (vi) virtual replica. Definitions not only vary based on the underlying DT structure and its capabilities, but there are also definitions based on the levels of integration among the digital and physical assets. For example, Kritzinger et al. [17] proposed three different definitions, i.e. digital model, digital shadow, and digital twin, which are characterised by increasing levels of automation and integration between the physical and digital asset. Some efforts have been focused on developing exact mathematical definitions for DT. For example, Worden et al. (2020) argue that a mathematical framework is required to quantify fidelity and ensure the correct operation of DTs. The authors propose mathematical DT definitions that enable measuring the fidelity of DTs and understanding the consequences of combining validated models. In sum, there is no clear consensus on exact definitions for the DT paradigm. The DT term originated for very specific use-cases, namely estimating structural integrity and supporting monitoring and maintenance. However, the DT paradigm —i.e. an accurate digital replica of a physical asset— can be beneficial for many industries and use-cases. This broad potential has driven the massive increase in diverse definitions as researchers envision different ways in which the DT paradigm can improve their application areas.

Some authors incorporate additional aspects to their definitions such as specific hardware or software components, intended behaviours, and the context in which the DT will operate. For example, Stark et al. (2019) use the term "dimensions" to describe different themes in which varied DT characteristics and behaviours can be mapped, and the term "design elements" to describe hardware and software requirements. In a different approach, Tao et al. (2018) use the term "dimensions" to refer to additional components in the conceptual models, such as the inclusion of services, rather than overall themes. Note, that these DT dimensions are different from the BIM models dimensions which define the different types of data that a BIM model contains [21]. Other authors enrich the DT definitions by embedding the DT in specific application frameworks, and by including potential use-cases and levels of sophistication, e.g. [22]. All these extended definitions provide additional detail specifying how and for what the DT will be used. In this paper, these additional aspects are addressed separately. Additional components are discussed in Section 5; behaviours and use-cases in Section 6; and levels of sophistication in Section 7.4.

3.3. Cyber-Physical Systems and the Digital Twin

The DT concept is very similar to the notion of cyber-physical systems (CPS). Both terms describe the integration between digital entities with physical entities. They were coined around the same time, DT in 2005 [13] and CPS in 2006 at a National Science Foundation (NSF) workshop [23], but published until later [24]. In a similar way, there is no agreed definition for CPS either and several definitions exist. For example, Baheti and Gill (2011) define CPS as a system "with integrated computational and physical capabilities that can interact with humans through many new modalities". Alur [25] defines CPS as "a collection of computing devices communicating with one another and interacting with the physical world via sensors and actuators in a feedback loop". While, Tao et al. (2019a) define CPS more broadly as "multidimensional and complex systems that integrate the cyber world and the dynamic physical world"; while emphasising the integration of computation, communication, and control of physical processes.

There is still no consensus on how both terms differ or fit together either. However, it appears to be three major trends that consider (1) DT as an aggregation of existing CPS concepts into a new package, e.g. [27]. This trend argues that DT is only a reformulation of the same CPS concepts developed specifically for aerospace and later for manufacturing. (2) DT as a subset of CPS, e.g. [28], in which CPS is the high-level term and DT is a subsidiary term used for specific use-cases, e.g. asset monitoring and maintenance. And, (3) as slightly different conceptualisations of the same "digital-physical" paradigm, e.g. [26]. In this case, it is argued that (i) CPS is primarily focused on fundamental scientific aspects, while DT focuses on practical implementations; (ii) DTs have a larger focus on digital models; whereas, CPS on computation, communication, and control; and (iii) that CPS research emphasises on sensors, actuators, and control while DT research focuses on models and data.

Table 1 presents a high-level comparison between CPS and DT that compiles information from the three trends discussed above. For a more exhaustive comparison between CPS and DT refer to Tao et al. (2019a). The comparison presented in Table 1 is divided into four aspects, i.e. attributes, functions, main use-cases, and key differences. Expanding on the comparison in Table 1, in the authors' view, an essential difference between CPS and DT is that DT refers to an information construct that describes a digital replica of a physical asset and its data connections; while, CPS refers to a system that integrates digital and physical components. This is a slight but important conceptual difference with significant implications. For instance, given the conceptual difference above it can be implied that in a DT solution a physical asset will have a digital replica, which behaviour can be simulated, and condition can be monitored and predicted. On the other hand, a CPS solution implies the improved control and optimisation of physical processes supported by other digital processes, without the need for correspondence among digital and physical components. Given the differences above, the study presented in this paper focused on DT literature instead of CPS literature, because it fits better the requirements of the built environment sectors.

Table 1
Main differences between CPS and DT. Information compiled from [26–28].

	CPS	Digital Twin
Attributes	• Integrating physical processes and computer systems • Networked systems, function distribution, connectivity among intelligent physical devices • Sensing, actuating, and control capabilities • Real-time capabilities • Autonomy and intelligence • Cybersecurity integrated into a holistic approach	• Near-real-time digital replica of a physical product or process • All relevant information throughout all lifecycle phases • Digital representations of physical products or processes • Includes static design and process documentation • Includes dynamic sensor and simulation data • Real-time and historical data of the physical product
Functions	• Continuous monitoring and control • Enhance transparency in production • Allow real-time production control • Planning and monitoring equipment operations	• Real-time monitoring • Physical asset simulation • Performance optimisation
Mainuse-cases	• Equipment monitoring and control	• Asset management, preventive maintenance
Keydifferences	• Scientific category • Focuses on communication, computation, and control of sensors and actuators • One-to-many correspondence (i.e. one digital system to many physical assets). • Focuses on enhancing physical processes with digital tools	• Engineering category • Focuses on data and digital models • One-to-one correspondence (i.e. one physical asset to one digital asset). • Focuses on digital associations with assets

3.4. BIM and the Digital Twin

The concept of BIM is very similar to the notion of DT as well. These two concepts are probably more alike than CPS and DT, because both of them refer to digital representations of physical assets. Nowadays, the term BIM is well defined and understood thanks to the culmination of a wealth of research in the subject, e.g. [29]. But, at the initial stages of BIM research, its meaning and scope were different and narrower. While the notion of building modelling was first introduced in the mid-80 s [30], a few years before, a Building Description System (BDS) had been already proposed; which, put forward the idea of a database capable of describing buildings in detail to support design and construction [31]. Then, the idea of "building models" appeared which referred to the encapsulation of data to describe all building components, attributes, and relationships [32], and the use of different models for different aspects of the building [33]. Later a more overarching definition of building model was developed, i.e. a representation of a building over all its life stages, adequate for most uses including feasibility studies, all aspects of design and construction, and later, operation and facility management [34]. Then, the focus was shifted from the object "model" to the action "modelling" to account for the information exchange between design and construction activities and to enable modelling abstract knowledge in building projects [35]. It was then considered as a method to manage all design and construction issues in building projects and process environments [36]; and as a methodology to improve the performance and productivity of an asset's design, construction, operation, and maintenance [37]. While early on, in BIM conceptualisation, support for building operations was envisioned, it was until decades later that BIM for facility management was defined more clearly [38]. Currently, is described as the technology that enables the creation of one or more digital models of a building to support all the phases of design, allowing better analysis and control. These models must contain geometrical and all other data needed to support construction, fabrication, and procurement activities for building delivery, operation, and maintenance [29].

3.4.1. DT definitions in the built environment context

As described by Sacks et al. (2020), within the AECO academic and industrial fields, the term DT is being used mainly in two ways: (1) informally, as a replacement term for BIM and (2) as a conceptual conduit to enable remote asset monitoring and to make more efficient the operations and maintenance of complex built assets such as airports, nuclear facilities, hospitals, e.g. [7,39]. However, inspecting the definitions used in literature in more detail, three distinct trends can be appreciated for DT definitions in the AECO context: (1) using the same original DT definition but constraining it to the built environment, e.g. a realistic digital representation of assets, processes, or systems in the built environment [40,41]. (2) As an extension of BIM that enables real-world data capture and feedback [5,6]. Note that DT has been used to replace BIM entirely as well. For example, by proposing distinct DTs for the three major phases of built assets' lifecycle, i.e. "digital product twin" for design, "digital construction twin" for construction, and "digital performance twin" for operations [6]. And, (3) as a complex closed-loop digital-physical system for built asset delivery and operations [4,7]; note that this last type of definition is more akin to CPS than to BIM.

3.4.2. A comparison between BIM and DT

In the three trends above there are significant overlaps between the definitions and scopes covered by BIM and DT. However, there are two major high-level differences. The first high-level difference is that, unlike BIM, DT considers both the replication of the physical asset and a two-way connection that enables to update the digital replica and to control the physical asset [41]. While a BIM model might contain all the information required to construct and operate a built asset, it does not have a well-defined connection with the physical asset. In contrast, DT is a responsive model that enables the exchange of data between the physical and the digital assets and vice versa [7].

The second high-level difference concerns its application throughout the asset's lifecycle. In general terms, BIM considers the entire asset's lifecycle, while the DT is focused only on operations and maintenance [42]. Most of the DT implementations in the built environment are focused on asset monitoring and managing operations, e.g. [43,44]; and there are no well-defined frameworks that outline how DTs can be leveraged to support design and construction.

Even though BIM has been considered for the whole asset's lifecycle, its implementation has been focused primarily on design and construction. More importantly, the BIM implementations for operations differ significantly from the DT vision for supporting built assets operations. For instance, BIM for facility management is focused on compiling information of the delivered built asset to support inventory and space management, general upkeep, and building services maintenance; but it is not envisioned as a responsive model that is continually updated resulting in an accurate replica of the condition and performance of the asset. As-built BIM models for facility management are created after the built asset has been constructed to provide owners and operators with a record of the built asset; but, they cannot directly enable asset monitoring and control because they are not conceptualised to include constantly updated data or to control physical assets. Building Management Systems (BMS), which are more akin to CPS, provide monitoring and control capabilities; but BMS focus entirely on operating the building without considering a model of the building, its components, and relationships [45,46]. Also, most of the estimations and simulations (structural, illumination, thermal and ventilation, acoustic) are carried out to predict future building performance rather than building operations.

Besides the high-level differences there are more granular aspects that differentiate BIM and DT in terms of (i) essential and optional capabilities, (ii) use-cases, (iii) enabling technologies, and (iv) Levels of Development (LOD) and fidelity, as presented in Table 2 and explained below. Note that the information regarding capabilities was drawn from the Bew-Richards (2008) BIM maturity model and the Grieves (2019) DT definition. The BIM capabilities referred to as "essential" include the

Table 2
Main differences between BIM and Digital Twin.

	BIM	Digital Twin
High-Level Differences		
Broad Definition	• Digital replica of a built asset throughout its life cycle.	• Digital replica of an existing built asset which is connected to the built asset and is continuously updated.
Lifecycle's Phase	• Design, Build, and Operations	• Operations
Granular Differences		
Essential Capabilities(BIM Level 2)	• 3D models for design and construction • Federated discipline-based models • Collaborative working and data exchange through open data formats • Design and construction support	• Instrumented physical asset • Digital model (not necessarily 3D) • Synchronisation • Real-world data capture
Optional Capabilities(BIM Level 3)	• Updated and integrated building model • Complete building data capture • Support for facility management	• Remote asset control • Asset condition estimation • Asset performance simulations • Optimal operations
MainUse-cases	**Design and Construction Coordination** • Quantification and cost estimation • Construction scheduling, logistics, and simulation • Clash detection • Safety management **Optimal asset delivery** • Progress monitoring • Quality control **Facility management** • Space management • Optimal maintenance • Optimal energy optimisation • Improved retrofit and renovations	• Asset and site monitoring • Optimal operations • Preventive maintenance • What-if analysis and simulations
Main Enabling Technologies	**Modelling of Topological Data** • Geometrical modelling tools • Data schemes and ontologies • Visualisation tools **Task Automation and Coordination** • Databases and common data environments • Discipline coordination and federation tools • Construction planning and scheduling tools	**Data Gathering** • Sensors and Internet of Things **Physical-Digital Connection** • Web communication frameworks and protocols • Mobile data connectivity **Processing Services** • Cloud and Edge computing
Levels of Developmentand Fidelity	**Levels of Development (LOD)** • Danish Levels of Information (BIPS, 2007) • Information Management	**Levels of Fidelity** • No agreed specification exists.

(*continued on next page*)

Table 2 (*continued*)

	BIM	Digital Twin
	Specification PAS 1192–2 (BSI, 2013) • Building Information Modeling and Digital Data Exhibit (AIA, 2013) • Level of Development Specification (BIM Forum, 2020)	

capabilities defined by the maturity Level 2, and the "optional" capabilities by the maturity level 3 outlined in the BIM maturity model [47]. The rest of the information was compiled from the references discussed above [4–7,40–42,48–50].

3.4.2.1. Essential and optional capabilities. The essential BIM capabilities include (i) development of 3D models for design and construction, (ii) the use of federated discipline-based models, (iii) collaborative working and data exchange through open data formats, and (iv) support for design and construction. The additional capabilities include (a) development of updated and integrated building model, (b) complete building data capture, and (c) support for facility management. The essential DT capabilities include (i) an instrumented physical asset, (ii) a digital model of the asset, not necessarily 3D. For instance, the geometrical data of stationary manufacturing equipment might not be necessary for most DT use-cases, e.g. monitoring the asset's performance. (iii) Data synchronisation between the physical and the digital asset, and (iv) real-world data capture of the asset context. The additional capabilities include (i) remote control of the physical asset, (ii) estimation of asset condition, (iii) asset performance simulations, and (iv) and optimal asset operation.

3.4.2.2. Main use-cases. A major difference between DT and BIM are the use-cases employed. BIM is employed primarily for (i) design and construction coordination, including quantification and cost estimation; construction scheduling, logistics, and simulation; clash detection; and safety management. (ii) Optimal asset delivery, including progress monitoring and quality control; and (iii) facility management, including space management, optimal maintenance, optimal energy optimisation, and improved retrofit and renovations [5,29]. While, DT is envisioned to be employed for asset and site monitoring, optimal operations, preventive maintenance, and what-if analysis and simulations [5,51].

3.4.2.3. Main enabling technologies. The primary technologies required to enable BIM can be grouped into two main categories (a) modelling of geometrical and asset data and (b) task automation and coordination [29,49]. The first category includes drafting and geometrical modelling tools (authoring tools), that enable the creation of BIM models; data schemes and ontologies that facilitate data exchange among parties, e.g. Industry Foundation Classes [52]; and visualisation tools. The second category includes databases, common data environments, and cloud storage, e.g. [53]; discipline coordination and federation tools; and construction planning and scheduling tools.

On the other hand, the technologies that enable the replication and connection between the physical and the digital asset can be grouped in three categories [50]: (a) data gathering, which includes sensors and Internet of Things (IoT) enabled devices; (b) physical-digital connection, which includes web communication frameworks, e.g. Node-RED [54], protocols, e.g. MQTT [55], and approaches to mobile data connectivity; and (c) processing services, which includes cloud and edge computing.

3.4.2.4. Levels of development and fidelity. An important aspect of BIM development has been finding ways to define how detailed and how much information a BIM model should contain. The currently agreed approach is to define Levels of Development (LOD) that define the graphical and non-graphical content of BIM models for specific use-cases. Initially, the term used was Levels of Detail that considered 3D geometry only; and which probably was inspired by the set of techniques used for real-time computer graphics [56]. In the built environment sector, the first systematic effort was the "Danish Information Levels", a 7-level scale, that outlines an increasing amount of information and detail to be added to the BIM models progressively during the project delivery phase [57]. Other national initiatives exist. For example, the Netherlands developed a very similar LOD approach to the Danish information levels [58]. And, in the UK, the BSI published the PAS 1192–2 specification [59], later expanded into an international standard [60], in which "levels of model detail" and "levels of information" are used to define the graphical and non-graphical content of BIM models.

Another notable example is the LOD definitions proposed by the American Institute of Architects [61] and later expanded by BIM Forum [62], which has gained wide-acceptance. It outlines six levels, as follows: (1) LOD 100 - Conceptual Design, in which only basic parameters of building elements (area, height, volume) are defined. Some elements may be graphically represented in the model with symbols or other generic representations. (2) LOD 200 - Schematic Design, in which building elements are modelled with approximate dimensions, shapes, locations, orientations and quantities. (3) LOD 300 - Detailed Design, in which elements are modelled with precise dimensions, shapes, locations, and quantities. (4) LOD 350 - Construction Documentation (added by BIM Forum), which includes precise parameters, as in LOD 300, as well as connections with other building elements. (5) LOD 400 - Fabrication and Assembly, which includes details about fabrication, assembly, and installation. Lastly, (6) LOD 500 - As-built, in which model elements are verified against constructed elements in terms of dimensions, shapes, locations, orientations, and quantities. Note that non-geometric information can be included in LOD 200 to 500.

In contrast, in DT literature the term fidelity has been used to refer to the level in which the digital replica reflects the actual condition of the physical asset by measuring the number of parameters, accuracy, and level of abstraction of the data transferred between the physical asset and the digital replica [51,63]. The higher the level of fidelity more accurate monitoring, simulations, and process optimisations can be achieved. However, unlike BIM, there are no agreed methods to define and measure the levels of fidelity. Note as well, that levels of fidelity are focused primarily on the amount of asset data being replicated, while BIM LODs are focus primarily on geometrical detail. While, for many use-cases in manufacturing DT asset geometrical information is not indispensable, for AECO use-cases is essential. Thus, well-defined DT geometrical standards similar to BIM-LOD should be in place to satisfy the built environment modelling requirements.

Summarising, it can be argued that BIM focuses on replicating the physical asset throughout the asset's lifecycle, while BIM replicates and enables a connection with the physical asset during operations. Fig. 4 illustrates the main differences and scopes between BIM and DT. In BIM, there is a hard division between the digital and the physical; while, for DT this division is blurred due to asset instrumentation and data synchronisation between the physical and the digital asset. BIM is used in the three main phases of the built asset's lifecycle, i.e. design, build, and operations; while, DT is focused primarily on operations. As-designed BIM models are used for BIM Levels 1 and 2, and as-built BIM models for BIM Level 3, with their corresponding LOD specifications. These models have a varying degree of detail for their specific use-cases, i.e. built asset design, design-construction coordination, optimal asset delivery, and facility management. For DT, there are no specifications for model detail or fidelity. BIM has limited support for asset monitoring and control and for asset performance simulations during operations; while, DT does not consider discipline coordination for built asset delivery.

Note that the term simulation has some similarities with BIM, DT, and CPS; however, in the context of this study which focuses on

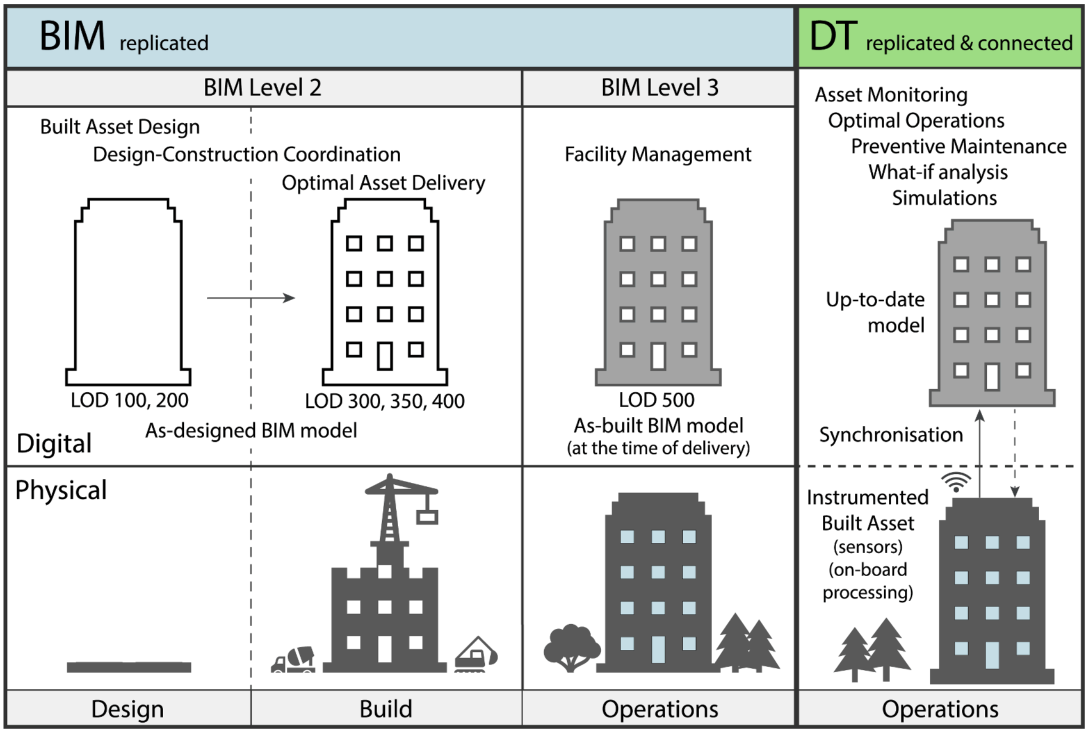

Fig. 4. Overall differences between BIM and DT.

manufacturing and the built environment, the term simulation is considered only as a non-essential component of BIM, DT, and CPS. This distinction was made because of two main considerations; first, simulation is not a conceptual construct like BIM, DT and CPS and it refers primarily to the process of imitating another process; and, secondly, simulations do not require a physical counterpart like BIM, DT, and CPS, as they can imitate non-physical processes.

4. DT's structural and functional models

Drawing inspiration from object-oriented approaches in software engineering to describe software and hardware systems, the two main Unified Modelling Language (UML) categories –i.e. structural and behavioural [64]– have been adopted to group the descriptions found in the DT literature into structural and functional categories. UML is a modelling language for describing, specifying, and visualising software and hardware systems [10,65], and can be used to describe non-software and complex systems as well, e.g. [66]. The two main UML categories are (a) structural diagrams, which describe the components and relationships of the system; and (b) behavioural diagrams, which describe how the system functions and interacts with users and other systems. This approach of describing separately the high-level structure and function (behaviour) of a system is an appropriate approach to describe DTs, which are a combination of hardware and software systems with various components, functions, and interfaces. Here, the two categories are renamed as "structural models" and "functional models" (Fig. 5).

In the DT literature analysed, there are three types of structural models, namely conceptual models, system architectures, and data models; and two types of functional models, i.e. process models and communication models. Maturity models have been also reported in the publications and have been included in this study; although, they do not correspond to either of the two categories above. All these models

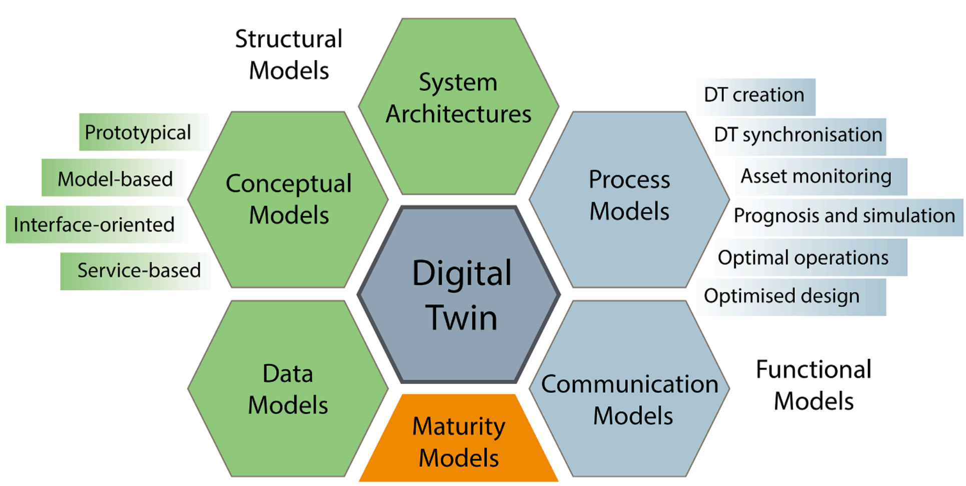

Fig. 5. DT's structural and functional models.

combined enable a complete description of a DT system (Fig. 5).

Table 3 and Table 4 list all the publications analysed in this study outlining the publication source (i.e. conference, journal, or report), the publication type (i.e. conceptual paper, literature review, expert survey, or practical case-study), and a brief description of the use-case addressed. Thirty-six publications are journal articles representing 67% of the total, 13 are conference papers (24%), and four are reports (9%). Regarding publication types, 31 publications are theoretical papers (57%), 10 are literature reviews (19%), two present expert surveys (4%), and 22 present practical case studies (41%). Note that the publications that address both theoretical aspects and present practical case studies are counted in the two corresponding categories. In this regard, the number of review papers analysed in this study is relatively high considering that the average number of DT review papers from 2015 to 2020 is about 7.6% of the total DT papers listed in Scopus while using the same search criteria. The relatively high number of review papers might be due to the search terms used that filter papers that include definitions.

The 37 publications related to manufacturing (68%) are presented in Table 3; while the publications related to AECO (14 publications, 24%), computer science (two publications, 2%), and aerospace (one publication, 2%) are presented in Table 4. Both tables indicate the types of structural and functional models addressed in each publication. Thirty-two papers describe conceptual models (49%), 34 present system architectures (52%), 11 discuss data models (17%), 24 describe process models (37%), eight present communication models (12%), and four discuss maturity models (6%).

5. DT's conceptual models

A conceptual model is an abstract representation of a system that helps in the understanding of its structure and inner functions. Many variations of the original DT conceptual model have been developed that fit better the varied requirements of different use-cases. Based on the literature review presented in this paper, four major categories of structural models are proposed, i.e. prototypical, model-based, interface-oriented, and service-based. Table 5 presents a summary of the four types of conceptual models discussed here, highlighting the main characteristics of the conceptual model, the use-case addressed, and key considerations for the AEO sectors.

5.1. Prototypical

This category includes conceptual models that are very similar to the original one presented in the seminal literature [15]; but, with slight formal variations, additions of components, and more detailed specifications. For instance, Madni et al. (2019) presented a conceptual model in which the physical asset transmits the occurrence of events and actions in addition to performance, health and, maintenance data. In another approach, Liu et al. (2020) proposed a conceptual model in which the digital asset contains separate representations for an information model and a decision-making model. Also, the conceptual model prescribes that the communication between the physical asset and the digital asset should include data concerning geometry, performance, and context. Wang and Luo (2021) present a prototypical DT conceptual model that considers the asset's life cycle and use-case descriptions. In

Table 3
List of publications analysed focused on manufacturing use-cases. A: concept models, B: system architectures, C: data models, D: process models, E: communication models.

Publication	Source	Publication type	Use-case	Model				
				A	B	C	D	E
[67]	Conference	Theoretical	NA	★	★		★	
[68]	Article	Theoretical	Machining		★	★		
[69]	Article	Theoretical	NA		★			★
[3]	Article	Review	NA	★				
[70]	Article	Theoretical	CNC machining	★	★			
[71]	Conference	Theoretical/Review	Digital factory		★			
[72]	Article	Theoretical	Circuit breaker production	★	★			
[73]	Article	Theoretical	NA		★		★	
[63]	Conference	Survey	NA	★	★	★	★	
[74]	Article	Theoretical/Practical	Assembly processes	★			★	
[48]	Report	Survey	NA		★		★	
[51]	Article	Review	NA	★			★	
[75]	Conference	Practical	Metal processing logistics		★		★	
[76]	Article	Practical	Smart shop floor	★				
[76]	Article	Theoretical/Practical	Product smart manufacturing	★	★			
[77]	Article	Theoretical/Practical	Machining		★		★	
[78]	Article	Theoretical	On-demand manufacturing		★	★	★	
[79]	Article	Review	NA	★	★		★	
[22]	Article	Theoretical	NA	★				★
[80]	Article	Theoretical	NA				★	
[2]	Article	Review	NA	★				
[81]	Article	Practical	Micro factories		★	★	★	
[82]	Article	Theoretical/Practical	Textile dyeing and finishing	★			★	
[83]	Article	Theoretical/Practical	Vehicle component manufacturing	★	★	★	★	★
[84]	Conference	Practical	Control and simulations		★		★	
[85]	Conference	Theoretical/Panel	NA	★	★	★	★	
[19]	Article	Theoretical/Practical	Smart factory	★				
[26]	Article	Review	NA	★	★	★		
[86]	Article	Theoretical	Product design	★	★		★	
[87]	Article	Practical	Planning of future shop floors		★	★	★	
[88]	Conference	Theoretical	Design and operation of mechatronic products	★	★		★	
[89]	Article	Practical	Manufacturing specialised vehicles		★		★	★
[90]	Article	Theoretical/Practical	Smart manufacturing electrical components	★	★			
[1]	Article	Theoretical	NA				★	
[91]	Conference	Theoretical/Practical	Dual-manipulator cooperation production unit	★				
[92]	Article	Theoretical/Practical	Manufacturing engine components				★	
[93]	Article	Practical	3D printer control	★	★	★	★	

Table 4
List of publications analysed focusing on AECO, computer science, and aerospace use-cases. A: concept models, B: system architectures, C: data models, D: process models, E: communication models. * Computer Science. ** Aerospace.

Publication	Source	Publication type	Use-case	Model				
				A	B	C	D	E
[94]	Article	Theoretical/Practical	Wetland maintenance	★	★			
[5]	Article	Review	NA	★				
[6]	Report	Theoretical	NA	★	★			★
[95]	Conference	Theoretical	City-wide DT	★				★
[41]	Report	Theoretical	NA	★				
[96]	Article	Theoretical	Disaster management	★	★			
[7]	Report	Theoretical	NA	★	★			★
[8]	Report	Review	NA	★				
[97]	Article	Practical	Estate management		★	★	★	
[43]	Article	Theoretical/Practical	Centrifugal pump monitoring	★	★	★		★
[98]	Conference	Practical	Borehole maintenance	★	★		★	★
[20]	Article	Theoretical/Practical	Monitoring wind turbine		★			
[18]	Conference	Theoretical	Change management					★
[99]	Conference	Review	Rail maintenance	★				
*[100]	Article	Practical	Wearable devices monitoring	★	★			
*[101]	Conference	Theoretical/Review	Systems communications	★				
**[11]	Article	Practical	Structural life prediction	★				

Table 5
The four types of DT conceptual models.

Type	Main characteristics	Use-case	Key considerations for AECO sectors	Examples
Prototypical	• Details the data exchanged between physical and digital assets. • Specifies the DT's capabilities through services. • Specifies the interaction with other DTs and users.	• Digital/Smart factory • On-demand manufacturing • Optimal manufacturing	• Represents a more detailed structural description of the DT paradigm. • Should include context data and contextual visualisations. • Should interface with BMS and other existing asset monitoring solutions (e.g. SHM). • Should consider the variety of stakeholders, i.e. operators, owners, authorities, and end-users.	[22,69,73,77,79,90]
Model-based	• Defines the digital replica as a collection of distinct models, e.g. geometry, physics, behaviour, rule models. • Specifies access to other types of data, such as domain knowledge and ontologies. • Defines user interaction through specific services, e.g. DT configuration and DT visualisation.	• Digital/Smart factory • Design and operation of products	• Specifies the different aspects of the digital asset explicitly helping to account for the varied disciplines in the AECO sectors. • The modular aspect enables to interface with existing AECO capabilities in ontologies, simulation, and visualisation. • Configurator node provides flexibility to address different use-cases and users.	[19,20,80,87,88,102]
Interface-oriented	• The DT is an interface between a "physical space" and a "digital space". • The link between specific physical and digital assets is not explicit. • Focus on processes rather than on individual physical assets.	• Monitoring products' lifecycle • Re-manufacturing	• Difficult to apply in the AECO because of its high-level of abstraction and the lack of an explicit link between physical and digital assets. • Enables to consider digital components and services without a physical counterpart.	[89,100]
Service-based	• The user takes a central position in the structural description. • The interaction among a multitude of different DTs is considered. • DTs represent physical assets and human operators. • DT services are modelled explicitly, and DTs are considered as wrappers of those services.	• Digital/Smart factory • Wetland maintenance scheduling	• Enable to manage complex workflows with a multitude of different types of DTs, e.g. site workers and plant equipment. • Facilitates description of complex workflows in which many parties and disciplines are involved. • Active user interaction. The DT proposes solutions. • Applicable to complex use-cases, e.g. construction and maintenance of industrial facilities.	[71,94].

this case, the physical asset compiles raw and processed data, process descriptions, and use-case descriptions. The digital asset is composed of a variety of data models, algorithms, and digital processes.

Other examples focus on remote control capabilities and include the interaction of the user interfacing with the DT. In those cases, the DT capabilities are considered as services. For example, the conceptual model proposed by Lu and Xu (2019) addresses on-demand manufacturing services in which the DT manages a series of physical controllers and interfaces with remote users through cloud services. Damjanovic-Behrendt and Behrendt (2019) propose a different way of conceptualising the interaction between the digital and the physical asset by defining three interoperability "managers" that are in charge of exchanging data and controlling the assets rather than specifying the data to be exchanged. The three managers enable monitoring, decision-making, and simulations, respectively. Lastly, other conceptual models also consider communication among various DTs and the ability to simulate those interactions, e.g. [69].

Fig. 6 presents a DT conceptual model, including all the new aspects discussed above in addition to slight adaptations for its use in the built environment. It details that the physical asset should be instrumented with sensors, actuators, and on-board processing capabilities. It should transmit condition, geometry, and behaviour data about the physical asset and context data regarding the environment. Also, the digital asset should be able to provide feedback and control the physical asset. The digital asset should include operational data, information about dependencies, and version management in addition to historical condition data. Most importantly, it prescribes that the user should interface with the DT through computing services and that the DT should have the

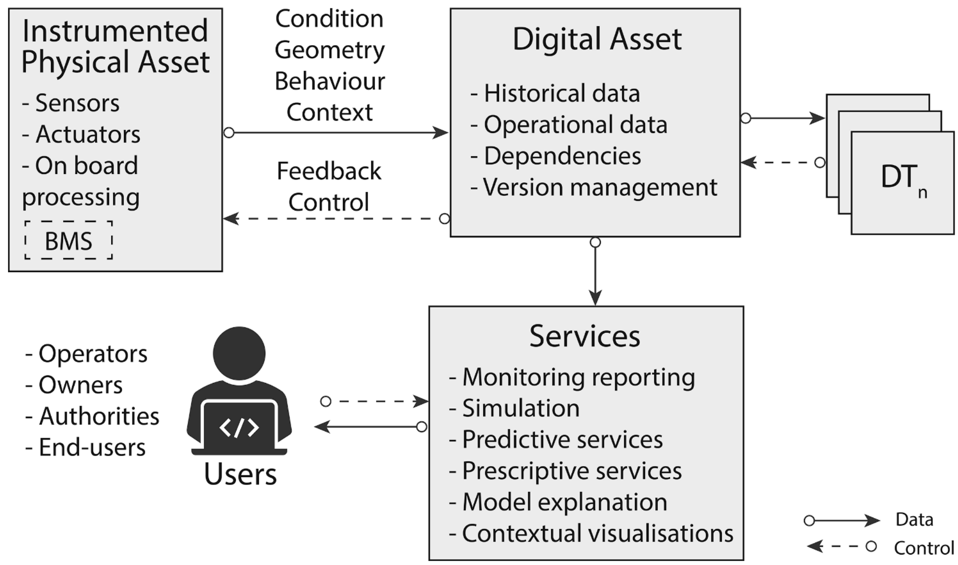

Fig. 6. Expanded prototypical DT concept model. Inspired by [69,77,79].

capability to interact with other DTs. Regarding AECO specific capabilities, it considers the integration with BMS solutions and other existing asset monitoring solutions; it specifies different users to interface with the DT, i.e. operators, owners, authorities, and end-users. The context in which an asset is located is very relevant for built assets, therefore contextual visualisations are included in the list of DT services.

5.2. Model-based

These types of conceptual models describe the DT structure as a collection of different models that interact within a communication framework, e.g. [80]. These types of models focus on making explicit the variety of models required to generate a digital asset that accurately represents a physical asset; which the original DT conceptual model does not describe clearly. For example, Zhang et al. (2019) propose that a DT should include a product definition model, a geometric shape model, a manufacturing attribution model, a behaviour rule model, and a data fusion model. Vrabič et al. (2018) propose separate models for geometry, environment, dynamics, control, sensors, machine learning, among others. More generally, Tao et al. (2018) presented a conceptual model that includes four models, i.e. (i) a geometry model, which describes the components' 3D geometrical attributes and assembly relations; (ii) a physics model, which describes physical properties of the components and performs analyses, e.g. stress analysis; (iii) a behaviour model, which describes procedures, e.g. power generation in a wind turbine DT; and (iv) a rule model, which outlines constraints and associations among parameters that guide the behaviour model. Note that this DT concept model also considers a model for user services and access to existing domain knowledge. In a similar way, Zheng and Sivabalan (2020) propose a DT concept model that has three main components a digital model, which is the agglutination of assets and environment models; a computational model that carries out simulations; and the graph-based model, which is a data model that organises and describes the interactions among different datasets. Note that in this case, the physical assets and the real environment have distinct digital replicas describing static and variable properties. In a different approach, Stark et al. (2019) propose an explicit differentiation between hardware and software components. It also considers different types of models (geometric, numeric, statistical), data, processes, and the communication among components. In all these cases, a correct interaction among the various models is essential in order to reflect the changing conditions of the physical asset accurately.

Terkaj et al. (2019) presented a DT conceptual model with a network configuration, in which a DT model interacts with different nodes that enable various capabilities. Fig. 7 presents a DT conceptual model using a similar network configuration but with additions from the other models reviewed above that can be applied to use-cases in the built environment. In this case, a collection of models communicates with four nodes, i.e. (1) a *configurator node*, which is a user-interface that enables different types of users in the built environment to configure the DT's structure, functions, and control policies; (2) an *ontologies node*, which is a catalogue of components and resources used to configure specific DT's according to the user's requirements; (3) a *simulation node*, which runs performance evaluations and simulations of different DT configurations; and (4) a *visualisation node*, which is a visualisation environment that displays visual representations of the carried out simulations and evaluations. Note that the model-based DT conceptual models are very similar to BIM concepts focusing on discipline coordination and interoperability; which could be more appropriate for AECO sectors as the physical assets are more complex requiring more detailed digital replicas. Note as well that in this model, other data sources, computing nodes, and user interaction are described explicitly, which provides more insight into the actual applicability for specific use-cases.

Regarding AECO applicability, it should be determined what models are relevant for the AECO use-cases, then the configurator can select the relevant models and provide the requested services through the visualisation node. This provides great flexibility because different configurations can be used for different use-cases, e.g. inspections, maintenance, or optimal operations; and different levels of detail can be presented depending on the users, e.g. high-detail for operators and low-detail for owners. The modular configuration of this conceptual model enables to interface with existing capabilities in the AECO sectors regarding ontologies, simulations, and contextual visualisations.

5.3. Interface-oriented

The interface-oriented conceptual models are a significantly different conceptual description, which considers the DT as an intermediary between a "physical space" and a "digital space" that brings together digital and physical entities, rather than being a digital replica of a physical asset. For example, Zheng et al. (2018) suggest a conceptual model in which the DT is an interface between the manufacturers, service providers, and users in the physical space and cloud-based services in the digital space. In a similar way, Wang et al. (2020) proposed a DT description in which the DT links together manufacturing, cloud processing, and physical inspections of products during operations.

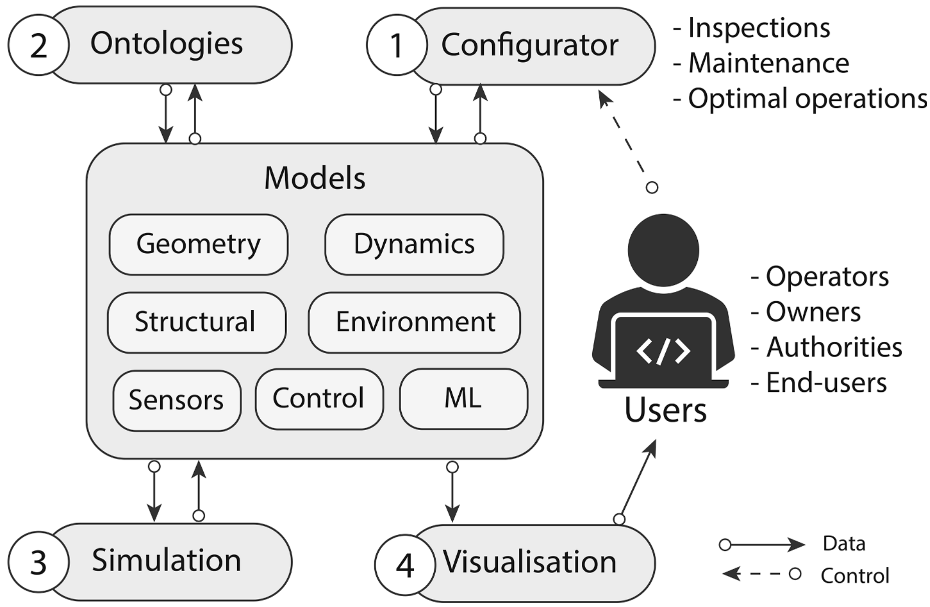

Fig. 7. Model-based concept model. .
Adapted from [20,87,88,102]

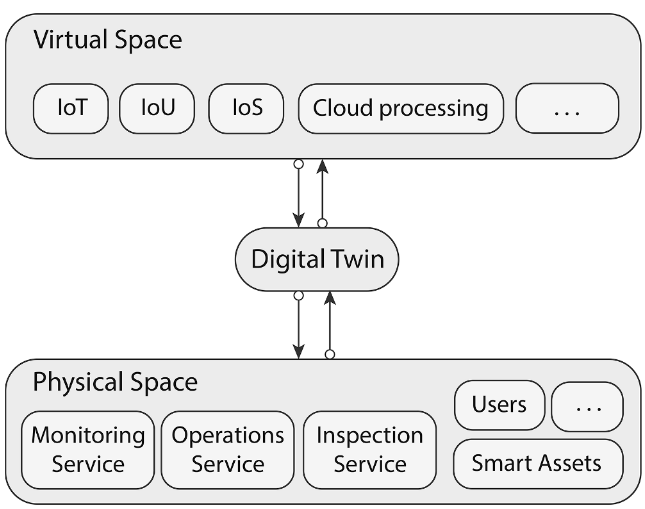

Fig. 8. DT as an interface between virtual and physical space. Adapted from [89,100]. IoT: Internet of Things, IoU: Internet of Users, IoS: Internet of Services.

Fig. 8 presents an example of an interface-oriented DT conceptual model that enables the interaction between users and assets in the physical space with cloud services, which in turn enable monitoring, operations, and inspection services.

In these types of conceptual models, the link between specific physical and digital assets is not explicit. The DT is only the conduit by which digital processes can enhance physical processes. Contrary to the previous two conceptual models discussed above, these conceptual models focus on the processes rather than on the assets. This differentiation is a disadvantage for the AECO sectors in which physical assets are very important. While for manufacturing, products are not as relevant as the manufacturing processes themselves. In sum, the higher level of abstraction and the lack of an explicit physical-digital correspondence among assets of this model limits its applicability for AECO use-cases. However, these types of models enable to consider digital components and services that do not necessarily have a physical counterpart.

5.4. *Service-based*

The key characteristic of these type of conceptual models is that the user takes a central position in the structural description. Service-based conceptual models enable complex workflows by considering the interaction among processes and people, e.g. [94]. Additionally, the services are modelled explicitly, and DTs are considered as wrappers of those services, e.g. [71]. The motivation for this type of structural description is to facilitate the automation of complex workflows through task orchestration. Generally, automation refers to automating a single task, while orchestration refers to automating many tasks in a process that involves multiple steps across various disparate systems. For example, the DT conceptual model presented by Aheleroff et al. (2021), was used to orchestrate a number of different processes with different underlying technologies to automate wetland maintenance scheduling involving real-time monitoring, control, and prioritisation of maintenance activities.

Fig. 9 presents a service-based DT conceptual model that can be applied for use-cases in the built environment, in which a supervisor set goals for the orchestrator, which is a machine-learning-enabled entity that manages a myriad of different DTs. The DTs can represent physical assets or human operators, which interface with the orchestrator through the services that they can provide. For instance, in construction, the DTs could represent plant equipment and site workers. The orchestrator has access to historical data in a data space, synthesises the goals defined by the supervisor, and proposes solutions. In turn, the supervisor selects a solution that the orchestrator then executes. This type of concept model is the most different conceptualisation of the DT paradigm, as it places the DT in a secondary level constituting it only as a component of a larger system. In this case, the orchestrator and the supervisor take important roles. Note that this conceptual model focuses on managing a multitude of DTs in complex workflows, which represents a very different use-case than originally intended by the DT paradigm. In this regard, this conceptual model can be considered as an edge case within the DT paradigm. Regarding AECO applicability, this type of conceptual model could be employed for managing complex construction or maintenance operations such as industrial assets in the nuclear and oil industries.

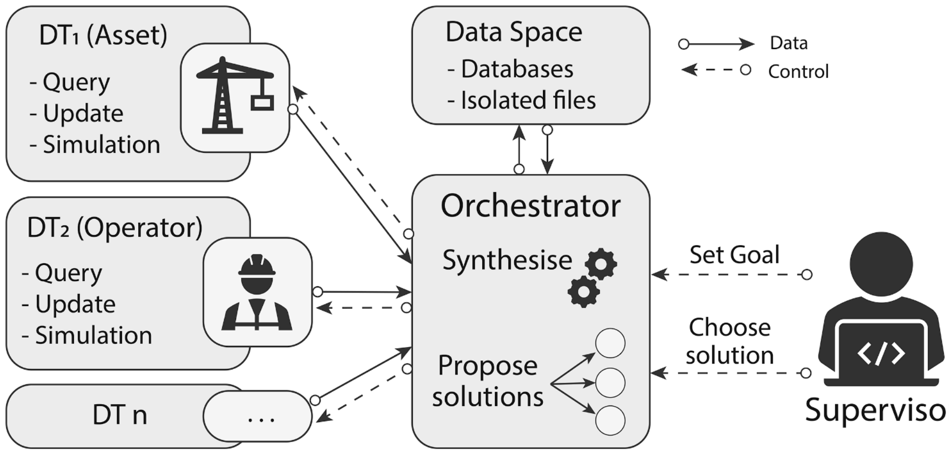

Fig. 9. Service-based concept model. Inspired by [71].

6. DT's process models

A process model is a high-level description of a set of sequential and parallel activities, rules, guidelines, and behaviour patterns that lead to a desired result. Regarding DT process models, Park et al. (2020) propose three categories, i.e. (a) creation of DTs, (b) synchronisation between physical and digital assets, and (c) operationalisation of the DT. In this section, examples of these three types of process models are presented condensed form the publications analysed. Four subcategories have been defined for the operational process models, i.e.: (1) asset monitoring, (2) simulations, (3) optimal operations, and (4) optimised design. Table 6 presents a summary of all the process models discussed here. Also, Park et al. (2020) proposes a distinction between resource-centric, process-centric, and hybrid processes models, which are a combination of the former two. The resource-centric process models give resources or manufacturing components a central role, in which the process model outlines the activities that transform those resources into a new product [74]. In the process-centric approaches, the activities are the central elements that ensure achieving the desired result, e.g. [92]. Note that he majority of AECO processes are resource-centric or "component-centric", in which the building component is the essential element from which all the processes are derived. For example, activities carried out during design and construction are not defined explicitly in BIM models, and can only be derived from the building components modelled.

6.1. DT creation

This type of process models refers to the automated process of creating an instance of a DT for manufacturing, as explained in Section 3.1 (Fig. 3). In these types of process models, a base DT model is initially defined, and then a DT instance is created for every product to be

Table 6
Types of DT process models.

Type	Description	Key considerations for AECO sectors	Examples
DT creation	• Refers to the automated process of creating an instance of a DT for manufacturing. • It defines the required resources, equipment, and work plans necessary to manufacture a product.	• Could be used to generate a federated model by combining different models. • Could be used to generate different DTs of the same asset for different assessments. • Integrates asset data from different disciplines to perform different design and operations assessments.	[81,82]
DT synchronisation	• Refers to the synchronisation of states between the physical asset and the digital asset. • Event-based synchronisation based on obtaining past, present, and future asset condition data.	• Synchronisation varies depending on use-cases, from real-time for anomaly detection, to periodically for performance analysis. • For most AECO processes, real-time synchronisation might not be feasible or required.	[51,76,79,81,82]
DT operationalisation			
Asset monitoring	• Monitoring the assets' performance to identify potential gradual and abrupt faults.	• Applicable for SHM and building service monitoring. • Integration with BMS and SHM must be considered.	[20,43,98]
Prognosis and simulations	• Prognostic simulations predict future trends or state-changes based on current asset states. • Reactive simulations predict future states due to unexpected disturbances and manual interventions in current processes.	• Could be used to predict the asset's performance through its lifetime and simulate degradation or loading capacities. • Could be used to simulate the condition and performance of built assets during extreme weather conditions or during sudden changes in demand.	[11,75,82,96,99]
Optimal operations	• Optimise operations by adjusting process parameters. • Two main approaches: o Optimising the operation of complex equipment. o Optimising manufacturing processes.	• Optimise the operation of a variety of plant equipment including the interaction with other equipment and workers in different site scenarios. • Approaches for optimising manufacturing processes could be applied for the production of prefabricated building components and to devise optimal retrofitting interventions.	[48,74,84,89,124]
Optimised design	Two main approaches: • Leverage DTs to simulate future performance and then optimise the designs of assets to be constructed based on the simulation results. • Optimise design by leveraging historical data recorded during the asset's lifecycle to inform design decisions for future assets.	• The first approach is very similar to current AECO simulations in which digital replicas are used to simulate performance and devise optimal designs. • Optimal design approaches do not usually employ context and asset data directly to calibrate models and simulations to devise optimal designs.	[3,86]

manufactured. An example of this type of process model is presented by Park et al. (2019), which outlines a four-step process, as follows: (1) to combine various digital components from a library to create a DT instance model; (2) to include representations of the manufacturing equipment required; (3) to import functional definitions, e.g. working plans, logic, configuration values, and assign them to the DT instance and equipment representations; and (4) to visualise the DT instance and additional data in a 3D environment.

Regarding AECO applicability, note that these procedures are very different from the approaches to generate BIM models or geometrical DT models for built assets. For instance, instantiation does not occur because usually only a single BIM model is generated at the design stage; and, only in some cases, it is updated after construction has concluded. When a DT is created for a facility, the geometrical model is only generated once as well. Furthermore, BIM models usually do not capture functional attributes, including logic and relationships among components, as is suggested for DT creation process models [82].

Note that current BIM software implements instantiation of BIM components in the background. All building components have generic definitions that are instantiated into specific BIM components; for example, a definition of a wall or column is used to create multiple instances of that component. Changing the definition will automatically change all the instances accordingly. However, these capabilities are not intended primarily for automating the creation of BIM models. Because the software's Application Programming Interface (API) needs to be used to automate BIM element instantiation, which requires programming skills and can be regarded as an advanced use-case that is not common in practice. Research on automating BIM model generation has yielded semi-automated approaches with limited results [103]. For instance, Bortoluzzi et al. [104] presented a semi-automated method for BIM model creation, which still requires manual pre-processing and result validations at each step.

More importantly, automating the creation of BIM models or DTs, in the AECO context, is not limited by the technical capabilities required to enable element instantiation; but, by three key characteristics of the types of assets in the built environment: (i) the assets are similar but not the same, (ii) the assets contain a large variety of different components, and (iii) the number of constructed assets and components is low when compared to other manufactured assets. Even for cases in which the number of components is reduced and repetition of similar assets is high (e.g. power transmission, rail, etc.), the small differences between projects and the relatively small number of instances to be created are enough limitations that limit approaches like the ones used in manufacturing, in which identical assets are created in very large quantities.

Nevertheless, approaches for automated DT creation can be used in the built environment to support BIM model federation instead of BIM model creation. A federated BIM model is the integration of several different BIM models focused on different aspects of the asset, e.g. structural, architectural, or mechanical, electrical, and plumbing (MEP) models. Note that efforts to federate different asset data into BIM models have been carried out, however, they focus on the manual integration of existing BIM models, e.g. [105]. In this case, the DT creation approaches above could be used to generate different DTs of the same asset that integrate asset data from different disciplines to perform different design and operations assessments. For instance, in the case of a bridge, different instances of the DT could be generated for assessing constructability, structural behaviour, traffic flow analysis, and degradation and maintenance. The DT creation process model will need to extract asset data from the different discipline-specific BIM models and integrate it into an instance of the DT for that specific assessment. The DT instantiation for the assessments of the same type of asset will be the same, thus similar automated approaches as the one presented by Park et al. (2019) could be used.

6.2. DT synchronisation

An essential requirement of the DT paradigm is the synchronisation of states between the physical asset and the digital asset [76]. The synchronisation entails a two-way data exchange, in which the digital asset obtains data regarding the current and previous states of the physical asset; and, the physical assets get information about how to update its operational parameters [51]. Note that in the manufacturing literature DT synchronisation is also referred to as "twinning"; while in the AECO literature the term twinning is being used as the sets of activities required to create a DT.

Important aspects in DT synchronisation regard to determining when and how often the synchronisation should occur, and what type of data should be synchronised. Park et al. (2019) suggested event-based synchronisations, in which different types of data are synchronised based on the occurrence of specific events and on the point in time that the event occurred. For instance, different synchronisation procedures are necessary to obtain data for tracking historical operation performance, real-time monitoring, or verification of future manufacturing schedules. Translating this idea to construction, the different event-based synchronisations could correspond, for example, to obtaining data regarding construction progress so far, obtaining information about constructions tasks being carried out currently, and obtaining information about future construction plans; all of which require different processes to obtain the required information.

The rate of synchronisation, often referred to as the twinning rate, is also a very important aspect as real-time data synchronisation is considered to be a must for DTs in Industry 4.0 manufacturing [63]. Latency requirements have been identified as a challenging aspect due to complexities in real-time transmission, processing, and storage of the large quantities of asset and context data that is continuously generated [79]. However, the authors note that the use-case should determine the latency requirements because not all processes require real-time synchronisation. For instance, anomaly detection requires a higher twinning rate than asset performance analysis. In this sense, the most common use-cases in the AECO sectors might not require latency requirements as high as in the manufacturing sector.

Park et al. (2020) proposed two different types of synchronisation procedures based on the type of collected data and the timing of the synchronisation. The first type is "footprint synchronisation", in which synchronisation is carried out at uniform intervals and all the time-series historical data is aggregated and synchronised. This procedure is appropriate for long-term asset monitoring. AECO examples include periodical building inspections and infrastructure inspections. The second type is "snapshot synchronisation", in which only data regarding a certain point in time is synchronised on demand. This type of procedure is suitable for anomaly detection, simulation update, real-time operational optimisation, among others.

6.3. Asset monitoring

Most of the monitoring procedures addressed by the DT paradigm focus on monitoring the assets' performance to identify potential faults in a timely manner and to execute effective maintenance, e.g. [98]. In the AECO sectors, two asset monitoring use-cases are predominant, i.e. Structural Health Monitoring (SHM) and building services monitoring. SHM focuses primarily on identifying structural faults in infrastructure assets [106]; while building service monitoring focuses on identifying faults in ventilation, power, and lighting systems among others [107]. Some advances have been reported that leverage DT-based approaches for both SHM and building service monitoring. For example, Davila Delgado et al. (2018) demonstrated a robust implementation of fully connected physical and digital infrastructure assets providing geometrically-registered structural condition data. Moreover, it presented a long-term asset management and decision-making framework for infrastructure assets based on continuous monitoring. Regarding building services, Q. Lu et al. (2020b) presented a DT process model for anomaly detection in heating and ventilation systems in buildings, which leverages current and historical sensor data.

Fig. 10 presents a DT process model, which can be used to address gradual faults, caused by gradual component degradation, and abrupt faults, caused by sudden disturbances, in infrastructure and other built assets for both SHM and building services monitoring. This model was adapted from Tao et al. (2018) work, which focused on monitoring wind turbines. The process model is composed of four major components addressing, observations, analysis, decision-making, and services. The process works as follows: first, the DT is initialised and calibrated using data collected from the physical asset; then, a simulation is carried out and anomalies are detected. If an anomaly is detected, then the potential cause of the anomaly is assessed. If a model defect causes the anomaly, then the DT is re-calibrated and initialised again. If the cause is not related to the model, then potential faults are identified, and the prediction of causes are performed. In case that an anomaly is not detected, then potential degradation signs are investigated. If no degradation is found, then the simulation is updated with the assessment data collected. If signs of degradation are found, then the identification and prediction of potential degradation causes is carried out. Lastly, maintenance regimes are prepared based on the anomalies and degradation signs detected. This is a flexible process model can be used for varied AECO monitoring services including model calibration, anomaly assessment, fault and degradation detection, and fault prediction. Note that the model considers the integration with existing BMS data for building services monitoring and a human supervisor that interfaces through services.

6.4. Prognosis and simulations

Simulation is also an essential aspect of the DT paradigm [85]; which can enable predictive maintenance, health management, and condition-based maintenance of complex equipment. There are two main types of simulations according to the timing of the state updates: (a) continuous simulations that update the model states continuously through time, and (b) discrete simulations, in which the states are updated only at discrete times [108]. Discrete simulations describe processes that change only in response to specific events and it is assumed that no change in the process occurs in between events. On the other hand, continuous simulations represent a continuously changing process in which all the states are continuously updated. State updates can be made synchronously, i.e. all the parameters are updated at the same time; or asynchronously, in which different parameters change at different times. Usually, discrete simulations are simpler to implement; while, continuous simulations are more complex, hard-to-code, and require larger processing power. For DT applications, both types of simulations are required as both type of processes, i.e. continuous, e.g. supply-chain operations [109] or earthmoving operations [110], and discrete, e.g. equipment damage due to discrete external events [111], need to be simulated.

In the AECO sectors, prognosis and simulations have been used to estimate asset performance at the design stage for a wide range of aspects from indoor occupation [112], façade performance [113], environmental qualities [114], construction delivery [115] and construction cost [116], among many others. However, prognosis and simulations carried out at the operational stage that leverage operational data are not as common, as most of them are carried out at the design stage simulating future behaviours rather than current operations [4]. This

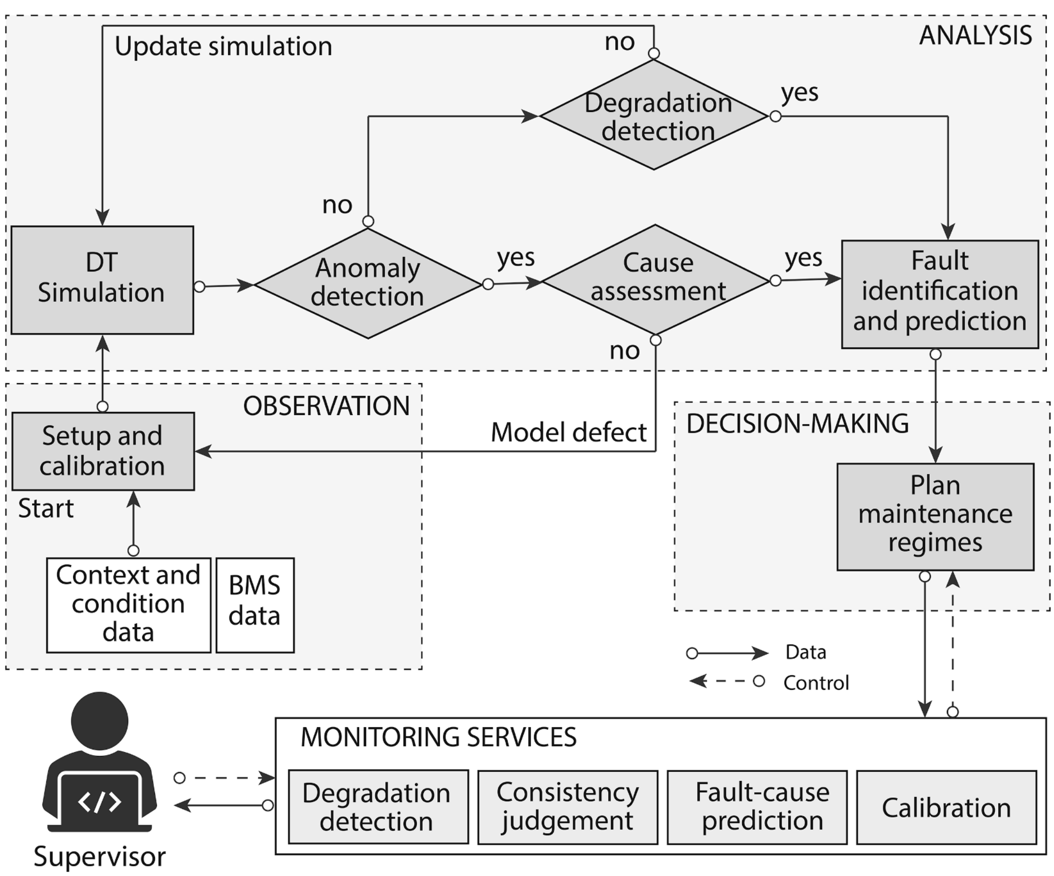

Fig. 10. DT monitoring process model that can be used in the AECO sectors for SHM and building services monitoring. . Adapted from [20]

difference can be due to the strong divide between the design and delivery phase and the operational phase of the built assets lifecycle. In contrast, DT prognosis and simulations have been focused on simulating future asset operations given current performance data [85].

In the DT context, simulations can be categorised in prognostic simulations, which predict future trends or state-changes based on current asset states; and reactive simulations, which predict future states due to unexpected disturbances and manual interventions in current processes [82]. A common use-case of prognostic simulations is to determine the performance of assets in the future. For example, Tuegel et al. [121] presented a DT process model that can be used for predicting the lifecycle of aircraft structures. The process model has four major steps, i.e.: (i) a specific task is selected to be carried out by the physical asset; (ii) the digital asset and environment variables are defined; (iii) then, a reliability assessment is carried out consisting of physical simulations and damage predictions; lastly (iv) if the assessment is positive, the physical process is carried out, after which data related to the actual asset performance is recorded and fed back to the DT. More recently, Park et al. (2020a) presented a DT process model for simulating manufacturing tasks and estimating the quality of the manufactured products. On the other hand, reactive simulations are commonly used to determine the impacts of unexpected damages on assets. For instance, Ford and Wolf (2020) proposed a DT process model to support cities in case of disasters. The overall workflow is as follows: when a disaster event occurs, sensor data is transmitted to a community model that simulates the impact of the disaster on the community's infrastructure. The simulation considers models of physical and non-physical infrastructure systems and predicts future conditions due to the disaster and due to management interventions. The simulations then inform authorities' decision making.

Fig. 11 presents a DT process model to enable simulations for AECO use-cases at the operational phase of the built asset lifecycle, which is based on the work of Korth et al. (2019). Note that unlike the type of simulations commonly carried out in the AECO, referenced above, this process model considers context and asset data collected from the physical assets. The process model has a network configuration in which the central component is a set of DTs that represents the current state of various physical assets, including their attributes and relationships with other assets. An event controller updates the DT models according to changes in the physical assets states. Note that the event-controller compiles the context and asset condition data and generates event-state mappings accordingly. The event-controller only provides state changes to the DT models and not the uncodified context and condition data. Then, a human supervisor can initiate prognostic simulations to evaluate future performance under normal circumstances, and reactive simulations in case anomalies are detected. The simulation component creates synthetic events that affect the model in future scenarios. The visualisation component provides graphic information about previous, current, and future states as well as support with reporting and replay. All the historical state changes and future simulated states will be recorded for evaluation and to restore every state that occurred.

This model can be used for AECO applications for prognostic and reactive simulations in the operational phase of the assets lifecycle. Regarding prognostic simulations, it can be used to predict the asset's performance through its lifetime and to simulate degradation, e.g. simulating the erosion of flood protection systems [117]. Also, the effective load-carrying capacity of the bridge could be simulated using the dynamic strain data gathered from existing bridges [118]. Concerning reactive simulations, the condition and performance of built assets could be simulated during extreme weather conditions, e.g. floods and storms, and natural disasters, e.g. fires [119]; or during sudden changes in demand and maintenance interventions [120].

Note that validating simulations is of utmost importance to ensure the accuracy of the results. In the context of the DT paradigm, the importance of validating simulations has been highlighted by Tuegel (2012). Simulation validation and model calibration, which ensure that the simulations describe reality as close as possible, are imperative especially for complex systems in which a variety of sensors, physical interactions, and dynamic environments interact in complex manners [122]. However, this is a relatively unexplored topic in the DT context and very few studies have been reported in the literature, e.g. [123]. In this regard, for the studies referred here, some include validations and some do not. Tuegel et al. (2011) and Ford and Wolf (2020) are theoretical studies that do not include validations for the simulations. Korth et al. (2019) work was validated by testing the process model in two real-life use-cases (i.e. work shifts planning and metal production control) and recording results onsite. Park et al. (2020a) process model was validated by comparing the results with previously recorded benchmark samples for the same processes (i.e. scheduling and quality prediction in manufacturing tasks).

6.5. Optimal operations

An operation can be optimised by adjusting parameters within

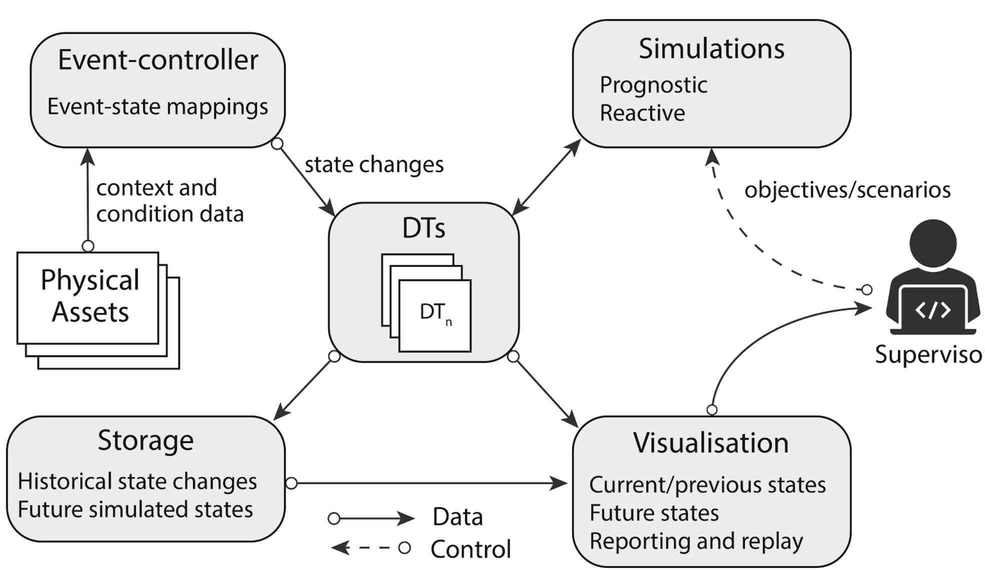

Fig. 11. DT process model for prognostic and reactive simulations at the operational phase of infrastructure and built assets. .
Adapted from [75]

certain limits in order to minimise costs or maximise throughput. Optimising complex operations is one of the key prospects that the DT paradigm can enable, as the digital replicas can be leveraged to test, simulate, and find an optimal set of parameters quicker than testing the parameter changes in the physical assets, e.g. [124]. There are two types of process models for optimal operations reported in the DT literature analysed. The first type focuses on optimising manufacturing processes and the other one focuses on optimising the operation of equipment.

Regarding the optimisation of equipment, Schluse et al. (2017) presented a DT process model for simulation-based optimal operations for complex equipment tasks. The main component of the model is a multi-objective optimisation controller that optimises three simulation environments. The first one simulates the real-world and the physical equipment within it, the second one simulates the digital equipment and real-world simulated data, and the third one simulates the interaction between users and physical equipment. The idea is that the multi-objective optimisation controller finds optimal parameters for the three simulated environments, thus enabling to optimise complex equipment tasks. The key characteristic of this DT optimisation approach is that it combines real-world and physical assets interaction with digital-world and digital assets interactions. More importantly, it simulates the users' interactions with the assets. This approach could be very useful in the built environment to optimise the operation of a variety of plant equipment. For example, the telemetry data for an excavator could be used to calibrate models and simulate its work and interaction with other equipment and workers in different site scenarios (e.g. a crowded site, work along live rail lines or roads, etc.). Note that similar approaches have been used to optimise oil drilling operations, e.g. [125].

Regarding process models for optimal manufacturing, Grégorio et al. (2020) presented a process model for managing geometrical deviations, facilitate assembly, and improve the quality of manufactured products. This DT process model prescribes that the first manufactured components of a product are geometrically scanned after they have been manufactured. Then, deviations from the design specifications are identified and used to update the geometry of the subsequent components to be manufactured. Thus, potentially improving subsequent assembly, as the individual manufacturing inconsistencies are taken into account for each product. In sum, this process model prescribes that deviations in manufactured products are used to update the DT and the assembly process model so that actual assembly and quality is improved. This approach could be used in the built environment to improve the quality of pre-fabricated construction components such as precast concrete elements. For instance, geometrical deviations in components could be identified during manufacturing and then the assembly specification could be amended accordingly avoiding unnecessary adjustments on-site, e.g. [126].

In another example, Wang et al. (2020) presented a DT process model to support remanufacturing, that is rebuilding a product to meet the original specifications using a combination of used, repaired, and new components. The paper presents a very complex process model that can be summarised in five steps (1) measuring performance, in which performance data of the manufactured components are recorded; (2) data analysis, the collected data is pre-processed and analysed; (3) predictive analysis, in which aspects affecting the remanufacturing process are estimated, e.g. disassembly and cleaning; (4) DT simulations, in which the manufacturing process is simulated considering the product reconfiguration using various components; and (5) remanufacturing process, in which data about the actual remanufacturing process is recorded to improve future DT simulations. This approach could be used in the built environment to support retrofitting activities. For example, a DT of an old building could be created, and its current energy performance recorded. Then, its future performance could be simulated given certain retrofitting interventions, and the retrofitting approach could be updated to meet an initial set of requirements. Lastly, the results of the simulations could be used to guide the actual retrofitting actions, e.g. [127].

A more detailed DT process model for optimal operations that can be used in the built environment is presented in Fig. 12, which is inspired by the work presented by Hamer et al. (2018) and the other process models above. The primary component of the process model is an optimisation engine that will provide optimal operational parameters based on data from actual physical processes and simulated digital processes. All physical processes have uncontrollable inputs that affect operations, e.g. changes in temperature or humidity, and operational variables that can be controlled. Data regarding uncontrollable inputs and the physical processes will be used in combination with simulated data to obtain optimal parameters. Note that three components are essential in this process model, the optimisation engine, the data collected from the actual physical process, and the synthetic data generated by the simulated process. Drawing inspiration from the service-based DT conceptual models discussed in Section 5.4, a human supervisor has been included in the model that can define certain optimisation goals and receive data on the current processes.

In the AECO context, this process model could be used to (a) optimise the management of large infrastructure assets such as airports, railway stations, industrial facilities (e.g. oil and nuclear), among others. And, (b) to optimise the management of large construction activities common in infrastructure (e.g. roads, railways, etc.). For example, managing concrete mixing and delivery operations for large infrastructure projects is a challenging task, in which the coordination of many distinct mixing facilities is required to satisfy the large quantities of concrete required [128]. This process could leverage real context and asset data (e.g. weather conditions and mixing equipment conditions) in combination with synthetic data and simulations to optimise the mixing and delivery of concrete, and enabling to adapt the operations to variable situations such as changes in demand, traffic, and sudden faults in equipment.

6.6. *Optimised design*

DTs have been also considered for improving the design of future assets using primarily two approaches. The first one is to use DTs to simulate the performance of physical assets and then amend the designs of the assets to be manufactured based on the simulation results. For example, Tao et al. (2019b) presented a collaborative design process in which designers leverage DTs to come up with improved products. In this case, the designers use DT simulations of the designed products to reduce inconsistencies between the expected performance of the designs and the actual performance in real-world conditions. This is similar to the use of simulations in the AECO sectors, in which digital replicas are used to simulate performance and devise optimal designs for a wide variety of aspects such as indoor occupation [112] or façade performance [113]. However, this approach does not leverage the essential DT characteristic, namely the connection between the physical asset and the digital replica.

The other approach leverages the connection between the physical and the digital asset by using the historical performance and condition data recorded from the physical asset to optimise future designs of similar assets. An AECO example would be optimising the design of infrastructure slopes, such as embankments, by using sensor data from existing embankments to minimise vulnerabilities due to extended periods of wet weather or severe rainfall, e.g. [129]. The recorded data could be used to determine the soundness of current designs and to devise better ones. Also, the historical asset data could be used to calibrate models and validate simulations, thus ensuring that the newly designed assets will perform better on real-world conditions than the original assets [3].

Fig. 13 illustrates a DT process model for optimised design that can be used for AECO applications. The model exploits both of the approaches discussed above i.e. the use of the current and historical asset and context data to improve future performance simulations and to develop new designs. The main component of the model is a so-called

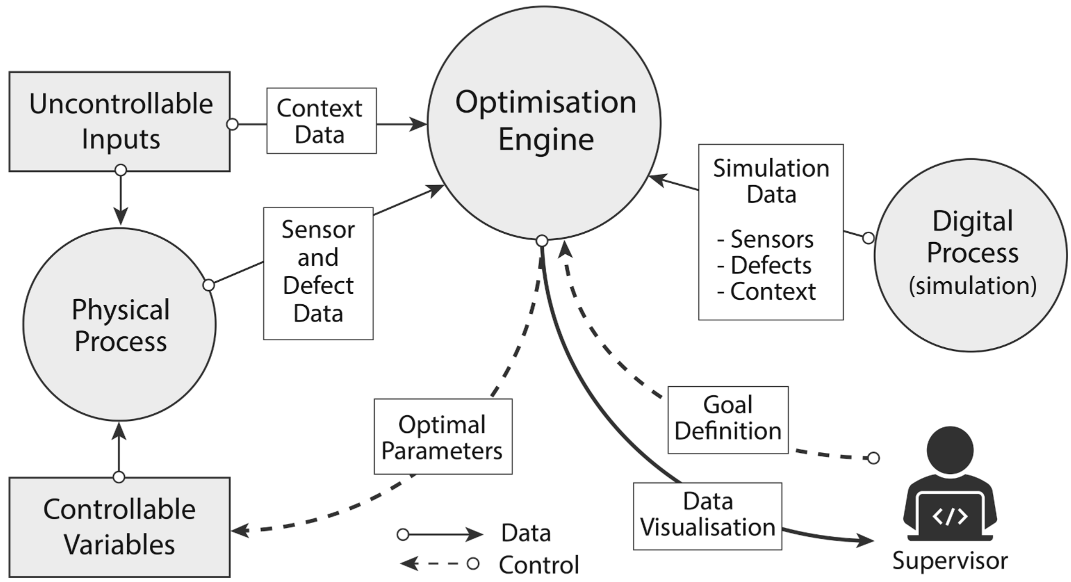

Fig. 12. Process model for optimal operations. .
Adapted from [48]

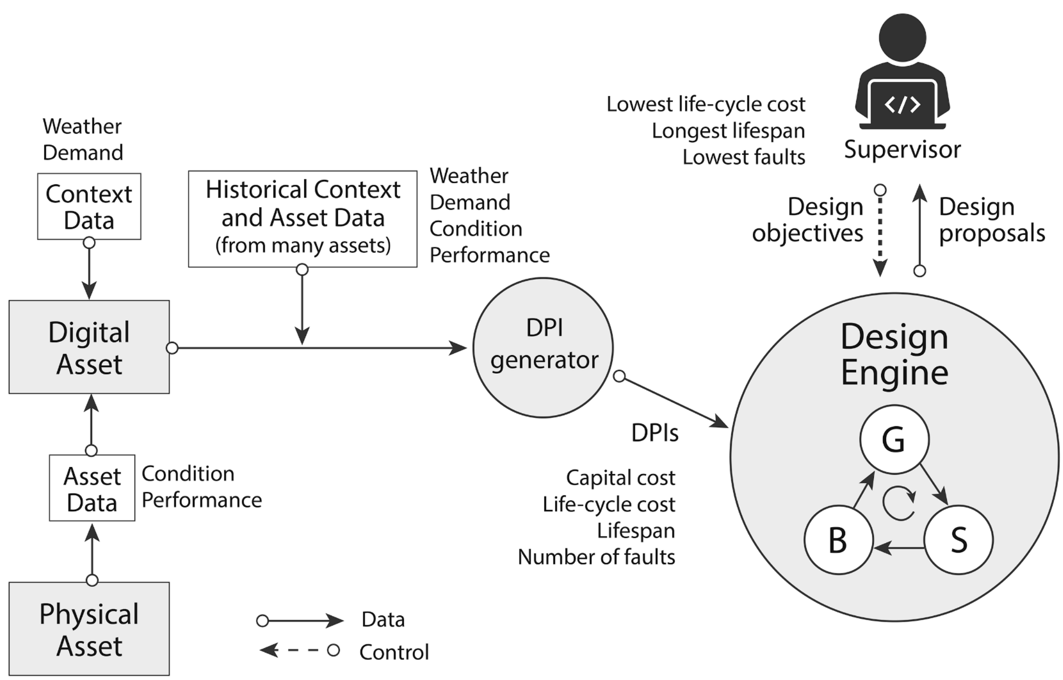

Fig. 13. DT process model for optimised design that can be used for AECO applications. G: design generator, S: design simulator, B: design benchmarking, DPI: design performance indicators.

"design engine", which leverages evolutionary processes to generate a variety of increasingly better design solutions according to predefined optimal parameters. The design engine has been inspired by previous work on automated design processes, i.e. [130,131]. In this case, the design engine consists of three modules, i.e. (i) a design generator (G in Fig. 13), (ii) a module that simulates the performance of the designs (S in Fig. 13), and (iii) a module for benchmarking (B in Fig. 13). The manner in which the three modules interact is based on the use of evolutionary and genetic algorithms for design generation, e.g. [132,133]. In this case, in addition to evolutionary methods, historical and current context and asset data are used to generate design performance indicators (DPIs); which, codify the data into a set of metrics that can be used to benchmark the design variants generated by the design engine. A supervisor initiates the process by providing a set of design objectives, and the design engine provides a set of optimal solutions in return.

An example of how this process model could be used for optimised rail embankment design is as follows. Firstly, current and historical context and asset data will be used to calibrate the models and simulations and to generate DPIs. Examples of data that could be used for this purpose are (a) current context data: weather conditions (humidity, temperature, etc.) and current demand data: the number of passing trains; (b) current asset data: asset condition (e.g. humidity in the soil of the embankment and whether landslips have occurred) and asset performance (e.g. carrying capacity). Note that historical data aggregates context and asset data for a number of similar embankments. Secondly, the research engine starts by developing a variety of embankment designs; then, the simulator simulates the performance of the generated designs; and, the benchmarking module tests the generated designs and ranks the designs using the generated DPIs. The supervisor interacts with the model by providing different design objectives, e.g. lowest cost, longest lifespan, lowest vulnerability; and, the design engine will provide the highest evaluated embankment designs for those objectives.

7. DT's system architectures, data models, communication models, and maturity models

This section presents an overview of the other two DT's structural models (system architectures and data models) and the remaining functional model (communication models). Work on DT's maturity models is reviewed as well.

7.1. System architectures

A system architecture is a structural model of a software or hardware system that outlines the system components, the relationship among components and to the environment, and the principles governing its function. System architectures are key to DT development as they help to structure the complex interaction between physical and digital assets. All the architectures presented in the papers analysed are very similar. All define a physical-space, e.g. a factory floor or a building, that is linked by a set of layers to a user-space. Note that here the term "layer" refers only to software and hardware descriptions and not to other more high-level descriptions, e.g. conceptual models or frameworks [94]; it is not equivalent either to other terms such as "dimensions" used in DT literature, e.g. [19,20].

Fig. 14 presents a generic DT system architecture based on the papers analysed. In most of the DT system architectures, the number and names of layers vary, but in general, all have at least three main layers, i.e. (i) a data layer, (ii) a control or processing layer, and (iii) an interaction or user interface layer, e.g. [68,93]. Bazaz et al. (2019) present a more detailed architecture consisting of a data layer, a processing layer, a model and algorithm layer, an analysis layer, and a user interface layer. Leng et al. (2019) present a 5-layer architecture consisting of a physical layer, which contains all the assets, sensors, materials, and workers; a network layer, which encapsulates all the software and protocols required for DT synchronisation; a data layer, which groups different data sources; a cyber layer, which contains all the digital models of assets and procedures; and lastly, the application layer that contains all the software applications with which the users interact. In a slightly different approach, Park et al. (2019) present a system architecture with four layers in a physical and a digital space. The physical space contains a layer with instrumented smart assets and a layer containing IoT networks and data sources. While in the digital space, there is a local application layer, which contains low-level operational services; and a cloud application layer, which contains high-level management services. These same types of system architectures have been employed in the AECO sectors as well, which have been leveraged to develop DT systems to support the management and operations of public buildings, e.g. [97].

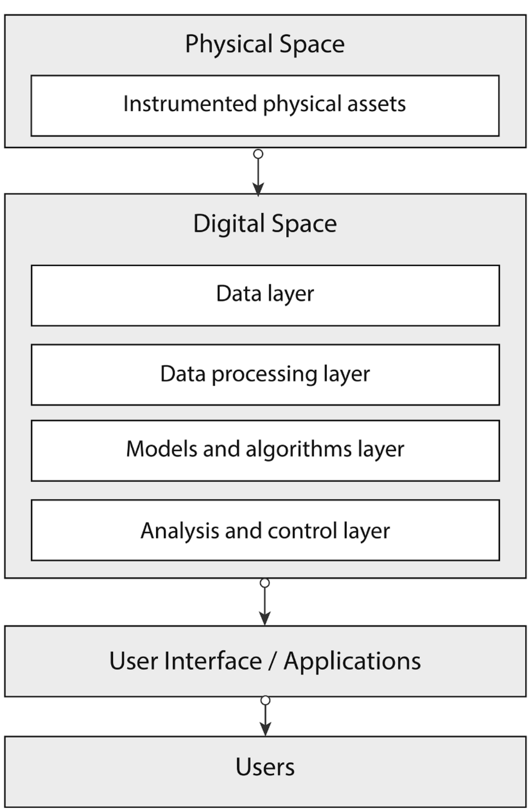

Fig. 14. Generic system architecture for a DT solution.

7.2. Data models

A data model is an abstraction that describes how varied sets of data are related to each other and their correspondences to real-world entities. More importantly, they are indispensable for interoperability among digital systems and will be essential to enable DTs in the AECO sector [95]. In the built environment, the most widely used data model is the so-called Industry Foundation Classes (IFC) developed and maintained by Building Smart [52]. However, IFC is not sufficient to enable the full requirements of BIM and DTs. Most notably, IFC does not have the capabilities required to fully describe asset operations and to enable asset condition monitoring [134,135]. For example, an IFC extension has been proposed to enable DT-based monitoring of heating and ventilation systems in buildings [43].

Regarding data models that are central for DTs in manufacturing, the various existing data models required for DT implementation have been mapped according to different use-cases, i.e. design, planning for manufacturing, planning for inspection, manufacturing, and inspection [79]. The authors note that, for manufacturing applications, a dedicated DT data model does not exist. More importantly, DT solutions usually employ data models that describe data structures as well as semantics, which is not readily available in IFC. Nevertheless, research efforts have been carried out to develop data models that are able to describe DT procedures in a complete and robust manner. For example, Park, Yang, et al. (2020) presented an exhaustive data model for DT-based manufacturing. The data model outlines all the data classes required to describe operation procedures. Also, similar to other traditional data models, it has a hierarchical structure and supports vertical integration and horizontal coordination. Other less-comprehensive examples include Angrish et al. (2017), which presented an unstructured data model for DTs enabling to manage data from different assets with minimal manual interventions; and Zheng and Sivabalan (2020), which proposed the use of a graph-based data model that enables describing complex relationships among different datasets.

7.3. Communication models

Communication models in the DT context refer to approaches for communication among processing units, sensors, and network devices that enable seamless data exchange between physical and digital assets. Communication among a large variety of DTs and physical assets is a very challenging task that requires specific communication approaches that consider the various types of devices, providers, and software applications [67]; which leads to different data sources, data formats, protocols, and sampling rates. Different communication protocols have been identified for industrial process monitoring and control, outlining various attributes and requirements such as network configurations, transmission rates, and limitations on the number of devices [79]. The authors note that standardised communication models are not widely used in DT solutions for manufacturing yet, which limits interoperability among DTs and hinder accessibility to potential DT benefits.

Nevertheless, research efforts have been reported that address the major challenges of communication ushered by the DT paradigm. Nilsson et al. (2019) presented a model that enables communication among various different DTs with different data representations and semantic definitions. Ashtari Talkhestani et al. (2019) also presented a communication model to address the variety of DT communication protocols. In this case, the DT communication model has two main components. A "filter" that scans the communication protocol extracts data, and processes protocol-specific messages; and, an "interpreter" that translates the transmitted data into certain formats. The model prescribes the use of semantic descriptions and the recording of a communication trail that identifies the physical assets from which the data originated.

Note as well that different kinds of communication between the physical and digital assets are required according to different use-cases. For example, in some cases, real-time communication and analysis are required while in others is not. Zhang et al. (2020) exemplified an approach to exchange data between a digital and a physical asset in real-time for asset monitoring, while also enabling intermitted communication and offline analyses for asset health assessment. In this sense, different processing approaches can also be used; for instance, server-based processing that centralises all the computation and edge-based processing that distributes processing across many devices [79]. For both cases, the communication approaches are different and represent the advantages and disadvantages that need to be considered.

7.4. Maturity models

Maturity models initiated in the software industry as a way to improve software development and maintenance capability [136]. Since then, its applicability has widened to many other fields, but the focus of most research publications is still on software engineering [137]. In the BIM and DT context, maturity models define a set of progressive phases that outline the required capabilities to achieve a mature technological solution; and, enable to benchmark and track progress in technological developments. Maturity levels helped guide the BIM research and development efforts and are a commonly addressed aspect in DT academic and professional literature. In this section an overview of the maturity levels proposed in both academic publications [5,8,22] and industry reports [7,41,48] is presented.

Hamer et al. (2018) proposed three levels to measure increasing DT capabilities for manufacturing, i.e.: (1) *supervisory*, in which only passive monitoring is used by collecting data streams from the instrumented physical asset; (2) *interactive*, in which the digital asset has some degree of control over the physical asset; and (3) *predictive*, in which the DT performs predictions leveraging the collected data and simulation techniques. In a similar way, Evans et al. (2019) presented a 6-level maturity level for the built environment. However, the first three levels correspond to the three BIM maturity levels [47], and the last three correspond to DT levels as presented by Hamer et al. (2018).

Boje et al. (2020) also suggested a 3-tiered maturity model for the AECO sector, similar to the ones above, but in this case, varying degrees of intelligence, autonomy, and complexity were considered as well. The three levels are (i) *monitoring platforms*, which enable sensing of physical assets and reporting; (ii) *intelligent semantic platforms*, in which semantics approaches are leveraged to provide some degree of asset intelligence, and feedback and control are carried out by experts; and (iii) *agent-driven socio-technical platforms*, in which a larger degree of intelligence and autonomy is driven by machine learning approaches. This maturity model also implies an increase of complexity and scale for the DTs application; starting from individual assets in the first level, to several interconnected assets in the second, to city-scale interaction among a multitude of DTs and users in the highest level. Madni et al. (2019) proposed a maturity model based on increasing machine learning capabilities. The first level is a pre-digital twin stage in which only a model for design and manufacturing is available. In the second level, a digital twin is able to acquire condition and maintenance data from the physical asset. In the third level, machine learning is used for real-time planning and maintenance support. The last fourth level considers reinforcement learning for a higher degree of autonomy and handling partially observable environments.

Gerber et al. (2019) proposed a 5-level maturity model for the AECO sector, in which four metrics are outlined explicitly to measure the maturity levels. The metrics are (i) autonomy, which is the ability to act without human involvement; (ii) intelligence, which is the ability to ability to process data; (iii) learning, which is the ability to learn from data; and (iv) fidelity, which is the degree to which the DT measurements and estimates approach true observations. The five levels are as follows: *Level 1*, an instrumented physical asset linked to a digital asset that enables asset monitoring; *Level 2*, a DT with some capacity for feedback and controlling physical assets; *Level 3*, a DT with analytics and predictive maintenance capabilities; *Level 4*, a DT with machine learning capabilities using data from various sources and the environment. More importantly, it has autonomous decision-making capabilities and can communicate recommendations in real-time; and *Level 5*, a DT that can reason and act autonomously on behalf of users. It has the ability to interact with other lower-level DTs.

In sum, all the maturity models above have three key levels outlining three key capabilities, i.e. (1) asset monitoring, (2) feedback and control, and (3) simulations and intelligence. Note that these levels correspond to the three levels initially presented by Hamer et al. (2018). The other levels, e.g. last two levels presented by Gerber et al. (2019), are not very well defined and can be regarded as a vision for future capabilities. For instance, the difference between level three and four is not very clear, and level five describes unfeasible capabilities for current existing technologies.

In a different approach, Lamb (2019) proposed a maturity model with four levels based on the communication capabilities among different DTs as well as the number and scale of interconnected DTs. In the first level, the DT does not interact with other DTs, and it only represents the interaction between a single physical asset and a digital asset. In the second level, various DTs representing assets from a single industry interact among them; for example, different rail infrastructure assets through their digital representations. In the third level, several groups of DTs from the same type of industries, e.g. transport (rail, bus, and air transport), interact seamlessly. Lastly, in the fourth level, various groups of DTs representing different industries, such as transport, energy, water, education, etc., are interconnected in what is referred to as a city-scale DT.

8. Discussion

8.1. An overall assessment on the applicability of DT conceptual and process models for the built environment

This section presents and overall assessment on the applicability of the DT conceptual and process models presented in Section 5 and 6, and discusses key aspects for its applicability for AECO use-cases.

8.1.1. DT conceptual models for the built environment

Table 7 presents an assessment of the applicability of the DT conceptual models analysed here for the built environment. Three categories of requirements have been defined, i.e. (i) AECO industries characteristics, (ii) use-cases characteristics, and (iii) integration with existing AECO technologies. The four conceptual models have been assessed to identify whether (i) the model can meet the requirements entirely (indicated with two stars in Table 7), (ii) meets the requirement only partially or indirectly (one star), and (iii) does not meet the

Table 7
DT conceptual models applicability in the built environment. One star = requirement partially met, two stars = requirement fully met, no star = requirements are not met.

AECO requirements	DT conceptual models			
	Prototypical	Model-based	Interface-oriented	Service-based
Industry characteristics				
- Integrator-subcontractor structure		★★		★★
- Varied supply-chain		★★		★★
- Many different disciplines	★	★★		★★
- Different users	★	★★	★	★
- Different lifecycle requirements		★		
- Consideration for asset end-user	★	★		
Use-cases characteristics				
- Large variety of use-cases and activities	★	★★	★	★★
- High complexity of activities		★		★★
- High interdependency of activities		★		★★
- Low compartmentalisation of activities		★		★
- Human in the loop	★	★★	★	★★
- Context data	★	★	★	★
- Contextual visualisations	★	★★	★	★★
- Physical-digital asset correspondence	★★	★		★★
- Asset's entire life-cycle		★	★	
Integration with existing AECO technologies				
- BIM	★	★		★
- BMS and SHM	★	★	★	★
- Data schemas and ontologies	★	★★	★	★

requirements at all (no stars).

The category industry characteristics compile industry-specific requirements that differ from other fields (e.g. manufacturing) that might limit the applicability of the conceptual models such as the fragmentation and variety of the supply-chain, the multitude of stakeholders and disciplines involved, the strong differences in lifecycle requirements, and the relevance of the services that the asset provides to the end-user. In this sense, the model-based conceptual model is able to fulfil more requirements than the others closely followed by the service-based model. The prototypical and the interface-oriented models can only partially meet some requirements.

Use-case categories compile requirements that characterise the activities common in AECO use-cases, such as the large variety, complexity, and the interdependency of activities, as well as their low potential for compartmentalisation and automatisation. For example, in manufacturing many processes can be modularised into relatively simple and separate tasks that can be repeated and automated; while in the AECO, modularisation is difficult, as tasks are similar but not the same and require input from many disciplines and stakeholders. The relevance of the context is also outlined, as even for very similar built assets, the assets are site-specific and are influenced by variations in local conditions such as weather, labour supply, local building codes, etc. Overall, the context, including the asset users, in which the physical assets reside has not been addressed entirely in DT conceptual models. Lastly, the potential to account for their applicability throughout the entire assets lifecycle is also considered. In this category, the service-based model fulfils more requirements closely followed by the model-based. The prototypical and the interface-oriented are in a similar position in their limitations to fulfil the requirements.

Lastly, the ability of the models to integrate with existing AECO technologies in terms of BIM, BMS, SHM, and data schemas and ontologies has been assessed. In this regard, all the models can meet the requirements only partially. Note that only the model-based considers explicitly the interface with different ontologies.

In sum, the model-based and the service-based models are able to fulfil most of the requirements defined. The model-based meets more requirements in the industry characteristics categories; while the service-based in the use-case characteristics category. The prototypical and the interface-oriented lag behind in all categories. Note that the model-based and service-based cannot meet about one-third of the requirements, thus there are still aspects of the models that need improvement and additions.

Nevertheless, all the models could be useful in specific circumstances. For instance, while the prototypical model is not sufficient to describe all use-cases in manufacturing and AECO, it is appropriate for high-level descriptions, in which a detailed description is not necessary, and for relatively simple use-cases, in which different disciplines and objectives are not required, e.g. for monitoring building services [43]. The model-based and the service-based provide more detail and flexibility for more complex use-cases, e.g. [94]; which is useful in cases when the digital representation of the physical assets in the built environment is very complex requiring many distinct models and interfaces for several stakeholders for an accurate representation. The model-based is the most suitable for AECO adoption because it explicitly accounts for various disciplines and stakeholders; while, the service-based enables the implementation of complex workflows but it is the most difficult to implement as well. The interface-oriented has the least applicability to the AECO sectors, but its major advantage is that it allows representing digital assets and processes without a physical counterpart.

8.1.2. *DT process models in the built environment*

In a similar way, this section presents an assessment of the applicability of the DT process models analysed above for AECO use-cases (Table 8). In this case, the applicability was assessed by identifying which of the four process models for DT operationalisation could be partially used (one star) or fully used (two stars) for the main use-cases throughout a built asset life cycle. Note that while most of the process models analysed here are heavily focused on operations, they could be used for other lifecycle phases as well. Moreover, the specific use-cases within the phases have been identified.

The asset monitoring process model can be employed for most of the use-cases during operations. For instance, it could be applied directly to support SHM activities, such as anomaly detection, inspections, and enabling optimal maintenance regimes. It could be applied for subcontractor coordination, progress monitoring, and cost control during construction as well. For example, instead of infrastructure assets, the performance of subcontractors and the works progress could be monitored using a similar process model enabling to identify delays in a timely manner.

Process models for prognosis and simulation can be used in all lifecycle phases but are particularly applicable for operations and to a lower degree for construction. Note that the DT simulation process models require actual asset data for model calibration, thus the assets to be simulated need to be instrumented. This is an important aspect as simulations that do not leverage asset data cannot be considered as DT simulations. In this sense, DT simulations could be used for stakeholder engagement, design support, and design review if asset data from other similar assets is employed. During construction, DT simulations could be used for cost and resource estimation, construction planning and scheduling, and progress and safety control. Lastly, DT simulations could be used to simulate infrastructure and building services performance, condition degradation, performance variation due to changing demand and external disruptions, and for understanding future retrofit interventions.

The optimal operations process models discussed here are applicable for built asset construction and operations; however, the models are

Table 8
DT process models applicability in the built environment. One star = partially employed, two stars = fully employed.

Main AECO's lifecycle use-cases	DT process models			
	Asset monitoring	Prognosis and simulation	Optimal operations	Optimised design
Design				
- Stakeholder engagement		★		★
- Design support		★		★★
- Design review		★		★★
- Construction documents				★★
Construction				
- Cost and resource estimation		★★		★
- Construction planning and scheduling		★★	★	
- Subcontractor coordination	★		★	
- Progress monitoring and cost control	★	★	★	
- Safety control		★	★	
- Quality assurance		★	★	
Operations				
- Optimal building maintenance	★★	★★		
- Optimal building operations	★	★★	★★	
- Anomaly detection and SHM inspections	★★	★	★	
- SHM preventive maintenance	★★	★★	★★	
- Optimal retrofitting interventions		★★		★

tailored specifically for manufacturing processes, which might limit their applicability in the built environment. For instance, most AECO operations during construction are very fragmented, with long activity cycles, and with high levels of human intervention. Thus, they are difficult to optimise. The main challenges are that (i) the uncontrollable variables might be too many and the controllable parameters to few to be able to optimise the process, (ii) all the required data to optimise the process might not be available due to the diverse equipment and parties involved, and (iii) the most important parameters might not be able to be controlled given the fragmentation of activities and the number of parties involved in the process. However, the challenge is not a large for building services and infrastructure operations, in which existing BMS and SHM solutions already provide, albeit limited, optimisation capabilities.

The optimised-design model can be applied for all use-cases in the design lifecycle phase; and, it can be applied for cost and resource estimation and for optimal retrofitting interventions as well. The main limitation for applicability in the AECO is the lack of access to historical condition and performance data and the low-level of instrumentation of built assets. This lack of asset data availability does not allow the use real-life data for model calibration and validation, an essential aspect of this process model.

Overall, the DT process models analysed here can be applied more widely during the operations phase of built assets, followed by the construction phase, and lastly in the design phase. For the AECO sectors, prognosis and simulation process models are the most applicable aspect of DTs because they can be employed for a large variety of use-cases throughout the entire asset's lifecycle. Asset monitoring is narrowly focused on operations and for infrastructure and large buildings and facilities for which asset instrumentation is required. Lastly, optimal operations require a significant adaptation to meet AECO requirements, since most of the optimal operation process models have been defined for modular, repetitive, short-cycle tasks common in manufacturing. While, asset monitoring, simulations, and optimised design are easier to implement directly or with minor adaptations.

8.2. The need for clear DT conceptual and process models for the AECO sectors

The original DT paradigm responds to very clear demands in the aerospace sector in which stringent monitoring and inspection requirements drove the development of an information construct that enables real-time and remote monitoring and simulation of physical assets performance. In the manufacturing sector, the DT notion has been used as the technology paradigm to fulfil the smart factory and Industry 4.0 requirements, with well-defined objectives and capabilities. However, for the built environment sectors, clear requirements and objectives have not been defined with enough detail. So far, only literal translations of the DT paradigm have been used for AECO use-cases. Nevertheless, these literal translations might not be the most appropriate to take full advantage of the DT paradigm.

This study presented a distillation and categorisation of the main DT conceptual and process models used in manufacturing; and, carried out an initial translation for their use in the built environment. The models were also assessed regarding the applicability and it was found that some can be applied directly, but some gaps remain and not all requirements are met. More importantly, the AECO sectors are very heterogeneous, representing varied types of industries, activities, stakeholders, and interests. Thus, the authors believe that in some cases a more detailed translation work is required. In any case, a direct adoption of DT concepts used in other fields such as aerospace and manufacturing is not advisable; because, there are significant differences among the requirements, processes, and industry structures between the manufacturing or aerospace sectors and the AECO sectors. For example, the maintenance and monitoring needs of aircraft are much more rigorous than those of an average building or facility; and, the number of the products created in manufacturing is higher by many orders of magnitude. Therefore, a careful translation is required that considers the specific characteristics and needs of the AECO use-cases.

Moreover, due to the large variation in types of building assets, different types of DTs conceptual and process models for different purposes are required. Based on the publications analysed here, there are indications of the suitability of different conceptual models for different use-cases. For instance, it might seem appropriate to develop a different conceptual model for infrastructure SHM monitoring than for building maintenance. In this sense, it is advisable to develop and fine-tune models for specific use-cases rather than developing a general DT conceptual model for all use-cases in the AECO. In sum, the authors believe that clear conceptual and process models must be defined for each use-case in the built environment after a careful analysis of the potential DT benefits and requirements has been carried out. In this regard, Aheleroff et al. (2021) work, discussed in Section 5.4, is a notable example of how a dedicated DT framework can be leveraged for complex workflows in the built environment.

8.3. DT and BIM as complementary technologies for the AECO

In the authors' view, at the moment both BIM and DT are sufficiently different conceptualisations, and both are necessary. The authors believe that DT does not represent an evolution of BIM, but rather that they both are different approaches that respond to different requirements. As described in Section 3.4, their key differences are not a matter of technological progression, but they are focused on the use of different technologies for different use-cases. For instance, BIM is focused on supporting optimal built asset delivery and facility management by enabling a coordinated approach to model a digital replica of the asset which facilitates construction and asset maintenance. While, DT focuses on asset continuous monitoring, simulation, and optimal operations, which facilitates management of infrastructure and large facilities.

We believe that both paradigms will continue to develop concurrently in the AECO industries to support built assets; and that their areas of applications will start overlapping gradually in the future. Thus, it is important to manage the development of both technologies to foster complementarity, leveraging the strengths of both technologies, and avoiding duplication of efforts. For instance, BIM existing capabilities in terms of, geometrical modelling, discipline coordination, LOD, data schemes, ontologies, among others should be integrated into DT solutions for the built environment rather than duplicated.

Additionally, objective analyses should be carried out to determine whether DTs are required for all the use-cases of a built asset lifecycle. It is conceivable that for specific cases only BIM is required or existing BMS and SHM solutions are sufficient. It is important to note that the DT paradigm resulted from the stringent monitoring requirements in aerospace engineering, which are not present in the AECO sectors. In this sense, it is imperative to identify in what use-cases DT implementation will have a substantial benefit and what aspects of the DT paradigm are more relevant for the built environment.

8.4. Research outlook

Besides the need for conceptual and process models specific to the AECO sectors, this section presents an outlook towards research needed for the development of the DT paradigm in the built environment.

8.4.1. DTs for the entire lifecycle of built assets

Additional research is needed to identify the requirements for DT implementation in the built environment throughout the entire built asset lifecycle. As this study shows, most of the research and implementation efforts have been focused on supporting assets during operations. More importantly, it should be analysed whether it is beneficial that DTs supplant BIM models or if DTs and BIM models should be employed together for different use-cases. In any case, it should be determined whether existing BIM approaches for other phases could be useful for DT implementations. In this sense, research is required to understand whether different DTs are needed for different phases. For instance, in BIM there are different BIM models for design and construction, i.e. as-designed, and for facility management (operations), i.e. as-built BIM models. Thus, it is important to determine the advantages and disadvantages of employing the BIM approach or devising another approach to address the complexities of managing a single digital representation for the entire lifecycle of an asset. The transition in between lifecycle phases should be addressed as well in terms of geometry, data, and capabilities. For example, in BIM, the transition between design and build is relatively well managed following BIM Level 2 guidelines; while, the transition from build to operate is very stark and undefined, requiring in most cases to generate the as-built BIM models from the ground up rather than reusing the exiting BIM models.

8.4.2. Stakeholder and discipline coordination

Stakeholder and discipline coordination are not specified directly in the DT conceptualisations reviewed here. In most of the examples analysed here, there are a limited number of stakeholders and disciplines involved in developing the DT. In contrast, in the built environment, a multitude of stakeholders and disciplines are usually involved, which represents a big challenge for DT implementation. In this sense, research should focus on developing or adopting existing approaches from other fields to effectively manage different parties from different disciplines. For instance, it is conceivable that different parties will be in charge of instrumenting the asset, deploying network capabilities on-site, managing data collection and storage, carrying out data modelling and analytics, and providing data visualisation and user interfaces. In this scenario, an effective approach to coordinate the stakeholder will be necessary to ensure a successful operationalisation of the DT.

8.4.3. Interoperability

Research efforts are required to enable the interoperability among several and different DTs, including physical asset to physical asset and digital asset to digital assets, as well as the integration with existing BIM, BMS, and SHM solutions. Development is needed primarily on (i) data schemas ontologies, and linked data, to allow robust data exchange; (ii) communication protocols that define the approach to communication among network devices; and (iii) new approaches to API development to facilitate third-party data consumption.

8.4.4. Levels of fidelity

Research is required to define the amount of detail required in a digital replica for specific use-cases. Levels of Fidelity have been proposed for such purpose, but there is no agreed specification yet, as LOD is for BIM. Research should focus on identifying the essential DT aspects that are relevant to measure fidelity (e.g. type and amount of collected data, accuracy, level of abstraction, etc.) and integrate or adopt the relevant geometrical aspects from BIM LOD.

8.4.5. BIM-DT maturity model

The development of a BIM-DT maturity model is required, which combines the BIM and the DT paradigms alongside clear metrics and desired capabilities beyond the initial attempts reviewed here. The maturity model should be achievable using current technologies, and it should consider AECO-specific characteristics such as the large difference in complexity and scale among DT potential use-cases. The BIM-DT maturity model should be able to guide the development of both technologies to ensure complementarity and avoid duplication of efforts.

8.4.6. New required skills and technologies

The DT paradigm represents a step-change in technological requirements for its application in the built environment. The AECO sectors are among the less digitised and BIM implementation has represented a big challenge for the industry as a whole. Thus, research efforts are required to identify, map, and characterise the skills and technologies required for DT implementation in the built environment. For instance, as BIM implementation led to the adoption of common data environments and the training of BIM managers; DT implementation will lead to the adoption of new technologies and will require new specialists as well.

8.4.7. New business and organisational models

Research is needed on new business and organisational models that enable the realisation of the DT paradigm in the AECO sectors, particularly for asset delivery [4]. The most common model for asset delivery is composed of a large integrator company, or general contractor, that provides management and coordination, while a variety of subcontractors provide labour, equipment, and materials. In this context, DT implementation will require business and organisational models that can provide —at least— monitoring capabilities (hardware and software) and data storage and processing. These additional services will require a larger and more diverse supply chain and new workflows that that are not considered by business and organisational models used by most general contractors. Regarding facility management, current business and organisational models that provide BMS services are better placed to adopt the DT paradigm because they already provide hardware and software to monitor certain aspects of building operation. More importantly, the newly developed business and organisational models should focus on the most valuable aspects that the DT paradigm, i.e. the collected data and the connection between the physical and digital assets, to provide optimal asset delivery and optimal operations services.

8.4.8. Data privacy and ownership

In the built environment is common that many parties are involved in the design, delivery, and operation of a built asset, which represents a big challenge to data privacy and ownership. There is a large gap in research on approaches that determine the data's ownership and accessibility, and how the value realised from the data should be shared among the involved stakeholders. This is particularly relevant to the AECO sector given its diverse supply-chain; several stakeholders, i.e. owners, operators, and end-users; and its relatively low digitisation. Since the DT paradigm will boost the collection and use of asset, context, and potentially user data, research is required to devise the best approaches to protect privacy, delegate responsibilities, and share the extracted value.

8.4.9. Quantification of potential benefits

Research should be conducted on approaches that enable the quantification of the potential benefits for DT adoption in the built environment. There is a lack of clarity on the magnitude of investments for DT implementation in terms of capital investments, upskilling, and changes in workflows; as well as in the magnitude of the potential value that DT implementation represents. Thus, research should focus on compiling and generating evidence, e.g. through case-studies, that justifies the required investments for DT implementation. Note that the case-studies should go beyond reporting implementation and carryout analysis on the efficiencies gained, limitations encountered, and the extracted added value.

8.5. Limitations of the study

The study presented here has two main limitations. The first one is that the majority of publications analysed are focused on manufacturing and not on the AECO sectors, with some exceptions, e.g. [94]. Therefore, readers should not apply the reviewed literature directly to the built environment's context. However, this study presented an initial translation deriving and condensing knowledge on DT conceptual and process models; and, assessed its potential application to the AECO sectors. The authors believe that this study constitutes a very relevant effort that will help to transfer existing knowledge from other fields and to facilitate the development of DT structural and functional models specific to the AECO sectors. The second limitation is that some relevant publications might not have been included in the analysis. In this sense, the authors believe that the sample of publications used for this study is sufficient to provide an accurate overview of DT's structural and functional models.

9. Conclusions

The DT paradigm has the potential of delivering huge benefits to the built environment as a whole; however, a lack of well-defined structural and functional descriptions will limit the extent to which this technological paradigm can benefit the AECO sectors. This study intended to address this issue by deriving knowledge from DT literature in manufacturing and carried out a preliminary translation and assessment for its application in the built environment. This study provides a detailed explanation of how the DTs reported in the manufacturing literature are structured and how they function, which will help establishing a meaningful interpretation of how the DT paradigm can improve the built environment industries.

To provide a robust context to this study, a thorough review of seminal literature on CPS, BIM, and DT, and a thorough comparison were presented. While there are no agreed stances on how these terms differ and large overlaps exist, in the authors' view the fundamental difference between CPS and DT is that DT implies a one-to-one correspondence between a physical and a digital asset; on the other hand, CPS only refers to an integration of physical and digital devices in a complex system. Regarding BIM and DT, both of them imply a correspondence between a physical and a digital asset. But, unlike BIM, DT defines a live connection between the two and implies a continuous update of the digital assets that reflects actual condition and performance. While BIM only considers digital representations of the physical asset.

A systematic review of structural and functional descriptions reported in DT literature has been carried out. DT conceptual and process models have been distilled from the reviewed examples in manufacturing. The models were not directly employed, rather their essential characteristics extracted and condensed into categories of models that can be potentially employed in the AECO sectors. The categories of models were described and their applicability to the AECO assessed. Regarding conceptual models, the model-based and service-based models are the most appropriate for the built environment; however, they do not meet all the requirements and some modifications are still required for their full applicability in the AECO sectors. Regarding process models, the prognosis and simulation models can be applied to a larger number of AECO use-cases; while, the asset monitoring model can be employed without the need for major modifications.

This study supports academics and practitioners in the AECO fields by (i) providing examples of types of DT conceptual and process models that can be applied to AECO use-cases; (ii) identifying key aspects for DT implementation in the built environment, e.g. considering a human in the loop (i.e. supervisor), user interfaces through services, and the integration of different discipline models and stakeholders; and, (iii) setting the basis for the development of specific conceptual and process models for DT solutions in the built environment.

In sum, this study provides relevant insights to the AECO fields by analysing existing knowledge on DT for manufacturing and distilling relevant information to facilitate its translation to the AECO sectors. This study contributes to the understanding of the DT paradigm and provides insights into its applicability in the AECO sectors. More concretely, this study contributed to existing knowledge by (1) outlining the main differences between the CPS, DT, and BIM paradigms; (2) reviewing the structural and functional descriptions of DT systems reported in the literature; (3) condensing and categorising DT conceptual models into four categories and the process models into six categories; and (4) assessing the models' applicability to use-cases in the AECO sectors. Regarding contributions to theory, this study is an example of how existing knowledge in other fields can be condensed and categorised to provide relevant understanding and insights.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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