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Review article

Digital Twins: State of the art theory and practice, challenges, and open research questions

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ABSTRACT

Digital Twin was introduced over a decade ago, as an innovative all-encompassing tool, with perceived benefits including real-time monitoring, simulation, optimisation and accurate forecasting. However, the theoretical framework and practical implementations of digital twin (DT) are yet to fully achieve this vision at scale. Although an increasing number of successful implementations exist in research and industrial works, sufficient implementation details are not publicly available, making it difficult to fully assess their components and effectiveness, to draw comparisons, identify successful solutions, share lessons, and thus to jointly advance and benefit from the DT methodology. This work first presents a review of relevant DT research and industrial works, focusing on the key DT features, current approaches in different domains, and successful DT implementations, to infer the key DT components and properties, and to identify current limitations and reasons behind the delay in the widespread implementation and adoption of digital twin. This work identifies that the major reasons for this delay are: the fact the DT is still a fast evolving concept; the lack of a universal DT reference framework, e.g. DT standards are scarce and still evolving; problem- and domain-dependence; security concerns over shared data; lack of DT performance metrics; and reliance of digital twin on other fast-evolving technologies. Advancements in machine learning, Internet of Things (IoT) and big data have led to significant improvements in DT features such as real-time monitoring and accurate forecasting. Despite this progress and individual company-based efforts, certain research and implementation gaps exist in the field, which have so far prevented the widespread adoption of the DT concept and technology; these gaps are also discussed in this work. Based on reviews of past work and the identified gaps, this work then defines a conceptualisation of DT which includes its components and properties; these also validate the uniqueness of DT as a concept, when compared to similar concepts such as simulation, autonomous systems and optimisation. Real-life case studies are used to showcase the application of the conceptualisation. This work discusses the state-of-the-art in DT, addresses relevant and timely DT questions, and identifies novel research questions, thus contributing to a better understanding of the DT paradigm and advancing the theory and practice of DT and its allied technologies.

1. Introduction

How can one reduce the cost of producing a prototype and performing tests on it? How can one perform extreme tests on a prototype which cannot be performed in a laboratory? How can a prototype imbibe all the information and outcome of these tests, to provide an accurate prediction of future behaviour? How can one monitor a physical asset in real-time[1] and be alerted before anything goes critically wrong? How can we humans have access to this real-time information of all the components involved in a physical asset, as well as of information of the asset as a whole, perform meaningful real-time analysis on this information, and make timely, robust and efficient decisions for future operations based on them? The answer — Digital Twin (DT).

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[1] Real-time refers to the time frequencies at which the state of a physical asset changes or is expected to change significantly. For example: for an aircraft it could be in seconds, minutes or hours, whereas for a manufacturing unit it could be in hours or days.

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Digital Twins are virtual copies of products, processes or services which encompass all the above qualities [1]. Grieves and Vickers [2] define the Digital Twin (DT) as “a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level. At its optimum, any information that could be obtained from inspecting a physical manufactured product can be obtained from its Digital Twin”. DT aims to combine the best of all worlds, namely, twinning, simulation, real-time monitoring, analytics and optimisation. Digital Twin has been recognised as the next breakthrough in digitisation, and also as the next wave in simulation [3,4]. It can save cost, time and resources for prototyping, as one does not need to develop the physical prototype(s), but can instead effectively and accurately perform the same tests on a virtual prototype, without affecting the real operation [5,6]. Gartner, a research and advisory company, listed Digital Twins as one of the “Top 10 Strategic Technology Trends” for 2017, 2018 and 2019 [7–9]. Furthermore, Market Research Future predicts that the Digital Twin market will reach 35 billion USD by 2025 [10].

Despite the stated advantages and potential of DT technology, certain research and implementation gaps exist [11,12], which have hindered the adoption and advancement of DT since its inception, around 2003: the diverse applicability of DT is a result of its reliance on advanced evolving technologies, mainly IoT, big data and machine learning. The real-time monitoring and data collection capability of a DT is reliant on real-time data, obtained via IoT devices integrated effectively in the environment and/or enterprise information systems, whereas the analytics is reliant on using the available big data and machine learning tools. Combining these technologies and implementing them for one or more physical assets requires extensive domain knowledge, as would be required while creating any physical asset’s physical prototype. Furthermore, the DT vision is continuously and fast evolving, as the technology, industry and customer needs evolve. Not only is the overall concept of DT not fully established, there is no universally accepted definition of DT, and there are very few early standards for implementing it [13–15]. As a technology which is used across various domains and is dependent on other evolving technologies, it eventually becomes dependent on the current state of these technologies, and it also has to be tailored for each problem and domain. Having very few still developing standards further impedes the widespread and large scale design, implementation and adoption of this technology.

This work aims to study these gaps and to propose and discuss possible solutions. As DT is a practical concept, this work emphasises the need for a comprehensive theoretical specification — via a DT reference framework, leading to an implementation and evaluation methodology. The contributions of this paper are:

1. Provide a thorough analysis of the past efforts at theoretically establishing, and practically implementing, digital twins, and a discussion of the current gap between the ideal DT concept and practical implementation.
2. Assess how advances in the DT-allied technologies such as machine learning and big data can lead to the advancement and adoption of the DT technology.
3. Review how domain (or sector, or type of industry) affects the DT implementations.
4. Evaluate current limitations and challenges of DT.
5. Collate and analyse key information scattered across research and industrial work, and use the results and insights from this analysis to develop a conceptualisation for the components of DT and their interdependencies.

The rest of the paper is organised as follows: Section 2 discusses and contrasts several representative reviews of DT. Section 3 discusses the concept, components, properties, versions, evolution and assumptions of DT. Section 4 discusses state-of-the-art theoretical, practical and industrial models of DT across different domains. Section 5 explores the existing use and potential of machine learning and big data in DT. Section 6 discusses the challenges and limitations with the existing DT models. Based on the analysis in the previous sections, Section 7 presents a conceptualisation for DT. Section 8 applies this conceptualisation to real-life case studies, to illustrate its application, validity and usefulness. Section 9 concludes the paper and discusses future directions of the DT research and application.

2. Previous work

As DT is a general concept that can be tailored for a particular problem and domain, there has been a significant amount of literature reviews focusing on the DT implementation, either for specific domains or in general. Specific domain examples include manufacturing [16], [17,18], aerospace [19] and production science [20], production systems [21], others are general [4,22–25]. Most reviews assess the current definition of DT and provide new insights. For example, Kritzinger et al. [20]’s categorical review focuses on production science and categorically lists the papers in the areas of Digital Twin, Digital Shadow and Digital Model, whereas Negri et al. [16] explores all the papers in industrial manufacturing, mainly differentiating whether big data and data models exist in the literature. Consequently, the insights of these reviews are domain-specific, rather than generic and transferable across domains. For example, [20] looks at similar concepts of Digital Shadow and Model from a manufacturing perspective, whereas [16] explores data models in a specific class of manufacturing systems. Jones et al. [23] propose a characterisation of the Digital Twin based on 13 parameters identified through a systematic literature review. They have also proposed a DT framework and identified seven Gaps and future research topics: Perceived Benefits; DT across the Product Life-Cycle; Use-Cases; Technical Implementations; Levels of Fidelity; Data Ownership; and Integration between Virtual Entities. Liu et al. [26] performs an in-depth literature review of previous DT research papers to analyse the DT concepts, definitions, technologies, and classes of industrial applications. They conclude that: (i) there is no industry consensus on Digital Twins; (ii) due to a large variety of DT frameworks, it is difficult to conduct systematic research on Digital Twins. Enders and Hoßbach [22] compares 87 DT applications and proposes a classification scheme, and a new definition of DT, based on their analysis.

However, although such reviews are extensive, white papers or industrial works are not discussed in detail, to keep the review focused on research papers. As DT is both a theoretical and applied concept, including the practical implementations provides a complete and sufficiently representative description, hence these are included in this work. Tao, Zhang, Liu and Nee [4] are among very few authors who explore the specific practical implementations of DT. Similarly, Jiang et al. [17] discuss the DT definitions and state of the art industrial applications within the smart manufacturing and plant optimisation context. They also discuss why and how DTs could create added value by swiftly processing the available wealth of data, and the benefit of connected and cooperative DTs.

To conclude, the previous works focus more on the categorisation of papers and development of theoretical models, and build very little on practical implementations. The reasoning behind this, as mentioned in Section 1 and further elaborated in Section 4.2, is that, because DTs are domain-dependent and rely on multiple technologies, the conceptualisation of DT – taking the domain into regard and proposing a valid, sufficiently-detailed and specified, yet universal model – is a difficult task. Nonetheless, these reviews pose the following questions and insights, which help to advance the DT concept further. In this paper the following key issues in DT are discussed further:

- The need for a proper definition of DT which could cover the different application domains [4,27].
- An investigation of concrete case-studies, and a reference model for domain-specific requirements [16,20].

- An investigation on how DT research could contribute to the Internet of Things (IoT) and Information Systems (IS) disciplines [22].
- The analysis of the debate initiated in 2013 [28] and further explored in [16], on whether DT covers the entire product lifecycle [3,29] or just the product [30,31].
- The scope and need of machine learning, big data and data models in DT [16], and data-related issues [3].

Apart from the above, this work poses new research questions and insights, which aim to help exploring and advancing the practical applications of DT discussed in Section 9.

There have been previous works focused on the architecture of DT and how the various DT components interact, focused on specific domains [32,33]. This work builds on previous work, and proposes a conceptualisation that defines the fundamental components of digital twin, essentially towards the end of the debate concerning the definition and components of digital twin. The discussion of the DT standards and sub-components that must be implemented for a functioning digital twin requires further progress and evaluation at specific case-study level, followed by abstraction. The International Organisation for Standardisation has already started this work, with several DT-related standards under development [34].

2.1. How this review differs

Previous reviews identified critical DT insights and questions. This review answers them and poses some new questions, to further advance the DT theory and practice. Also, this review presents the limitations, challenges, and new properties of DT, by researching through the practical implementations of DT, which was previously under-explored. Compared to the previous reviews, this paper does not focus on the categorisation and statistics of the literature (e.g. based on models or domain), but rather presents a conceptual view of the implementation of the DT concept by investigating the root causes behind the challenges of implementing DT. The papers presented in this work were chosen to cover the various domains of application of DT and the numerous definitions and components present in different works, with the focus on presenting the current state of DT and putting forth the existing gaps to be filled and questions to be answered. Specifically, the following novel aspects and questions are addressed in this work:

1. The research gap between the actual DT concept and implementation.
2. The importance of machine learning and big data in DT.
3. What is impeding the spread of DT?
4. How domains affect the implementation of DT?
5. How is the success of the existing implementations of DT measured?
6. A conceptualisation for DT.

3. Digital twin history and evolution

Digital Twins were first introduced in early 2000s by Michael Grieves in a course presentation for product lifecycle management [35]. In 2011, implementing DT was considered a complex procedure, which required many developments in different technologies [36]. Despite being coined in 2003, the first description to use of Digital Twin was years later by NASA in Technology Roadmaps [37], where a twin was used to mirror conditions in space and to perform tests for flight preparation (another example of such hardware twin was the Airbus Iron Bird). Dawned with the aerospace industry, the DT methodology extended to the manufacturing industry around 2012. So what took the concept nearly a decade to be implemented?

With the advancements in technologies like cloud computing, IoT and big data, many domains have seen major developments, such as Industry 4.0 [38], Physical Internet [39,40], Cyber-manufacturing [41], Made in China 2025 [42], and Cloud Manufacturing [43]. Industry 4.0 has seen a revolution mainly because of digital advancements, IoT and big data [16,44]. It was because of the Industry 4.0, the storage of all data in digital format, and sensors being inbuilt into the industrial spaces, that digital twin implementations became possible, rejuvenating the concept. Moreover, with the emerging extensive simulation capabilities and significant increase in computational resources, it became feasible to perform realistic tests in a virtual environment. Due to these technical advancements, companies such as IBM, Siemens and GE, started implementing a functional DT as a utility for themselves and for their clients.

3.1. Defining DT

On the journey to define the model and properties of DT, various previous related terms have existed, such as: 'ultra-high fidelity' [45], 'cradle-to-grave' [46], 'integrated' model [46], and 'integral digital mock-up (IDMU)' [19]. These terms are important and relevant to the evolution and current stage of the DT concept, however, as now the DT concept is much more widespread and has gained significant traction, there would be significant benefits from reaching a consensus on a single, sufficiently representative, unifying definition.

In the simplest words, a digital twin is a 'digital' 'twin' of an existing physical entity. What makes a DT all of the above are its properties, which will be discussed in Section 7. Though the literal meaning of digital twin seems simple at first, the definition of DT has been a subject of debate and evolution. For example, Abramovici et al. [30] and Schroeder et al. [31] consider the Digital Twin as the final product, whereas Gabor et al. [29] and Rosen et al. [3] consider it as the entire product lifecycle.

Note that, for consistency and generality, this work refers to the conventionally termed 'product', within the DT context, as 'asset', in the rest of the paper.

Components of DT: DT was first introduced by Grieves [35] with three components: the digital (virtual part), the real physical product, and the connection between them. However, other authors, such as Tao et al. [47], have extended this concept to have five components, by including data and service as a part of DT. Tao et al. [4] also identify VV&A (verification, validation and accreditation) as DT components, and state that "DTs are characterised by the seamless integration between the cyber and physical spaces". With data models coming into the picture, Miller et al. [48] extend the definition of DT to be an integration of multiple models of a model-based enterprise (by creating associations between different models and relations between data stored in different parts, a digital twin can be formed).

As conceptually sound the above definitions are, reaching consensus on a DT definition requires specifying the fundamental requirements for a DT. With the advancements in the technologies on which DT depends (such as machine learning, big data and cybersecurity), these requirements have changed over time. Moreover, the domain-dependence property of DT calls for defining the components which can be generalised across domains, though their level of involvement and measurement can be different depending on the domain.

3.2. How is DT different from existing technologies

The diverse applications of DT such as simulation, real-time monitoring, testing, analytics, prototyping, end-to-end visibility [49], can be broadly classified as sub-systems of DT (for example, a DT can be used for testing during prototyping, for real-time monitoring and evaluation, or for both). It is the presence of all the components discussed in the previous section that makes a DT different from these, as described in Table 1.

Table 1
How DT differs from existing technologies.

Technology	How the technology differs from DT
Simulation	No real-time twinning
Machine Learning	No twinning
Digital Prototype	No IoT components necessarily
Optimisation	No simulation and real-time tests
Autonomous Systems	No self-learning (learning from its past outcomes) necessarily
Agent-based modelling	No real-time twinning

3.3. A brief overview of other similar concepts that preceded DT

The concept of digitising and twinning are not new. Many similar concepts have preceded DT, however, for the reasons briefly described below, they differ.

- **Digital Shadow, Digital Model** A Digital Model has only manual exchange of data and it does not showcase the real time state of the model. Digital Shadow is a saved data copy of the physical state, with one-way data flow from physical object to the digital object [20,50]. DT, on the other hand, has fully integrated data flow, so that it properly and consistently reflects the actual state of the physical object.
- Semantic **Virtual Factory Data Models** (VFDM) are virtual representations of factory entities [51]. These were used in manufacturing and industrial spaces [52]. DT differs from VFDMs due to the real-time synchronisation property. VF is a data model only, whereas DT is real-time and synchronised.
- **Product Avatar** is a distributed and decentralised approach for product information management with no feedback concept; it may capture information of only parts of the product [19].
- **Digital Product Memory** Miller et al. [48] see DT as an extension of semantic/digital product memory, where a digital product memory senses and captures information related only to a specific physical part, and thus it can be viewed as a DT instantiation.
- **Intelligent Product** A DT can be seen as an extension of an Intelligent Product which uses new technologies such as IoT, big data and machine learning [53–55].
- **Holons** As an initial computer-integrated manufacturing tool, holons formed the basis for all the technologies described above [56–58].
- **Product Lifecycle Management (PLM)**: [59] discuss the difference between PLM and DT, where PLM are focused more on 'managing' the components, products and systems of a company across its lifecycles, whereas a DT can be a set of models for real-time data monitoring and processing.

3.4. More than one DT (DT composed of sub-DTs; collection of DTs)

Generally, a DT might be that of a product or a product lifecycle components. However, one might also find it more feasible and easier to break down the product or product lifecycle's components to sub-components, create several DTs, and establish connections between them ([32,60] mention this concept slightly). For example, for a car one might not want a DT for the entire car, but only the engine, brakes and gearbox, to understand the functionality of these components interacting with each other; or if we take the example of the car's product lifecycle, one could create different DTs for raw materials procurement, manufacturing, production and supply, for reasons like avoiding data sharing, if different components are handled by different vendors. The mechanism through which a DT interacts with other DTs is dependent on the extent of data sharing allowed and the IoT devices used. The dynamic property of synchronisation again comes into play here, during regular updates among different DTs [17]. Strong security protocols may form an important part of this communication.

As mentioned in Section 1, DT proves to be a cost-effective and feasible solution for scenarios where creating the physical prototype is expensive or imitating the actual conditions in a lab is not possible (for example, achieving certain temperature ranges or testing a variety of parameters for the same component). In such cases, creating several DTs for the same entity can be highly beneficial. For example, having multiple DTs of a tyre and experimenting different settings and temperatures on multiple DTs.

[33] discusses a 6-layer architecture for twin-to-twin interaction where smaller or lower-level digital twins aggregate to form larger or higher-level digital twins.

Having discussed the DT definition and evolution of components, the next sections discuss classes of DT models.

4. Existing DT models

4.1. Theoretical DT models

This section explores the various attempts to define the architecture of DT. Most of these are for particular domains/sectors, while few are general-purpose models.

The most popular sector for implementing a DT is Product Lifecycle Management. This is chiefly because DT provides a holistic view to the widespread components of PLM, which is useful to solve the existing problems in this domain [61]; in terms of limitations of PLM, Tao et al. [47] discuss how data in PLM is isolated, fragmented and stagnant. [47] also presents a theoretical framework of applying DT to PLM by proposing three design steps: conceptual design, detailed design and virtual verification. It also gives an example of DT for bicycles as a case study, but does not mention the implementation methodology (e.g. to perform tests on the bike with parameters involving brakes, speed, and user weight, proper physics simulators are needed, and the simulation software and frameworks have to be defined).

Liu et al. [62] propose using Unity3d open source engine for implementing DT. They create a reference model to handle and synchronise complex Automated Flow-Shop Manufacturing System (AFMS) systems using DT, which also deals with decoupling multi-objective optimisation problems. As mentioned in Section 3, if DT is an entire product lifecycle, then using analytics and machine learning in DT would mean defining a joint optimisation problem for the lifecycle. Handling a multitude of parameters, and solving multi-objective optimisation problems is an existing challenge for complex systems. However, Liu et al. [62] apply the sheet processing DT prototype successfully to Chengdu, China, and use heuristic measures such as production packages, unified system cost, and unified system performance to evaluate the performance of DT (resulting in a domain-dependent DT).

This domain dependence property is also discussed in [22], where a generalised architecture of DT is presented by defining six dimensions for defining the concept of DT — industrial sector, purpose, physical reference object, completeness, creation time, and connection (some of which were inspired from previous works). The self-evolving property of DT is explored in [47], where the authors discuss many cases of using DT in product design and manufacturing.

Continuing the debate on whether DT should be the product or the product lifecycle, Schleich et al. [1] propose a DT reference model for production systems for geometrical product specification (GPS), where they pitch the idea to represent the DT as an abstract form of the physical product, mentioning clearly that DT is the entire product lifecycle and not just the product.

As Digital Twins can be considered as artificially intelligent systems, they are closely linked to autonomous systems. This link is explored in [3], where the authors discuss the importance of DT in simulating the autonomous systems' decisions. As autonomous systems need real-time information, the paper argues that digital twin will be very useful and efficient for the autonomous systems to function properly, as DT can collect all data and prior knowledge needed. They discuss the driving aspects for the future of manufacturing, which are: Digital Twin, modularity, connectivity and autonomy. These aspects are also important for the concept of DT — to see the individual components of DT and then integrate them into a single model. The authors also support the claim that DT is the next wave in simulation, as it encompasses real time operation and data. Despite a well-explored evaluation, the examples considered in [3] for implementing a real DT are limited to using DT as a memory buffer to draw data, and do not explore the machine learning and analytics potential.

International Standards: ISO 23247 [63] series defines international standards for DT in manufacturing. According to this standard's specification, a DT monitors its observable manufacturing elements by constantly updating relevant operational and environmental data. The visibility into process and execution enabled by a DT enhances manufacturing operation and business cooperation. This standard also specifies that a DT assists with detecting anomalies in manufacturing processes to achieve functional objectives such as real-time control, predictive maintenance, in-process adaptation, Big Data analytics, and machine learning.

IPC 2551 [64] is another related, recently released international standard for DT product, manufacturing, and lifecycle frameworks. ISO/IEC JTC 1/SC 41 [65] focuses on standardisation in Internet of Things, DT, and their related technologies and applications. Most of these standards are still under development and less known to wider audience for general purpose usage.

Despite being conceptually sound and well-explored, the current DT literature does not fully address the gap between theory and practice. We discuss this aspect in more detail in Section 6.

4.2. Practical models and their domain-dependence

The applications of DT spans across various domains from manufacturing, aerospace, to cyber–physical systems, prognostics, health and management. The description of these practical models in literature is scanty. Moreover, available descriptions of DT implementations for large, complex systems are insufficiently detailed and informative. Not to forget, this complete methodology is domain-dependent, sometimes requiring intricate domain-knowledge to fully understand the DT implementation. These practical attempts and the affect of domain on these attempts are discussed below.

Owing to the number of parameters and intricacies of the operations involved, the most complex but most beneficial implementation of a DT is in the aerospace domain. [66] discusses the application of DT for NASA and U.S. Air Force vehicles. The main advantage of using a DT for aerospace is that a DT can replicate the extreme conditions (thermal, mechanical and acoustic loadings) which cannot be physically performed in a laboratory because laboratory tests cannot go below or above a certain limit. Moreover, conventional approaches in this domain do not consider the specific materials involved and type of the component during testing, which is highly desirable. On the other hand, a DT can be tailored according to tail number to take into account the specification of the materials and its types. Additionally, the current analytics approaches are mostly based on statistical distributions, material properties, heuristic design properties, physical testing and assumed similarities between testing and real operation. But, as stated in [66], these techniques are unable to represent the future extreme requirements, whereas the DT can use maintenance history and other historical fleet data to continuously forecast health and probability of mission success. A DT can also test the future extreme requirements in real time, as and when they appear. This real-time support is needed, as external support is not always possible. The machine learning capabilities of a DT can make predictions and recommendations for in-flight changes to a mission. A DT also provides self-mitigating mechanisms or recommendations. It is due to the plethora of advantages of using a DT, mainly as an alternative form of testing, which cannot be performed in the lab, that DT in aerospace is highly desirable; nonetheless, it is hard to implement, because of the multitude of parameters involved. The maritime industry requires DT out of a similar reason as the aerospace industry, which is, the lack of physical contact between ships or any marine vehicles and the base station [67]. [67] views DT as an enabler of 'digital thread', to combine the information scattered across devices on and off-shore.

Ríos et al. [19] present a review of DT applications in aerospace; the authors describe that, because a commercial aircraft may have more than half a million different component references, it is challenging to create a bijective relation between a particular physical aircraft and its unique digital twin. The complexity in implementation of DT also arises due to the interoperability issues among the different pieces of software used in production, such as PLM, Enterprise Resource Planning (ERP), Manufacturing Execution System (MES), and Computer-aided technologies (CAx). Ríos et al. [19] suggests to make use of each product's individuality such as Manufacturers Serial Number (MSN), the EPC (electronic product code), Tail Number (TN), aircraft registration, VIN (vehicle identification number), to create an effective DT, which is similarly difficult, due to the number of parameters involved.

On the other hand, Tao et al. [4] discuss how prognostics and health management (PHM) have the biggest advantage of using DT, as the DT concept considers ultrafidelity, behaviour and rules modelling, and merges physical, virtual, historical and real-time data to provide trends, optimisation and maintenance strategy. The work also discusses the challenges pertaining to the cyber–physical fusion which occurs while implementing DT; these challenges are: security, robustness, applicability, data acquisition, mining and collaborative control.

The advantages and challenges of using a DT are thus different for different domains. Therefore, a DT has to be tailored according to these different sectors. These differences are explored in [16]. This work discusses the history of DT and highlights briefly the expectations from DT in different areas such as CPS (the focus is on avoiding failures, support health analysis of systems and deformation of materials in the physical twin, and study the long term-behaviour in different environments), aerospace (maintenance and intervention needs of the aircraft with the use of Finite Element Methods (FEM), Computational Fluid Dynamics (CFD), Monte Carlo and Computer-Aided Engineering (CAE) applications-based simulations), manufacturing (to simulate complex and numerous parameters of the system) and robotics (to optimise control algorithms during development phase). These highlight how a DT is expected to behave differently for different domains, depending on the primary functions of these domains.

Details of the use of ML in DT are scarce in the public domain. In the research field, this could be because of the challenging implementation, the cost overload of using GPUs, or because it is not required at the moment, for proof of concept research projects (for example, if a DT is just used for monitoring, using ML might add to the cost, without adding value), whereas in real-world industry DTs, ML-related information could be a competitive advantage, and hence private. [68] describes a proof of concept for implementing DT with machine learning, in the petrochemical industry. The paper provides some time series data preprocessing solutions for unifying frequency of time series data, resolving time lag issues between time series data, reducing data dimensions, and regenerating new time series data. They have provided few implementation details: the authors use many production service systems for data gathering and training the digital twin (such as supervisory control and data acquisition (SCADA), programmable logic controller system (PLC), manufacturing execution system (MES), laboratory information management system (LIMS), distributed control system (DCS)). They access IoT data through APIs, and use simulation and optimisation systems, namely advanced process control (APC) and real-time optimisation (RTO). The DT itself is not evaluated, but the prediction model is assessed using four evaluation criteria: the model accuracy ratio (MAR), the root mean square error (RMSE), the variance interpretation rate (VIR), and Pearson's correlation coefficient (PCC). Mixed reality applications such as DT coupled with augmented reality [69–71] and virtual reality [72] are gaining traction for applications like human–robot collaboration and building construction, respectively.

Since DT is a twin of the physical asset, implementing it requires the same amount of knowledge that is required when creating the physical twin. For any domain, it is essential to have the domain knowledge to understand the intricacies involved in building and operating the physical asset, such as how different components link together and how much to weigh parameters during optimisation. Hence, domain experts are essential to implement a DT. [5] suggests the use of adaptive intelligence for DT, which demands a great deal of human expertise, as human knowledge forms the cardinal element for this artificially intelligent system. [73] offers a promising approach of adaptive reconstruction using transfer learning, which can reduce the effort to construct different DTs for different working conditions for machining systems, which is helpful within the same domain.

The above analysis of DT in various sectors indicates how DT is domain-dependent, and so are the related challenges; this is discussed in the next section.

4.2.1. Similarities & differences across different domains

To further lay a clear foundation of the concept of DT, this section discusses the similarities and differences that DTs possess when being implemented across different domains:

Similarities The building blocks of DT should remain the same (though the level of implementation is domain-specific).

Differences The following domain-dependent questions and implications arise:

1. Particular domains pose greater challenges for the implementation of DT: Some digital twins might be more feasible and easier to implement than others (due to scale, resources required and number of components). The same is true for data collection. For instance, the aerospace sector has numerous components to handle; similarly, a global supply chain has many parameters and multiple inventory points; these cases will prove to be challenging and complex optimisation problems.
2. How realistic is the implementation of the DT with respect to the actual physical asset: Depending on the complexity of the physical asset, the implementation of the DT will differ from domain to domain. The gap between the ideal design and the actual practical design might be significant for domains like aerospace and supply chains (this kind of domain dependence for simulation is discussed in [74]); the gap is often minor for PLM, and for health and prognostics. This tailoring for domain and its consequential complexity is also discussed in [75,76], where the authors develop DT solutions for structural health management solution.
3. Evaluation of the implementation of DT: The evaluation metrics for performance of DT are dependent on the domain. As some domains will place more importance on some sub-components or features, such as prediction or real-time monitoring, the DT performance evaluation will focus on the parameters most important for the specific domain (such as, for aerospace, it generally is the mitigation plan).
4. The interoperability issues in the range of different software being used: If domains use a particular type of software (such as SCADA, ERP) for sub-tasks of product and logistics management, the DT software has to be compatible with these systems.

This discussion also notes the effect of domain knowledge on the implementation of DT: Domain experts are imperative for designing a DT. A thorough knowledge of the particular domain and its key features is crucial for effective DT design, and it can be a game-changing capability on the 'twinning' factor of a DT. Some works have focused on defining the requirements and methodology for the generation of DT for niche areas such as for brownfield process plants [77], and for popular areas such as manufacturing [78].

4.3. Industrial implementations

Examples of companies investing in DT technology, or providing DT software for clients, or using DT functionality for themselves, include:

1. Investing in DT
   - Signify Philips is exploring the concept of digital twin for lighting, by digitising lighting [79]. They claim DT to offer emergency services, real-time monitoring and predictive maintenance.
2. Providing DT as a service
   - Philips is also providing DT technology for the use of healthcare systems to get early signs of warning regarding technical issues in Magnetic resonance imaging (MRI), computerised tomography (CT) scan like medical systems [5]. This could save the downtime that faulty technical systems have in clinical spaces.
   - IBM is transforming the Port of Rotterdam using Digital Twin for monitoring and efficiency [80]. IBM is also providing a DT software for PLM [81]. Along similar lines, Siemens has a model to implement the digital twin of power grid in Finland [82,83], and another for Red Bull in Formula 1 racing [84].
   - Companies such as Dassault System's 3DEXPERIENCE [85] (which has also built digital twin of Singapore [86]), AnyLogic [87], Ansys [88], PwC [89], Bosch [90], SAP [91] and Azure [92,93] provide DT implementation software for clients (though the use of ML in these software solutions is not disclosed). Apart from these, Oracle provides a DT simulator as part of its cloud service [94]. GE has contributed to the DT literature: it holds two patents for DT [95,96] and has developed commercial software Predix [97]. The open source community has also explored the concept of DT: Eclipse Ditto is an open source technology that implements IoT-based DT models [98].
3. Using DT for own use
   - DHL has implemented its first supply chain digital twin for Tetra Pak's warehouse in Asia Pacific in Singapore [99]. Though this is real-time monitoring, the use of machine learning either does not exist, or is not in the public domain, possibly due to its competitive advantage.
   - BP has employed a surveillance and simulation system called APEX for creating virtual copies of its production systems (again ML use is not disclosed) [100].

To the best of our knowledge, none of the above software solutions is implemented at global level (but only at country level or local area level), and more detailed and concrete analysis on this is subject to further investigation.

The gap between the ideal DT and practical DT: Depending on the technologies such as IoT, big data and machine learning, there may be a huge gap between the ideal implementation of DT and the practical one (such as whether the required advancement in technology is currently available or is subject to further research). Cost and the number of available resources could also contribute to increase this implementation gap. This discussion is subject to more investigation and availability of the actual DT software and its initial design model. The review from the previous sections does not provide any information on the level of implementation. Some solutions use outsourced DT software, but do not describe the frameworks. Some papers have claimed the following successful uses of DT — data handling, real-time monitoring, simulation testing and optimisation [4,68]. However, without evaluation-, metric-based evidence, it is hard to know how successful the current implementations of DT are. A consensus on a unified, standard DT architecture will reduce the gap between the DT concept and DT implementations.

4.4. Scenarios or Cases where DT can be majorly beneficial

Though DT is a technology which benefits any product/product lifecycle in general, there are certain cases which can benefit majorly:

1. When creating physical prototypes is expensive, requires resources and is time-consuming (such as aerospace, supply chain, manufacturing): Rather than spending time and money for building multiple prototypes for testing a product, digital twin offers a much more efficient and cost-effective solution.
2. Physical assets/Products in which extreme testing is required and performing such tests is hard/not possible in the labs (such as aerospace and PHM): Tests which cannot be performed in the lab can be simulated by the DT.
3. Cases/Scenarios which require real-time monitoring and mitigation plans for dealing with 'emergent behaviour' [2] (such as health systems and supply chain): Keeping an eye on the real-time status of the physical asset, and being alerted through predictions about an imminent problem can be both efficient and effective. This is especially useful for those organisations which need to make very quick decisions, to prevent critical situations such as huge losses.
4. Products/Product lifecycles with multiple parameters, which could be optimised jointly (such as those in manufacturing and supply chains): For very large organisations, maintaining and monitoring all sub-components can be an extremely difficult task. Real-time monitoring of all sub-components and joint holistic analytics on such huge models can be beneficial (this goes along the obstacle of 'siloing' presented in [2], where, due to multiple sub-domains in the system, information remains fragmented).

Despite being dependent on multiple technologies (explored in detail in [101]), which requires experts and resources, DT can lead to huge cost reductions for the one time investment [2]. DT can enable shorter design cycles [102], save cost, resources and time on prototyping [5,6], and predict impending dangers in time to mitigate them. This cost reduction could possibly be used as a metric of the performance of DT for profit-oriented companies, i.e., the DT-enabled cost reductions.

5. Machine learning and big data in DT

5.1. Machine learning in DT

Conventional knowledge-based methods are based on one-time machine learning output, whereas a digital twin is a continuous interactive process. Real-time machine learning capacity is what differentiates a DT from a simulator or a real-time monitoring tool. Analytics is essential, as one of the cardinal uses of a DT is to be able to reliably and accurately output how a physical asset would behave in conditions which have not arisen yet, using the real-time data it is receiving – in other words – for 'testing' the physical asset in an unforeseen situation. The other cardinal use of ML in DT is to predict an impending problem which needs attention, while revealing the imperfections in the system (anomaly detection [103]).

One work that explores the digital twin with machine learning is [68]. It presents a proof of concept for using machine learning with digital twin in the petrochemical industry, by making use of ML algorithms such as random forest, AdaBoost, XGBoost, gradient boosting decision tree (GBDT), LightGBM, and neural networks. However, information on the exact implementation methodology and software for DT, and how the entire proof of concept was implemented in real time feedback loop, is absent.

Another work, [104], discusses using a simulation software along with machine learning for a product, and terms this as 'the digital twin approach'. This is the result of inconsistency in a unified architecture and definition of digital twin, as calling a simulation software with no real-time synchronous connection to the physical product as a digital twin might be correct according to some definitions, and inaccurate, according to others. Hence, it is important for a technology to have its components defined, to define and differentiate it from other technologies.

The 'self-evolving' nature of DT, where a DT can improve itself from the true results of its predictions, can only be implemented using machine learning. Machine learning can also help in creating resilient DTs. The promising work [105] uses machine learning in DT not as a feedback mechanism/ analytical tool, but as an error resolver. Cronrath et al. [105] use reinforcement learning to make the digital twin resilient to either data or model errors, and to learn to fix such inconsistencies itself.

Despite being popularly marketed as a DT software by companies like IBM [81], SAP [91] and Siemens [83], the published literature on using ML for Digital Twin is scanty, and the extent of use of ML by these companies is uncertain.

Latest methods in ML research, like continual learning [106] and federated learning [107] are considered extremely relevant and potentially useful in DT. With continual learning a ML model gets updated with the incoming data stream. Although potentially prone to catastrophic forgetting, novel research methods and results have started to address this problem [108]. This could aid implementing the 'self-evolving' property of DT. Federated learning aims to address scenarios where competing companies or partners do not want to share their data, for privacy and security reasons. In federated learning, only the model parameters are shared with the partners, whereas the data never leaves the host; along with blockchain technology, federated learning could provide improved privacy solutions in industrial IoT-based applications [27].

The following technical challenges are associated with the lack of ML in existing DT implementations:

1. Joint optimisation for all the sub-problems: As described in Section 4.2, for the case of aerospace industries, multiple parameters lead to a complex multi-objective optimisation problem. Depending on the size of the industry, the number of parameters involved in the machine learning optimisation problem can be huge. Although each industry has smaller optimisation problems which are solved at various sub-levels, effectively combining these sub-problems into one optimisation problem and choosing the right machine learning tools is a challenging task which requires knowledge of both the domain and machine learning. Better predictions of the entire physical asset can be made if majority of the components of the asset are taken into consideration, resulting in a joint machine learning-based optimisation problem. This kind of unified ML model will facilitate and weigh priorities in a system, and perform systemic analytics.
2. Deep learning with DT: Implementing deep learning solutions requires computational resources, expertise and research [17, 62]. Managing high dimensional data, with the various other software used by an industry, and combining these with expert

deep learning skills and equipment is a tedious task. New methods like continual learning [106] and federated learning [107] are promising for the use of DT, and require further research. Also, methods like continual learning require high-fidelity synchronisation for continuous feedback, which depends on the IoT devices and network connection. This can be hugely complex for large systems having different latencies and data formats.
3. ML methods depend to a great extent on the quality of data available and hence rely on this data. The availability of good quality data is a requirement and a challenge, as fetching/processing this data might depend on a number of other factors such as the resources available to store the data and GPUs to process high-dimensional data.

5.2. Big data in DT

DT is used in sectors which have multiple components resulting in multiple parameters. Hence the data collected from these sources ends up being a large high-dimensional dataset. Moreover, if the time frequencies of the data collected from these different components do not match, the resulting data can be fragmented. Therefore, there exist time lags in time series data. Additionally, collection of data from multiple inter-connected and not-connected components, with high-stream synchronisation and integrating this data, is a challenging task in terms of technology, implementation, cost and resources [68].

Min et al. [68] identify two major issues related to implementing digital twin in real world with its data component:

1. As a dynamic environment requires a well-researched tool, better concrete and practical frameworks are needed for big data application to the continuously changing environment of DT.
2. Data processing issues for time series data: Data gathered from IoT devices in the factory have large dimensions. Moreover, the data collected may have different time cycles.

The authors identify the above problems and solve the problem of using data from different time frequencies, by proposing a method to generate same frequency time series data.

Tao et al. [4] make an attempt to define the steps for data preprocessing, data mining and data optimisation for DT, which are essential for large datasets. Another work, [47], discusses the limitations of gathering large datasets. The work also assesses the problems in data management specific to the PLM domain, such as the existence of duplicate data, absence of big data analysis, and existence of disintegrated data in different phases of PLM. The paper proposes DT as a solution for comparing this inconsistent data with real values in PLM. Lu et al. [27] points out that domain knowledge could help dealing with missing data issues.

Qi and Tao [109] compare and contrast big data and DT, within the context of smart manufacturing & Industry 4.0. They consider that the main role of DT is the cyber–physical integration, so that DT maintains an accurate representation of the real system, which could then be used to predict and feed back optimisation decisions to the real system.

Huang et al. [110], and Suhail et al. [111] present a blockchain solution to deal with the problem of data integrity in a system. Despite being promising for health systems, financial systems and cross-industry collaborations, this concept adds to the complexity of data handling. Adding blockchain technology to DT and optimising it with the rest of the components would be the next challenge [112] after integrating big data solutions in DT.

The latest methods in data management can facilitate the inclusion of big data implementation in DT. One such tool is hybrid cloud, where clients can use multiple cloud vendors along with information systems, and manage the incurred fluctuating costs as per requirement, securely combining private and more than one public clouds [113]. Another tool is augmented data management, which uses artificial intelligence methods to automate data management tasks; this can help in reducing manual data management tasks by 45 percent, thereby saving resources and increasing deployment speed [114]. Related to data and information flow, the 'digital thread' framework concept provides a complete data view of a product, from its inception till its end goal i.e., throughout its lifecycle, rather than isolated information silos [115]. It provides a view of the continuous flow of information, which can then be used to improve product designs, discover enhanced strategies and make informed decisions based on the data overview. It has been mainly used in aerospace and military to enhance traceability and engagement with the digital twin, as digital thread can feed digital twin with data and updates.

Despite being domain-dependent, there are challenges regarding data in DT which exist across domains, these are data handling (high dimensional [1], time series, multi-modal and multi-source data communication [47], uncertainty being modelled into data transfer standards [116] or in the data being transferred [117]. In large organisations the time-series data is collected from numerous IoT devices, resulting in high dimensions for the dataset. Moreover, collecting data from a considerably large number of IoT devices, collating it according to time frequencies and preprocessing it for input to machine learning is another challenging task. Handling these large datasets also requires proper resources for storage and preprocessing steps.

6. Challenges in DT

Currently DT models face the following challenges, some of which are weighed more depending on the domain the DT is being implemented. These challenges are majorly technical:

1. High-fidelity 2-way synchronisation is especially hard for large-scale industries, requires resources and high-stream IoT connection [1,35,47].
2. Interoperability with existing software being used in a production lifecycle [118]: Industries use various software for tasks such as inventory, product management, operations. The compatibility of DT with these is a challenging issue, tackling which might lead to delay in implementations.
3. Cybersecurity concerns, IoT security, cross industrial partners security [118]: With the digital twin operating across multiple industrial partners and inventory sites, the security concerns are inevitable. Not only the cross industry security concerns but also the leak of real-time monitoring data can be hazardous to a firm.
4. Add-Ons: Using DT entails certain add-ons like cost, resources and research. Since implementing DT and profiting from it is a timely process, DT can be costly if the life and span of a project are short. Building a software for DT also demands a team of programmers, developers and domain experts to test the suitability of the software for the particular task. Moreover, like any technology, DT also needs to be updated according to the recent developments in the technologies it relies on (IoT, big data, machine learning). Industries with long-term DT use will therefore need to continuously invest in this research, which might lead to added cost. As DT requires interoperability among various components, real-time tools, formulating a joint optimisation problem, and big data resources, putting these together can be time-consuming for an industry, and may lead to unwanted distractions.

7. DT conceptualisation

To build a common understanding of the DT concept and have a consolidated overview about the information of DT scattered across different research and industrial works, it is essential to have a conceptualisation which defines the basic components of a DT. The extent of inclusion or exclusion of these components will depend on the domain for which they are being used, as noted in Section 4.2. A conceptualisation will also facilitate the distinction between DT and similar technologies, as noted in Table 1.

Key components and properties across different works have been identified. This information is collated in Table 2. The properties and components stated are necessary as a result of their existence in the literature, and the authors' understanding of the DT concept. Thus, this work integrates the contributions of previous works, some of which have only been concerned with some components of DT, to provide a holistic definition of DT. Based on this analysis, the elementary and imperative components of a DT are defined as follows:

7.1. Components of DT

7.1.1. Elementary components

The elementary components are those without which a DT cannot exist:

1. Physical Asset (could be either a product or a product lifecyle)
2. Digital Asset (the virtual component)
3. Information flow between the physical and digital asset (this could be 1-way or 2-way/bijective)

7.1.2. Imperative components

The imperative components add to the properties of DT, to make it an all-encompassing tool of simulation, real-time monitoring and analytics. Without these, the uniqueness of DT ceases to exist. The existence of each of these components depends majorly on the domain and application of DT. This would be further clarified when evaluating the case studies, in Section 8.4.

1. IoT devices — to collect sensors' information from different sub-components of the physical asset and edge devices.
   Requires: High-fidelity connection between IoT devices, for accurate and timely flow of information.
2. Data — gathered from different IoT components and software; it is required to monitor the system, guarantee correct behaviour and provide input to the machine learning system.
   Requires: Big data analysis and storage tools for extracting useful information from data.
3. Machine learning — for predictions and feedback, as well as to identify effective mitigation strategies, in exceptional circumstances.
   Requires: A joint optimisation feature for the sub-components of the DT.
4. Security of data and information flow among various components involved in the DT.
   Requires: Security protocols for information sharing and authentication, and authorisation mechanisms.
5. DT Performance evaluation.
   Requires: Evaluation metrics (e.g. accuracy, resilience, robustness, costs), and evaluation methods and tests.

Table 3 depicts a summary of how each component contributes to the different functions of DT. (These components are derived from the analysis present in Table 2.)

7.2. Properties of a DT

As simple as the DT definition may sound, the properties of the DT are what makes it more than just a 'digital' 'twin'. These are the properties inherent to any digital twin; the extent to which these properties are incorporated in the DT depends on the main application of the DT, as some properties that may incur additional cost might not necessarily be required:

- Self-evolution: A key property introduced in [47]) which has not been explored much. With this property DT can learn and adapt in real-time, by providing feedback to both physical asset (via the human asset) and to the DT itself. This can be more feasibly harnessed now, due to the uprise of machine learning tools: to remodel and redesign itself (such as via reinforcement learning). The frequency of this synchronisation depends on the update scenarios, such as event-based (supply chain), periodic intervals (aircraft) and condition-based (logistics).
- Domain dependence (or Domain specific services): According to the domain, a DT may provide or prioritise services specific to the industry. These are the same 'domain specific' services which exist in the physical asset (for example the optimisation problems for an aircraft and a manufacturing unit will prioritise or add more weight to different parameters).
- Autonomy: A DT (or for that matter any information provider [124]) could either make changes to the physical asset itself, or a human in control could make changes to the DT. This applies differently to the different components present in the twin, such as to some parts of the machine learning system, or some part of the decision making system. Hence, the property of a DT to be autonomous, not autonomous, or partly autonomous is case-dependent. This classification also includes the self-evolution mechanism of DT (what changes must it make to itself, and what changes must be approved by a human).
- Synchronisation: Synchronisation of data could be either continuously or at certain time intervals. This depends on a number of factors such as technology, resources available, need for the data and type of machine learning algorithm being used. A DT could have sub-components which could be partly continuously synchronised and partly event-based synchronised.
  This synchronisation can result in different DT types, based on the following:
  -How often the data is collected?
  -How often the data is stored?
  -How often the DT is updated? (note that this is different to the property of autonomy, as that deals with 'who' rather than 'when')

Answering the debate concerning whether a DT should be a product or product lifecycle, after analysing key previous related research and case-study results, this work concludes that a DT can be both, for example, DT of a car or DT of the car's production lifecycle (the car's production lifecyle would include all the components involved, from the procurement of raw materials to the end production systems). This stems from the components of DT defined in Section 7.1; as long as all the components are present, any physical asset could have its Digital Twin.

8. Application of the DT conceptualisation to real-life and published case studies

In this section we illustrate and discuss how the conceptualisation proposed in this work is applied to various real-life and published case studies.

8.1. Case 1: Case study of west Cambridge campus [125]

An evaluation study of DT was conducted at the West Cambridge site of the University of Cambridge in the UK. For the building level, this study used the Institute for Manufacturing (IfM) building, which is a 3-storey building at the West Cambridge site. They follow the Gemini principles published by the UK Digital Framework Task Group and the Centre for Digital Built Britain for following the guidelines prepared for a national digital twin. Their DT demonstrator consists of sub-DTs. Two DT instances were developed, one for research purposes with the help of researchers, and a commercial one, with the help of Bentley Systems.

Table 2
Adjacency matrix showing the various components present and absent in literature ['•' indicates present and ' ' indicates absent, '*' means indication, but not explicitly]. These components were chosen as they were the present in *almost* all the past works and in the 'future work' section of some papers, as established features and innovative features.

Papers	Components								
	Transfer of Info.	Bijective relationship	IoT	Static Data	Time-continuous data	Statistical Analysis	ML	Domain Specific Services	Testing	Security
[69]	•	•	•	•	•	•		•	•*	
[119]	•	•	•	•	•	•		•*	•	•*
[120]	•	•	•*	•	•		•	•	•	
[121]	•	•	•	•	•	•	•	•	•	
[122]	•		•	•		•	•		•*	
[123]	•	•	•	•	•	•		•*		
[37]	•	•	•	•	•	•	•	•	•*	•
[36]	•	•	•	•	•*	•	•*	•	•*	
[66]	•	•	•	•	•	•	•	•	•*	
[19]	•		•	•		•		•		
[3]	•		•*	•				•		
[35]	•	•	•	•	•	•	•	•		
[31]	•		•	•		•		•		
[1]	•					•			•	
[16]	•	•	•	•		•		•		
[20]	•	•	•	•		•				
[47]	•	•	•	•	•	•	•	•		
[104]			•			•			•*	
[62]	•	•	•	•	•*	•	•*	•	•*	
[4]	•	•	•	•*		•		•	•	•
[22]	•	•	•*	*		*		•		
[68]	•	•	•	•	•	•	•	•	•*	•
[105]	•	•	•	•	•*	•	•		•	•*
[101]	•	•	•	•	•*	•	•	•	•*	•*
[118]	•	•	•	•	•*	•		•*	•*	•
[27]	•	•	•	•	•*	•				•

Table 3
The different components of DT and their key roles.

Component	Role
Physical Asset	what the digital twin is a twin of
Digital Asset	the digital twin
Continuous Bijective Relation	for synchronisation and twinning
IoT	for data collection and information sharing
Data	for synchronisation, analysis and input to machine learning
Machine learning	for analytics and prediction
Security	to prevent data leaks and information compromises
Evaluation metrics/Testing	to evaluate the performance of DT

- The data was acquired from the building management system (BMS) (for data related to power, HVAC and security systems), asset management system (AMS) (data related to asset management) used in Cambridge, and space management system (SMS) (data related to room and space utilisation), which are My Structured Query Language (MySQL)-based and with real-time sensors.
- Real-time data collection was facilitated using IoT-enabled wireless sensor network (WSN), which used Monnit wireless sensors and QR codes were attached to different assets. Then the data from the sensor manager and asset manager is sent to DynamoDB NoSQL database supported by the Amazon Web Services (AWS). The data is shared at short intervals, to ensure timeliness.
- Industry Foundation Classes (IFC) and AI are used in the data integration layer, to address interoperability issues.
- Anomaly detection is done for the pumps, based on the vibration data. This diagnostic information relates to the mechanical condition of pumps. Detection of change points in this data indicates suspicious faults on pumps in the HVAC system.
- Ambient temperature and humidity are monitored using the DT platform, with is a status indicator in the DT. Real-time and historical temperature and humidity data are available.
- Machine learning is used for planning optimiser and predicting temperature drops caused due to malfunction of biomass boiler. The data used is of building management systems and failure/maintenance logs. ML is also used in repair optimisation.
- Challenges related to data synchronisation, data quality, data integration and heterogeneity of source data systems were identified.

Table 4
Comparison of the conceptualisation components in the case study.

Conceptualisation	Case 1 Cambridge Building	Case 2 Italferr Bridge	Case 3 Mater Hospital
Elementary Components			
Physical Asset	Building	Replacement Bridge	Hospital workflow and physical layout
Digital Asset	Digital model, data and analysis of the building and its components	DT 3D and 4D models	software to depict layout and workflow
Information Flow	real-time	1-way: digital asset to physical asset	2-way
Imperative Components			
IoT devices	IoT, RFID, sensors, WiFi environment	None	None
Data	real-time data collection from sub-DTs	to the DT from multidisciplinary teams and their software	to the DT after assessment, to the Physical Asset after testing scenarios in DT
ML	ML, usage optimisation, asset anomaly detection, AI-supported knowledge learning	None	None
Security	University security firewall	Data contained within the company	Data contained within the hospital
Evaluation	ML used at various stages along with human feedback	None	Performed within the DT before implementation

Table 5
Comparison of DT properties in the case study.

Properties	Case 1 Cambridge Building	Case 2 Italferr Bridge	Case 3 Mater Hospital
Self-evolution	ML used at various components	based on feedback from multidisciplinary teams	based on scenarios tested in DT before implementation
Domain Dependence	Gemini principles and BIM used	BIM used to facilitate construction	assessment in the form of interviews, surveys, observations was conducted
Autonomy	Not discussed	Software used to facilitate autonomous behaviour. Extent unknown	None
Synchronisation	Data synchronisation done for different components, based on their utility	Not discussed in detail	Done before every implementation to the physical asset

8.2. Case 2: Italferr uses digital twins to build pergenova viaduct in Genoa, Italy [126]

Italferr was assigned to build a replacement bridge in a tight three-month timeframe. The other challenges included incorporating new Italian safety standards while following the same footprint of the previous bridge. It makes use of various 3D modelling and other software to reduce clashes in the system, increase accuracy, improve decision-making and multidisciplinary collaboration.

1. Italferr used BIM methodology, which follows DT approach, to accelerate the design work and reduce clashes. Using Bentley's BIM methodology, Italferr designed a DT for their viaduct.
2. ProjectWise was used to use a single source as source of truth, enabling open and connected data across multidisciplinary teams.
3. They used software like MicroStation, OpenRoads, and Open-Buildings Designer, to design 3D models of the complete infrastructure. LiDAR surveys of the terrain were imported with Descartes.
4. Parametric modelling of individual components was used to produce an information model to enable assembly of the components with improved precision and accuracy.
5. They used SYNCHRO to create 4D scripts, automating the manual processes.
6. OpenBuildings Designer was also used to determine height changes and related tasks.
7. LumenRT was used to visualise the process and determine exact volumes and quantities of construction materials required. This led to accurate prediction of construction costs.
8. As the complex project worked across multidisciplinary teams, this resulted in incorporating 34 separate models. Any contradictions were resolved using Navigator.

Note how in this case the DT has resulted from usage of multiple software offering functionalities such as visualisation and 3D modelling, coupled with the BIM model.

8.3. Case 3: Mater private hospital digital twin [127]

Mater Private Hospital in Dublin partnered with Siemens to create a DT for the Radiology department, to improve its layout and workflow. After running a series of workshops, interviews and observations, a DT was created. The use of the DT was mainly to try different scenarios for the partners to identify the best use of equipment. This allowed the partners to automate the previously trial-and-error method to a quicker digital form.

8.4. Evaluation of our conceptualisation based on the case studies

As can be observed, not all the imperative components from the proposed DT conceptualisation are present at all times, neither are all properties satisfied. This is due to the variety of applications and domains where DT is used. For example, in case 2 (Italferr DT), the DT does not make use of any ML and IoT devices (as per the information in the public domain), though it still falls under the category of DT for its use, i.e., visualisation, modelling and data sharing. The lack of complete transparency of these models, potentially due to the competitive nature of the market, may lead to such information not being made available in the public domain. A summary of how the conceptualisation provided in this work relates to these real-life case studies is shown in Tables 4 and 5.

9. Conclusion and future steps

Digital twin is a powerful methodology with great capabilities combining real-time modelling, simulation, autonomy, agent-based modelling, machine learning, prototyping, optimisation and big data into one. As DTs can have many sub-components distributed across collaborators and industry partners, developing regulations and security mechanisms and a universal DT reference framework, as well as complex DT case studies, are imperative for the widespread adoption of DT. The technology does depend on its counterparts of IoT, machine learning and data, however, a seamless integration of all these leads to the powerful and efficient product that a DT is. The latest research methods in ML and big data may contribute to increase the effectiveness of DT and to reduce the complexities in the implementation of DT methodology.

We have presented a multi- and inter-disciplinary conceptualisation of Digital Twin. Although it does not fully solve the bigger problem of not having a universal DT definition, methodology framework and established comprehensive standards, we believe that it starts with the essential step of solving the smaller problem of defining DT key components and properties. We believe this can help lay the foundation of a DT framework to be built on. This review has posed and answered several key DT-related questions. Nevertheless, there are still questions which do not have a definite answer yet, for example, how to fully and meaningfully quantify the performance of a DT: Quantitative metrics are essential to understand the accuracy and effectiveness of a digital twin. For a complete evaluation of the performance of DT and its suitability to the domain concerned, these error metrics have to be categorised as domain-dependent and domain-independent (such as [128] proposed error metrics specific to an aircraft model). This could also include uncertainty quantification to estimate the confidence levels of DT outputs and recommendations. Also, the self-evolving nature of DT can be better implemented if the DT can assess its own performance.

Apart from tackling these issues, we propose the following future steps to speed-up the advancement of DT and lead to a wider and at scale adoption:

1. A Formal Definition of DT: As a lack of consensus still exists for the definition of digital twin, having a formal definition would help clarify the concept and progress towards a universally accepted definition.
2. IoT standards required for DT: Since DT relies heavily on IoT devices for capturing and sharing data, real-time synchronisation and monitoring, knowing what IoT standards are best-suited for these operations will enhance the acceptance of DT and make it easier for widespread adoption. Lu et al. [27] recognises the same need for a data communication standard.
3. Regulations at enterprise and global levels [47]: As many companies collaborate across industries, having legal-binding regulations on the data used in DT is crucial for smooth and effective DT operation. This also applies to sites distributed across the globe, which need to adhere to laws applicable of the particular country.
4. Liaising with domain experts to extend the use of DT across sectors: Communicating with domain experts will facilitate easier implementation and acceptance of DT into new domains. Once an informed domain-specific design is ready, the implementation of the DT framework can be managed by programmers and developers.
5. Global Implementations: Currently only local area level or country level implementations exist. For larger systems such as supply chain networks and logistics, global implementations could be much more impactful.

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.

Data availability

No data was used for the research described in the article.

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