Interoperability of Digital Twins: Challenges, Success Factors, and Future Research Directions

Istvan David[1], Guodong Shao[2],
Claudio Gomes[3], Dawn Tilbury[4], and Bassam Zarkout[5]

[1] McMaster University, Canada – istvan.david@mcmaster.ca
[2] National Institute of Standards and Technology, USA – guodong.shao@nist.gov
[3] Aarhus University, Denmark – claudio.gomes@ece.au.dk
[4] University of Michigan, USA – tilbury@umich.edu
[5] IGnPower, Inc., Canada – bzarkout@ignpower.com

Abstract. The widespread adoption of digital twins gave rise to emerging systems of interconnected digital twins, often dubbed aggregated or hierarchical digital twins. In such emerging systems, interoperability of digital twins is key in determining the capabilities and qualitative properties of the emerging system. Despite the elevated interest in practice, there is little research on the emerging topic of interoperability of digital twins. In this paper, we report on a panel discussion that took place at the 2023 Annual Simulation Conference with four esteemed experts representing four distinct perspectives on the topic: strategic (why do aggregated digital twins matter?), technical (how does co-simulation support a distributed set of concerns over multiple digital twins?), standardization (how can standards enable interoperability?), and organizational (how do organizations deal with advanced digital twinning scenarios?). We report the panelists' main arguments and synthesize them into a discussion. The main takeaway of the panel is that contrary to the state of affairs in digital twinning that limits interoperability to low levels, there is a clear need to reach higher levels of interoperability in digital twinning scenarios that necessitate a distributed approach. Moreover, there are emerging solutions to achieve these higher levels. To provide researchers with tangible leads, we distill challenges, success factors, and recommend future research directions in digital twin interoperability.

Keywords: ISO23247 · panel report · standardization · systems of systems

1 Introduction

Digital twins are virtual representations of physical assets connected through real-time data streams and control loops to their physical counterparts [33]. As such, digital twins mirror the prevalent state of the physical asset and provide safe, cost-efficient, and time-efficient alternatives to interacting with the physical system, e.g., for virtual experimentation purposes. In addition, the control loop allows the digital twin to actuate the physical system based on analysis and simulation, e.g., in run-time optimization, real-time reconfiguration, and intelligent adaptation scenarios. Thanks to their numerous benefits, digital twins have seen a steep adoption curve in a wide array of domains, including smart manufacturing [32], smart healthcare [1], and urban ecosystems [6].

As the complexity of physical systems subject to digital twinning increases, architectural concerns about monolithic digital twins become relevant. By decomposing into specialized units with a finer-grained scope, the accidental complexity of the digital twin can be exchanged for better-managed essential complexity [31], enhancing the separation of concerns, reconfigurability, and scalability when reflecting complex physical systems with multiple digital twins [23]. This mechanism gives rise to the need for compositionality in digital twins, resulting in a System of Digital Twins (SoDT) [34], analogous to the dynamics of systems-of-systems. In SoDTs, digital twins are not necessarily designed by the same vendor or implemented using the same technology. In such cases, ensuring the ability to exchange information despite lacking convergence by design is key to leveraging the benefits of tasks-specific digital twins [16]. Interoperability between single digital twins in an aggregated digital twin structure is key in leveraging the power of specialized, domain-specific digital twins. The widespread adoption of digital twins has attracted numerous vendors offering digital twin frameworks and platforms. The lack of technological convergence and common APIs render digital twin compositionality a challenging endeavor.

A definition of interoperability

For our purposes, we resort to the definition of interoperability set by the ISO/IEC 25010 standard. According to the standard, interoperability is the "*degree to which two or more systems, products or components can exchange information and use the information that has been exchanged*".[6]

There are two crucial elements in this definition: (i) the ability to exchange information and (ii) the ability to use the exchanged information. Both are challenging in general SoDTs as digital twins in such structures lack any premeditated convergence mechanisms. The Levels of Conceptual Interoperability Model framework [41] defines seven such convergence levels, ranging from the low level of technical interoperability focusing on integrability with mere bits and bytes being exchanged, to the highest level of conceptual interoperability focusing on composability with high-context information being exchanged. Currently, SoDTs are far from the highest levels of interoperability, mostly relying on ad-hoc alignment of APIs, stemming from community convergence rather than proper design for interoperability. With the surging interest in digital twins in a wide array of domains, it is important to understand the challenges and success factors of fostering interoperability among digital twins.

[6] https://iso25000.com/index.php/en/iso-25000-standards/iso-25010/60-compatibility

The panel – four complementary perspectives

To investigate the challenges and success factors of interoperability of digital twins, we organized a panel discussion at the digital twins track of the 2023 Annual Modeling and Simulation Conference (ANNSIM) in May 2023. We invited four esteemed panelists who represented four complementary perspectives.

– **Strategic perspective**: digital twins with multiplicities and why do aggregated digital twins matter? – **Dawn Tilbury** (University of Michigan, US).
– **Technical perspective**: how does co-simulation support concerns distributed over multiple digital twins? – **Claudio Gomes** (Aarhus University, Denmark).
– **Standardization perspective**: the role of standards in interoperability – **Guodong Shao** (National Institute of Standards and Technology, US).
– **Organizational perspective**: how do organizations deal with advanced digital twinning scenarios, specifically in the light of various data challenges – **Bassam Zarkout** (IGnPower Inc., Canada).

The strategic perspective articulates why interoperability is an issue and identifies two such areas of problems: (i) multiple digital twins for components that are integrated/aggregated into a system digital twin, and (ii) multiple digital twins for the same component/system, with different outputs (e.g., one to predict/estimate quality and the other to predict/estimate needed maintenance). The technical and standardization perspectives focus on how interoperability could be approached. The technical perspective builds on the assumption that complex digital twin scenarios are often enabled by simulators [3] and identifies co-simulation as the viable option to support simulation under interoperability constraints. The standardization perspective builds on the assumption that single digital twins in a SoDT are not necessarily provided by the same supplier and convergence might not be attained without proper standards. Finally, the organizational aspect focuses on what should be done by organizations to put digital twin solutions in place, especially SoDTs with interoperability concerns.

Each panelist was asked to reflect on a set of previously agreed questions that span a sufficiently wide scope allowing us to draw meaningful conclusions from the discussion. We made it a point to adhere to the MECE (Mutually Exclusive, Collectively Exhaustive) principles as much as possible to elicit a diverse set of arguments. In this paper, we report and synthesize these arguments and identify the main challenges, success factors, and impactful research directions ahead.

2 Strategic view: multiplicities of Digital Twins (Dawn Tilbury)

A digital twin is a virtual replica of a physical object or process, its “twin”. A digital twin needs to be synchronized with its physical counterpart through the collection of real-time data (at appropriate intervals, which will depend on the application) and should output some useful metric about the condition or state of its physical twin, along with a confidence estimate in that metric [32].

A digital twin uses some form of a model to create its output and can be built using subject-matter expertise, data analytics, and/or artificial intelligence. Although the term "digital twin" is more recent, in reality, what we now call "digital twins" have existed for many years. State estimators for control systems, virtual metrology, and predictive maintenance systems are examples of existing software systems that fit the digital twin definition. For example, a state estimator, e.g., Kalman filter [42], takes the inputs and outputs (u and y) of a system modeled as a linear system of differential or difference equations $\dot{x} = Ax + Bu$ and produces an estimate of the state x over time. Virtual metrology [15] uses measurements from semiconductor fabrication to predict the quality of a process without needing to measure every wafer.

As systems become more complex, it can be advantageous to build multiple digital twins for the sub-components of a system and then aggregate them together into a digital twin for the system. For this type of aggregation, the digital twins need to have the same purpose. Consider a digital twin that predicts the remaining useful life (RUL) of a system, that could be used for predictive maintenance. For example, in a pump with a rotating motor, there could be a digital twin for each bearing in the motor, another digital twin for the shaft, and one for the seal. Each digital twin could collect data from its respective component (temperature, vibration, pressure, flow, etc.) and use that data, together with a model, to predict the RUL. The model could be as simple as a threshold (if the vibration is greater than X then predict failure within 1 week) or could be tuned based on historical data to give a more precise prediction with greater confidence. The system digital twin would aggregate all of the outputs of the sub-components to predict the RUL of the pump. Again, a simple aggregation could just choose the minimum failure time, or a more complex aggregation could use a weighted average.

A more complex scenario could include a manufacturing cell, including multiple Computer Numerical Control (CNC) machine tools and robots that move the parts between the different machines. Each machine and robot may have a digital twin that predicts its RUL, based on data from its internal control system and perhaps external sensors. To integrate these digital twins into a prediction of the RUL for the cell, they must be able to interoperate – the outputs must be presented in an understandable format so that the integrator who puts the cell together can create the cell-level (and also a system-level) digital twin. In the future, the digital twins for the machines and robots may be supplied by their vendors, and trained on historical data for these particular machines operating in different contexts. In this case, the context or environmental parameters must either be measurable by the digital twin or specified by the integrator.

In addition to aggregating digital twins in a hierarchy for a given system, each component (or sub-component) could have multiple digital twins with different output metrics (and confidence levels). In a multi-axis machine tool, each motor could have a digital twin predicting its RUL as well as one estimating its accuracy or tolerance. The overall precision of the machine could be estimated by combining the different axes, appropriately for the relevant geometry.

As computing, storage, and bandwidth become more accessible and affordable, the amount of data available to be used in digital twins for improving manufacturing performance is increasing exponentially. Taking advantage of the data requires significant effort by subject-matter experts, who understand the processes, what metrics are important, and what measurements are most likely to be useful for the intended purpose. Once a digital twin has been successfully verified and deployed, it needs to be maintained and potentially updated (especially if the context changes). Ideally, the successful digital twin can be used as a template to create digital twins for similar processes, or in similar contexts.

A digital twin framework that includes the eight "ilities" of Modularity, Reusability, Interoperability, Interchangeability, Verification and Validation (V&V) capability, Maintainability, Extensibility, and Sustainability enables the successful lifecycle of a collection of digital twins to exploit the promise of translating manufacturing data into manufacturing intelligence [32]. Many open research questions consider how best to realize these properties, from transfer learning to uncertainty analysis and automation.

3 Technical view: co-simulation for interoperability (Claudio Gomes)

Co-simulation is the field that studies how to conduct the coupling of heterogeneous models through their behavior traces, i.e., through their simulations. It is therefore the key to simulator interoperability. The following aspects constitute the essential elements to perform a co-simulation and thus allow simulator interoperability: simulators that allow explicit control of when (not how) to progress in simulated time; a standardized API for controlling such progression and accessing variables; and an orchestration algorithm that uses such an API.

While there are many appropriate co-simulation interfaces – Discrete Event System Specification (DEVS), Simulink's S-Function, the interface used in Ptolemy [5], the interface used in CyPhySim [28], the High-Level Architecture (HLA) – in this manuscript, we focus on an interface that has been proposed by industry and is currently being adopted by more than 170 companies for modeling their simulation tools. The functional mockup interface (FMI) standard[7] was proposed in 2007 and is currently in version 3.0 [24]. It defines a container and an interface to exchange dynamic simulation models using a combination of XML files, binaries, and C code, distributed as a ZIP file, called a Functional Mockup Unit (FMU). Under the FMI standard, each simulator declares the operations corresponding to the API. We refer the reader for more details to Gomes et al. [20].

Role of Co-simulation in Digital Twins

We envision the emergence of standardized interfaces to interact with digital twins. If digital twins leverage dynamic models to make sense of the data as well

[7] https://fmi-standard.org/

as provide a number of other useful services such as monitoring, fault diagnosis, and self-adaptation, then the role of co-simulation in digital twins is clear: to provide a standard interface to interact with models. Every application of simulation in digital twins has an analogous counterpart with co-simulation when the systems under study are coupled and heterogeneous.

The work of Feng et al. [17, 18] describes a number of services that are based on modeling and simulation, each of which is enabled by using the co-simulation interface. These services play crucial roles in the functioning of a digital twin. They include (1) state estimation, which combines data and simulations for accurate evaluation of model variables; (2) visualization, which displays relevant variables and physical twin properties for a comprehensive understanding; (3) decision-making support, allowing simulations and evaluation of different configurations for the physical twin; (4) monitoring, assessing performance, and detecting anomalies or faults; (5) predictive maintenance, identifying long-term trends for breakdown prediction; (6) fault diagnosis, classifying and explaining detected faults; and (7) self-adaptation, enabling automated or semi-automated adjustments to cope with changing environments.

In the above services, the role of co-simulation is to decouple the technology used to simulate models from the digital twin implementation. Its role in decision-making is to provide the decision-maker with insights into the current and potential future states of the physical twin. The state estimation service will often correct the predictions made by a model in order to align them better with the observed data and thereby obtain a more accurate estimate of all other variables in the model that affects those predictions. The co-simulation interface is, therefore, important for the development of simulation tool agnostics state estimation services because these services rely only on the co-simulation interface to perform the prediction and correction. Further implementations of state estimation using the FMI standard are presented in [21, 27, 35].

In summary, co-simulation and the standardized interface it promotes allow digital twin technology to be decoupled from modeling and simulation tools.

Co-simulation and Interoperability in Digital Twins

As written in the previous section, one of the responsibilities of the digital twin is to keep track of the physical twin's environment (the state estimation example we have used is focused on sensing latent variables in the physical twin but it could also be used to sense latent variables in the environment of the physical twin). In scenarios where a physical twin's environment includes other physical twins which may have their own digital twins, it is reasonable to conclude that there are advantages for the former's digital twin to be able to interact with the latter's digital twins. As proposed by Esterle et al. [16], there might be two main types of operations to be carried out between digital twins: (1) model exchange operations happen when a digital twin requests a model from another; and (2) service request operations happen when a digital twin invokes an operation to be executed in another. An example of model exchange is a digital twin asking for a model of another physical twin that can be used for predictions of the future behavior of that physical twin. An example of a service request operation is subscribing to the sensory data from another physical twin.

The role of co-simulation is more prominent in case 1 as the model can be transferred as an FMU. As for case 2, the FMI interface is poorly suited, because we envision many digital twins to be running 24/7, undergoing updates, and generally present non-functional requirements not covered in the FMI standard.

The following represents the most important lesson learned from the standardization of co-simulation interfaces: Intellectual Property (IP) protection based on exchangeable black box models is not seen as being strong enough by the industry. The main reason is that, given the freedom to interact with a simulator as much as possible, it is theoretically possible to learn some of its model's underlying structure using system identification techniques. Discussions with industrial partners also reveal the need for a way to control access to simulators to prevent abuse. This leads to solutions where the simulation of a particular company remains on-premises and requests can be made for simulations. This further aggravates issues such as cyber security and naturally presents performance challenges due to the increased latency.

The above challenges suggest the following questions. (1) What are the essential operations for a digital twin interface to enable the corporation and interoperability between digital twins? (2) What mechanisms can be put in place to enable full access control to industrial partners who own a particular digital twin while at the same time not harming security and performance?

4 Standardization: a key enabler (Guodong Shao)

Digital twins involve highly complex collections of data and functional subsystems including data collection, data processing, data modeling, data analytics, data visualization, modeling and simulation, optimization, and control. Some of these subsystems could be distributed systems. There are significant challenges to seamlessly integrating these diverse functional subsystems with data in various formats, e.g., 3D models, sensor data, and simulation results. In addition, digital twins will need to interact with many other systems to achieve their goals. Interoperability is essential for the development and adoption of digital twins as it enables systems to work together. Standardization plays a critical role in achieving interoperability by defining common rules, protocols, data formats, and interfaces that ensure consistency and compatibility across different systems. Standards can also enable vendor neutrality, which means that they are not tied to proprietary technologies. Various vendors and solutions that comply with the same standards will guarantee compatibility and interchangeability of components or systems. Standards foster the development of ecosystems and markets by creating a level playing field and encouraging innovation on interoperable solutions. Using a standard approach, companies do not need custom integration solutions, which helps reduce development and maintenance costs.

Developing standards can be a complex and time-consuming process. It requires extensive collaboration, consensus-building, and coordination among various participating stakeholders. Technology evolves rapidly nowadays, so standardization efforts need to keep up with the latest advancements. The standardization process typically involves several stages with various stakeholders. It could take up to several years to complete, depending on the complexity of the subject matter, the level of consensus required, and the involved stakeholders' engagement. Although specific steps may vary depending on the context, the main phases of standardization include: (1) needs identification, (2) work item proposal, (3) committee identification or formulation, (4) committee drafting, (5) consensus building, (6) review and comment, (7) approval and publication, (8) implementation and adoption, and (9) maintenance and revision.

While standardization offers many benefits, there are misconceptions too that hinder the process. For example, (1) adherence to standards may limit companies' ability to differentiate their products or services from their competitors and (2) complying with standards will require modifying existing systems, processes, and practices, leading to more costs than benefits. These misconceptions can be addressed through proper collaboration, communication, stakeholder engagement, standards education, and implementation demonstration. The success of a standard relies on several key factors that contribute to the development, adoption, and effectiveness of standards: (1) consensus and collaboration among stakeholders; (2) clear objectives and scope; (3) broad stakeholder engagement especially from industries; (4) technical excellence and relevance to address current and emerging challenges; (5) flexibility and adaptability to accommodate evolving technologies, market dynamics, and user needs; (6) promotion and education to build confidence, facilitate adoption, and foster a culture of standardization; (7) continuous improvement and governance to ensure accountability and the long-term sustainability of standards.

Since digital twins are still in their early stages of maturity, there are fewer standards specifically developed for digital twins. However, existing standards for data collection, data security, information modeling, simulation, visualization, and networking can be used to support the development of digital twin applications. For example, OPC Unified Architecture (OPC UA) provides a standardized framework for secure, reliable, and platform-independent communication, allowing digital twins to integrate with diverse systems and components and MTConnect supports digital twin interoperability by providing a semantic vocabulary for manufacturing equipment, making possible structured contextualized data and avoiding proprietary format. Data sources include equipment, sensor packages, and other factory floor hardware. A relatively new digital twin standard published by International Organization for Standardization (ISO), ISO 23247 - Digital Twin Manufacturing Framework, provides a generic development framework that can be instantiated for case-specific implementations of digital twins in manufacturing. The standard defines a digital twin as "A fit for purpose digital representation of an observable manufacturing element (OME) with synchronization between the element and its digital representation." An OME could be any physical artifact, process, or behavior on the manufacturing floor. ISO 23247 promotes common terminology usage, provides a generic reference architecture, supports information modeling of OMEs, and synchronizes a digital twin with its OME, facilitating interoperability and collaboration among different manufacturing systems and stakeholders (Shao, 2021). The framework reference architecture, in part 2 of the standard, consists of functional entities in each domain entity, i.e., User Entity, Digital Twin Entity (DTE), and Device Communication Entity (DCE). Each functional entity (FE) performs specific tasks. For example the Interoperability Support FE enables integration between digital twins and other systems such as Enterprise Resource Planning and Product Lifecycle Management systems. The Data Collecting FE in DCE collects data from OMEs and interacts with relevant systems in DTE and sensors.

There are a few other ongoing standardization efforts on digital twins including new additions of ISO 23247, ISO/IEC JTC1 efforts on digital twin definitions, concept, terminology, reference architecture, and maturity models. Object Management Group (OMG) Industry IoT Consortium (IIC) Digital Twin Interoperability Task Group has worked on a technical report on Digital Twin Core Conceptual Models and Services, the technical content could potentially serve as standardization requirements and foundational material to facilitate the interoperability and reuse of digital twin components. In addition, OMG's Digital Twin Consortium is an industry consortium that promotes the development, adoption, and standardization of digital twin technologies. It brings together organizations from various sectors to collaborate on advancing digital twin standards and best practices. The consortium's activities support cross-domain standardization efforts, creating a common foundation for interoperability and knowledge sharing.

The standardization of digital twins is still evolving. Here are a few directions that can be pursued to further advance the standardization efforts: (1) develop common data models that capture the essential information and relationships within digital twins, it will promote consistency, reusability, and integration across diverse digital twin ecosystems; (2) establish interoperability frameworks that define common interfaces, protocols, and integration patterns for digital twins, this can facilitate communication and collaboration between different systems; (3) foster semantic alignment by developing standardized ontologies and semantic models for effective communication and understanding of concepts, relationships, and context; (4) develop security and privacy standards for digital twins to enable authentication, access control, data encryption, and secure communication protocols that support the confidentiality, integrity, and privacy of data so that trust and confidence in digital twins can be enhanced; (5) develop frameworks and guidelines for managing the entire lifecycle of digital twins to promote consistency, traceability, and scalability of digital twins; and (6) establish standardized testing and validation procedures for digital twins to ensure their reliability, accuracy, and performance, and enhance their credibility and trustworthiness. These procedures should cover data quality assessment, model validation, conformance testing, and performance evaluation.

5 Organizational view: the role of data (Bassam Zarkout)

Data used and produced by digital twins should be considered as part of enterprise data assets. Organizations are increasingly interested in exploring the value of their data assets and how this value can be leveraged to support the corporate objectives of the organization. It is important to distinguish between intangible and tangible data value. While both types contribute to other values for the organization, such as IP and efficient operation, the latter type of data is also readily available for monetization [11, 26]. Data can also be valued at its present or future value. The latter type of value can be unlocked through analytics and Artificial Intelligence (AI). The steady emergence of increasingly more powerful AI tools—such as ChatGPT and other LLM—that are capable of unlocking such future value from "dead" data is pressing organizations to re-examine their assumptions and strategies about what to do with data and information beyond their immediate operational use. It is a classic case of "you do not know what you do not know". An integral part of the discussion about the value of data, including digital twin data, is the management of the lifecycle of that data. In addition to the operational lifecycle of that data, there may be other lifecycle tracks such as the lifecycle of the physical asset that is being twinned, the lifecycle of business value (discussed above), and the compliance lifecycle (as required by regulations, laws, insurance, etc.) The above will invariably translate into additional functional and architectural requirements that must be catered for during the development of the digital twin, for example, the requirements for interoperability, scalability, and performance of the digital twin.

The implementation methodologies and best practices for digital twins do not have to be developed in a vacuum. Organizations have well-established implementation methodologies and best practices for IT-based business systems, widely referenced in sectors such as government, military, banking, insurance, telcos, healthcare, manufacturing (business side), and many others. These implementation methodologies and best practices should be adapted to accommodate the unique characteristics of digital twins.

One trend worth noting is that more and more digital twins will be implemented with advanced analytics and AI components. The unique characteristics of AI, place additional demands in the manner in which the digital twin must deal with data, including response time, latency, security, temporal data correlation, orchestration, and reusability. The implementation methodologies and best practices that are adopted for digital twins must cater to the additional considerations related to the AI data (e.g., training and operation data sets).

Along that same evolutionary trend, digital twins will increasingly be implemented within the wider concept of a system of systems , imposing unique characteristics, such as operational and managerial independence of the individual systems, emergent behavior of geographically distributed components, and evolutionary development of the overall system and its subsystems.

6 Discussion

We now synthesize key takeaways from the panelists' positions. First, we contextualize the panelists' insights by relating them to the Levels of Conceptual Interoperability Model (LCIM) by Wang et al. [41], highlighting motivations for reaching high levels of interoperability and discussing potential enablers to achieve this (Sec. 6.1). Then, we distill the main challenges (Sec. 6.2) and success factors of digital twin interoperability (Sec. 6.3), and identify directions for prospective researchers (Sec. 6.4).

6.1 Towards higher level of interoperability

The overarching theme of the panel discussion was the meeting of ambitions and opportunities to achieve higher levels of interoperability in modern systems subject to digital twinning. It seems that **there is a clear need for more advanced interoperability in digital twins**. This need, coupled with the fact that current digital twins exhibit relatively simplistic interoperability mechanisms, should draw the attention of prospective researchers to this topic.

Levels of interoperability. The Levels of Conceptual Interoperability Model framework (LCIM) [41] defines seven interoperability levels. At the first level, *L0*, there is no interoperability between systems. At the *L1 (Technical)* level, systems have technical links through which they can exchange data, restricted to the low level of bits and bytes. At the *L2 (Syntactic)* level, systems have an agreed protocol to exchange data in the proper form, but there is no semantics to the data, i.e., the "meaning" of data is not established. At the *L3 (Semantic)* level, systems exchange a set of terms that they can semantically interpret.

Ferko et al. [19] report that current digital twins are restricted to these latter two levels, *L2* and *L3*, and digital twinning scenarios typically do not show ambitions to reach higher levels.

In contrast, emerging evidence from this panel suggests that there is indeed motivation to reach higher levels of interoperability, and that there are methods to achieve this. These higher levels are covered in the LCIM as follows. At the *L4 (Pragmatic)* level, systems are aware of their context, such as system states and processes, as well as the meaning of the information they exchange. At the *L5 (Dynamic)* level, systems are able to influence the production and consumption of data, based on the analysis they need to carry out, triggered by changes in the context over time. Finally, at the *L6 (Conceptual)*, systems are completely aware of each other's information, context, and modeling assumptions, resulting in coherent, collective reasoning faculties.

In the following, we give an account of three important transitions in interoperability levels, summarized in Tab. 1.

From L3 (Semantic) to L4 (Pragmatic) interoperability. As Dawn Tilbury puts it forward in her strategic perspective on digital twin multiplicities (Sec. 2),

Table 1. Motivations and enablers of interoperability transitions in twinned systems

Transition	Motivation	Enablers
L3→L4	Deployment of vendor-supplied digital twins into a system of digital twins (Sec. 2)	Co-simulation (Sec. 3)
L4→L5	Maintenance needs of digital twins, reuse of previously developed digital twins (Sec. 2)	Digital twin evolution [10], technical sustainability [13]
L5→L6	AI-driven advanced analytics in systems of digital twins (Sec. 5)	Validity frames [30, 40], ontologies [8]

"*In the future, the digital twins for the machines and robots may be supplied by their vendors, and trained on historical data for these particular machines operating in different contexts. In this case, the context or environmental parameters must either be measurable by the digital twin or specified by the integrator.*" The deployment of such vendor-supplied digital twins into an organization's existing system of digital twins requires sound alignment of digital twins. Digital twins need to be able to exchange metadata that enriches data and promotes it to information; business and technical workflows need to be put in place to orchestrate or coordinate digital twins; and contextual information of the deployed environment must be taken into account. These requirements are the same as the requirements of the *L4* level of pragmatic interoperability in the LCIM.

Apart from these requirements, the key enabler to achieve the *L4* level, according to the LCIM [41, Table 1], is simulation implementation. As highlighted by Claudio Gomes in his technical perspective (Sec. 3), co-simulation offers mature solutions here. For example, models can be transferred as FMUs, providing semantic information between digital twins in a compact fashion.

From L4 (Pragmatic) to L5 (Dynamic) interoperability. The strategic perspective motivates further improvements in interoperability. "*Once a digital twin has been successfully verified and deployed, it needs to be maintained and potentially updated (especially if the context changes). Ideally, the successful digital twin can be used as a template to create digital twins for similar processes, or in similar contexts.*" Indeed, as digital twinning is a costly and resource-intensive endeavor, it is expected that developed and deployed solutions exhibit elevated technical sustainability, i.e., the ability to preserve their function over a prolonged time [22]. This is especially true in open-ended and reactive systems, such as digital ecosystems, that are typically driven by digital twins [13]. The *L5* level of interoperability requires the ability to react to contextual changes, specifically in terms of data collection and processing.

Digital twin evolution methods [10], e.g., through automation by reinforcement learning [9] offer high potential. However, digital twin evolution is an emerging field still in its infancy, limiting the possibility of reaching higher levels of interoperability.

From L5 (Dynamic) to L6 (Conceptual) interoperability. As explained by Bassam Zarkout in his organizational and data perspective, "*One trend worth noting is that more and more digital twins will be implemented with advanced analytics and AI components.*" Sound conclusions require congruent context and model assumptions, which are foundational assumptions in traditional modeling and simulation [2, 29]. In AI, however, it is not trivial to assess the congruence of models that have been trained on large volumes of data and are typically black boxes for the human eye. At the *L6* level of interoperability, systems are required to understand each other's information, context, and modeling assumptions. As such, AI-driven systems of digital twins require *L6* level interoperability.

The LCIM is vague about the potential solutions and simply requires a documented conceptual model to achieve the *L6* level [41, Table 1]. Better-suited techniques are offered by model-driven and model-based engineering. Validity frames—structured and formal descriptions of contextual information under which the soundness of analyses can be guaranteed—have been a topic of interest for decades in the simulation community [43]. Recent developments in semantic validity [30, 40], position validity frames as potential enablers of coordinated AI systems that drive digital twins at the *L6* level of interoperability. Additionally, ontological techniques can be used to take steps towards explaining AI [8], allowing for a better representation of AI model assumptions.

Cross-cutting concerns. There are two concerns in our scope that arch through the *L3-L4-L5-L6* trajectory of transitions and support each step.

First, standardization, as explained by Gordon Shao (Sec. 4), can accelerate improvements in interoperability by providing common frameworks for all involved parties. For example, the commonly used ISO 23247 Digital Twin Framework for Manufacturing defines a dedicated functional entity in support of interoperability: "*the Interoperability Support FE enables integration between digital twins and other systems such as Enterprise Resource Planning and Product Lifecycle Management systems*".

Second, data valuation, as explained by Bassam Zarkout (Sec. 5), is becoming an increasingly more pronounced interest of organizations. "*Organizations are increasingly interested in exploring the value of their data assets and how this value can be leveraged to support the corporate objectives of the organization.*" Infonomics, the discipline of asserting economic value to information [26], is a prime candidate to support organizations in connecting data value to corporate objectives. Assessing the economic value of information helps organizations treat information as a financial asset and leverage traditional value management techniques companies are familiar with. Infonomics has been a success in driving corporate data strategies, and thanks to its recent adoption for digital twins [11], it is ready to be used in support of improving the interoperability of digital twins.

6.2 Challenges

Complexity seems to be an overarching concern among viewpoints. Indeed, the vast and elaborate functionality of digital twins and the hierarchical structure of SoDTs are pushing the boundaries of the state-of-the-art and have effectively rendered prevalent systems engineering methods unsustainable [12]. This complexity challenges establishing reliable and stable interoperability among digital twins. The multiplicities of digital twins in modern SoDTs help deal with increasingly more elaborate physical twins. However, this comes at the cost of increased operational independence and often, geographic distribution of SoDTs. In such settings, traditional enterprise architecture models might face limitations and need to be adapted to accommodate the particularities of digital twins [4].

One such particularity is **data and its management**. There are substantial challenges to seamlessly integrating diverse functional subsystems in which data typically do not follow a common format. Interoperability is substantially hindered by these challenges as no common data representation might be assumed. This is especially concerning in real-time data processing typical in digital twins. The unique characteristics of AI—such as (1) the need for voluminous data of the numeric type, (2) the need for labeled data for supervised learning, and (3) the recency and relevance of data—further exacerbate these concerns and place additional demands on how the digital twin must deal with data.

The much-needed **interplay between different suppliers** along the supply chain poses additional challenges to interoperability. IP protection bears elevated importance for companies, and techniques that might work in traditional systems engineering settings, such as exchangeable black box models, are often not considered strong enough and resistant to special forms of cryptographic attacks and system identification. This is due to the ability to freely interact with a black box to a sufficient extent allowing it to extract its underlying structure. These threats hinder interoperability to an extent that is particularly challenging to overcome. Soon, digital twins may be supplied by hardware and machine vendors with models pre-trained on historical data of the particular machine. This raises the need for adaptability of digital twin models and integration with other digital twins within companies. Currently, no development methods and tools exist to support the integrator or adopter organization in these tasks.

Standards seem to be crucial in overcoming these challenges. However, there are fewer standards developed for digital twins thus far. SoDTs, distributed, and high-availability digital twins pose a particular challenge to current technical standards such as FMI/FMU. The lack of standards is due to the complex and time-consuming nature of their development. These endeavors require extensive collaboration and consensus-building among government bodies, industry experts, and academic researchers.

6.3 Success factors

On the flip side of data management challenges, the exponential increase of **available data** in digital twins creates opportunities [7, 39]. Companies that are able to tame data-related challenges can leverage a central data infrastructure to drive the interoperability of digital twins. For example, well-managed data lakes with stable APIs can serve as the information glue between digital twins [37].

Standardization plays a critical role in achieving interoperability by defining common rules and specifications. While being part of standardization efforts might be beyond the reach of the majority of companies, adopting standards creates an immense competitive edge. For example, standardized interfaces, such as those defined by the FMI standard enable an array of benefits, e.g., the uniform exchange of models, reuse of simulation units, and black-box simulator support along the supply chain. Adopting standardized digital twin architectures [36] further aids establishing interoperability.

Among the **organizational success factors** of digital twin interoperability, two big groups emerge: the ability to leverage existing know-how, and staffing with the right mindset. Leveraging organizational best practices and existing IT systems can be achieved by properly adapting them to digital twins. On a related note, existing standards (e.g., for data collection, data security, and simulation) can help avoid fragmentation and duplication of efforts. The proper usage of standards allows for important technical success factors, such as deferring security control to companies, e.g., through on-prem simulators governed by traditional IT security rules. All this requires recruiting the right subject-matter experts who are also able to utilize the benefits of digital twins and aid their evolution while ensuring proper interoperability principles [38].

6.4 Future research directions

Digital twin **interoperability frameworks and lifecycle models** have emerged as the most important research direction for the near future. This primarily includes interoperability frameworks that define common interfaces, protocols, and integration patterns for digital twins. To this end, semantic techniques seem particularly promising, e.g., semantic alignment by developing standardized ontologies and semantic models. End-to-end digital twin lifecycle models are also crucial in understanding and controlling the proper interoperability in SoDTs. This also includes data lifecycle models and common data models that capture the essential information and relationships within digital twins.

As we build increasingly more complex SoDTs, their **testing and validation** might need more standardization, especially with a focus on enhancing the credibility and trustworthiness of single digital twins—two crucial prerequisites of interoperability. On a related note, traditional **certification methods have to evolve** to deal with the uncertainty that stems from the often ambiguous scope of the digital twin's responsibility at the time of deployment. The challenge here is analogous to the certification of systems that contain AI components.

Ensuring **security and privacy** in digital twins subject to interoperable behavior is currently in the early stages of research, leaving substantial room for improvement both in research and application communities. In a broader context, ensuring the **eight "ility"s** of modularity, re-usability, interoperability, interchangeability, V&V capability, maintainability, extensibility, and sustainability have plenty of research potential, for example, supporting them through **AI and Machine Learning** based digital twin engineering techniques [14], supporting technical sustainability by systematic **digital twin evolution** mechanisms [10], and defining libraries of **digital twin building blocks** in support of modularity and re-usability [25].

7 Conclusion

In this paper, we reported on a panel discussion on the interoperability of digital twins organized at the 2023 Annual Modeling and Simulation Conference (ANNSIM). The complexity of systems subject to digital twinning often necessitates the development of subject matter specific digital twins and subsequently organizing them into a system of digital twins, in which interoperability is a key enabling mechanism. Such scenarios regularly emerge in companies that exhibit siloed forms and strict organizational boundaries: digital twins developed within single siloes must be able to cooperate as well. Digital twin interoperability has been gaining particular interest among academic scholars, industry experts, and standardization bodies.

By approaching digital twin Interoperability from four different, complementary viewpoints-—strategic, technical, standardization, and organizational—we drew key takeaways regarding the challenges, success factors, and future research directions in interoperability of digital twins. The main takeaway of the panel is that contrary to the state of affairs in digital twinning that limits interoperability to low levels, there is a clear need to reach higher levels of interoperability in digital twinning scenarios that necessitate a distributed approach. Moreover, there are emerging solutions to achieve these higher levels—three of which have been discussed here (co-simulation, standardization, infonomics).

Our report contributes to a rapidly growing body of knowledge on digital twins, and aims to support academists in steering their research, and practitioners and decision-makers in assessing the potential of digital twins in their organizations.

References

1. Ahmadi-Assalemi, et al.: Digital Twins for Precision Healthcare, pp. 133–158. Springer (2020), https://doi.org/10.1007/978-3-030-35746-7_8
2. Bézivin, J.: On the unification power of models. Software & Systems Modeling **4**(2), 171–188 (May 2005), ISSN 1619-1374, https://doi.org/10.1007/s10270-005-0079-0, URL `https://doi.org/10.1007/s10270-005-0079-0`
3. Bordeleau, F., et al.: Towards model-driven digital twin engineering: Current opportunities and future challenges. In: Systems Modelling and Management, pp. 43–54, Springer (2020), ISBN 978-3-030-58167-1

4. Bork, D., et al.: The Role of Modeling in the Analysis and Design of Sustainable Systems: A Panel Report. Communications of the Association for Information Systems (2024)
5. Buck, J.T., Ha, S., Lee, E.A., Messerschmitt, D.G.: Ptolemy: A framework for simulating and prototyping heterogeneous systems **4**, 155–182 (1994)
6. Caprari, G., Castelli, G., Montuori, M., Camardelli, M., Malvezzi, R.: Digital twin for urban planning in the green deal era: A state of the art and future perspectives. Sustainability **14**(10) (2022), ISSN 2071-1050, https://doi.org/10.3390/su14106263, URL https://www.mdpi.com/2071-1050/14/10/6263
7. Combemale, B., et al.: A hitchhiker's guide to model-driven engineering for data-centric systems. IEEE Software (2020)
8. Confalonieri, R., Guizzardi, G.: On the multiple roles of ontologies in explainable ai (2023)
9. Cronrath, C., Aderiani, A.R., Lennartson, B.: Enhancing digital twins through reinforcement learning. In: 2019 IEEE 15th International conference on automation science and engineering (CASE), pp. 293–298, IEEE (2019)
10. David, I., Bork, D.: Towards a taxonomy of digital twin evolution for technical sustainability. In: ACM/IEEE International Conference on Model Driven Engineering Languages and Systems Companion, MODELS-C, pp. 934–938, IEEE (2023), https://doi.org/10.1109/MODELS-C59198.2023.00147
11. David, I., Bork, D.: Infonomics of Autonomous Digital Twins. In: Advanced Information Systems Engineering - 36th International Conference, CAiSE 2024, Limassol, Cyprus, 2024, Proceedings, LNCS (2024)
12. David, I., Bork, D., Kappel, G.: Circular Systems Engineering. Software and Systems Modeling (2024), https://doi.org/10.1007/s10270-024-01154-4
13. David, I., Michael, J., Bork, D.: Digital twin evolution for sustainable smart ecosystems (2024)
14. David, I., Syriani, E.: Automated Inference of Simulators in Digital Twins. CRC Press (2023), ISBN 978-1-032-54607-0, to appear
15. Dreyfus, P.A., Psarommatis, F., May, G., Kiritsis, D.: Virtual metrology as an approach for product quality estimation in industry 4.0: a systematic review and integrative conceptual framework. International Journal of Production Research **60**(2), 742–765 (2022), https://doi.org/10.1080/00207543.2021.1976433
16. Esterle, L., Gomes, C., Frasheri, M., Ejersbo, H., Tomforde, S., Larsen, P.G.: Digital twins for collaboration and self-integration. In: 2021 IEEE International Conference on Autonomic Computing and Self-Organizing Systems Companion (ACSOS-C), pp. 172–177, IEEE (2021), ISBN 978-1-66544-393-7, https://doi.org/10.1109/ACSOS-C52956.2021.00040
17. Feng, H., Gomes, C., Gil, S., Mikkelsen, P.H., Tola, D., Larsen, P.G., Sandberg, M.: Integration Of The Mape-K Loop In Digital Twins. In: 2022 Annual Modeling and Simulation Conference (ANNSIM), pp. 102–113, IEEE (2022), ISBN 978-1-71385-288-9, https://doi.org/10.23919/ANNSIM55834.2022.9859489

18. Feng, H., et al.: Introduction to Digital Twin Engineering. In: 2021 Annual Modeling and Sim. Conf. (ANNSIM), pp. 1–12, IEEE (2021), ISBN 978-1-56555-375-0, https://doi.org/10.23919/ANNSIM52504.2021.9552135
19. Ferko, E., Bucaioni, A., Behnam, M., Pelliccione, P.: Analysing interoperability in digital twin software architectures for manufacturing. In: 17th European Conf. on Software Architecture (2023)
20. Gomes, C., Thule, C., Broman, D., Larsen, P.G., Vangheluwe, H.: Co-simulation: A Survey **51**(3), 49:1–49:33 (2018), https://doi.org/10.1145/3179993
21. Gräber, M., Kirches, C., Scharff, D., Tegethoff, W.: Using functional mock-up units for nonlinear model predictive control. In: Linköping Electronic Conference Proceedings, Linköping University Electronic Press (Nov 2012), https://doi.org/10.3384/ecp12076781
22. Hilty, L.M., Arnfalk, P., Erdmann, L., Goodman, J., Lehmann, M., Wäger, P.A.: The relevance of information and communication technologies for environmental sustainability – a prospective simulation study. Environmental Modelling & Software **21**(11), 1618–1629 (2006), ISSN 1364-8152, https://doi.org/https://doi.org/10.1016/j.envsoft.2006.05.007, environmental Informatics
23. Human, C., Basson, A., Kruger, K.: A design framework for a system of digital twins and services. Computers in Industry **144**, 103796 (2023), ISSN 0166-3615, https://doi.org/https://doi.org/10.1016/j.compind.2022.103796
24. Junghanns, A., et al.: The Functional Mock-up Interface 3.0 - New Features Enabling New Applications. In: Proceedings of the 14th International Modelica Conference, Linköping University Electronic Press, Linköpings Universitet (2021), https://doi.org/10.3384/ecp2118117
25. Kapteyn, M., Knezevic, D., Huynh, D., Tran, M., Willcox, K.: Data-driven physics-based digital twins via a library of component-based reduced-order models. International Journal for Numerical Methods in Engineering **123**(13), 2986–3003 (2022), https://doi.org/https://doi.org/10.1002/nme.6423
26. Laney, D.B.: Infonomics. Routledge (Sep 2017), https://doi.org/10.4324/9781315108650
27. Laughman, C., Bortoff, S.A.: Nonlinear state estimation with FMI: Tutorial and applications. In: Linköping Electronic Conf. Proceedings, Linköping University Electronic Press (Nov 2020), https://doi.org/10.3384/ecp20169186
28. Lee, E.A., Niknami, M., Nouidui, T.S., Wetter, M.: Modeling and Simulating Cyber-physical Systems Using CyPhySim. In: 12th Intl. Conf. on Embedded Software, pp. 115–124, IEEE (2015), ISBN 978-1-4673-8079-9, https://doi.org/10.1109/EMSOFT.2015.7318266
29. Minsky, M.: Matter, mind and models. In: Proceedings of the International Federation of Information Processing Congress, pp. 45–49 (1965), available at http://web.media.mit. edu/ minsky/papers/MatterMindModels.html
30. Mittal, R., Eslampanah, R., Lima, L., Vangheluwe, H., Blouin, D.: Towards an ontological framework for validity frames. In: 2023

ACM/IEEE International Conference on Model Driven Engineering Languages and Systems Companion (MODELS-C), pp. 801–805 (2023), https://doi.org/10.1109/MODELS-C59198.2023.00128
31. Mosterman, P.J., Vangheluwe, H.: Computer automated multi-paradigm modeling: An introduction. SIMULATION **80**(9), 433–450 (2004), https://doi.org/10.1177/0037549704050532
32. Moyne, J., Qamsane, Y., Balta, E.C., Kovalenko, I., Faris, J., Barton, K., Tilbury, D.M.: A requirements driven digital twin framework: Specification and opportunities. IEEE Access **8**, 107781–107801 (2020), https://doi.org/10.1109/ACCESS.2020.3000437
33. Rasheed, A., San, O., Kvamsdal, T.: Digital twin: Values, challenges and enablers from a modeling perspective. IEEE Access **8**, 21980–22012 (2020), https://doi.org/10.1109/ACCESS.2020.2970143
34. Redelinghuys, A.J.H., Kruger, K., Basson, A.: A six-layer architecture for digital twins with aggregation. In: Service Oriented, Holonic and Multi-agent Manufacturing Systems for Industry of the Future, pp. 171–182, Springer International Publishing, Cham (2020), ISBN 978-3-030-27477-1
35. Schweers, C., Kruse, D., Oesterwinter, T., Trächtler, A.: Automated design of an Unscented Kalman Filter for state- and parameter estimation on unknown models. In: 2013 International Conference on Control, Automation, Robotics and Embedded Systems (CARE), pp. 1–6 (2013), https://doi.org/10.1109/CARE.2013.6733760
36. Shao, G.: Use case scenarios for digital twin implementation based on ISO 23247. Tech. rep. (2021), https://nvlpubs.nist.gov/nistpubs/ams/NIST.AMS.400-2.pdf
37. Singh, S., Shehab, E., Higgins, N., Fowler, K., Tomiyama, T., Fowler, C.: Challenges of digital twin in high value manufacturing. In: SAE Technical Paper Series, SAE Intl. (2018), https://doi.org/10.4271/2018-01-1928
38. Stoewer, H., Nichols, D.: Building the systems engineering workforce of the future (2022)
39. Tao, F., Zhang, H., Liu, A., Nee, A.Y.C.: Digital twin in industry: State-of-the-art. IEEE Transactions on Industrial Informatics **15**(4), 2405–2415 (2019), https://doi.org/10.1109/TII.2018.2873186
40. Van Acker, B., De Meulenaere, P., Vangheluwe, H., Denil, J.: Validity frame–enabled model-based engineering processes. SIMULATION **100**(2), 185–226 (2024), https://doi.org/10.1177/00375497231205035, URL https://doi.org/10.1177/00375497231205035
41. Wang, W., Tolk, A., Wang, W.: The Levels of Conceptual Interoperability Model: Applying Systems Engineering Principles to M&S. In: Proceedings of the 2009 Spring Simulation Multiconference, SCS (2009)
42. Welch, G., Bishop, G.: An introduction to the kalman filter. In: Proc of SIGGRAPH, Course 8, no. 27599–23175 (2001)
43. Zeigler, B.P., Praehofer, H., Kim, T.G.: Theory of modeling and simulation. Academic press (2000)