Automation in Construction 114 (2020) 103179

Contents lists available at ScienceDirect

Automation in Construction

journal homepage: www.elsevier.com/locate/autcon

Review

# Towards a semantic Construction Digital Twin: Directions for future research

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A R T I C L E I N F O

*Keywords:*
Digital Twin
BIM
Review
Industry Foundation Classes (IFC)
Internet of Things (IoT)
Framework
Artificial Intelligence (AI)
Big data
Construction safety
Construction site

A B S T R A C T

As the Architecture, Engineering and Construction sector is embracing the digital age, the processes involved in the design, construction and operation of built assets are more and more influenced by technologies dealing with value-added monitoring of data from sensor networks, management of this data in secure and resilient storage systems underpinned by semantic models, as well as the simulation and optimisation of engineering systems. Aside from enhancing the efficiency of the value chain, such information-intensive models and associated technologies play a decisive role in minimising the lifecycle impacts of our buildings. While Building Information Modelling provides procedures, technologies and data schemas enabling a standardised semantic representation of building components and systems, the concept of a Digital Twin conveys a more holistic socio-technical and process-oriented characterisation of the complex artefacts involved by leveraging the synchronicity of the cyber-physical bi-directional data flows. Moreover, BIM lacks semantic completeness in areas such as control systems, including sensor networks, social systems, and urban artefacts beyond the scope of buildings, thus requiring a holistic, scalable semantic approach that factors in dynamic data at different levels. The paper reviews the multi-faceted applications of BIM during the construction stage and highlights limits and requirements, paving the way to the concept of a Construction Digital Twin. A definition of such a concept is then given, described in terms of underpinning research themes, while elaborating on areas for future research.

## 1. Introduction

Emerging Building Information Modelling (BIM) tools and technologies have gradually changed the way information about our built environment is created, stored and exchanged between involved stakeholders [1,2]. Since the advent of the Industry Foundation Classes (IFC), more integrated methods to share construction data have emerged and have since become adopted industry-wide. The proliferation of IFC alone has had a major impact on how current tools and methods are developed in research and development. However, digital technologies across the board are advancing at an ever-increasing pace, taking advantage of the Internet of Things (IoT) and Artificial Intelligence (AI) agents (data analytics, machine learning, deep learning, etc.). Thus, the evolution of BIM should be carefully framed within a paradigm that factors in people, processes and these emerging technologies [1] in an increasingly inter-connected world [3].

While the BIM paradigm was introduced to improve collaboration during design and construction, it quickly became involved into adjacent research areas across the built environment lifecycle, at building, infrastructure and city levels. As it was initially envisaged to facilitate the effective exchange of information between segregated silos [4], BIM now faces significant challenges where leveraging big data, IoT and AI are heralded as potential solutions to automation and the inclusion of wider environmental contexts. The evolution of BIM interoperability solutions, from ISO STEP to IFC and more recently IfcOwl are seemingly not able to effectively leap from a static BIM to a web-based paradigm [6]. Conversely, design and construction stages project data has increased almost exponentially since BIM adoption, experiencing what is termed ‘drowning in data’ [7], wielding little added benefit to the construction supply chain to date.

Parallel to developments within the construction industry, external pressure for a smarter built environment is exerted by more ambitious energy and carbon emissions agendas across the world. From smart cities and grids perspectives, the inclusion of IoT and AI is demanded to deliver improved energy efficiency and lower operation costs [8]. The inclusion of BIM represents but a small part (a narrow building-level view) within the wider environmental context. Although BIM uses have extended to include lifecycle management of built assets, the current

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https://doi.org/10.1016/j.autcon.2020.103179
Received 29 November 2019; Received in revised form 21 January 2020; Accepted 10 March 2020
Available online 27 March 2020

state of BIM is not compatible with IoT integration [1], specifically because of its legacy formats and standards which limits BIM usability and extensibility with a semantic web paradigm.

Therefore, this paper elaborates on viable ways of crossing from a BIM world view with its existing knowledge domain and specific technologies, towards a Digital Twin (DT) world view which promises greater potential at the intersection of IoT and AI through semantic models. This should address the challenge to change from its static, closed data with recursive interoperability issues, towards a linked data paradigm, where the building product can be fully represented in the form of a Digital Twin. In order to help clarify the subject, this article aims to tackle the following main objectives:

1. Review and elicit the current state of BIM use during the construction stage;
2. Analyse the components and perceived abilities of Digital Twins as applied across a wide range of engineering domains;
3. Identify current gaps and directions for future research.

Following this introduction, background research is presented in Section 2, elaborating on the concepts of nD BIM, the Semantic Web and Digital Twins. Section 3 outlines the methodology in selecting the research for analysis. Section 4 presents the results of the review, scoping in on the nD BIM uses (Section 4.1) and then shifting towards the topic of DT from various adjacent fields (Section 4.2). Following a holistic outline of research, Section 5 discusses the potential roadmap for realising a Construction Digital Twin (CDT) from various perspectives (abilities, smart services and evolution). Finally, the limitations and future research directions are summarised in the Conclusion.

## 2. Background research

Following a review of the manufacturing sector, Tao et al. [9] conclude that there is an urgent need to define a unified framework for developing “Digital Twins”. From the construction perspective, the Digital Twin paradigm aims to enhance existing construction processes and models (nD BIMs), with their underpinning semantics (e.g. IFC, COBie) within the context of a cyber-physical synchronicity, where the digital models are a reflection of the construction physical assets at any given moment in time. As such, a review of existing BIM uses (across the nD spectrum) and their underlying semantics is necessary to understand the dynamics of construction data models, which needs to be re-integrated factoring in newer technologies demanded by the DT concept.

### *2.1. The complexity of BIM dimensions and domains*

Within the context of BIM, the 4D modelling process brings in a virtual representation of another dimension (time), which means that all aspects of the BIM process (graphical models, management, costs, resources, safety issues, etc.) can now be represented, viewed and analysed from a temporal perspective. Research on nBIM modelling argues that each of these aspects is a further dimension of BIM in their own right [10,11]. In contrast to this it can be argued that the 4D is the final dimension of BIM, as the time component is the final one that can be measured and considered in a time-space continuum. However, the fifth dimension (5D) which encompasses cost estimation [12], seems to be accepted by many researchers and industry professionals [13], with it being specifically defined within the BIM Dictionary [14]. Despite this, several studies focused around 5D BIM do not consider the 4D BIM as the point of departure, but often limit the methodologies for cost estimation at 3D model and cost information [15]. The emergence of the nD BIM paradigm has consequently changed the meaning of ‘dimension’, more likely referring to application domains, uses or use-cases of 3D and 4D modelling which add different contexts, expanding upon the view of BIM fields and lenses [16]. A survey on this particular topic concluded that there is still much confusion when referring to the nBIM paradigm, with the vast majority of respondents recognising 4D BIM, with some 5D BIM, but no consensus on the successive dimensions [13]. While the correct terminology is still regarded as evasive by many, the prospective uses of 3D and 4D models continue to be explored in research and development, and are considered fundamental models for design construction management.

More recent research reveals newer application domains, particularly looking at lean construction [17], site monitoring [18,19], health & safety [20] or environmental aspects [21] which provide new ways to view and utilise nD model data. This in turn brings new degrees of complexity, with more input data required by each domain. This data often originates from heterogeneous sources (tools, sensors, building management systems, etc.), which need to be correlated to existing BIM models on object levels, be consistent across project models and documentation, as well as over time.

Even though in the past they showed great promise, the use of 3D and 4D models was rarely used during construction phases [22]. Today however, the use of BIM models has become mandatory to ensure faster and more collaborative processes [23], often also being considered as giving practitioners an edge on the market. Where BIM is now applied throughout the full building lifecycle from design to decommissioning, 4D and 5D BIM has been traditionally applied at the pre-construction and construction stages [24]. This is in part due to increased coordination and collaboration needs during these stages, the involvement of several new actors, and multiple fragmented data models. Logically, it is during these stages that the apex of the BIM implementation is reached, where all stakeholders converge and collaborate using 4-5D BIM, producing a vast amount of information in return. However, much of the information built during design and construction is lost, with only a minuscule amount of structured data being transferred to the facility management stage, usually in the form of a COBie spreadsheet [25] with additional 3D information, depending on client specifications. Thus, the BIMs produced remain closed and serve little uses after the completion of the construction project, completely neglecting its uses for the future lifecycles and the creation and maintenance of Digital Twins. Additionally, the engineering models and BIM uses across 3-4-5D BIM processes are generally decoupled, often defaulting to a generic, incomplete 3D geometric model. There is a need to connect these distributed sources of data, information and knowledge across the spectrum, to fully take advantage of nD BIMs.

### *2.2. Achieving integration using semantic models*

Industry requirements for model interoperability have been partly fulfilled by commercial vendors, which try to facilitate seamless integration via import/export capabilities from one BIM tool to another. However, this can quickly become overwhelming as the number of tools and platforms shared amongst project actors increases over time. The IFC standard [26] was specifically designed to deal with the industry's interoperability problem, including concepts across several well defined application domains [27]. Although the IFC schema has evolved significantly in the last decades, it still has not fully solved the interoperability problem for all application domains, with the creation of Model View Definitions (MVDs) being an arduous process [28]. Additionally, the IFC format was designed for transferring model data from one tool to the next, and not to be modified or used dynamically.

The inclusion of Linked Data (LD) and Web Ontology Language (OWL) models has more recently tried to address these old challenges. A pilot study investigated the capabilities of semantic web, applied to acoustic building design closely tied to IFC concepts [29]. Such an approach enables rule checking process to go beyond the schema scope, thus allowing for more flexible MVDs, which are crucial in including non-traditional application domains under the BIM umbrella. Many recent developments rely on IFC, which is seen as an underlying schema for structuring data, while its ontology representation - IfcOwl [30,31], provides better interoperability and reasoning capabilities on top. As developments around this topic grew, it became apparent that ontology representations of the IFC schema allow for a flexible and more robust backbone for interoperability requirements [32]. Due to being computer-interpretable, by definition OWL models allow the inclusion of Description Logics (DL) rules, enriched semantic representations with a higher degree of 'meaning', while being part of The Semantic Web Stack [33] for sharing resources over the web.

When faced with the challenge of representing a complex socio-technological system, the use of OWL models is a mandatory step to ensure correct alignment between multiple domains such as: actors, sensors, management workflows, web resources, BIM model data, etc. Most importantly, these representations can be used for intelligent processing and reasoning, which is not supported by legacy formats. An ontology approach is also considered more suited for future-proofing when compared to older standard file formats, and has also become part of the UK's government strategy for defining and developing BIM level 3 and beyond [35]. This reflects current research trends on utilising the connectivity and richness of the Semantic Web [6]. As such, it is logical for BIM to adopt a semantic web world view if it is to remain relevant and continue to add value to our built environment [1].

### 2.3. The Digital Twin paradigm

The need to monitor and control assets (manufactured elements, buildings, bridges, etc.) throughout their lifecycle, coupled with advances in technological capabilities, have moved several research fields into investigating Digital Twin uses and potential. Although many of these applications have been investigated in their own right under the BIM field, the DT paradigm requires an increased level of detail and precision, which ranges from small manufactured assets, buildings, city districts to potentially nation-wide digital twins [37].

Digital twin is an old term, which was coined 20 years ago, surfacing now as our society becomes more interconnected [3]. The concept of a Digital Twin was introduced in 2003, as part of a university course on Product Lifecycle Management [38] – the idea of the concept later proliferated in adjacent fields with the rise of new technologies. The DT concept was initially published in the aerospace field and was defined as "*a reengineering of structural life prediction and management*" [39], later appearing in product manufacturing [40,41] and more recently into smart cities [1,42]. Several studies refer to a DT as a "cyber-physical integration" [43–45], with the term "Digital Twin" representing the ultimate, unachievable goal, as no model abstraction can mirror real world things with identical fidelity. The term "System of Systems" is also mentioned [8,46], which is supposed to deal with the scalability and sustainability of systems aimed to communicate data in a more effective and intelligent manner. For the purposes of this research, we adopt the approach provided by Grieves [38], granting a holistic view of the complex system representing a DT. Thus, the main DT components (as shown in Fig. 1) considered here are:

1) The Physical components,
2) The Virtual models and
3) The Data that connects them.

The connection loop between the "Virtual-Physical" duality of the system is provided by the "Data" in its various forms. For example, Grieves [38] considers the data from the "Physical" to the "Virtual" to be raw and to require processing, while the data in the opposite direction is subject to several transformations, which can be processed information and stored knowledge across digital models – with higher degrees of meaning. However, this is ultimately reflected back to the "Physical" as data through actuators. As such, the "Physical" part collects real world data which is sent for processing. In return, the "Virtual" part applies its imbedded engineering models and AI to discover information which is used for managing the day to day usage of the "Physical".

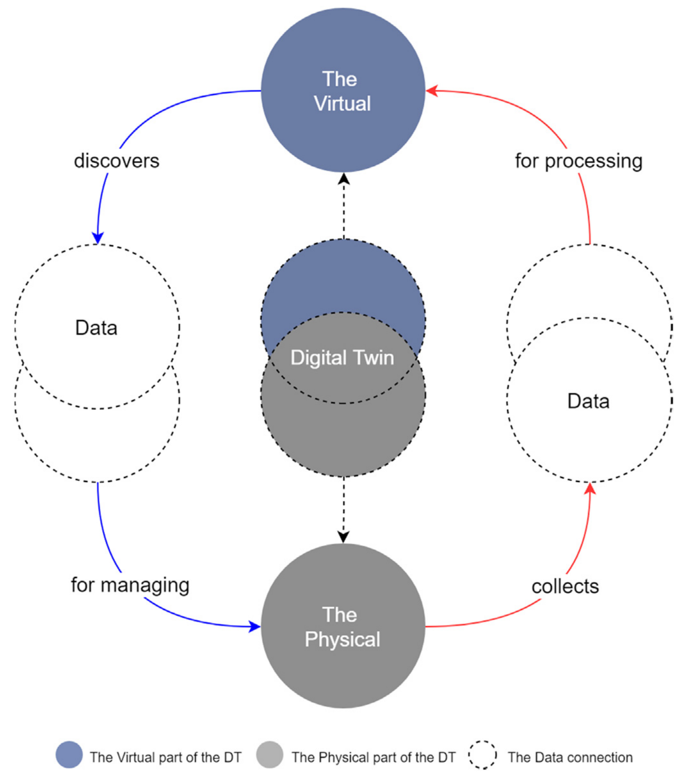


**Fig. 1.** The Digital Twin paradigm.

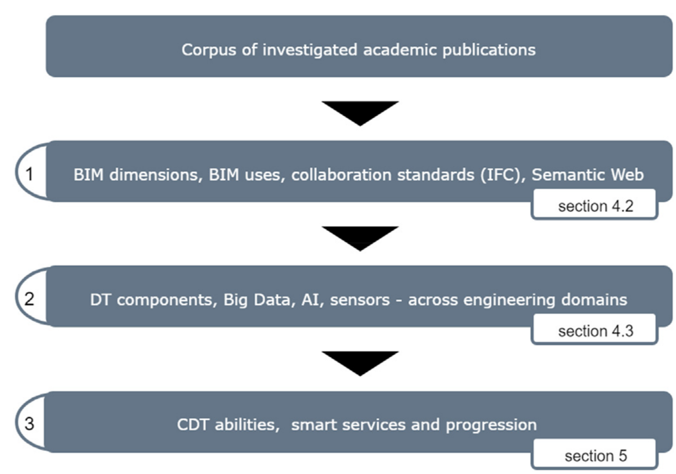


**Fig. 2.** Employed research methodology steps.

## 3. Methodology

The research approach within this article is divided into several steps (Fig. 2) attempting to provide answers to the 3 main research questions from the introduction:

1) Review BIM for construction application - by identifying previous literature reviews around the subject and structuring more recent research into several uses of BIM. Additionally, the use of common collaboration standards and more recent semantic web technologies were considered important to deal with model semantics and the meaning of the data within the construction field.
2) Analyse DT uses in adjacent fields – by identifying existing literature from construction, energy, manufacturing and smart cities and

outlining common DT concepts, features and technologies;
3) Identify research gaps – by contrasting the previous two steps through the lenses of creating a Construction Digital Twin.

The overall research analysis considers 196 studies, 25 of which are concerned with the definition and application domains of the DT paradigm. The vast majority of these studies were published in several renowned journals within the field of construction information technologies. Additional studies from conference proceedings within the same fields of research were also included, depending on their perceived quality. The initial search keywords were "Building Information Modelling (BIM)", "nD" in combination with "planning", "scheduling", "management", "monitoring", which were later widened to include "Industry Foundation Classes (IFC)", but also "ontology", "linked data" and "digital twin" to identify newer methodologies for the scope of this research.

## 4. Analysis of the research landscape

### 4.1. Distribution by publication date

In line with the aim to provide an overview of the research landscape around the subject at hand, Fig. 3 outlines the 196 research articles reviewed by their publication date. Although the IFC schema and standard have been released almost three decades ago, their increase in popularity in the context of nD BIM comes relatively late. More recently, however, there has been an increase in use of linked data technologies to integrate the traditionally dispersed data across the construction industry. The Digital Twin term re-emerges in several adjacent engineering fields in more recent years.

### 4.2. Construction BIM uses

#### 4.2.1. Previous literature reviews

Several relevant reviews were identified on the use of 4D modelling [10,11,47]. While the early research did not envisage BIM as a process, it explored most of the benefits and current use-cases of 4D modelling methods, with [47] having proposed the inclusion of a health and safety use-case. A recent review on the status of 5D BIM further sub-divides it into several uses according to the literature [12]. The most recent reviews on the "nD BIM" paradigm add views on safety management and quality assessment [10], as well as on energy and environmental concerns [11].

The status of semantic web technologies within the construction sector has been revised previously, with [48] having provided a view of the forming trends and [6] having discussed the latest implementations around interoperability, linking of data across domains, as well as logical inferencing.

#### 4.2.2. Distribution by applied use-cases

This section provides a structured in-depth view of each identified BIM use during construction, as is summarised in Fig. 4 below. The figure should be interpreted considering the fact that the BIM uses are highly inter-related, with the majority of studies spanning across multiple BIM uses. As such, many articles appear in multiple columns, with only a few standing out across all topics, which are often referenced below.

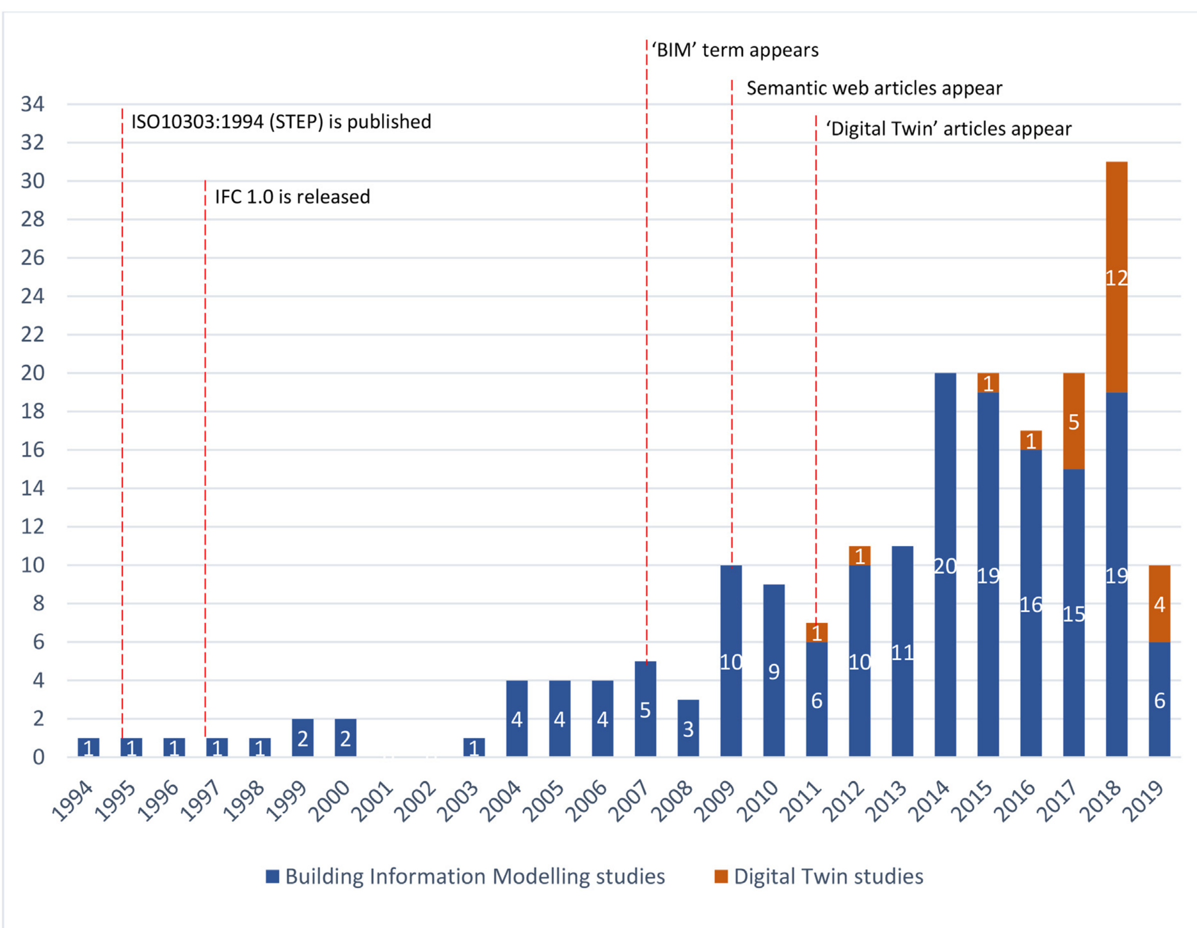


Fig. 3. Distribution of reviewed papers by publication date with important milestones in the construction sector.

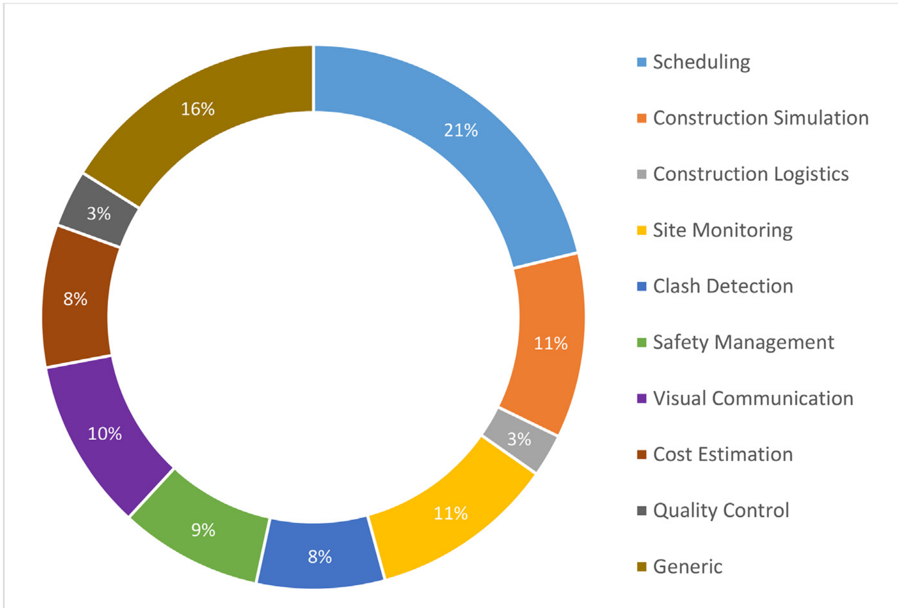


**Fig. 4.** Distribution of studies on BIM uses in construction.

*4.2.2.1. Construction logistics.* A system for simulating the site layout in terms of zones, resources and positioning of equipment and construction cranes was developed by Li et al. [49]. The visualisation of such a method was envisaged to help planners foresee possible future problems. However, there is no apparent use of common formats, and little means of automation. More recent developments on this use-case are concerned with correct deployment of temporary works and the dynamics of large construction vehicles, which fall under the clash detection use-case as well.

*4.2.2.2. Clash detection.* Located under 4D modelling, Hu and Zhang [50] distinguish clash detection between three sub-uses: schedule conflict, resources and cost conflict analysis and site conflict analysis. This classification corresponds with the already defined BIM uses, with resources and cost considered as part of the 5D BIM. The division of clash detection between 3D objects and temporal objects seems to have become more evident in research trends as well. Additionally, Moon et al. [51] present a method to carry out clash detection regarding work-spaces, effectively referring to temporary site areas and objects and how they interact over time with existing or newly constructed ones. The placement of cranes on a construction site using genetic algorithms was also investigated by Marzouk and Abubakr [52]. The use of a schedule is seen as important in order to avoid spatial clashes by optimising the temporal programming, essentially avoiding the physical clash up-front [53,54]. A detailed case study on the use of clash detection outlines the benefits it brings to site temporary works management [55]. The trend around clash detection overlaps consistently with the Construction Logistics use-case, where the placement of materials and equipment is analysed over time. A recent surveys shows that 4D simulations are used mostly for communication purposes with clients during planning stages, revising site logistics, but rarely for clash detection [56].

*4.2.2.3. Site monitoring.* The threads of research on this topic are more concerned with accurately monitoring the site, correctly interpreting the gathered information and matching it with existing digital models. The inclusion of RFID (Radio Frequency Identification) tags is often considered, getting the 4D process in line with product manufacturing [57]. Park et al. [58] offer a technical view using cameras in an attempt to track workers on site. On a similar subject, considering the participation of construction managers, Sacks et al. [59] use lean principles to monitor site activities more effectively. From a technological point of view, the use of laser scanning and photogrammetry to track site progress to an already developed 4D model have attracted more and more interest [60,61], not without limitations of their own [62].

Hamledari et al. [63] explore the use of drones to capture site status and update the schedules back into an IFC model based on photogrammetry. A similar study was conducted by Kim et al. [64] on processing images on site of a bridge project, but without common data standards. Similarly, Kropp et al. [65] developed a method to improve the automatic updating of 4D models using computer vision, by considering the interior spaces of a building under construction. Another study focused on detecting the types of materials on site to track the progress in more detail and relate it to managing resources [66].

*4.2.2.4. Quality control.* Quality management techniques around BIM are envisaged as part of a nD modelling process, where the 3D information (product) is attributed to quality inspection checks (depending on an organisational body) which are linked to a scheduled process [10,67]. This is strictly dependent on adequate site monitoring techniques, with known integration limitations between site information captures (e.g. photos, forms, scans, etc.) and BIM [67]. A case study on a newly constructed bridge equipped with sensors during its construction suggest a practical approach to dealing with these types of monitoring and quality management issues [68]. Although not focused on the idea of a DT, the applied case study methodology shows the trend of integrating sensors with buildings and infrastructure, showcasing the growing trend of cyber-physical integration, and thus expanding on what ‘useful’ information is required for future lifecycle stages.

*4.2.2.5. Safety management.* Site safety should be monitored using management tools, as the risks to safety vary in space and time [10]. A methodology for combining several construction sequences and identifying potential hazards related to scaffolding was introduced by Kim et al. [69]. This was tested using typical BIM platforms, which usually lack of BIM safety planning object libraries that can relate to temporary site structures [70]. This makes safety management around sites particularly difficult, as relying on digital objects may not be enough to effectively predict and omit safety concerns in complex spatio-temporal contexts. Shang and Shen [20] present a way in which the safety of a construction site is analysed based on spatio-temporal collisions and their frequency, as opposed to risk factors. These sort of methods inherently improve health and safety on site as it helps planners visualise and detect them beforehand [71]. Similarly, Benjaoran and Bhokha [72] apply certain knowledge rules on a model to detect hazards when working at elevated altitudes. However, the application of such methods in practice requires constant surveillance and in-time hazard identification, which is often the main limitation of BIM-based tools and methods. With more modern site monitoring equipment, machine learning is at the forefront of site safety prediction [73], potentially providing a more automatic way to gather and classify safety events, making safety management more reliable.

*4.2.2.6. Construction simulation.* The more recent trend on this topic seems to be around the automation of the process using different techniques, which need to rely on the BIM as a source of data and semantics [74,75]. The correct animation of the construction sequence has always been the main focus on construction simulation [76], with newer techniques used to estimate the project duration based on different assumptions about the 3D model, resources and working hours [77,78]. The common ground around this subject is that they all require an enriched BIM with additional resources which are inputted manually as assumptions or imported from different sources. The existing automation techniques remain limited to input errors or misinterpretations of the model's semantics.

*4.2.2.7. Visual communication.* The concept of visualising nD on large BIMs remains a challenge. The visualisation needs to be clear and specific to user's needs and to support collaborative and coordination meetings, from a functional as well as from an ergonomic perspective [2]. A method is introduced by Russell et al. [79] on visualising the data easier and in a more meaningful manner using linear programming of the construction schedules. The use of colour schemes and dynamic animations have always been the prime features of 4D models, aiding the viewer to better understand the data [81]. A more recent work by Zhang et al. [82] uses colour schemes for element degradation over time in a 4D modelling tool, specifically targeted at infrastructure maintenance. This is intended to be integrated with site monitoring techniques, improving the management of large infrastructure data. Some argue that there is a need to standardise 4D visualisation [83]. This would have to be linked to each of the actors' disciplines and their role within the collaborative effort [2].

*4.2.2.8. Scheduling.* The latest trends on applying scheduling are more focused on the processes of demolition and waste management, which are strictly related to the materials within the model, and the different dynamics which this lifecycle stage brings [21,84]. The deconstruction methods can vary greatly depending on building type, from disorderly concrete structural demolition to a more modular deconstruction process of oil and gas rigs [84] where the structure is divided in multiple parts, describing a different composition than that of a construction process.

It can be argued that scheduling models are not comprehensive enough, with missing relationships between the components as they are scheduled or monitored, Dang and Bargstädt [85] proposing to add several relationships related to time and workflow dependencies, aimed to enrich the BIM. Although this method would traditionally require significant manual input, the presence within the model of such detailed relationships would greatly benefit from automation in future developments.

Several studies have been identified to implement lean techniques for construction scheduling [17,59], thus focusing not on making the modelling process more efficient, but rather optimising the entire project planning in light of BIM adoption and its potential to support lean processes.

*4.2.2.9. Cost estimation.* The key areas of development around cost analysis and estimation focus on frameworks for easier adoption and use of the 5D BIM. Several studies point out the barriers for 5D BIM adoption in industry and recommend frameworks on decision-making [88], entire building lifecycle estimation [89], or on choosing the adequate tools or platforms for adoption [12]. Considering that costing has been a developed subject before the BIM term appeared, the tendency was to link 3D model materials with cost databases [15], and therefore skip the 4D model entirely. Correctly including all 3-4-5D factors for accurate and up-to-date lifecycle project costing remains a challenge due to a lack of interoperability to deal with such a scale in an effective manner.

*4.2.3. Technologies for managing semantics*

*4.2.3.1. Industry foundation classes.* The use of standardised formats such as the IFC is constantly being improved to account for more efficient site management via BIM virtual models [17]. Although the IFC schema has evolved significantly and added new modelling concepts, there is a low level of IFC adoption concerning nD modelling in general. As each use-case within the nD BIM paradigm is very specific, the federation and transfer of information is still challenging, with practitioners relying on external formats or tools. For example, although a 4D BIM can be expressed and used in IFC, this is often kept separate with the 3D BIM model (in IFC) and a scheduling model (in various formats). The federation of multiple modelling documents (in multiple formats) which evolve in parallel can cause disruptions and conflicts which could greatly benefit from automation and linked data.

The suggestion to use IFC for directly modelling in 4D, and thus associating 3D elements with time components has been done for some time [90], and more recently within the context of automation [54,63]. Several studies consider sub-parts of the IFC schema for the site monitoring uses, where more recent technologies are integrated to update BIM models [18,91]. For example, Tauscher et al. [74] developed a method to generate construction sequences based on IFC objects at task level. Similarly, Kim et al. [75] import IFC model data and generate a schedule based on materials and pre-defined algorithms, to export a Microsoft Project schedule. The use of the IFC schema for 4D uses seems to be very limited, with most studies referring to the IFC model as solely the source of the building elements, especially those with a 3D geometry present.

Several studies assume the BIM and costing information datasets to be separate [88,89,92], with no concern for a common format. There are mentions of overall lack of standards to model costs [93], but the issues remains on deciding a common format which is suitable across domains. A more recent study outlines the features of a variety of tools supporting IFC and various commercial formats for cost analysis [12], but it is unlikely these tools can incorporate a comprehensive 4-5D BIM model view in its holistic sense.

*4.2.3.2. Semantic web ontologies.* An overview of ontology and semantic web linked data trends in research over the last decade is outlined by Abanda et al. [48]. There is clear interest in the fields of risk analysis, project management knowledge sharing and energy performance analysis. The authors mention that semantic web and linked data are seen as beneficial because they facilitate interoperability between the large spectrums of application domains involved in the construction sector. However, they point out that very few applications exist commercially which are using ontology support. This is likely due to complex requirements for ontology-based collaboration in the field of design and construction. There is however a trend towards interoperability using ontology layers [94].

The inclusion of IFC to an RDF (Resource Description Framework) format has been considered for a modular data-linking way, where the IFC is seen as only a part of the overall vision for managing building data [95]. Several methods have been introduced to use ontologies for integration and reasoning support for BIM in conjunction with the IFC schema in non-construction contexts [96–98]. More advanced relationships between 4D concepts are proposed by Dang and Bargstädt [85] at almost to an ontological level, but their alignment to the IFC schema, the management process and the actors involved are not considered. Similarly, Niknam and Karshenas [99] represent the BIM and a schedule model using a simple ontology, without considering existing concepts from the collaborative process side, or any other existing schemas such as the IFC. A safety management ontology with rules which incorporates certain 4D concepts was also developed and investigated [100]. From a 5D perspective, Aram et al. [101] propose a knowledge-based framework for costs estimation and quantity take-offs, enabling storage of knowledge for more accurate future costing estimation.

The more important developments within the linked data field are related to interoperability issues. Prudhomme et al. [102] addresses the gathering and increasing heterogeneity of spatial data on the web, which requires more automatic and efficient methods for data management. Ontologies such as IfcOwl or the Building Topology Ontology (BOT) [103] are expected to express and use building data more effectively, adding value to the entire supply chain by making the right data available at the right time [104]. These developments may hint towards the hidden potential of a linked data paradigm, which would benefit BIM uses overall. Expressing building model data into semantic web compatible formats such as OWL or RDF provide the unique benefit of linking data over the web using schema independent models, as opposed to relational database or file structures [4]. OWL and RDF are graph-based models, allowing more flexible representation of syntax which can facilitate a more dynamic process for information governance.

Outlining the evolution of technologies and information models [1] position the DT to be fully reliant on the IFC schema (in its various file formats), ensuring semantic rich structured data, which would form the foundation for more efficient ontology based tools and agents. More recent developments under the W3C Linked Building Data group have overseen the advancement of newer, more lightweight ontologies capable of representing digital building information on the web. Although BIM use during construction is on the rise, with several tools being used, from the research analysis there is clear indication that the level of BIM development towards Digital Twins is still very low, with very few relying on IFC, as will become clearer in the following section.

### *4.3. Cross-domain Digital Twin uses*

This section highlights the research state of the art on the subject of Digital Twins. Relying on previous research focused on defining this concept from nearby engineering fields [1,43,106–108], several recurring keywords and themes stand out. Each of these terms has been investigated across the 21 studies selected for discussion and analysis, shown in Table 1. It should be noted that although not all studies discuss certain DT components or features, it does not mean that their authors do not consider that component as part of the DT.

Despite the re-emergence of interest around the concept of 'Digital Twin', the research within this area is still scarce. However, many past concepts and applications are re-used and re-branded as constituent parts of Digital Twins due to the increased needs within our society for interoperability, automation and intelligent systems. Several recent studies adopt various perspectives in terms of the conceptual composition of a DT, such as a virtual-data-physical integration paradigm [43,106,108,109], or a sensing-agency-immune system paradigm [44]. Four distinct levels for the DT are defined by Madni et al. [107], depending on the available information and its level of detail. In addition to this, we advocate that a DT be considered from a technological perspective within the context of its field of application. Per se, a DT in construction should consider different models, tools and technologies to a DT in manufacturing. However, the overall architecture, functionalities and features of a DT are expected to be generic across the board.

#### *4.3.1. Sensing and monitoring the physical*

*4.3.1.1. Sensing.* The majority of studies (Table 1) consider sensing a vital ability of the DT, with the application of various sensor devices being the common reference. Although sensor device data is considered by many of these studies as a source of real-time data [9,43,45,115], the details on types of sensors, networks or how to make best use of them for each domain DT are omitted. Conversely, several studies focused on construction asset cyber-physical systems have used RFID tags and scanners, with additional sensors (location, load, displacement etc.). These are integrated via a sensor network to facilitate constant communication between site sensors and a virtual model [116–118]. While these studies employ detailed methods on constructing the two-way communication bridge, as well as highlighting the challenges in installing and maintaining sensors on site [117], they do not address the alignment of data to the BIM model itself. For more detailed site captures, the scan-to-BIM methods (mentioned in Section 4.2.2) focus on capturing very detailed site imagery, feeding a large amount of visual data for processing, but face limitations in storing, filtering and matching the "sensor" data with digital assets on the BIM side.

The use of physical sensors to simulated virtual sensors is compared in one study [46], both of which are used to feed engineering simulations and make predictions. Similarly, Martinez et al. [111] consider the simulated virtual environment to be a 'virtual sensor' as a whole, used to predict facility behaviour. Consequently, the question on what is considered a 'sensor' appears. For example, the Semantic Sensor Network (SSN) ontology [119] definition of a sensor includes devices, software agents and human agents, which are able to make an observation on particular values or features of interest.

The main challenge on using sensors with DT appears when dealing with the spatio-temporal resolutions [44], demanding a successful integration of sensors of different capabilities, reading frequencies, accuracies, their respective locations and the inter-dependencies between sensor clusters and networks. The research literature seems to point towards the use of IoT as a means of sensor data capture, almost being taken for granted. However, the delicate intricacies of sensor dynamics for each DT application domain and interoperability with the rest of the DT components remain largely un-explored.

*4.3.1.2. Monitoring.* The nature of sensing is a continual data influx, similar to biological organisms which are constantly bombarded with stimuli from various sources [44]. Although strictly dependent on sensing capabilities, the concept of monitoring is achieved at the stage when the influx of sensor data has pre-defined structure and meaning. This coincides with the building automation systems [1,111] in the case of the built environment, by which actuations are triggered when certain conditions occur. The notion of real-time remote-monitoring [115] is also pervasive, where sensor data is plotted for human visualisation, verification, analysis and learning (graphs, tables, simulations and comparisons). This is certainly the case for nuclear power plants which require constant monitoring on the structural integrity of the facility, where human intervention on site is hazardous [113].

The process of monitoring relies on the sensor network underneath, to select and filter data which is relevant for day-to-day operational management. This data has to be conveyed in a machine interpretable way and subsequently be used for decision making by remote agents (AI or humans) on its Virtual counterpart. On the subject of construction site cyber-physical systems, several methods to monitor risks on site have been explored, which can issue immediate warnings to workers on site [116,118], or issuing warnings on showcasing the potential benefits of monitoring rules on site sensor data.

*4.3.1.3. Lifecycle.* All studies agree and consider that a DT should

**Table 1**
List of articles and the abilities considered important to a Digital Twin across several industry sectors – ordered by number of occurrences.

| No. | Reference | Domain | What does a study consider as being part of a digital twin? | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Prediction | Simulation | Monitoring | Lifecycle | Sensing | Optimisation | IoT | AI | BIM | Knowledge base | Linked data |
| 1 | [41] | Manufacturing | ✓ | ✓ | | ✓ | ✓ | ✓ | | | | | |
| 2 | [45] | Manufacturing | ✓ | ✓ | ✓ | ✓ | ✓ | | | | | | |
| 3 | [42] | Smart cities | ✓ | ✓ | ✓ | | ✓ | | ✓ | | | | |
| 4 | [39] | Aircraft | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | | | | |
| 5 | [109] | Systems | ✓ | | ✓ | | ✓ | ✓ | ✓ | ✓ | | | |
| 6 | [110] | Aircraft | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | | | | |
| 7 | [111] | FM | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | | | |
| 8 | [38] | Manufacturing | ✓ | ✓ | ✓ | ✓ | ✓ | | | | | | |
| 9 | [112] | FM | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | | ✓ | | |
| 10 | [44] | Smart cities | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | | | |
| 11 | [3] | Smart cities | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | | | |
| 12 | [9] | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | | | |
| 13 | [46] | Manufacturing | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | | |
| 14 | [113] | AEC/FM, nuclear | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | | |
| 15 | [114] | AEC/FM | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | | |
| 16 | [107] | Aircraft | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | | |
| 17 | [115] | AEC, bridges | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| 18 | [43] | Manufacturing | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | |
| 19 | [108] | Manufacturing | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | |
| 20 | [8] | Energy grids | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 21 | [1] | AEC/FM, smart cities, energy grids | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

encompass the entire lifecycle of the physical asset, with long-term cost reduction considered the primary added benefit. Planning for the entire lifecycle will naturally produce profound differences, depending on the application domain. Manufactured assets will generally experience shorter lifespans, with more predictable design-manufacturing-operation processes. The knowledge gained here will have more immediate yields, contributing to better future generations. However, when considering buildings, infrastructures or city districts, this is regarded as an ongoing process of optimising running costs, structural integrity and safety.

#### *4.3.2. Ensuring the data connection*

*4.3.2.1. BIM.* All studies related to smart cities or the Architecture, Engineering and Construction (AEC) industry consider BIM to be part of the DT as an important source of data. BIM is seen as the starting point for the DT [1,113], acting as a semantically rich 3D reference model for the DT to use in various applications. The BIM shell is enriched with time and sensor data, to formulate parallel offline and online simulations for energy, safety, human comfort and well-being.

*4.3.2.2. IoT.* Many studies consider the inclusion of IoT for a DT, as its increased adoption rate has made devices more affordable and their applications wider. Once again, interoperability is cited as the main challenge, due to the laborious efforts required to connect DT sensor data to simulations [111]. Zheng et al. [108] propose a DT framework for manufacturing implementation, which relies heavily on IoT, and outline a comprehensive view of available technologies and their interactions within this field. On the construction side, Ding et al. [115] present a conceptual framework for integrating BIM models with IoT devices to monitor the real assets on site, but do not address technological issues. In contrast to this Howell and Rezgui [1] argue that BIM is not ready to be integrated with IoT devices, due to the its legacy formats, which are not aligned with the view of the semantic web. The status of distributed energy systems was reviewed by Howell et al. [8] who argue the need for a semantic web approach to ensure interoperability between all systems and agents exchanging information across grids. The IoT is considered here to fill the gap between the physical and virtual worlds, where IoT has the primary role in health monitoring [107] by bridging physical component's sensors and actuators with its digital part [118]. Additionally, IoT can be used to survey the way physical products are used by customers – and deliver further value to cost benefits for the multiple parties involved.

*4.3.2.3. Linked data.* Semantic web linked data paradigms are absent from most studies looking at DT. On the other hand, significant progress has been made to integrate web semantics with IoT in parallel engineering fields [120]. The same is true for the BIM domain, where significant research was carried out on the subject (outlined in Section 4.2.3). The fields of energy, facility management and smart cities are incentivised to use liked data standards simply due to the scale of the infrastructure, and the benefits they bring in terms of interoperability. The use of ontologies seems to be the logical choice. This however raises the question on which semantic models best match the circumstances of each DT in terms of data model structure and logics, but also in terms of practical deployment and optimised processing efficiency. These aspects have to be considered carefully in light of integration requirements between IoT, BIMs and manufactured assets across the supply chain. In terms of efficiency, ontologies can range from very abstract and verbose models to very simple ones, with the latter bringing significantly improved performance.

*4.3.2.4. Knowledge bases.* The viability of a DT depends on the capability to represent data and its semantics correctly, and make the entire data sets available for knowledge processing. Both [43,108] consider the knowledge base as a part of the AI capabilities of the DT, allowing it to learn and take decisions. This facilitates reasoning and knowledge discovery capabilities. However, when in the context of semantics and linked data, the value of knowledge bases is emphasised on the conceptual representation of real-world things, integration and web-based communication of the DT data [1,8]. Thus, the use of graph databases has been gaining traction within the built environment domain.

Outlining the evolution of technologies and information models, Howell and Rezgui [1] position the DT to be fully reliant on the IFC models (in its OWL representation), ensuring semantic rich structured data, which would form the foundation for more efficient ontology based tools and agents. The knowledge base would therefore be positioned to offer a robust semantic, knowledge-driven data store, which would in return be used as a resource to be fully exploited by AI technologies, such as machine learning.

#### 4.3.3. Leveraging artificial intelligence

*4.3.3.1. Simulation.* The ability to simulate the real via the digital is a core DT feature. The idealisation is that a DT should be able to simulate the real world things with the highest level of fidelity [3]. Schluse et al. [46] see potential in developing 'experimental' DTs, which would be used to shift the experimentation of manufactured assets within the virtual world using so called "virtual testbeds", thus taking full advantage of simulation-based engineering. While this high-fidelity simulation virtual environment certainly seems feasible on smaller scales for mass manufacturing [45], the expectations are different when fixating on larger buildings, entire infrastructures or city districts. A finite-element analysis of structural integrity on nuclear power plants is important [113] as is for bridge lifecycle monitoring [115], but might be less relevant for other buildings types. Thus, the level of simulation applications and their respective levels of precision are expected to vary by domain and use case. The platform which hosts a digital twin therefore needs to be adaptable to these needs.

In the context of sensor-data based simulations, as is to be expected for a DT, the input for the simulation is dependent on sensor quality, their accuracy, precision, etc. In effect, this will influence the costs of implementing sensing on site, versus the required precision for each use case.

*4.3.3.2. Artificial intelligence for prediction and optimisation.* Generic and imprecise references for 'prediction' and 'optimisation' are repeatedly used. Additionally, the term AI itself encompasses a large spectrum of methodologies, applications and technologies, such as Machine Learning, Data Mining, Logics-based AI, Knowledge-based AI, etc.

The term 'intelligence', is usually referred to in a generic manner, with a majority of studies considering DT to be AI supported, in order to deal with IoT (sensing and actuation). Some studies consider AI to be a vital component of a higher level computation, allowing the DT to predict, optimise and take decisions dynamically. On the subject of Digital Twin maturity levels, [107] consider that the higher levels should allow the DT to be intelligent and adaptive, predicting and issuing warnings on the performance of the physical asset.

*4.3.3.3. Prediction.* Where simulations are able to reproduce the physical conditions with high fidelity (using input data and initial conditions), predictions need to be able to forecast successive environment states in time (using the current and past values of measured input and output values, as well as the initial conditions) [122,123]. Predicting future asset behaviour or health status is a common DT requirement. Terms such as "predictive modelling" [43,107,113], "structural life prediction" [39], or even "predict and act" [44] suggest that prediction should be used for immediate actuation on the physical side as a response.

'Big Data' fed prediction [43,114] is a common view of leveraging the use of IoT. However, the term 'big data' itself is ambiguous, encompassing not just size (volume), but also its speed of movement and change (velocity), and several states of existence (variety) from unstructured, semi-structured to structured data [124]. Thus, dealing with large amounts of data has the potential to yield significant value to the DT deployment [1,43]. Prediction techniques on big data often resort to Machine learning or Data Mining, with the first focusing on reproducing known knowledge, while the latter focuses on discovering new patterns and implicitly knowledge about the data itself. Machine Learning is proposed by Howell and Rezgui [1] to act as the top layer for smarter BIM-based building management. Similarly, Qi and Tao [43] compare data analysis to DTs in a comprehensive manner, emphasising the need for an eventual fusion between the two, providing overall interoperability and higher DT self-reliance. The challenge lies in the gathering, cleansing and structuring methods used on the data itself, which is later fused together for higher meaning and used for processing intelligent tasks [108].

The reliability of the source data should also be cause for concern. A distinction should be made on predictions based on real sensor data vs simulated sensor data, or even a hybrid approach. Verifying the validity of the prediction and its consequences on actuating the physical part needs to be considered. In other words, are current AI methods 'smart' enough to make a viable decision in that regard?

*4.3.3.4. Optimisation.* If the DT is envisaged to include all aspects of the physical twin in great detail (depending on domain and applied use case), this creates an optimisation problem in terms of effectively operating the asset according to a variety of objectives. The simulation, prediction and optimisation abilities of a DT are inter-dependent and act in unison in solving this problem. The decision-making ("what to do?") posed question of the optimisation process depends on the simulated prediction ("what will happen?") question [125].

In a similar way to the previous concepts using AI, the aspect of optimisation is a broadly used term around the field of DT. The universal driver for optimisation appears to be reducing the costs of manufacturing and operation of the Physical Twin. The primary use case for the manufacturing industry is to optimise the entire process by ensuring smart resource allocation [9,109], such as in the case of experimental test-beds looking to optimise the assembly algorithms [46]. For example, Alam and Saddik [109] make use of Bayesian networks to represent the decision model within the field of engineering systems design. For the built environment [1] and energy sectors [8], the scaling of costs is significantly higher during the operation stage, where balancing consumptions versus demand of energy and resources is the primary challenge. The design and construction process of infrastructure and buildings has a considerable impact on the operation costs across the lifecycle. Unfortunately, the construction optimisation goals do not always coincide with the operation ones, creating a rift during the lifecycle period, thus setting the built environment apart from manufacturing industries.

## 5. Recommendations for CDT realisation

Considering the current research landscape, this section aims to highlight the key considerations associated with the deployment and use of a DT during the construction stage, by looking at the perceived DT abilities and features from adjacent domains, and super imposing this onto construction site nD BIM uses. We consider the creation of a DT to be a continuous, evolving process hence the last part of this section introduces several generations of DT, depending on the implemented technologies discussed previously in Section 4.3.

### 5.1. Digital twin abilities

Several recurring concepts in literature around the subject of DT are defined in Table 2, which are segregated under the Virtual-Data-Physical paradigm in Fig. 5. We consider each sub-part as a feature or "ability" of the DT, which are deemed important to facilitate specific services. These abilities operate over the entire building lifecycle, but change in terms of technologies and tools used at each stage. In addition to the discussed concepts in Section 4.3, we consider actuation to be an important ability which allows a DT to stimulate real world actions whether reactive or proactive to environment changes.

### 5.2. CDT-enabled smart services

Within the manufacturing sector, the DT is referred to as having all the "useful" information across the entire product lifecycle [40]. This also applies to the building and infrastructure lifecycles, but at a much larger scale and inherently different dynamics, influencing how we plan and maintain our built environment with the use of digital assets. The abilities of the CDT rely on the various process and data layers which are aimed to facilitate smart construction services and applications [106], as depicted in Fig. 5. These would benefit from a digital twin

**Table 2**
Identified Digital Twin abilities and their roles within the Virtual-Data-Physical paradigm.

| Part | Ability | Description |
|---|---|---|
| The Physical | Sense | The ability to observe the physical world in real-time via the use of sensors. |
| | Monitor | The ability to keep track, inform and issue warnings on relevant physical alterations. |
| | Actuate | The ability to change/activate/deactivate physical components based on Virtual decisions/stimuli. |
| The Data | BIM | The ability to integrate and consume BIM specific data sets in its various formats and standards. |
| | IoT | The ability to integrate and share data communicated by Internet of Things devices. |
| | Data linking | The ability to integrate and share data via Semantic Web protocols. |
| | Knowledge storing | The ability to store facts about the system, support rules and reasoning capabilities. |
| The Virtual | Simulate | The ability to apply engineering simulation models from various application domains. |
| | Predict | The ability to predict the behaviour of the physical based on digital simulations and sensing. |
| | Optimise | The ability to apply optimisation methods and recommend smart allocation of resources dynamically. |
| | Agency | The ability to delegate AI agents capable of managing (and actuating) the physical based on digital data, following well-defined behaviours, protocols and objectives. |

integration on several levels, assuming a robust framework is in place to support the various heterogeneous systems and technologies encountered in research, as discussed in Section 4.2.

#### 5.2.1. Enhanced site sensing

Current efforts for construction site sensing are limited to regular laser scans, manual management updates and inputs in various forms and documents carried out by human actors. By default, this limits the capability of the BIM and eventual DT to accurately simulate and

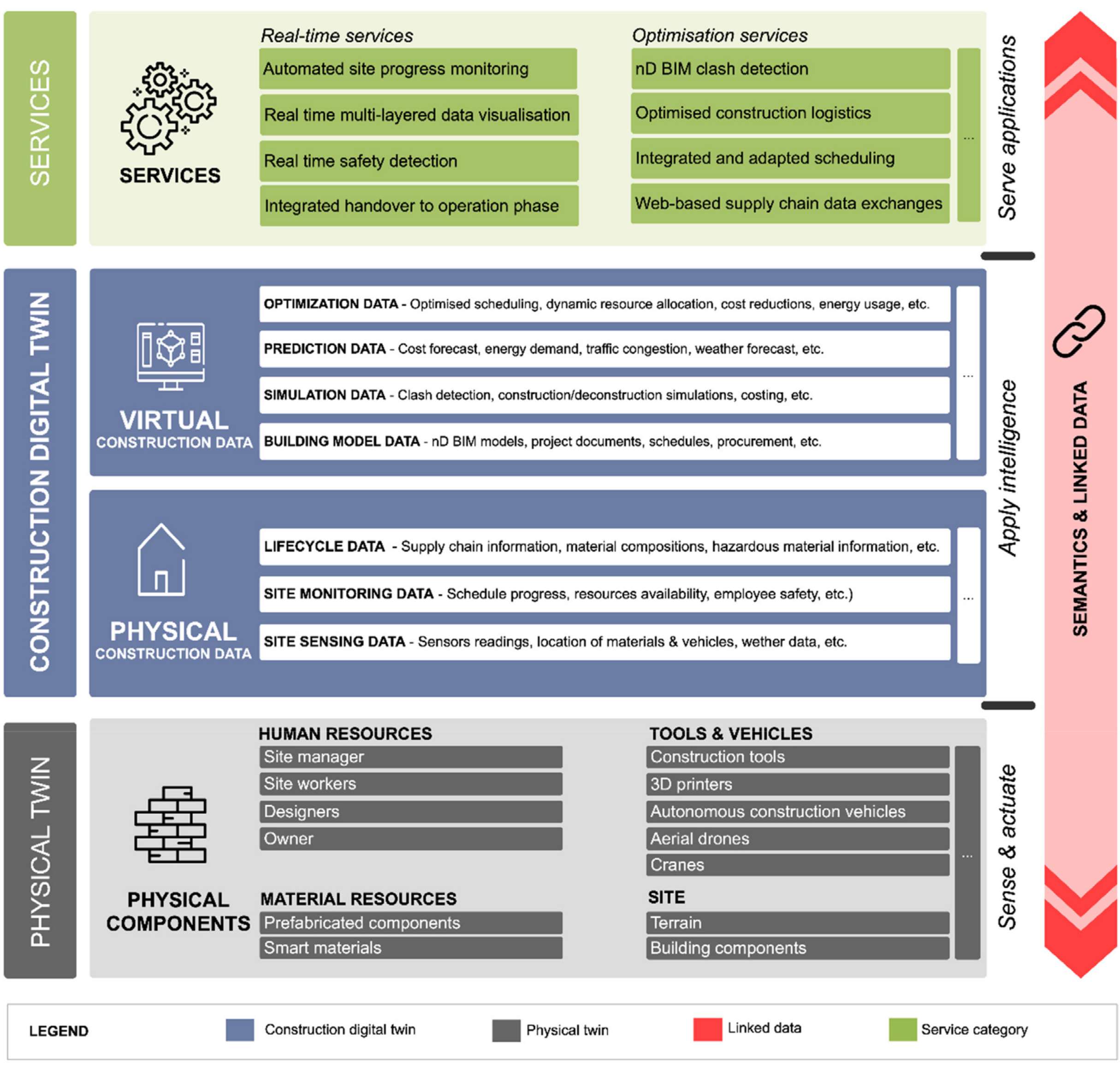


**Fig. 5.** Construction Digital Twin data usage for facilitating smart construction services (based on Tao et al. [106]).

predict in the nD modelling sense, given that the information is out-of-date and out of sync with the physical twin (the real world). Therefore, a substantial increase in the efforts for sensing the site is recommended across the board (fixed sensors, video-feeds, tracking of vehicles and resources, etc.), and enable a continuous and real-time flow of data from the site to the virtual models.

*5.2.1.1. Automated site progress monitoring.* The analysed 4D BIM use-cases show the forming trends and technologies used to capture site data and automate the BIM during construction. The use-cases of safety management, site monitoring and construction logistics as reviewed in Section 4.2.2 rely on various novel methods and technologies to monitor the site using photogrammetry and laser scanning on hand-held mobile devices and aerial drones. These technologies employ various processes on site scanning and reflecting that within the BIM [60,63,118,127]. Several research initiatives previously addressed the difficulty in making sense of the overwhelming amounts of data flowing from a site to its digital model, as well as the challenges of equipping and maintaining construction site sensors [117]. Thus, issues persist in terms of validating the data (correctness and completion), correctly interpreting it (applying semantics) and processing it in an effective manner to facilitate real-time responses. The application of automated site monitoring techniques would initially benefit site logistics [60,116], safety [118] and subsequently reflect this in terms of quality assessment and cost reductions long term.

*5.2.1.2. Real-time multi-layered data visualisation.* Visualisation is an important subject within the construction sector, being at the core of team communication and decision-making. Assuming a holistic and enhanced real-time site monitoring, the idiom of "drowning in data" [7] can be traversed by applying proven data visualisation techniques for project management, benefiting of up-to-date, real-time data feeds from multiple sources. Cross-checking and cross-referencing data from different devices and models would bring forth more valuable insights to users and construction site decision-making. Already established nD BIM concepts and uses would become easier to contrast and compare construction simulations to real-time site developments.

#### *5.2.2. Increased application of AI*

Construction site dynamics levitate around effectively planning tasks, keeping costs at predicted levels, and wisely utilising resources (labour, equipment, etc.). Assuming a more integrated complex system, the DT should be able to adapt scheduling and cost information automatically according to dynamic site changes, trigger the correct estimation algorithms and inform managers by issuing timely warnings on disruptions as well as their possible causes.

*5.2.2.1. Real-time site safety detection.* Construction sites have traditionally been amongst the most dangerous working environments. Most studies and practitioners recognise the advantages of using 4D modelling and agree that it brings an inherent benefit to health and safety improvement. However, the process of how to apply safety management following systematic and meaningful workflows with clear indicators is still lacking considering the way data is collected on-site. The fact that many subcontracting companies work only temporarily on the sites, and that a large share of the workforce consists of temporary workers makes safety management a BIM use with constant data changes, which are often neglected or not considered in a wider context.

Construction Digital Twins should collect information on the presence of workers on-site, including their numbers and locations. Besides checking compliance to safety rules (e.g. wearing helmets) it could also further detect eventual abnormal behaviours such as motionlessness, fall, or even monitor their fatigue and attention during dangerous activities [128]. Additionally, parallel virtual simulations of site safety and evacuations could offer more insight into previously unforeseen short term predictions on safety hazards and risks.

*5.2.2.2. nD BIM clash detection simulation.* In construction research, nD modelling has been addressed in Section 4.2 where several references discussed the simulation of 4D clashes. The added value being demonstrated, such innovation often faces the reluctance of construction practitioners, who often cannot rely on BIM data completion or validity during construction. The associated human effort to achieve such a BIM use is a key barrier, that automated sensing may help overcome. Thus we consider the ability of sensing, coupled to semantic enrichment of 4D/BIM models as a basis to carry on 4D/nD clash detection simulations. The DT would therefore reflect the status (as-is) and allow construction teams to run alternative (what-if) planning simulations including building tasks as well as temporary logistics activities or equipment allocations plans. Going further, optimisation can be applied to the simulations in order to achieve the optimised planning, or various other construction management objectives.

*5.2.2.3. Optimised construction logistics and scheduling.* Construction productivity suffers from a lack of integration of the processes and supply-chains actors involved on-site and off-site. While micro-management may improve the day-to-day work on-site, it is known that it can also be realized if tasks are connected to pre-requisites related to the whole supply chain (including logistics of delivery of materials/equipment from off-site production systems). Lean Construction methods, amongst others the Last Planner System [129], usually rely on forms, collection of information from all parties and look ahead planning. However, a lack of efficient information integration on all levels persists. Semantic Digital Twin applications promise the ability to connect the various planning systems, as well as to link the heterogeneous datasets. Artificial Intelligence may also bring added-value to human agents in such negotiation-intensive management approaches, like advising the professionals on optimised duration, sequencing etc. Likewise, the higher the traffic on site in terms of people, vehicles and materials the more challenging it is. The Semantic Digital Twin should enable pro-active modelling, tracking and optimisation of construction processes and their associated off- and on-site resources.

#### *5.2.3. Holistic web-based integration*

A fully semantic data environment brings several benefits, as previously mentioned in Sections 2.3 and 4.2.3, allowing the design and construction supply chain to leverage web-based linked data. As-designed BIMs can vary significantly during the construction phase, e.g. specified equipment for a particular manufacturer may change during purchase orders, optimising costs or unavailability of equipment within the timeframe of the project. Linked data over the web with project supplier databases, products and order changes can help reduce the effects of such disruptions on productivity. Additionally, this would improve the transition from handover to operation of the delivered facility, by transferring a holistic context of vital suppliers and products for use during future maintenance and potential renovations. Conversely, building components themselves can have a DT from a manufacturing domain, a core subject around DT in manufacturing (Section 4.3). Suppliers of intelligent DT products will have a need to monitor and collect data about its use, customers and wider lifecycle context.

From the urban environment point of view, web-based integration of IoT is demanded across the board, as evident from the literature. Therefore, the transition from construction handover to operation needs to be complemented by considering the wider urban level requirements. This would also make the BIM more compatible by improving urban level interoperability, where these technologies begin to thrive, as was outlined in Section 4.3.

### 5.3. Value chain of the construction process

When considering that the value chain management of a construction company is measured by increasing profits and adding value to its customers while at the same time reducing costs of implementation, the benefits of implementing a CDT should be carefully evaluated for each project type (based on size, client needs, procurement methods, etc). With BIM now being part of the initial procurement and the design-construction-demolition stages, the emphasis of the CDT should be at the pre-construction and construction stages when the “Physical Twin” gets built. While BIM processes and models are able to facilitate improved collaboration through the use of common standards and formats (as discussed in Sections 2.1, 4.2.3 and 4.3.2), a BIM paradigm is limited when in the scope of IoT and dynamic site data. A CDT assumes a cohesive integration of models, sensors and services, enhanced by synchronicity. This value can be unlocked through semantic web technologies, as was argued in the previous section. Enhanced construction services (Fig. 5), would implicitly benefit from an increased level of integration and automation, allowing construction workflows to better allocate resources between tasks which are better performed by robots, drones and sensors, and those which require human input.

The importance of using digital twins is measured in the added value to society by strengthening the lower carbon emission and clean energy agendas. Current research challenges lie in the capability to adapt to the complex social systems which exist around our built environment. The dynamics of human interaction with built assets is often a limitation of many intelligent building management systems, which need to better adapt and respond to occupant needs, while at the same time optimise the use of resources. Transposing this to the construction site, a CDT should be able to access the full data of the construction project, grasp the holistic context and return valuable insights. Additionally, users from different social and educational backgrounds should be able to interface with the CDT, which is set to vary according to application domains over the lifecycle [46].

### 5.4. A progressive evolution approach

Considering the current research landscape around the concept of DT, we propose an evolutionary 3-tier level CDT paradigm, as represented in Fig. 6. Other similar industry views have been taken into account [37,130], with [130] outlining a five stage process of creating a DT during a construction stage. However, there is still a lack of clarity on the potential technologies for higher tiers, mainly due to a lack of implementation and research at such levels of sophistication. We consider the implementation efforts for a CDT to be gradual, but continuous over the building lifecycle, while considering the supply chain integration and the sophistication of technologies adopted. The eventual merge between virtual models and sensing would converge on a common semantic web platform. The transition from legacy tools and formats depends on the application domains and existing models to adopt, but would prove an invaluable step towards interoperability and expansion into future lifecycle stages. The adoption of advanced forms of AI represents the final step, which is expected to progress after sufficient training and verification of the AI behaviour is carried out; this represents the transition of certain tasks from human expert control and guidance to limited DT agency.

#### 5.4.1. Generation #1 – monitoring platforms

The initial attempt at a DT, monitoring platforms enable sensing of the physical, with some degree of reporting and analysis capabilities. Actuation on the physical world is restricted to imbedded emergency procedures. The virtual data models at this stage can consider legacy digital models. This should be considered as the first step towards the real-time integration of site sensing and digital models, offering limited insights open to user interpretation and decision-making. This step is an enhanced version of BIM on construction sites to date. However, the BIM on its own cannot deliver all the information requirements for subsequent lifecycle stages, nor is it extensible for including more complex computations (prediction, optimisation).

#### 5.4.2. Generation #2 – intelligent semantic platforms

Taking the first major step towards semantics, these are enhanced monitoring platforms with limited intelligence where a common web language framework is deployed to represent the DT with all its integrated IoT devices, thus forming a knowledge base. Limited intelligence is achieved via the use of embedded knowledge rules, and separate AI-based algorithms for enabling simulations and predictions. Optimisation would be a process largely carried out by trained human actors. Actuation capabilities are limited to security, safety and energy consumption, issuing detailed warnings and recommendations requiring user validation and authorisation for more complex situations.

However, a building does not live in isolation and should therefore be regarded from the perspective of the city district level. Interactions with its immediate environment (city traffic, pollution, social events, etc.) should be considered for a larger construction site management context. This projects the DT into a complex socio-technical dilemma, where the DT needs to adapt and respond in real time to its users and dynamic changes which occur on a daily basis.

#### 5.4.3. Generation #3 – agent driven socio-technical platforms

The apex of the DT implementation possible to date represents a fully semantic DT, leveraging acquired knowledge with the use of AI-enabled agents. Machine learning, deep learning, data mining and analysis capabilities are required to construct a self-reliant, self-updatable and self-learning DT. Optimisation would be fully entrusted to the DT's goals and learning patterns. In addition to the semantic layer, the social aspects of the building need to be considered. Enabling a user-driven experience is mandated, where the DT can adapt to social requirements and engage with end-users to support holistic decision-making. Actuation of the environment becomes fully autonomous to the DT system, requiring human supervision.

## 6. Conclusion

This article advocates that in order for BIM to adapt to newer, more integrated approaches on micro (construction site) and macro (city districts) levels, the adoption of a Digital Twin paradigm is required. The construction industry sector has already made magnificent strides since the conception of BIM, and has gained sufficient recognition and momentum to enable a shift from a static, closed information environment to a dynamic, web-based one, embracing IoT integration and a higher degree of AI implementation. This would help deliver smarter construction services, increased automation and information cohesion.

Current research landscape around the subject of BIM uses was outlined (Section 4.2), tackling the first of three research objectives. This reveals current trends and the more recent technologies employed during design and construction. Although nD modelling has been a research subject for several decades, the level of collaboration between systems and actors which use it is still relatively weak. Although schemas like the IFC have contributed to overall industry collaboration, the complex nature of nD models, their overall lack of cohesion and out-of-sync issues, comprised by the many use-cases applied at design and construction stages has left the BIM lacking in terms of interoperability and automation. This presents a serious challenge for the creation of a comprehensive Construction Digital Twin, which demands a real-time connection to the Physical Twin and all its relevant components.

An analysis of the DT paradigm from nearby engineering domains (Section 4.3) was carried out, tackling the second research objective. This reveals disparate potential methods and technologies to be considered for DTs. The use of several technologies ranging from sensors, IoT, simulation models and AI, was compiled and presented from a “Physical-Data-Virtual” paradigm perspective, as introduced in Section

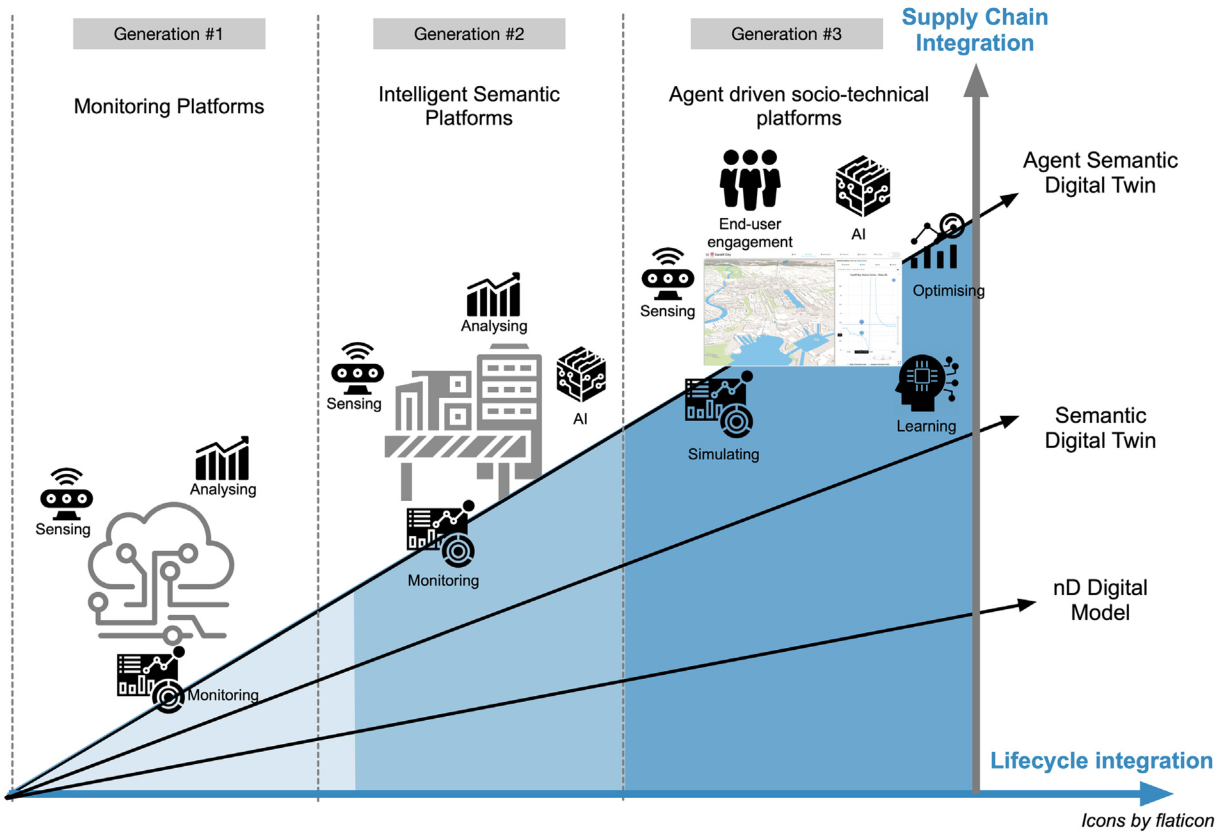


**Fig. 6.** The 3-tier Generation evolution of the Construction Digital Twin.

2.3. Within the symbiotic relationship between the physical and virtual parts of the DT, BIM is often treated as a DT sub-component. Instinctively, this is because in the case of buildings and infrastructure, the conception of the DT begins with the BIM, which is the digital representation of the building, enriched by the addition of sensing capabilities, big data and the Internet of Things from site to building operation. Several important overlaps are identified from the conception of BIM during design, its enrichment during construction, and its completion towards becoming a valid DT.

Following the logical thread from BIM to DTs, the final research objectives are tackled in Section 5. The article lists several DT abilities or features which would enable real-time, web integrated, intelligent CDTs (Section 5.1). These abilities were then extrapolated onto the construction site landscape (Section 5.2), where existing methods and tools can be greatly enhanced to provide overall smarter construction services. The change from the static nature of information exchanges using the IFC format, to a more open, web linked data paradigm would ensure that the right data is available at the right time. This would represent the first step towards finding the undiscovered methods and tools which would allow the delivery of more intelligent, automated construction sites and built environments.

The eventual added value that a digital twin would convey is not just the abundance of dynamic data it would manage, but also its meaning (semantics), and its constant accrual of knowledge about the physical world. The benefits to the built environment are in the long term, from a smart and lean construction process towards a smart lifecycle management. This would inherently deliver improved lifecycle costs, built asset resilience and reduced carbon emissions, in an ever-increasing environmental aware society.

### 6.1. Limitations of review method

This article presents a conceptual framework for realising a CDT mostly based on a review of the existing literature. The authors have presented their world view based on the analysis of 196 research articles. Due to the design of the research methodology, not all aspects of nD BIM or DT fell within the scope of this review, therefore leaving out some trails around the subject. To compensate for the statistical view of the results, an in-depth review was conducted to bring out the essential works and discuss aspects considered important for debate for future construction industry research. Additionally, topics like cyber-security issues of large scale infrastructure will probably remain the main issue for years to come, which is not addressed here.

## 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.

## Acknowledgements

The authors acknowledge financial support from Fonds National de la Recherche Luxembourg, and Agence Nationale de la Recherche France, to 4DCollab project, grant reference: 11237662 (LU)/ANR-16-CE10-0006-01 (FR).

## References


[1] S. Howell, Y, Rezgui, Beyond BIM, Knowledge management for a smarter built environment, 2018https://www.brebookshop.com/details.jsp?id=327975 (978-1-84806-476-8).

[2] S. Kubicki, A. Guerriero, L. Schwartz, E. Daher, B. Idris, Assessment of synchronous interactive devices for BIM project coordination: prospective ergonomics approach, Autom. Constr. 101 (2019) 160–178, https://doi.org/10.1016/j.autcon.2018.12.009.

[3] M. Batty, Digital twins, Environment and Planning B: Urban Analytics and City Science 45 (2018) 817–820, https://doi.org/10.1177/2399808318796416.

[4] A. Bradley, H. Li, R. Lark, S. Dunn, BIM for infrastructure: an overall review and constructor perspective, Autom. Constr. 71 (2016) 139–152, https://doi.org/10.1016/j.autcon.2016.08.019.
[6] P. Pauwels, S. Zhang, Y.-C. Lee, Semantic web technologies in AEC industry: a literature overview, Autom. Constr. 73 (2017) 145–165, https://doi.org/10.1016/j.autcon.2016.10.003.
[7] D. Remund, D. "Deb" Aikat, Drowning in data: a review of information overload within organizations and the viability of strategic communication principles, Information Overload, John Wiley & Sons, Inc, Hoboken, NJ, USA, 2012, pp. 231–250, , https://doi.org/10.1002/9781118360491.ch11.
[8] S. Howell, Y. Rezgui, J.-L. Hippolyte, B. Jayan, H. Li, Towards the next generation of smart grids: semantic and holonic multi-agent management of distributed energy resources, Renew. Sust. Energ. Rev. 77 (2017) 193–214, https://doi.org/10.1016/j.rser.2017.03.107.
[9] F. Tao, H. Zhang, A. Liu, A.Y.C. Nee, Digital twin in industry: state-of-the-art, IEEE Transactions on Industrial Informatics 15 (2019) 2405–2415, https://doi.org/10.1109/TII.2018.2873186.
[10] L. Ding, Y. Zhou, B. Akinci, Building Information Modeling (BIM) application framework: the process of expanding from 3D to computable nD, Autom. Constr. 46 (2014) 82–93, https://doi.org/10.1016/j.autcon.2014.04.009.
[11] A. GhaffarianHoseini, T. Zhang, O. Nwadigo, A. GhaffarianHoseini, N. Naismith, J. Tookey, K. Raahemifar, Application of nD BIM Integrated Knowledge-based Building Management System (BIM-IKBMS) for inspecting post-construction energy efficiency, Renew. Sust. Energ. Rev. 72 (2017) 935–949, https://doi.org/10.1016/j.rser.2016.12.061.
[12] M.-A. Vigneault, C. Boton, H.-Y. Chong, B. Cooper-Cooke, An innovative framework of 5D BIM solutions for construction cost management: a systematic review, Archives of Computational Methods in Engineering (2019), https://doi.org/10.1007/s11831-019-09341-z.
[13] R. Charef, H. Alaka, S. Emmitt, Beyond the third dimension of BIM: a systematic review of literature and assessment of professional views, Journal of Building Engineering 19 (2018) 242–257, https://doi.org/10.1016/j.jobe.2018.04.028.
[14] B.I.M. Dictionary, 5D, English, Version 1 (2020), https://bimdictionary.com/en/5d/1 (accessed January 15, 2020).
[15] A. Sattineni, J.A. Macdonald, 5.D. BIM, A case study of an implementation strategy in the construction industry, 31st International Symposium on Automation and Robotics in Construction and Mining, ISARC 2014 - Proceedings, 2014, pp. 361–367 https://doi.org/10.22260/ISARC2014/0048.
[16] B. Succar, Building information modelling framework: a research and delivery foundation for industry stakeholders, Autom. Constr. 18 (2009) 357–375, https://doi.org/10.1016/j.autcon.2008.10.003.
[17] A. Guerriero, S. Kubicki, F. Berroir, C. Lemaire, BIM-enhanced collaborative smart technologies for LEAN construction processes, 2017 International Conference on Engineering, Technology and Innovation (ICE/ITMC), IEEE, 2017, pp. 1023–1030, , https://doi.org/10.1109/ICE.2017.8279994.
[18] M. Golparvar-Fard, F. Peña-Mora, S. Savarese, Integrated sequential as-built and as-planned representation with D4AR tools in support of decision-making tasks in the AEC/FM industry, J. Constr. Eng. Manag. 137 (2011) 1099–1116, https://doi.org/10.1061/(ASCE)CO.1943-7862.0000371.
[19] C. Kim, H. Son, C. Kim, Automated construction progress measurement using a 4D building information model and 3D data, Autom. Constr. 31 (2013) 75–82, https://doi.org/10.1016/j.autcon.2012.11.041.
[20] Z. Shang, Z. Shen, A framework for a site safety assessment model using statistical 4D BIM-based spatial-temporal collision detection, in: Construction Research Congress, American Society of Civil Engineers, Reston, VA 2016 (2016) 2187–2196, https://doi.org/10.1061/9780784479827.218.
[21] J. Jupp, 4D BIM for environmental planning and management, Procedia Engineering 180 (2017) 190–201, https://doi.org/10.1016/j.proeng.2017.04.178.
[22] E. Collier, M. Fischer, Four-dimensional Modeling in Design and Construction, (1995), pp. 1–76 https://purl.stanford.edu/zd669fn2067 (accessed January 15, 2020).
[23] L.L. Olde Scholtenhuis, T. Hartmann, A.G. Dorée, Comparing Mindfulness in Manual and 4D-supported Coordination Practices, in: Construction Research Congress 2014, American Society of Civil Engineers, Reston, VA, 2014, pp. 160–168, https://doi.org/10.1061/9780784413517.017.
[24] K. Whitlock, F.H. Abanda, M.B. Manjia, C. Pettang, G.E. Nkeng, BIM for construction site logistics management, Journal of Engineering, Project, and Production Management 8 (2018) 47–55 https://doi.org/10.32738/JEPPM.201801.0006.
[25] B. East, Using COBie, in: BIM for Facility Managers, John Wiley & Sons, Inc, Hoboken, NJ, USA, 2018, pp. 107–143, https://doi.org/10.1002/9781119572633.ch5.
[26] International Organization for Standardization (ISO), ISO 16739-1:2018 Industry Foundation Classes (IFC) for Data Sharing in the Construction and Facility Management Industries—Part 1: Data Schema, https://www.iso.org/standard/70303.html, (2018).
[27] M. Laakso, A. Kiviniemi, The IFC standard: a review of history, development, and standardization, Information Technology, Journal of Information Technology in Construction (ITcon) 17 (2012) 134–161 https://www.itcon.org/paper/2012/9 (ISSN: 1874-4753).
[28] Y.-C. Lee, C.M. Eastman, J.-K. Lee, Validations for ensuring the interoperability of data exchange of a building information model, Autom. Constr. 58 (2015) 176–195, https://doi.org/10.1016/j.autcon.2015.07.010.
[29] P. Pauwels, D. Van Deursen, R. Verstraeten, J. De Roo, R. De Meyer, R. Van de Walle, J. Van Campenhout, A semantic rule checking environment for building performance checking, Autom. Constr. 20 (2011) 506–518, https://doi.org/10.1016/j.autcon.2010.11.017.
[30] J. Beetz, J. van Leeuwen, B. de Vries, IfcOWL: a case of transforming EXPRESS schemas into ontologies, Artificial Intelligence for Engineering Design, Analysis and Manufacturing 23 (2009) 89–101, https://doi.org/10.1017/S0890060409000122.
[31] P. Pauwels, W. Terkaj, EXPRESS to OWL for construction industry: towards a recommendable and usable ifcOWL ontology, Autom. Constr. 63 (2016) 100–133, https://doi.org/10.1016/j.autcon.2015.12.003.
[32] M. Venugopal, C.M. Eastman, J. Teizer, An ontology-based analysis of the industry foundation class schema for building information model exchanges, Adv. Eng. Inform. 29 (2015) 940–957, https://doi.org/10.1016/j.aei.2015.09.006.
[33] I. Horrocks, B. Parsia, P. Patel-Schneider, J. Hendler, F. Fages, S. Soliman (Eds.), Semantic Web Architecture: Stack or Two Towers? Springer Berlin Heidelberg, Berlin, Heidelberg, 2005, pp. 37–41, , https://doi.org/10.1007/11552222_4.
[35] HM Government, Digital Built Britain Level 3 Building Information Modelling - Strategic Plan, (2015) https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/410096/bis-15-155-digital-built-britain-level-3-strategy.pdf , Accessed date: 15 January 2020.
[37] A. Bolton, L. Butler, I. Dabson, M. Enzer, M. Evans, T. Fenemore, F. Harradence, The Gemini Principles, https://doi.org/10.17863/CAM.32260, (2018).
[38] M. Grieves, Digital Twin: Manufacturing Excellence Through Virtual Factory Replication, White Paper, https://www.researchgate.net/publication/275211047_Digital_Twin_Manufacturing_Excellence_through_Virtual_Factory_Replication, (2014).
[39] E.J. Tuegel, A.R. Ingraffea, T.G. Eason, S.M. Spottswood, Reengineering aircraft structural life prediction using a digital twin, International Journal of Aerospace Engineering 2011 (2011) 1–14, https://doi.org/10.1155/2011/154798.
[40] S. Boschert, R. Rosen, P. Hehenberger, D. Bradley (Eds.), Digital twin—the simulation aspect, Springer International Publishing, Cham, 2016, pp. 59–74, , https://doi.org/10.1007/978-3-319-32156-1_5 Mechatronic Futures.
[41] B. Schleich, N. Anwer, L. Mathieu, S. Wartzack, Shaping the digital twin for design and production engineering, CIRP Ann. 66 (2017) 141–144, https://doi.org/10.1016/j.cirp.2017.04.040.
[42] N. Mohammadi, J.E. Taylor, Smart city digital twins, IEEE Symposium Series on Computational Intelligence (SSCI), IEEE 2017 (2017) 1–5, https://doi.org/10.1109/SSCI.2017.8285439.
[43] Q. Qi, F. Tao, Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison, IEEE Access 6 (2018) 3585–3593, https://doi.org/10.1109/ACCESS.2018.2793265.
[44] M. Tomko, S. Winter, Beyond digital twins – a commentary, Environment and Planning B: Urban Analytics and City Science 46 (2019) 395–399, https://doi.org/10.1177/2399808318816992.
[45] S. Haag, R. Anderl, Digital twin – proof of concept, Manufacturing Letters 15 (2018) 64–66, https://doi.org/10.1016/j.mfglet.2018.02.006.
[46] M. Schluse, M. Priggemeyer, L. Atorf, J. Rossmann, Experimentable digital twins—streamlining simulation-based systems engineering for industry 4.0, IEEE Transactions on Industrial Informatics 14 (2018) 1722–1731, https://doi.org/10.1109/TII.2018.2804917.
[47] D. Heesom, L. Mahdjoubi, Trends of 4D CAD applications for construction planning, Constr. Manag. Econ. 22 (2004) 171–182, https://doi.org/10.1080/0144619042000201376.
[48] F.H. Abanda, J.H.M. Tah, R. Keivani, Trends in built environment semantic web applications: where are we today? Expert Syst. Appl. 40 (2013) 5563–5577, https://doi.org/10.1016/j.eswa.2013.04.027.
[49] H. Li, N. Chan, T. Huang, H.L. Guo, W. Lu, M. Skitmore, Optimizing construction planning schedules by virtual prototyping enabled resource analysis, Autom. Constr. 18 (2009) 912–918, https://doi.org/10.1016/j.autcon.2009.04.002.
[50] Z. Hu, J. Zhang, BIM- and 4D-based integrated solution of analysis and management for conflicts and structural safety problems during construction: 2. Development and site trials, Autom. Constr. 20 (2011) 167–180, https://doi.org/10.1016/j.autcon.2010.09.014.
[51] H. Moon, N. Dawood, L. Kang, Development of workspace conflict visualization system using 4D object of work schedule, Adv. Eng. Inform. 28 (2014) 50–65, https://doi.org/10.1016/j.aei.2013.12.001.
[52] M. Marzouk, A. Abubakr, Decision support for tower crane selection with building information models and genetic algorithms, Autom. Constr. 61 (2016) 1–15, https://doi.org/10.1016/j.autcon.2015.09.008.
[53] M. Mawlana, F. Vahdatikhaki, A. Doriani, A. Hammad, Integrating 4D modeling and discrete event simulation for phasing evaluation of elevated urban highway reconstruction projects, Autom. Constr. 60 (2015) 25–38, https://doi.org/10.1016/j.autcon.2015.09.005.
[54] M. Kassem, N. Dawood, R. Chavada, Construction workspace management within an industry foundation class-compliant 4D tool, Autom. Constr. 52 (2015) 42–58, https://doi.org/10.1016/j.autcon.2015.02.008.
[55] M. Trebbe, T. Hartmann, A. Dorée, 4D CAD models to support the coordination of construction activities between contractors, Autom. Constr. 49 (2015) 83–91, https://doi.org/10.1016/j.autcon.2014.10.002.
[56] B. Butkovic, D. Heesom, D. Oloke, The need for multi-LOD 4D simulations in construction projects, Journal of Information Technology in Construction (ITcon) 24 (2019) 256–272 http://www.itcon.org/2019/14 (ISSN: 1874-4753).
[57] S. Chin, S. Yoon, Y.-S. Kim, J. Ryu, C. Choi, C.-Y. Cho, Realtime 4D CAD = RFID for project progress management, in: Construction Research Congress, American Society of Civil Engineers, Reston, VA 2005 (2005) 1–10, https://doi.org/10.1061/40754(183)33.
[58] M. Park, C. Koch, I. Brilakis, Three-dimensional tracking of construction resources using an on-site camera system, J. Comput. Civ. Eng. 26 (2012) 541–549, https://

doi.org/10.1061/(ASCE)CP.1943-5487.0000168.
[59] R. Sacks, M. Treckmann, O. Rozenfeld, Visualization of work flow to support lean construction, J. Constr. Eng. Manag. 135 (2009) 1307–1315, https://doi.org/10.1061/(ASCE)CO.1943-7862.0000102.
[60] K.K. Han, M. Golparvar-Fard, Potential of big visual data and building information modeling for construction performance analytics: an exploratory study, Autom. Constr. 73 (2017) 184–198, https://doi.org/10.1016/j.autcon.2016.11.004.
[61] Y. Turkan, F. Bosche, C.T. Haas, R. Haas, Automated progress tracking using 4D schedule and 3D sensing technologies, Autom. Constr. 22 (2012) 414–421, https://doi.org/10.1016/j.autcon.2011.10.003.
[62] S. Tuttas, A. Braun, A. Borrmann, U. Stilla, Acquisition and consecutive registration of photogrammetric point clouds for construction progress monitoring using a 4D BIM, PFG – Journal of Photogrammetry, Remote Sensing and Geoinformation Science 85 (2017) 3–15, https://doi.org/10.1007/s41064-016-0002-z.
[63] H. Hamledari, B. McCabe, S. Davari, A. Shahi, Automated schedule and progress updating of IFC-based 4D BIMs, J. Comput. Civ. Eng. 31 (2017) 04017012, , https://doi.org/10.1061/(ASCE)CP.1943-5487.0000660.
[64] C. Kim, B. Kim, H. Kim, 4D CAD model updating using image processing-based construction progress monitoring, Autom. Constr. 35 (2013) 44–52, https://doi.org/10.1016/j.autcon.2013.03.005.
[65] C. Kropp, C. Koch, M. König, Interior construction state recognition with 4D BIM registered image sequences, Autom. Constr. 86 (2018) 11–32, https://doi.org/10.1016/j.autcon.2017.10.027.
[66] K.K. Han, M. Golparvar-Fard, Appearance-based material classification for monitoring of operation-level construction progress using 4D BIM and site photologs, Autom. Constr. 53 (2015) 44–57, https://doi.org/10.1016/j.autcon.2015.02.007.
[67] L. Chen, H. Luo, A BIM-based construction quality management model and its applications, Autom. Constr. 46 (2014) 64–73, https://doi.org/10.1016/j.autcon.2014.05.009.
[68] J.M. Davila Delgado, L.J. Butler, I. Brilakis, M.Z.E.B. Elshafie, C.R. Middleton, Structural performance monitoring using a dynamic data-driven BIM environment, J. Comput. Civ. Eng. 32 (2018) 04018009, , https://doi.org/10.1061/(ASCE)CP.1943-5487.0000749.
[69] K. Kim, Y. Cho, S. Zhang, Integrating work sequences and temporary structures into safety planning: automated scaffolding-related safety hazard identification and prevention in BIM, Autom. Constr. 70 (2016) 128–142, https://doi.org/10.1016/j.autcon.2016.06.012.
[70] S. Zhang, K. Sulankivi, M. Kiviniemi, I. Romo, C.M. Eastman, J. Teizer, BIM-based fall hazard identification and prevention in construction safety planning, Saf. Sci. 72 (2015) 31–45, https://doi.org/10.1016/j.ssci.2014.08.001.
[71] R. Rwamamara, H. Norberg, T. Olofsson, O. Lagerqvist, Using visualization technologies for design and planning of a healthy construction workplace, Constr. Innov. 10 (2010) 248–266, https://doi.org/10.1108/14714171011060060.
[72] V. Benjaoran, S. Bhokha, An integrated safety management with construction management using 4D CAD model, Saf. Sci. 48 (2010) 395–403, https://doi.org/10.1016/j.ssci.2009.09.009.
[73] S. Sakhakarmi, J. Park, C. Cho, Enhanced machine learning classification accuracy for scaffolding safety using increased features, J. Constr. Eng. Manag. 145 (2019) 04018133, , https://doi.org/10.1061/(ASCE)CO.1943-7862.0001601.
[74] E. Tauscher, K. Smarsly, M. König, K. Beucke, Automated generation of construction sequences using building information models, in: Computing in Civil and Building Engineering (2014), American Society of Civil Engineers, Reston, VA, 2014, pp. 745–752, https://doi.org/10.1061/9780784413616.093.
[75] H. Kim, K. Anderson, S. Lee, J. Hildreth, Generating construction schedules through automatic data extraction using open BIM (building information modeling) technology, Autom. Constr. 35 (2013) 285–295, https://doi.org/10.1016/j.autcon.2013.05.020.
[76] W. Huhnt, S. Richter, S. Wallner, T. Habashi, T. Krämer, Data management for animation of construction processes, Adv. Eng. Inform. 24 (2010) 404–416, https://doi.org/10.1016/j.aei.2010.07.009.
[77] W.-C. Wang, S.-W. Weng, S.-H. Wang, C.-Y. Chen, Integrating building information models with construction process simulations for project scheduling support, Autom. Constr. 37 (2014) 68–80, https://doi.org/10.1016/j.autcon.2013.10.009.
[78] H. Liu, M. Al-Hussein, M. Lu, BIM-based integrated approach for detailed construction scheduling under resource constraints, Autom. Constr. 53 (2015) 29–43, https://doi.org/10.1016/j.autcon.2015.03.008.
[79] A. Russell, S. Staub-French, N. Tran, W. Wong, Visualizing high-rise building construction strategies using linear scheduling and 4D CAD, Autom. Constr. 18 (2009) 219–236, https://doi.org/10.1016/j.autcon.2008.08.001.
[81] C. Ya-Hsin, M.-H. Tsai, S.-C. Kang, C.-W. Liu, Selection and evaluation of color scheme for 4D construction models, Journal of Information Technology in Construction (ITcon) 18 (2013) 1–19 http://www.itcon.org/2013/1 (ISSN: 1874-4753).
[82] Z. Zhang, H. Hamledari, S. Billington, M. Fischer, 4D beyond construction: spatio-temporal and life-cyclic modeling and visualization of infrastructure data, Journal of Information Technology in Construction (ITcon) 23 (2018) 285–304 http://www.itcon.org/2018/14 (ISSN: 1874-4753).
[83] F. Castronovo, S. Lee, D. Nikolic, J.I. Messner, Visualization in 4D construction management software: a review of standards and guidelines, in: Computing in Civil and Building Engineering, 2014 American Society of Civil Engineers, Reston, VA, 2014, pp. 315–322, https://doi.org/10.1061/9780784413616.040.
[84] J.C.P. Cheng, Y. Tan, Y. Song, X. Liu, X. Wang, A semi-automated approach to generate 4D/5D BIM models for evaluating different offshore oil and gas platform decommissioning options, Visualization in Engineering 5 (2017) 12, https://doi.org/10.1186/s40327-017-0053-2.
[85] T. Dang, H.-J. Bargstädt, 4D relationships: the missing link in 4D scheduling, J. Constr. Eng. Manag. 142 (2016) 04015072, , https://doi.org/10.1061/(ASCE)CO.1943-7862.0001007.
[88] Q. Lu, J. Won, J.C.P. Cheng, A financial decision making framework for construction projects based on 5D Building Information Modeling (BIM), Int. J. Proj. Manag. 34 (2016) 3–21, https://doi.org/10.1016/j.ijproman.2015.09.004.
[89] M. Marzouk, S. Azab, M. Metawie, BIM-based approach for optimizing life cycle costs of sustainable buildings, J. Clean. Prod. 188 (2018) 217–226, https://doi.org/10.1016/j.jclepro.2018.03.280.
[90] A.M. Tanyer, G. Aouad, Moving beyond the fourth dimension with an IFC-based single project database, Autom. Constr. 14 (2005) 15–32, https://doi.org/10.1016/j.autcon.2004.06.002.
[91] H. Hamledari, E. Rezazadeh Azar, B. McCabe, IFC-based development of as-built and as-is BIMs using construction and facility inspection data: site-to-BIM data transfer automation, J. Comput. Civ. Eng. 32 (2018) 04017075, , https://doi.org/10.1061/(ASCE)CP.1943-5487.0000727.
[92] M. Lawrence, R. Pottinger, S. Staub-French, M.P. Nepal, Creating flexible mappings between Building Information Models and cost information, Autom. Constr. 45 (2014) 107–118, https://doi.org/10.1016/j.autcon.2014.05.006.
[93] P. Smith, BIM & the 5D project cost manager, Procedia - Social and Behavioral Sciences 119 (2014) 475–484, https://doi.org/10.1016/j.sbspro.2014.03.053.
[94] J.L. Hernández, P.M. Lerones, Á. Sonia, P. Bonsma, van D. Andrè, R. Deighton, J.-D. Braun, An IFC-based interoperable framework for building linked-data, 6th Linked Data in Architecture and Construction Workshop (LDAC), CEUR Workshop Proceedings, 1613-00732018, pp. 44–51 http://ceur-ws.org/Vol-2159/05paper.pdf.
[95] E. Curry, J. O'Donnell, E. Corry, S. Hasan, M. Keane, S. O'Riain, Linking building data in the cloud: integrating cross-domain building data using linked data, Adv. Eng. Inform. 27 (2013) 206–219, https://doi.org/10.1016/j.aei.2012.10.003.
[96] G. Costa, L. Madrazo, Connecting building component catalogues with BIM models using semantic technologies: an application for precast concrete components, Autom. Constr. 57 (2015) 239–248, https://doi.org/10.1016/j.autcon.2015.05.007.
[97] Z. Ma, Z. Liu, Ontology- and freeware-based platform for rapid development of BIM applications with reasoning support, Autom. Constr. 90 (2018) 1–8, https://doi.org/10.1016/j.autcon.2018.02.004.
[98] C. Boje, H. Li, Crowd simulation-based knowledge mining supporting building evacuation design, Adv. Eng. Inform. 37 (2018) 103–118, https://doi.org/10.1016/j.aei.2018.05.002.
[99] M. Niknam, S. Karshenas, Integrating BIM and project schedule information using semantic web technology, in: Construction Research Congress, American Society of Civil Engineers, Reston, VA 2016 (2016) 689–697, https://doi.org/10.1061/9780784479827.070.
[100] S. Zhang, F. Boukamp, J. Teizer, Ontology-based semantic modeling of construction safety knowledge: towards automated safety planning for job hazard analysis (JHA), Autom. Constr. 52 (2015) 29–41, https://doi.org/10.1016/j.autcon.2015.02.005.
[101] S. Aram, C. Eastman, R. Sacks, A knowledge-based framework for quantity takeoff and cost estimation in the AEC industry using BIM, 31st International Symposium on Automation and Robotics in Construction and Mining, ISARC 2014 - Proceedings, 2014, pp. 434–442 https://doi.org/10.22260/ISARC2014/0058.
[102] C. Prudhomme, T. Homburg, J.-J. Ponciano, F. Boochs, C. Cruz, A.-M. Roxin, Interpretation and automatic integration of geospatial data into the semantic web, Computing (2019), https://doi.org/10.1007/s00607-019-00701-y.
[103] G.F. Schneider, Towards Aligning Domain Ontologies With the Building Topology Ontology, 5th LDAC Workshop, 13–15 November, https://doi.org/10.13140/RG.2.2.21802.52169, (2017).
[104] B. Godager, Critical review of the integration of BIM to semantic web technology, ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLII–4 2018, pp. 233–240, , https://doi.org/10.5194/isprs-archives-XLII-4-233-2018.
[106] F. Tao, J. Cheng, Q. Qi, M. Zhang, H. Zhang, F. Sui, Digital twin-driven product design, manufacturing and service with big data, Int. J. Adv. Manuf. Technol. 94 (2018) 3563–3576, https://doi.org/10.1007/s00170-017-0233-1.
[107] A. Madni, C. Madni, S. Lucero, Leveraging digital twin technology in model-based systems engineering, Systems 7 (2019) 7, https://doi.org/10.3390/systems7010007.
[108] Y. Zheng, S. Yang, H. Cheng, An application framework of digital twin and its case study, J. Ambient. Intell. Humaniz. Comput. 10 (2019) 1141–1153, https://doi.org/10.1007/s12652-018-0911-3.
[109] K.M. Alam, A. El Saddik, C2PS: a digital twin architecture reference model for the cloud-based cyber-physical systems, IEEE Access 5 (2017) 2050–2062, https://doi.org/10.1109/ACCESS.2017.2657006.
[110] E. Glaessgen, D. Stargel, The digital twin paradigm for future NASA and U.S. Air Force vehicles, 53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference < BR > 20th AIAA/ASME/AHS Adaptive Structures Conference < BR > 14th AIAA, American Institute of Aeronautics and Astronautics, Reston, Virigina, 2012, pp. 1–14, , https://doi.org/10.2514/6.2012-1818.
[111] G.S. Martinez, S. Sierla, T. Karhela, V. Vyatkin, Automatic generation of a simulation-based digital twin of an industrial process plant, IECON 2018 - 44th Annual Conference of the IEEE Industrial Electronics Society, IEEE, 2018, pp. 3084–3089, , https://doi.org/10.1109/IECON.2018.8591464.
[112] H. Pargmann, D. Euhausen, R. Faber, Intelligent big data processing for wind farm monitoring and analysis based on cloud-technologies and digital twins: a quantitative approach, IEEE 3rd International Conference on Cloud Computing and Big

Data Analysis (ICCCBDA), IEEE 2018 (2018) 233–237, https://doi.org/10.1109/ICCCBDA.2018.8386518.

[113] E.A. Patterson, R.J. Taylor, M. Bankhead, A framework for an integrated nuclear digital environment, Prog. Nucl. Energy 87 (2016) 97–103, https://doi.org/10.1016/j.pnucene.2015.11.009.

[114] X. Yusen, N.F. Bondaletova, V.I. Kovalev, A.V. Komrakov, Digital twin concept in managing industrial capital construction projects life cycle, in, Eleventh International Conference “Management of Large-Scale System Development” (MLSD, IEEE 2018 (2018) 1–3, https://doi.org/10.1109/MLSD.2018.8551867.

[115] K. Ding, H. Shi, J. Hui, Y. Liu, B. Zhu, F. Zhang, W. Cao, Smart steel bridge construction enabled by BIM and Internet of Things in industry 4.0: a framework, 2018 IEEE 15th International Conference on Networking, Sensing and Control (ICNSC), IEEE, 2018, pp. 1–5, , https://doi.org/10.1109/ICNSC.2018.8361339.

[116] Y. Srewil, R.J. Scherer, Effective construction process monitoring and control through a collaborative cyber-physical approach, IFIP Advances in Information and Communication Technology, 2013, pp. 172–179, , https://doi.org/10.1007/978-3-642-40543-3_19.

[117] A. Akanmu, C.J. Anumba, Cyber-physical systems integration of building information models and the physical construction, Eng. Constr. Archit. Manag. 22 (2015) 516–535, https://doi.org/10.1108/ECAM-07-2014-0097.

[118] X. Yuan, C.J. Anumba, M.K. Parfitt, Cyber-physical systems for temporary structure monitoring, Autom. Constr. 66 (2016) 1–14, https://doi.org/10.1016/j.autcon.2016.02.005.

[119] M. Compton, P. Barnaghi, L. Bermudez, R. García-Castro, O. Corcho, S. Cox, J. Graybeal, M. Hauswirth, C. Henson, A. Herzog, V. Huang, K. Janowicz, W.D. Kelsey, D. Le Phuoc, L. Lefort, M. Leggieri, H. Neuhaus, A. Nikolov, K. Page, A. Passant, A. Sheth, K. Taylor, The SSN ontology of the W3C semantic sensor network incubator group, Journal of Web Semantics 17 (2012) 25–32, https://doi.org/10.1016/j.websem.2012.05.003.

[120] P. Barnaghi, W. Wang, C. Henson, K. Taylor, Semantics for the Internet of Things, Int. J. Semant. Web Inf. Syst. 8 (2012) 1–21, https://doi.org/10.4018/jswis.2012010101.

[122] C. Kuster, Y. Rezgui, M. Mourshed, Electrical load forecasting models: a critical systematic review, Sustain. Cities Soc. 35 (2017) 257–270, https://doi.org/10.1016/j.scs.2017.08.009.

[123] H. Tongal, M.J. Booij, Simulation and forecasting of streamflows using machine learning models coupled with base flow separation, J. Hydrol. 564 (2018) 266–282, https://doi.org/10.1016/j.jhydrol.2018.07.004.

[124] M.M. Gobble, Big data: the next big thing in innovation, Res. Technol. Manag. 56 (2013) 64–67, https://doi.org/10.5437/08956308X5601005.

[125] H. Díaz, L.F. Alarcón, C. Mourgues, S. García, Multidisciplinary design optimization through process integration in the AEC industry: strategies and challenges, Autom. Constr. 73 (2017) 102–119, https://doi.org/10.1016/j.autcon.2016.09.007.

[127] M. Krämer, Z. Besenyői, Towards digitalization of building operations with BIM, IOP Conference Series: Materials Science and Engineering 365 (2018) 022067, , https://doi.org/10.1088/1757-899X/365/2/022067.

[128] D. Wang, J. Chen, D. Zhao, F. Dai, C. Zheng, X. Wu, Monitoring workers' attention and vigilance in construction activities through a wireless and wearable electroencephalography system, Autom. Constr. 82 (2017) 122–137, https://doi.org/10.1016/j.autcon.2017.02.001.

[129] Last Planner®, Handbook for Construction Planning and Scheduling, (2014), p. ch7, https://doi.org/10.1002/9781118838167.

[130] S. Evans, C. Savian, A. Burns, C. Cooper, Digital Twins for the Built Environment, (2019), p. 24 https://www.snclavalin.com/~/media/Files/S/SNC-Lavalin/documents/beyond-engineering/digital-twins-for-the-built-environment-iet-atkins.pdf (accessed January 14, 2020).