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In-depth analysis of organisational structures for digital twin ecosystems

Victória Melo[a], Flávia Pires[a], José Barbosa[a], Fernando de la Prieta[b] and Paulo Leitao[a]

[a]Research Centre in Digitalization and Intelligent Robotics (CeDRI), Laboratório Associado para a Sustentabilidade e Tecnologia em Regiões de Montanha (SusTEC), Instituto Politécnico de Bragança, Bragança, Portugal; [b]BISITE Research Group, University of Salamanca, Salamanca, Spain

ABSTRACT

The Digital Twin (DT) plays a crucial role in the digital transformation era by providing a bidirectional synchronized digital representation of an asset, capable of performing real-time monitoring, simulation, and data analysis. Generally, DTs are designed as single units following a centralised approach. However, this paradigm is evolving towards DT ecosystems, consisting of a network of multiple interconnected DTs. The benefits of such ecosystems depend on their intended purpose and application, which are strongly influenced by the design and structural configuration adopted during implementation. This paper aims to analyse different organisational structures, namely centralised, hierarchical, heterarchical, and holonic, for the design, development, and implementation of DT ecosystems, assessing their benefits and challenges across a set of aspects. A case study of a modular conveyor transfer system was used to test the different organisational structures, supporting the comparative analysis and the discussion of the research challenges related to this topic.

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KEYWORDS
Digital twin ecosystems; organisational structures; distributed systems; holonic systems

1. Introduction

The digital twin (DT) represents an essential element of digital transformation and, therefore, an important concept for the development of smart, digital and sustainable systems. Coupled with Industry 4.0 (I4.0) technologies, including Internet-of-Things (IoT), artificial intelligence (AI), big data, and cyber-physical systems (CPSs), it promotes innovative transformations, enabling productivity, efficiency, and competitiveness across various industry sectors, particularly manufacturing (Zhong et al., 2017).

In the most common definitions, a DT is considered the bidirectional synchronized digital representation of an asset, capable of modelling, monitoring, simulating, analysing, and continually optimising its real-world assets, being a major pillar of the industry's digital transformation (Capgemini Research Institute, 2022; Shao, 2021). In particular, the Digital Twin Consortium defines the DT as '*an integrated data-driven virtual representation of real-world entities and processes, with synchronised interaction at a specified frequency and fidelity*' (Digital Twin Consortium, 2025).

The interest in the DT concept has been growing over the last few years, both in industry and academia. According to (Gartner, 2024), the DT has been listed in the Gartner Emerging Tech Impact Radar of 2024 as one of the 30 emerging technologies and trends with the highest impact, classified under the Smart World topic and presenting an expected adoption time of 1–3 years. The global DT market size is projected to grow at a compound annual growth rate (CAGR) of 37.29% from 2025 to 2034 (Precedence Research, 2025).

Generally, DT systems are based on creating a single DT for the entire asset under analysis (i.e. a machine, process or system), considering a centralised organisational structure. Meanwhile, the virtual representation of an asset can be analysed under different levels of granularity according to the level of detail required for its

CONTACT Victória Melo victoria@ipb.pt Research Centre in Digitalization and Intelligent Robotics (CeDRI), Laboratório Associado para a Sustentabilidade e Tecnologia em Regiões de Montanha (SusTEC), Instituto Politécnico de Bragança, Bragança, Portugal

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representation, e.g. a simple component/part or an entire process. When an asset is a complex system, e.g. an entire multistage production line, several questions emerge concerning the efficiency of centralised approaches. Adopting distributed organisational structures to implement DT systems, such as hierarchical or heterarchical systems, enables the exploitation of characteristics that allow the improvement of the efficiency and responsiveness and the simplification of the implementation (Cohen et al., 2021; Dietz & Pernul, 2020; Human et al., 2023). This distributed approach enables the split of a complex DT in a network of interconnected small and simple DTs. In this setting, individual DTs interact to provide a holistic view of the complex asset, creating DT ecosystems.

The ISO 23247 standard (ISO 23247, 2021), which establishes a framework for the development of DTs in the manufacturing context, already considers the creation of these DT ecosystems by specifying the *interoperability*, *peer interface* and *plug and play* modules within the *Resource Access and Interchange subentity*, which foresee the interconnection between different DTs. Furthermore, several studies have also focused on the development of hierarchical DT addressing the aggregation of models. For example, (Human et al., 2023) presented a reference architecture and design framework for aggregating DTs of complex systems. Similarly, (Redelinghuys et al., 2020), a six-layer architecture for DTs with aggregation is presented, which approaches DT communication in a multisystem environment. (Villalonga et al., 2021) designed and implemented a framework for decision-making in cyber-physical production systems based on the local and global DT aggregation. More recently, (San et al., 2023) explored this distribution of DTs based on federated learning principles, with an in-depth analysis of collaboration models. Despite these advances, the selection of the most appropriate organisational structure to implement DTs remains a challenge, as it requires the analysis of applicability guidelines, advantages and limitations, according to certain aspects, namely, granularity, scalability, reconfigurability, model design complexity, and security.

Having this in mind, this paper extends the work presented by Melo et al. (2024) and aims to analyse the different organisational structures that can be used for the design and development of an ecosystem of interconnected DTs representing complex assets. For this purpose, centralised, hierarchical, heterarchical, and holonic configurations are deeply analysed, being discussed their benefits and challenges related to, among others, flexibility, scalability and adaptability aspects. Several DT ecosystems were experimentally implemented following different organisational configurations for a case study of a modular conveyor transfer system, enriching the discussion on the best practices for the design guidelines of DT ecosystems (pros and cons of each structure) and the research challenges in this field.

The rest of the paper is organised as follows: Section 2 overviews the related work regarding the design and implementation of DTs systems for complex assets, considering the systems of systems (SoS) perspective. Section 3 discusses different organisational structures to design DTs, particularly exhibiting complex aspects, bringing also an analysis of the advantages and challenges of each configuration according to different highlighted aspects. Section 4 presents an experimental implementation of DT systems, following different organisational structures, for a case study related to a modular conveyor transfer system, which allows for consolidating the discussion of these organisational configurations. Section 5 discusses the research challenges for developing distributed DT solutions. Finally, Section 6 rounds up the paper with the conclusions and highlights the future work.

2. Digital twin ecosystem architecture

The concept of the DT has been widely used in diverse areas, but its definition, organisational structure, implementation guidelines, and associated components are constantly evolving. Several studies found in the literature, e.g. Boyes and Watson (2022), and standards, e.g. ISO 23247 (2021), address these topics, covering the key components and features involved in implementing a DT. However, the different connections between the asset and its DT, along with the level of granularity at which these relationships can be examined, require further exploration. This opens an opportunity for analysing the way to structure the network of DTs, exploring the potential configurations that DTs can adopt based on their relationships and interactions with assets and with other DTs within a DT ecosystem.

Although the ISO 23247 standard already defines the main components of a single DT structure, it does not explicitly detail the dynamic relationships between these components when considering several DTs

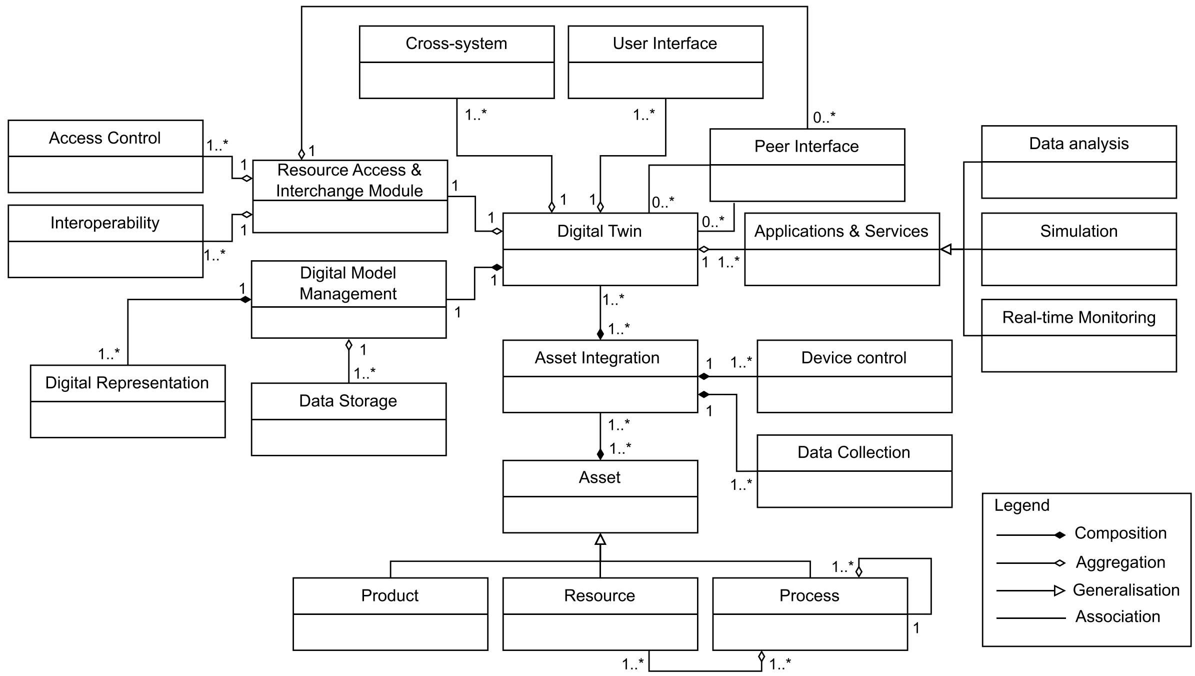

Figure 1. UML class diagram representing components and relationships of a distributed DT ecosystem.

that can coexist as part of a broader solution, particularly in terms of the relationship between the DT and the assets and between DTs. In this context, the specification of the distributed DT ecosystem from an SoS perspective and extending the ISO 23247 standard can be expressed in the unified modeling language (UML) class diagram, as illustrated in Figure 1. The classes presented in this diagram are based on the components specified by ISO 23247 for a single DT, aiming to bring the support needed to achieve a structured definition of the DT ecosystem while ensuring compliance with this recognised industrial framework and envisaging the interoperability across DT systems.

In advance, before describing the role of each class and the associations that define their interactions within the proposed model, the *DT* class represents these functional subsystems that collectively implement the DT features. This perspective follows the description presented by ISO 23247 and is reinforced by the Digital Twin Consortium with the definition of a DT system that is composed of a set of functional subsystems that provide its features (Digital Twin Consortium, 2025). From this core component, several associations can be identified, i.e. the link to the *Asset* via the *Asset Integration* class, the link to the *Digital Model Management*, the association to the *Application & Services*, the connections to *Resource Access & Interchange*, *Cross-system* and *User Interface* classes, and the self-association within the *DT* class itself.

The first analysis explores the relationship between DT and the asset *(Asset–DT)*. The *Asset* class represents the objects of the real world from which all the data are obtained to feed the digital representation within the DT. The instances of this generic class can be specified following the product-process-resource (PPR) model (Schleipen & Drath, 2009), with the *resource* instance covering, e.g. *personnel*, *material*, and *equipment*. Nevertheless, one or many resources can be aggregated into one or many processes, considering, for example, that a process can represent the operations that many resources (e.g. equipment or machines) would perform on a product to be manufactured. Additionally, a process can be aggregated into many other processes, representing, for example, subprocesses that compose a more complex process. The levels of granularity with which they can be represented, i.e. in terms of the individual components defined within the asset, can determine the number of DTs connected with them to provide a complete representation of the system. From this perspective, some works, e.g. (Woods, 2018) and (Singh et al., 2021), classify DT types in hierarchical levels based on the granularity of the asset, namely:

- *Component/Part Twin*, corresponding to a single component from the asset, mainly bringing information about the performance and functionality at a lower level.
- *Asset/Product Twin*, comprising the individual components at a higher level as an entire asset.
- *System Twin*, combining individual assets and their combined performance.
- *Process Twin*, the highest level, comprising the entire production.

Therefore, in terms of the relationship between the *Asset* and *DT* classes, one or more assets can be associated with one or more DTs. This association occurs through the *asset integration* class, which reflects the classification of DTs based on the level of data integration between the physical and digital parts (Singh et al., 2021). This classification is divided into three subcategories according to the data flow between physical and digital parts, i.e. *digital model*, *digital shadow*, and *digital twin* (Kritzinger et al., 2018). The *digital model* considers the existence of manual data flow in both directions, and the *digital shadow* considers the automatic data flow of the status from the physical to the digital part and the manual data flow in the opposite direction. Finally, the *digital twin* should present an automatic bidirectional flow of data between physical and digital parts, leading to a change in the status of one part to directly affect the other. Following this classification, the *asset integration* class presents a relationship of composition with the *data collection* and *device control* classes. The first encompasses the instances related to acquiring the relevant data from the asset to be used by the digital representation, including software, hardware, communication technologies and protocols, and all the infrastructure that enables the data acquisition. The second includes the instances that enable sending control commands or actions to the asset based on the outcomes from the DT functionalities. In both cases, the relationships have one-to-many multiplicity, depending on the number of involved assets and DTs.

A second analysis can be conducted by focusing on the relationship between DTs, specifically looking at their interaction with each other *(DT–DT)*. This is modelled through the self-association of the *DT* class, which refers to the associations that can involve multiple DT instances. Although these instances are entities from the same class (DT), each one might perform a specific role, e.g. representing different parts of processes carried out on assembly lines, or the several resources used in these processes, also providing different services for each of them, justifying their distinction. This self-association can be further explored in terms of the different types of interactions that may occur among interrelated DTs, in which the DTs operate independently but need to communicate to share information and knowledge, contributing to the overall performance of the system (holistic view of the system). Additionally, different DTs can be associated to form compositional relationships, in which a DT can be composed of other DTs following the principles of holonic systems or Service-oriented Architecture (SoA) in a useful combination when modelling more complex systems. This approach brings the SoS perspective to the development of DT ecosystems, which is directly linked to the concepts of holon and recursiveness (Koestler, 1969; Wan et al., 2021), considering that a DT can be an independent entity while also being part of a larger DT ecosystem. It can be better exploited by analysing the different organisational structures that a DT architecture can assume, according to its level of iteration with the asset and with the other DT instances. This is expressed in the class diagram of Figure 1, as a multiplicity of zero-to-many, considering that a DT may not be associated with any other DT or may be linked to many other DTs, depending on the structural configuration adopted for the design.

In the context of *DT–DT* interactions, the terms 'System of Systems' (Dietz & Pernul, 2020), 'system of DTs' (Human et al., 2023), 'DT of twins' (Redelinghuys et al., 2020), 'network of DTs' (Reiche et al., 2021), 'federated DT' (Vergara et al., 2023) and 'Internet of DTs (IoDT)' (Wang et al., 2023) have been used to address these associations. The interaction between the multiple DTs' instances can be accomplished through the *resource access and interchange module* class, which contains the instances that enable the *peer interface* to other DTs, *interoperability* across DTs or systems, and manage the access to the DT's functionalities, presenting a one-to-one aggregation relation with the *DT* class.

Furthermore, by its definition, the DT must include a digital model, which is represented through the *digital model management* class that presents a one-to-one composition relationship with the DT class, representing a relationship of dependency and uniqueness. Therefore, this class has a one-to-many composition relationship with the *digital representation* class, which is related to the digital model that represents the main features of the asset, and a one-to-many aggregation relationship with the *data storage* class, which represents the storage and maintenance of the asset-related historical data.

The *application & Services* class generalises the capabilities provided by the DT, which can be specified in terms of simulation, real-time monitoring, and data analytics services, e.g. for monitoring, diagnosis, prediction, optimisation and recommendation functionalities. Considering the relationship between classes, a DT can be associated with one or many functionalities, according to the purpose for which the DT is being designed. The *cross-system* class provides data translation, security support and data assurance across the components/modules of the DT system, considering that a DT can be associated with one or many of its instances. Finally, the *user interface* class interfaces the final user with functionalities or services provided by the DT, following a one-to-many relation with the *DT* class, meaning that one DT can be associated with multiple interfaces.

A third analysis is carried out based on the complexity reflected in the asset granularity and the life cycle coverage. In this context, products, resources and processes can have different DTs throughout their life cycle stages, e.g. design, production, and maintenance (Capgemini Research Institute, 2022), each of them designed to represent the functionalities and data of these assets at different stages. This approach shares similarities with the concepts of *digital thread* (Negri & Abdel-Aty, 2023) and *cognitive DTs* (Zheng et al., 2022) and is also addressed for a DT classification type based on its creation time (Singh et al., 2021).

The three previously analysed perspectives are aligned with the three dimensions proposed by the Reference Architectural Model Industrie 4.0 (RAMI 4.0) (DIN-91345, 2016), namely, the *Layers*, *Hierarchy Levels*, and *Life Cycle Value Stream* (Melo et al., 2023). Although RAMI 4.0 is not directly focused on the development of DTs, it is a well-established reference architecture for the development of I4.0 solutions. In this sense, the design of a DT following ISO 23247 can be aligned with the *Layers* dimension of RAMI 4.0, which specifies the IT perspectives on digitising assets, specifically focusing on communication protocols, data models, and functional descriptions. The analysis of the DT granularity can be aligned with the *Hierarchy Levels* dimension, which addresses the roles and functions of hardware and software assets within the factory or plant. Finally, the life cycle coverage is aligned with the *Life Cycle Value Stream* dimension, which addresses the life cycle of assets, more specifically considering a distinction between 'type' and 'instance' throughout its life cycle.

3. Organisational structures for digital twins ecosystems

This section analyses the different types of DT structural configurations and the main aspects that can be highlighted from them, exploring their benefits and challenges to support the development of DT ecosystems.

3.1. Organisational structures

From a systems perspective, the structural configurations have traditionally been analysed in terms of the distribution of the control and data flow, typically organised as centralised, hierarchical, heterarchical structures (Dilts et al., 1991). However, these organisational patterns can also be explored for the design of DT systems, in which the DT instances may be arranged as one central twin for the entire system, several distributed twins for individual assets, or a multilevel aggregation of twins following a hierarchical structure. Therefore, the relationships between *Asset–DT* and *DT–DT*, as previously discussed, can be better exploited by analysing the different structural configurations that a DT can assume according to its level of interaction with the asset(s) and with the other DT instances, as illustrated in Figure 2.

The first structure, represented in Figure 2a, follows a centralised approach, representing a single DT designed to encompass interrelated assets that can be analysed under different levels of granularity. This structure considers that all assets (e.g. a sensor, a machine, a system, or the entire process, including all its subprocesses) have their digital representation in a common and single model designed to represent all the characteristics associated with the dynamic behaviour of this global asset. Therefore, in this type of structural configuration, there is an overview of the whole that is represented as a larger asset in the digital model. In this

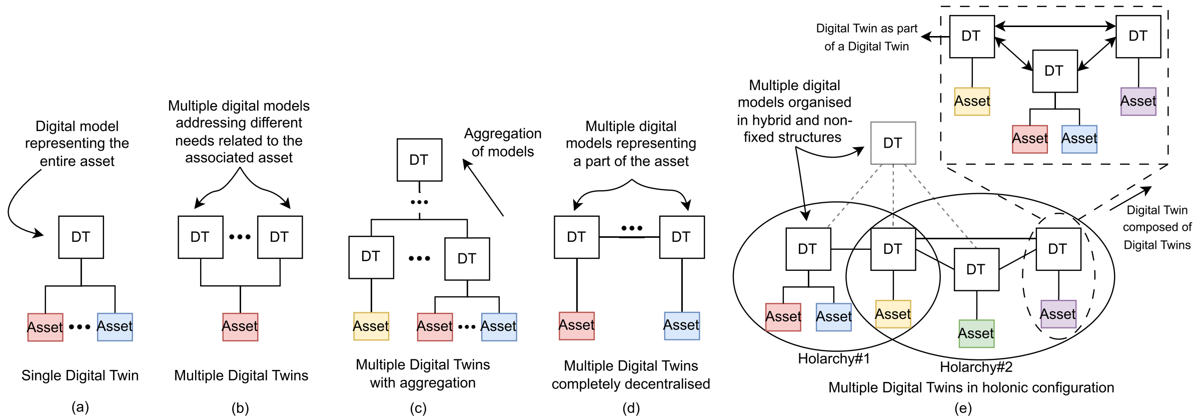

Figure 2. Main digital twin structural configurations.

regard, as more details are required to accurately represent the key characteristics or dynamic behaviour of the asset, as more complex the model must be to effectively reflect the depicted physical scenario. On the other hand, this unique representation allows to aggregate all the functionalities and services in one single mode designed for this DT to access the general data coming from this single point. This removes the need for interoperability and coordination with other models and enables the outcomes of data analysis or simulations to be based on this macro view, ensuring efficiency in terms of optimising simulation results or data analysis, such as in cases of recommendation systems and what-if simulations. However, the data processing for analysis or simulation can be extremely time-consuming depending on the complexity of the model, demanding higher computational costs. Another constraint is the lack of flexibility and robustness, as it represents a single point of failure where the entire asset is connected.

The second structure, illustrated in Figure 2b, represents the possibility of an asset having multiple DTs depending on the retrieved data used to feed its digital representation. This can be used to represent different stages of the asset life cycle, in which different DTs can be designed to cover a specific set of data and features of the asset to deal with the specific needs of the design, production, operation, and end-of-life (EoL) stages. In this condition, the interoperability component can be integrated into the designed DTs to enable their interaction through forward and backward loops (Melo et al., 2023). These mechanisms enable the exchange of data along different stages of life, which allows for the improvement of the asset based on its performance at individual stages. Additionally, it may reflect the diversity of information needed to be processed and analysed according to the levels of employed roles and hierarchy, ensuring differentiated access to information based on the different levels of authority within the processes.

The third configuration, represented in Figure 2c, represents an aggregation structure in which individual DTs can send data to a central DT containing knowledge about the entire system, contributing to the distribution of the system and bringing benefits in terms of processing, optimisation, and overall view of the system-level asset. This type of structure provides a balance between representing the whole and addressing multiple levels of granularity, allowing for more detailed representation of the lower levels while offering a holistic perspective at upper levels. From this perspective, low-level DTs can be designed to offer specific services and functionalities to meet the needs of the individual asset to which they are related, e.g. for anomaly detection, diagnosis or monitoring. On the other hand, high-level DTs can be more generic, offering feedback with perspectives for optimisation, prediction, and recommendation, which are based on data analysis or simulation models that consider the whole perspective (Reiche et al., 2021; Villalonga et al., 2021). This approach also brings flexibility in terms of modularity and reconfigurability without ignoring the complexities that the interdependence and interconnection between DTs bring concerning the changes required for reconfiguration (Redelinghuys et al., 2020).

In terms of managing the data flow, this structure allows higher-level models to handle the data received from lower levels, facilitating the orchestration, synchronisation, and coordination. Aligned with this structure, (Dilts et al., 1991) presented a modified hierarchical structure, considering that exchanged data can also occur between entities belonging to the same hierarchical level and not only between different levels, bringing more flexibility.

From this perspective, DTs at the same hierarchical level can also communicate with each other to respond quickly to anomalous behaviour while also sending data to high-level DTs for optimisation analysis, which also recalls the holarchy concept (Leitão et al., 2022) in order to bring more flexibility to the solution. The representation in Figure 2c also suggests that the DTs at the lowest level of the hierarchy can be designed according to the level of granularity needed to represent the related asset.

The structure presented in Figure 2d addresses a completely decentralised structure, also known as heterarchical, considering that each asset has its own dedicated DT. The main difference of this type of structure from the previous ones is related to the absence of fixed levels of authority, meaning that interrelated entities need to interact autonomously to achieve a global objective or decision-making. Analysing its applicability to cover complex assets or multistage processes, it is possible to consider that manufacturing processes can be divided into different areas in which subprocesses are carried out, each with its particular purpose, but collectively contributing to the final result. Each of these subprocesses may have different types of interrelated assets that require a DT, and they need to exchange data among them to contribute to the overall performance, for example, for the early identification of defects and preventing their propagation, reducing the rework, maintaining the production efficiency, and improving the product quality.

Heterarchical structures offer a high flexibility and scalability, as new DTs can be added or removed without significantly impacting the others. These also enable high responsiveness since local DTs can act immediately on changes in their associated assets and enhance robustness, as the failure of one DT does not compromise the entire system. Furthermore, this modularity facilitates the reusability of DTs for similar assets, reducing the development time. On the other hand, the distribution and need for interaction between the entities involved in this type of structure bring the need to ensure interoperability between them, along with the definition of mechanisms for communication and orchestration. In addition, the model synchronization, data fidelity, and the latency resulting from the interaction between different models must be managed.

In addition to the previous organisational structures, other approaches can rely on hybrid structures that can combine more than one organisational structure. One of the most well-known examples is the holonic systems approach, illustrated in Figure 2e, which takes advantage of composition and recursive design principles. The term *holon* is the core element in holonics, which can be defined as a basic unit that is simultaneously the part and the whole, being simultaneously self-contained wholes to their subordinated parts and dependent parts when seen from higher levels (Koestler, 1969; Leitão et al., 2022). The use of the holon principles allows for reducing the problem complexity by applying recursivity and enables, from this perspective, that a DT can be perceived as a holon, and consequently, a DT representing an asset that is part of a more complex one and at the same time composed of several other DTs. A holarchy is defined as a set of holons organised in a hierarchical structure and cooperating to achieve system goals by combining their individual skills and knowledge. Each holon can belong dynamically and simultaneously to multiple holarchies, preserving at the same time its autonomy and individuality. Since a holon can be composed of other holons, centralised and heterarchical structures can also be found in the holarchy system, combined with other organisational structures.

These characteristics are explored in Figure 2e, considering that the DTs can be organised into different structures within different holarchies to represent the assets with the required level of granularity. Furthermore, holarchies do not have rigid structures and can be dynamically adapted to the evolving relationships between assets and DTs, providing the required adaptability and flexibility to support scalability and reconfigurability. This characteristic extends to the compositional relationships formed by the interactions between DTs and assets. In this configuration, a scenario is depicted in which an asset can be represented by a DT that can be composed of different specialised DT instances representing subsystems, with their respective digital models adapted to satisfy the different levels of granularity with which the asset can be represented.

3.2. Comparative analysis

Each analysed configuration, i.e. centralised, hierarchical, heterarchical, or holonic, offers different advantages and challenges, in terms of e.g. flexibility, robustness, scalability, optimisation, and security. In this regard, it is possible to assess these structures in the design of DT ecosystems according to the aspects that most influence their choice based on the value they can add to the proposed solutions, as listed in Table 1.

Table 1. Comparative main aspects of DTs organisational structures.

Key aspects	Centralised	Hierarchical	Heterarchical	Holonic
Granularity	Lower as the model represents the whole asset.	Decreasing level across the hierarchical levels.	Higher, with the capability to decompose and distribute a complex model into several simpler and smaller models.	
Model design & complexity	Unique (complex/larger) model that captures the behaviour of the entire asset.	Complexity is split across levels, requiring synchronization of models.	Set of small and simple models with complexity arising from the synchronization among them.	Complexity dependent on the structural organisation to form the holarchies.
Scalability & reconfigurability	Rigid and monolithic structure, being difficult to scale and adapt to condition changes (complex and time-consuming).	Scalable by adding layers or nodes and reconfigurable respecting authority levels.	Flexible and modular structure, being highly scalable and reconfigurable, supporting the easy plug-and-play and reconfiguration on the fly.	
Reusability	Model fits only the current configuration.	Individual models can be reused for similar assets.		
Robustness	Low due to a single point of failure.	Resilient due to redundancy across levels.	High with the possibility to continue working even if a single node fails.	
Optimisation and myopia	Holistic view allowing for reaching optimised solutions.	Individual and global perspectives across levels, balancing optimisation and system context.	Individual and limited views, which can lead to non-optimal long-term solutions.	Dependent on the structural organisation to form the holarchies.
Responsiveness	Low due to the time-consuming processing and simulation tasks.	Distribution of data processing across levels reduces computational costs and increases responsiveness.	High responsiveness in terms of processing, but latency in DT-DT communication exists.	
Confidentiality, integrity & availability	Easier since no data is shared with other DTs.	Higher risk in terms of data privacy, availability, and integrity due to the DT-DT connections.		

The selected aspects took into consideration works related to the systems control theory and the author's interpretation of the digital twin composition modules defined in the ISO 23247 standard.

Related to the granularity aspect, two key characteristics need to be considered, i.e. the asset complexity and digital model complexity. The asset complexity is reflected in the degree of granularity with which the asset can be represented, while the digital model complexity refers to the integration of the representations into a system. In centralised approaches, the asset granularity is reduced, as the model must capture the entire system in a single structure. Consequently, a balance is required between the amount of information incorporated and the resulting model complexity. In the case of hierarchical approaches, the granularity decreases as the hierarchy levels ascend, with lower levels having higher granularity and higher levels having lower granularity. In heterarchical approaches, the level of granularity is higher, as each asset is modelled individually within the SoS perspective. Holonic approaches present a balanced alternative of granularity, since holons can simultaneously represent both the whole and the part entities, thereby supporting multiple nested levels of representation.

In terms of model design and complexity, centralised structures account for all the interdependencies across all the assets, reflecting the global system. This requires maintaining the balance between the level of abstraction, which reduces the computational demand, and the level of detail, which increases the model fidelity but increases the model complexity. Focusing on the needed interoperability and synchronisation, these are only required between the Asset-DT, which contributes to a simplified design. The hierarchical structures present a distribution of complexity regarding the balance of the information represented across the different levels, with lower levels focusing on individual perspectives, presenting lower complexity, and higher levels offering aggregated views, with higher complexity. Heterarchical structures are simpler regarding the asset level but are more complex at the interaction capabilities (e.g. collaboration, negotiation, and coordination), requiring additional interoperability mechanisms to manage not only the Asset–DT but also the DT–DT interactions. Considering that holonic structures combine different organisational structures, the complexity of the models is flexible and dependent on the chosen organisation and, in the related combination into holarchies, therefore reflecting the previous analysis for each of them.

The adaptability can be assessed through scalability, reconfigurability, and reusability aspects. In centralised structures, modifications at the asset level, e.g. adding, removing, replacing, or changing the interrelated components, are difficult since these are rigid and monolithic structures. For hierarchical structures, scalability can be achieved in two dimensions, vertically by adding layers and horizontally by adding DTs on the same level. Reconfigurability is also possible but must respect the authority of higher-level models to preserve coherence. On the other hand, the heterarchical structures are inherently modular and flexible, as changes in one model do not directly affect others, being mandatory to maintain the coordination to ensure consistency throughout. Holonic structures offer a high degree of scalability, reconfigurability, and reusability since holons inherently have the capacity to dynamically form, dissolve, and reorganise, while maintaining autonomy and coordination. While centralised models fit only the current configuration of the larger asset, individual models of the distributed organisational structures can be reused/replicated for similar assets (respecting hierarchical levels in hierarchical structures).

From an operational perspective, robustness, optimisation, myopia, and responsiveness should be assessed. Centralised structures have low robustness, as the existence of a single point of failure can compromise the entire system but exhibit high levels of optimisation. The hierarchical structures are resilient by incorporating redundancy across levels, but similar to the heterarchical approach, they require synchronisation between Asset–DT and DT–DT to avoid inconsistencies in the decision-making process, which offers a mix of both individual and global perspectives according to the level in terms of optimization and myopia. The heterarchical structures are highly robust, as a failure in one DT does not compromise the entire operation. This approach enables the local optimisation but may overlook the overall efficiency of the system and is limited in terms of system context, relying on the interaction models for a broader perspective. The holonic structure presents high robustness since each holon is autonomous and cooperative, allowing failures to be contained locally, while the system has the capability to reconfigure around this. For the optimisation aspect, the holons have the capacity to perform local optimisations and still participate in the global perspective. In this context, atomic holons present greater myopia and reduced optimization, while a more complex/composed holon provides a broader perspective of the system and an enhanced ability for optimization.

The responsiveness aspect concerns the system's ability to react to changing conditions. The centralised structures exhibit low responsiveness since the entire system is represented in a single but computationally complex model, which requires more time to process and simulate larger quantities of data. Consequently, this increases the computational demand and slows the response time. In the hierarchical structure, the response capability is dependent on which level of the hierarchy the decisions are being made. At lower levels, the models are local and can react faster to the condition changes. However, as the decision moves up in the hierarchy levels, the information may need to be aggregated and transferred across the different layers, introducing the need to communicate. These factors lead to a reduction in the responsiveness capability of the structure at higher levels. In the heterarchical structure, the responsiveness is higher since the decomposition of the models can make the local changes processed more quickly without requiring running the entire model, which can enable faster decision-making and adaptation to the condition changes. However, this may not always be the case since it is necessary to account for the communication delays between the DT-DT interactions, which leads to latency in the response. Finally, regarding the holonic systems, the responsiveness is going to be adaptive and context-dependent since each holon can react quickly to local changes and can also participate in the decisions across the system without requiring passing information through layers.

Finally, the confidentiality, integrity and availability (CIA) triad highlights the security implications for each structure. Centralised structures are easier to secure because of the absence of DT-DT communication, though they create a single vulnerability point, guaranteeing greater data privacy since the data exchange is unnecessary. For the same reason, security mechanisms are required only for the Asset–DT connection. Hierarchical and heterarchical structures involve frequent data exchange across DTs, requiring additional security mechanisms to deal with more security weaknesses, but they mitigate risks by avoiding a single point of failure. For the holonic structure, the holons manage their own security, but when looking at the whole system, they still need to exchange information interholon, making it necessary to ensure this security as referred to the hierarchical and heterarchical approaches.

In summary, each structure presents distinct benefits and limitations for the design and development of DT ecosystems. Centralised structures are most appropriate for simple, static systems with limited interdependencies, where reconfigurability and scalability are not requirements. Heterarchical structures are ideal for dynamic and complex systems involving a large number of assets, requiring flexibility and adaptability to changes. The hierarchical structure offers an intermediate solution between the centralised and the heterarchical, offering a balance between individual autonomy and global supervision. Although not explored in detail in this work, the modified hierarchical structure may also be a viable option for the development of DT ecosystems, offering a mix of hierarchical perspectives while ensuring flexibility between models of the same level, combining the benefits that both approaches can bring. Finally, the holonic structures extend these advantages further, combining modularity, robustness, scalability, and adaptability, making them especially suitable for advanced SoS contexts.

4. Experimental implementation

This section presents an in-depth analysis of structural configurations for designing and implementing DTs using a conveyor transfer system case study, enabling the testing of different structures to represent the DT.

4.1. Case study description

The system under study is composed of cyber-physical components representing a modular conveyor transfer system. The physical part of each transfer component comprises a conveyor belt, two photoelectric sensors for input and output detection of parts, vibration and current sensors, and a DC motor to operate the belt. The sensors enable the collection of data to be used in the DT functionalities as parameters for monitoring the system's health condition. The control of this system is performed through the employment of an agent-based system, considering that each module has an agent running on a Raspberry Pi platform, composing the cyber part of the cyber-physical component. The applied control logic enables the transport of parts from a starting point (entrance to the first conveyor) to an endpoint (exit from the last conveyor) using self-organisation mechanisms (Leitão et al., 2020), bringing a dynamic behaviour to the system, which is reflected mainly in its characteristics of reconfigurability and scalability and allows the removal, addition or modification of the position of the modules on the fly.

The design and implementation of a DT for this system enables the monitoring of its operation and the early detection of faults, aiming to implement mitigation actions. The observed parameters are related to the system's operational data, i.e. the states of motors and sensors (activate or deactivate), the motor operating time, the battery level, the current drawn by the motor's operation, the vibration, the time needed to transport a piece, the number of pieces transported and the position of each module in the sequence (more details about the system digitalisation, namely, the data acquisition, storage, analysis and visualisation can be found in (Pires et al., 2020)).

The use of this modular and dynamic asset allows for testing the different DT structural configurations, e.g. implementing one DT for the entire system (centralised approach), individual DTs for each module (heterarchical approach), a combination of different levels of DTs (hierarchical approach) and a holarchical perspective on their organisation (holonic approach). The results of the experimental implementation enable the comparison of the characteristics of each type of structure, the evaluation of the key advantages and challenges encountered, and the assessment of their performance in terms of the functionalities provided.

4.2. Implementation

Initially, a centralised approach for the DT was considered, as illustrated in Figure 3a, in which a unified digital representation of the entire process was created. The collected operational data from all assets (i.e.

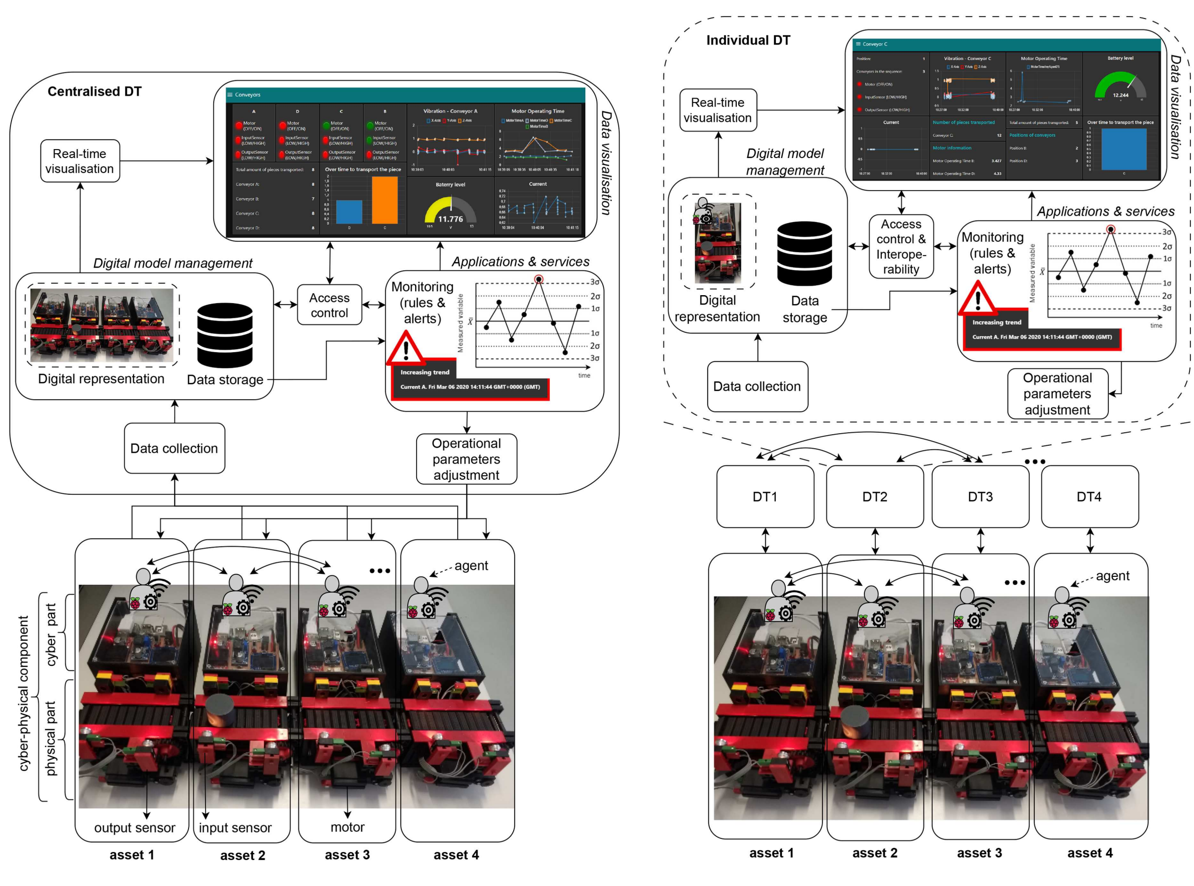

Figure 3. Digital twin for monitoring the operating conditions of a conveyor transfer system considering the centralised (a) and the heterarchical (b) structural configurations.

the different conveyor modules) are stored in a database to feed real-time visualisation and monitoring analysis.

Regarding the provided functionalities, real-time visualisation is performed by presenting the data of the entire system directly on a dashboard, allowing users to access these data in real time for the simultaneous monitoring of the process. The historical data are used to perform the process analysis, aiming to evaluate the system performance and enable the early detection of abnormal situations. The results of these analyses create alerts regarding the system's operation, displayed to the maintenance team via the user interface, allowing interventions to be performed to avoid problems from disrupting the overall transport operation, as well as the adjustment of the conveyor operation parameters through the device control module, represented by the operational parameters adjustment module in Figure 3a. The access control of the exchanged data can be carried out using certificates and user authentication.

The heterarchical approach, presented in Figure 3b, considers each conveyor module as an asset having its own DT. The components of these DTs are similar to those described in the previous approach with an individual perspective, as each DT encompasses a digital representation and mechanisms for storing, monitoring, and analysing data from a single conveyor. Considering that the modules are similar assets, the DT developed for one module is replicated to the other modules, exploring the characteristic of reusability, which facilitates the development. In this configuration, the individual module-level twins interact via the interoperability component represented in the architecture to enable the holistic view of the system, enabling each DT to be aware of the operation of its associated assets and the general information about the other assets involved in the process. The DTs of each conveyor communicate via the MQTT protocol and exchange messages about their position in the sequence, the motor's operating time, the number of pieces transported, and alerts.

A hierarchical configuration combines module-level and system-level perspectives, where the individual DTs presented in the heterarchical structure remain identical, containing individual representations of the modules with which they are associated and the components for storing, monitoring, analysing, and visualising the data from a single conveyor. The main difference is that the interoperability component in this case allows the data exchange with the system-level DT and no longer between the individual DTs. Therefore, the system-level DT has the overall representation of the system, allowing data from each module to be presented in real-time on the user interface while also being aware of alerts generated through anomaly detection analysis performed individually. Under this condition, the feedback returned by the DT at the system level is limited to a report containing information from other modules so that the component-level DTs can have a broader view of the system operation as an overall analysis.

The holonic configuration considers that each conveyor is a holon, represented by its own DT that encapsulates the physical and cyber components (e.g. sensors, actuators, and control), thus forming the Asset-DT holon. Each holon operates autonomously, enabling monitoring, analysis, and decision-making, but also retains the ability to interact with other holons (corresponding to the association of the other conveyor modules with their related DTs) to achieve system-level goals. Unlike purely heterarchical DTs, holons can dynamically form holarchies, i.e. nested groupings of modules that act as both self-contained units and parts of a larger system. In this case, this group of holons can temporarily form a holarchy that is not fixed, allowing the participating entities to organise themselves dynamically, adapting to the conditions change of the system, more specifically, in the occurrence of a removal or addition of any Asset-DT holon.

4.3. Discussion

The experimental implementation of the structural configurations demonstrated clear distinctions in performance when applied to the modular conveyor transfer system. A comparative analysis regarding the different experimental implementations was conducted based on the aspects previously analysed in Table 1.

In terms of model design and complexity, the centralised configuration is the most demanding, as the DT must capture the behaviour of the entire conveyor line and synchronise a single model with multiple interdependent assets. In contrast, the heterarchical configuration simplifies the digital representation by developing one DT per conveyor module, allowing greater granularity and detail at the local level. The reusability is also enhanced since the DT developed for one conveyor can be replicated for others, facilitating scalability. The hierarchical approach distributes the complexity across different levels, with individual conveyor DTs operating at lower levels, while higher-level DTs aggregate and coordinate the system information. Finally, the holonic approach introduces flexibility by allowing each conveyor module to act as a holon, i.e. a self-contained DT that can dynamically form part-whole relationships, allowing for simplification of the design task based on its recursivity capability.

Regarding scalability, reconfigurability, and reusability, the heterarchical and holonic approaches clearly outperformed the centralised structure. In the experiments, conveyor modules could be added, removed, or repositioned with minimal disruption since their DTs remained modular and reusable. In contrast, the centralised model proved to be rigid since changes at the asset level required adjustments to the entire model. The hierarchical approach offered an intermediate performance, since the scalability was feasible both vertically (adding layers) and horizontally (adding DTs at the same level), but reconfigurability was constrained by the need for coordination at higher levels.

Considering the DT functionalities, analytics services differ in centralised and distributed approaches. In the centralised approach, the operation parameters are analysed as a whole, enabling a global view of the system operation. In the heterarchical and holonic approaches, the analysis is performed individually, which affects the degree of myopia since the DT only knows what is happening with its respective module. In this case, the interoperability between DTs becomes a key aspect since it is essential to communicate and exchange information about data analysis and process monitoring in the overall process. In this scenario, the DTs receive alerts triggered by others, allowing a self-analysis of whether they have the same problem or when it was detected individually. In this sense, the centralised approach allows a dynamic view of the system, while distributed models need to receive data from others to obtain a view of the whole process. The hierarchical approach brings the intermediate perspective by combining individual and global analysis across layers but also requires the interoperability aspect between the hierarchical levels.

In terms of data processing and responsiveness, in the centralised approach, the monitoring analysis is performed centrally for the entire conveyor system (including the four conveyor modules), requiring more time and computing power than in the heterarchical approach. In this last approach, each DT analyses the data from a single conveyor, processes smaller datasets, reduces the computational power required, and improves the responsiveness. This factor can have a major impact on more complex applications involving more parameters and volumes of data. In the hierarchical approach, this is balanced since local issues were processed quickly at lower levels, while a wide-system is performed at higher levels. In the holonic approach, the responsiveness can be managed considering that each Asset-DT holon can react to local events while still contributing to a collective analysis without compromising the response.

5. Research challenges

The design and implementation of DT ecosystems is still a recent research topic, and several research challenges and open issues can be identified, as summarised in Table 2.

The design and modelling of DT ecosystems is directly related to the complexity of DT–DT and Asset–DT interactions, which is influenced by asset granularity within a SoS perspective. One main challenge is the lack of well-established strategies on how to handle these different levels of interaction and complexity. Furthermore, another important challenge is the definition of design patterns that specify not only the structural organisation of the system (e.g. centralised, hierarchical, heterarchical, and holonic configurations) but also the components of DT entities and the interaction protocols that enable the communication among DTs and between the DT and the asset. Establishing patterns and robust models is particularly challenging due to the heterogeneity of assets, varying levels of abstraction, and the dynamic nature of operational environments. One research direction is related to establishing formal methodologies for defining the appropriate DT structure and components and designing interaction models that can enable interactions, e.g. composition and collaboration, among the several entities part of the ecosystem. In this context, multi-agent system (MAS) provides the required infrastructure for modelling autonomy, interaction, and distributed decision-making among DTs, while SoA supports the interoperability, modularity, and dynamic orchestration of heterogeneous DT services.

Table 2. Main research challenges related to the development of DT ecosystems.

Research challenge	Coverage
Design, modelling, and patterns	Establish strategies to handle the complexity of DT-DT and Asset-DT interactions, along with the definition of design patterns to develop DTs within the ecosystem, addressing distributed structural configurations, interaction protocols and MAS and SoA as means to support modularity, decentralisation, and dynamic orchestration of the DT entities.
Data management	Enable efficient data handling through the collection, storage and analysis (e.g. ML or LLMs) capabilities, ensuring the seamless data flow, and scalable data spaces, considering their heterogeneity and the multiple sources that can originate them.
Interoperability and compatibility	Maintain the interoperability between Asset-DT, between the different modules within the DT, and between DT-DT to ensure the seamless communication and exchange of data, using standardised data models, ontologies and semantics.
Standardization	Ensure compliance with industrial standards (e.g. ISO 23247, AAS and IEEE 2660.1) and reference architectures (e.g. RAMI 4.0), ensuring universal consistency for the different aspects involving a DT ecosystem.
Fidelity and synchronisation	Ensure fidelity and synchronisation of the digital models to provide precise and consistent data, enabling reliable decision-making within the DT ecosystem.
Distributed simulation	Develop scalable and accurate simulation capabilities to support the design, testing, and validation of DT ecosystems, where the model is distributed by a network of DTs, enabling what-if analyses, performance optimisation, and predictive assessments.
Aggregation and composition of DTs	Define models to manage the compositional relationships between correlated DTs, exploring synchronisation, orchestration, choreography/coordination and organisational structures, recalling holonic and holarchical principles.
Self-organisation and emergence	Manage and control emergent behaviours that may arise from the interactions of different entities in complex contexts, as DT ecosystems, as well as nervousness in self-organised systems, aligned with the definition of the self-reconfigurable models.
Life cycle coverage	Manage, integrate, and represent assets throughout its entire life cycle (e.g. design, production, operation, and maintenance), enabling feedback loops for continuous improvement and complementarity with correlated concepts, as the digital product passport.
Human integration	Enhance the human capabilities and interaction within the automation loop, and particularly in the DT representation, at both operational and strategic levels, while fostering trustworthy human decision-making.
Security and traceability	Ensure data integrity, privacy, and controlled data access across all networked components, even under resource constraints, through security mechanisms, as authentication, authorisation and encryption, and deployment of AI algorithms to support, e.g. cyber threat detection.

Data management in distributed DTs is a major challenge, given the heterogeneity and growing volume of data originating from multiple assets and DTs. New research directions must address the definition of new models for distributed and scalable data storage and data spaces (Bakopoulos et al., 2024) to facilitate the development of DT ecosystems, as well as data governance strategies that consider quality, consistency, availability, and integrity. In addition, significant challenges remain in terms of data collection, which requires handling data from diverse sensors and acquisition protocols while ensuring reliability and timeliness. Finally, data analysis poses difficulties related to processing high-volume and high-velocity streams in real time, integrating predictive and prescriptive analytics. In this context, advanced machine learning (ML) techniques are required to extract patterns and predictions from complex datasets, while emerging large language models (LLMs) can contribute to semantic understanding, knowledge extraction, and natural language interaction with DT data.

In this context, another important challenge is related to ensure the interoperability and compatibility between the different digital models that need to communicate and exchange data. Standardising the data exchange, for instance, improves the comprehension across multiple components. The asset administration shell (AAS) (Plattform-I4.0, 2022) fulfils this requirement, acting as a standardised communication interface for linking assets to their digital representation regarding the Asset-DT interaction. Extending to the DT–DT interaction, the DT should be compliant with standards or reference architectures, such as ISO 23247 or RAMI 4.0, to ensure terminology consistency, interpretability and industrial adoption. In particular, ISO 23247, which is the standard directly related to DTs for manufacturing, must be extended to provide more support for the development of DT ecosystems, mainly focusing on providing further specifications for the *interoperability* and *peer interface* components. Achieving this level of interoperability capability requires integrating assets and DTs, internal DT modules, and enabling communication among heterogeneous DTs. The application of semantic models, ontologies, semantic webs (Burattini et al., 2024) and standardised data models, e.g. Automation ML, is essential for engineering the data exchange in this context. In general, the distributed approaches demand advanced interoperability mechanisms to support DT–DT communication when exchanging data that contribute to the collective performance of the overall process. Such interaction can be realised through feedback loops (using both forward and backward mechanisms) to ensure continuous knowledge sharing and system improvement from a multistage perspective. At the same time, these mechanisms should also provide flexibility, thereby enhancing the reconfigurability and scalability of DT ecosystems.

Another aspect that should be considered is the design of high-fidelity models for the digital representation of assets. The model's accuracy ensures the synchronisation between the asset and the DT, consequently enabling the synchronisation among the DTs. This aspect has a direct impact on the decision-making capacity of the DT system, as each DT requires precise and consistent data to make autonomous decisions that contribute to improving the system's performance. The complexity of the interaction between different DTs must also be considered, requiring the development of coordination and orchestration strategies and the definition of communication models between the DTs, thus contributing to the collaborative decision-making process. The research challenges in this context include the development of techniques for the real-time synchronisation of models, mechanisms to reduce the latency in the data exchange, methods for the adaptive update of models, and formal metrics for evaluating the fidelity of digital models.

The simulation capability is a fundamental challenge within the DT ecosystem scope, as it enables the testing, validation, and optimisation of models before the deployment in real-world conditions. The increasing complexity and dynamic behaviour of CPSs demand the ability to distribute the simulation in order to handle large-scale, heterogeneous, and interconnected DTs under a SoS perspective. Key issues include ensuring fidelity by accurately replicating the physical processes and their interdependencies to achieve scalability, being able to simulate multiple DTs interacting in real time, and supporting interoperability so that heterogeneous simulation models can be integrated across different domains. Moreover, simulation must extend beyond traditional deterministic modelling to incorporate stochastic behaviours, uncertainty, and adaptive scenarios, reflecting the variability of real-world conditions. Another critical challenge is the coupling of simulation with real-time data streams, enabling hybrid approaches that combine predictive simulations with live system updates.

Considering the composition relationships among correlated DTs, the research challenges are related to the definition of formal models to identify, represent and manage the relationships of correlation and dependency among different DTs. Examples may include mechanisms for finding the dynamic correlation of models to support the evolution and adaptation of systems, alongside with the synchronisation, orchestration and choreography techniques. This topic can be further explored under holonic and SoS perspectives, exploring how DT compositions can be structured according to the asset complexity. Additionally, it can be explored through emergent or aggregated models, e.g. the DT of an assembly line is an entity that aggregates and coordinates submodels representing individual stations or as a composition emerging from the interaction of models, recalling holarchical principles without a rigid structure.

Along with the distribution and interactions among the different entities that are part of the interconnected network of DTs, self-organisation and emergence are also concepts commonly addressed when dealing with this kind of structure to design complex systems (Leitão et al., 2022), which are aspects that should be managed and controlled. The interactions between individual DTs can give rise to a collective behaviour that is more significant than the sum of their individual behaviours, potentially leading to the emergence of a DT for the whole. The challenge related to emergence is managing the desired and undesired behaviours that can arise from interactions and collective behaviour. For self-organization, the challenge is related to define mechanisms that enable the dynamic and on-the-fly adaptation/evolution of DT systems while also controlling the nervousness with which systems react to condition changes, as well as the boundaries for the self-* features. In this context, MAS have stood out as a suitable approach for addressing the dynamism and adaptability inherent in this distributed ecosystem, mainly because of the advantages that they can offer in terms of decentralisation, scalability, and autonomy. The development of MAS-based DTs has become a viable alternative from this perspective due to its distributed infrastructure, which provides support based on its inherent characteristic of enabling collaboration between the different entities involved (Melo et al., 2023; Reinpold et al., 2024). Agentic AI is an emerging approach in this area, in which the reasoning capabilities of agents are based on LLMs (Sapkota et al., 2026) and was pointed out by (Lee & Su, 2025) with potential application for DT integration.

For the life cycle coverage, the challenge is related to creating models to represent the different aspects of assets throughout the life cycle stages, along with interaction models to provide feedback loops (e.g. through backward and forward communication), allowing the continuous improvement of the asset. Additionally, emerging concepts that are also related to digital representation and life cycle management, as the digital product passport (DPP), can be aligned from the ecosystem perspective to be used in a complementary way, with the data from DTs and DPPs of products being dynamically exchanged to complement the information of each other and providing a more comprehensive view of the product and its evolution.

The human integration within DT ecosystems, aligned with Industry 5.0 principles, represents a challenge from two perspectives. First, when considered as a 'personnel' type of asset, requiring a digital representation that captures knowledge, skills, availability, ergonomics, or personal parameters such as fatigue indicators, enabling feedback for safety and performance. Second, considered as a user capable of interacting in the ecosystem, either at operational or strategic levels, collaborating with DTs or validating models and acting in the decision-making process. The research directions from this perspective may be focused on maintaining these interactions reliable and trustworthy, together with the enhancement of human-in-the-loop approaches, designing interfaces that augment human cognitive capabilities, applying augmented reality and immersive visualisation techniques, and adopting explainable AI (XAI) to enhance transparency, interpretability, and interactivity.

The data exchange inherent to these distributed DTs systems, which are composed of a network of interconnected components, makes security and privacy a critical challenge. Therefore, the definition and implementation of security mechanisms should also be considered, for example, in terms of authentication, authorisation and encryption, to guarantee data integrity, privacy, and access management. This security aspect must be ensured across all the networked components, even under resource constraints, with AI algorithms supporting cyber threat detection. Additionally, blockchain technology is also emerging as a viable option, offering a secure method for recording data exchanges between different DTs while maintaining data integrity and traceability.

6. Conclusion

The DT is generally designed and implemented as a single unit, following a centralised organisational structure. However, this paradigm is evolving with the development of DT ecosystems, which have a network of multiple interconnected twins. One of the main challenges of these ecosystems is the selection of the best structural configuration, e.g. centralised, hierarchical, heterarchical or holonic structures, for their design and implementation.

This paper focused initially on the main variables involved in the establishment of a DT ecosystem architecture, analysing the relationships between Asset-DT and DT-DT through a UML class diagram with the main components and relationships. Afterwards, a more in-depth analysis was performed on the organisational structures, namely, centralised, hierarchical, heterarchical, and holonic structures, for the DT ecosystems focusing on the main advantages and challenges. These were analysed according to the main aspects that influence the selection of an organisational structure, as granularity, model design and complexity, scalability, reconfigurability, reusability, robustness, optimisation and myopia, responsiveness, and security.

Subsequently, a case study was presented based on a modular conveyor transfer system, which served as a basis for testing the different organisational configurations, highlighting the main experimental results in terms of the values aggregated to the DTs functionalities. The experimental results demonstrated how the DT system behaved under different structural configurations, having reached the conclusion that each organisational structure has unique implementation requirements and features. In the case of centralised structures, these are more suitable for simpler systems, the heterarchical structures are optimal for modular and dynamic environments, the hierarchical structures provide a compromise between individual autonomy and global supervision, and finally, holonic configurations offer the highest adaptability, scalability, and robustness, making them especially suitable for complex SoS applications.

Future work includes the specification of the design principles for the development of DT ecosystems based on holonic architectures, including the definition of design patterns to enable the implementation of self-organisation models for dynamic reconfiguration of DTs, and the coverage of the life cycle perspective.

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Author contributions

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