Harnessing hybrid digital twinning for decision-support in smart infrastructures

Journal Article

Author(s):
Liang, Huangbin; Moya, Beatriz; Seah, Eugene; Ng Kwok Weng, Ashley; Baillargeat, Dominique; Joerin, Jonas; Zhang, Xiaozheng; Chinesta, Francisco; Chatzi, Eleni

Publication date:
2025-08

Permanent link:
https://doi.org/https://doi.org/10.3929/ethz-c-000785247

Originally published in:
Data-Centric Engineering 6, https://doi.org/10.1017/dce.2025.10015

Data-Centric Engineering (2025), 6: e43
doi:10.1017/dce.2025.10015

CAMBRIDGE
UNIVERSITY PRESS

POSITION PAPER

Harnessing hybrid digital twinning for decision-support in smart infrastructures

Huangbin Liang[1], Beatriz Moya[2,3], Eugene Seah[4], Ashley Ng Kwok Weng[5], Dominique Baillargeat[2], Jonas Joerin[1], Xiaozheng Zhang[6], Francisco Chinesta[2,3] and Eleni Chatzi[1,7]

[1]Singapore-ETH Centre, Singapore, Singapore
[2]CNRS@CREATE, Singapore, Singapore
[3]PIMM Laboratory, ENSAM Institute of Technology, Paris, France
[4]Meinhardt Group, Singapore, Singapore
[5]CETIM-Matcor, Singapore, Singapore
[6]TÜV SÜD, Singapore, Singapore
[7]Department of Civil Environmental and Geomatic Engineering, ETH Zurich, Zurich, Switzerland
Corresponding author: Beatriz Moya; Email: beatriz.moya_garcia@ensam.eu

Received: 05 August 2024; **Revised:** 01 April 2025; **Accepted:** 01 May 2025

Keywords: decision-making; hybrid digital twin; resilience support; smart infrastructures; infrastructural management

Abstract
Digital Twinning (DT) has become a main instrument for Industry 4.0 and the digital transformation of manufacturing and industrial processes. In this statement paper, we elaborate on the potential of DT as a valuable tool in support of the management of intelligent infrastructures throughout all stages of their life cycle. We highlight the associated needs, opportunities, and challenges and discuss the needs from both the research and applied perspectives. We elucidate the transformative impact of digital twin applications for strategic decision-making, discussing its potential for situation awareness, as well as enhancement of system resilience, with a particular focus on applications that necessitate efficient, and often real-time, or near real-time, diagnostic and prognostic processes. In doing so, we elaborate on the separate classes of DT, ranging from simple images of a system, all the way to interactive replicas that are continually updated to reflect a monitored system at hand. We root our approach in the adoption of hybrid modeling as a seminal tool for facilitating twinning applications. Hybrid modeling refers to the synergistic use of data with models that carry engineering or empirical intuition on the system behavior. We postulate that modern infrastructures can be viewed as cyber-physical systems comprising, on the one hand, an array of heterogeneous data of diversified granularity and, on the other, a model (analytical, numerical, or other) that carries information on the system behavior. We therefore propose hybrid digital twins (HDT) as the main enabler of smart and resilient infrastructures.

Impact Statement
We advocate for the adoption of Hybrid Digital Twinning (HDT) as a main enabler for transforming strategic decision-making and enhancing system resilience within the domain of infrastructure. In clarifying the modus operandi of DT technologies, this paper highlights the strengths and potential of digital twin technologies and aspires to lay the foundations for the development of next-generation digital twins for smart infrastructures. This study summarizes the insights gained from a round-table discussion on Decision Support for Infrastructural Asset

H.L. and B.M. contributed equally to this work.

Management, which was held as a joint initiative of the Future Resilient Systems (FRS) program at the Singapore-ETH Centre and the DESCARTES interdisciplinary excellence program at CNRS@CREATE.

1. Introduction

Engineering infrastructures form the backbones of our society. Under the mandate of Industry 4.0, the digital revolution has brought about a paradigm shift in how we design, produce, and interact with physical assets (Oztemel and Gursev, 2020). While digitization has been broadly adopted in the context of manufacturing and production technologies and the handling of industrial assets, it remains underutilized in large-scale built environments, such as infrastructures. Building Information Modelings (BIMs) dominate the field, primarily serving as static images for the design and construction phases (Sacks et al., 2020). However, also on this scale, the concept of Digital Twinning (DT) has the potential not only to deliver information on the state of the system "as is," but also to inform decision support frameworks further. These frameworks operate throughout the structural life cycle, namely from the stage of manufacturing/construction, to the stage of operation under standard as well as extreme loads and hazards, and finally to the decommissioning phase. To add value, DT representations should enable a closed-loop exchange between digital and physical assets. This involves extracting information garnered from operating physical systems (e.g., by means of monitoring) and distilling this information via the use of digital representation. Finally, this analysis would be exploited to act on the physical asset to protect critical infrastructure and guarantee its resilience (Argyroudis et al., 2022).

Infrastructure resilience is used here as the main criterion based on which strategic decision-making can be made. It can be defined as the ability to anticipate, prepare for, and adapt to environmental changes, as well as cope with, respond to, and recover rapidly from extreme disruptions (Cimellaro et al., 2016). Numerous studies in recent years have focused on infrastructure resilience under adverse environmental impacts and exposure to extreme events. These studies put forth frameworks for quantifying and enhancing resilience across scales, from components and individual assets, to interconnected networks (Ouyang et al., 2012; Cimellaro et al., 2016; Dhar and Khirfan, 2017; Koliou et al., 2020; Blagojević et al., 2023; Liang et al., 2023). This analysis is typically conducted in the pre-incident phase using simulated scenarios with stochastic deterioration/fragility and restoration models, without accounting for information that is gathered from the actual system over time. Our primary focus lies on decision-making in the context of *during-incident* and *post-incident* phases, which usually require fast (sometimes even real-time) decision-making. The premise for such an investigation assumes the availability of data from infrastructural assets and systems. This is nowadays justified by the growing availability of information, which includes not just digitized logs with inspection information on structural systems, but also the increasing use of sensing technologies to monitor these systems, on both a periodic (e.g., Non Destructive Evaluation) and continuous (e.g., Structural Health Monitoring) evaluation (Kamariotis et al., 2024).

Currently, there is no integrated framework for quantifying and enhancing infrastructure resilience based on the fusion of such data within DT techniques. Hence, the objective of this paper is to

- clarify the current landscape in terms of available DT representations,
- define Hybrid Digital Twins (HDTs) as a class of DTs that is particularly suited for infrastructural assets, when viewed under the prism of cyber-physical systems,
- illustrate the potential application of HDTs in support of decision-making for performant and resilient infrastructures,
- and finally, highlight the associated challenges and opportunities in this respect.

2. Motivation for integrating HDTs in infrastructural management

DT refers to the development the creation of virtual representations of physical assets that integrate sensor data, system simulations, and analytics. This integration provides decision-makers with

https://doi.org/10.1017/dce.2025.10015 Published online by Cambridge University Press

unprecedented, often real-time, insights into the condition and behavior of physical assets, which refer to any physical object, system, or infrastructure holding economic value to an organization(e.g., building, bridge, wind energy structures). Unlike traditional periodical and reactive decision-making methods, the integration of DT introduces predictive analytics, which are informed based on real-time and historical data collected from the physical asset in operation. This forecasting potential supports proactive management of operations, maintenance, and resilience against risks and hazards. A significant limitation of purely data-driven Digital Twin (DT) models is their lack of generalizability and interpretability. This issue often arises from the insufficiency of representative data, which can lead to overfitting and poor performance in unseen scenarios. Additionally, the absence of physical knowledge integration in these models can hinder the ability to interpret model predictions and accurately capture intricate dynamics needed for accurate predictions, limiting their effectiveness in decision support for infrastructure management.

Aiming for greater accuracy and effective decision-making, we use the term hybrid digital twinning (HDT) to refer to an advanced form of digital twinning that explicitly incorporates a physics-based model of the system (which can be numerical, analytical, or empirical) within a process that further feeds from data. The integration of physics-based models fundamentally distinguishes HDTs from purely data-driven DTs by enhancing predictive capabilities and ensuring physically grounded predictions. HDTs uniquely enable the generalization of predictions beyond the positions of sensor observations, facilitating virtual sensing of system responses in critical, unmonitored locations (Papatheou et al., 2023; Vettori et al., 2023). This generalization capability is essential for managing assets under extreme and changing conditions, where reliance solely on available sensor data would be insufficient. By grounding predictions in physical principles, HDTs enhance interpretability, ensuring that predicted outcomes can be validated and trusted, which is particularly crucial for critical decision-making processes. Consequently, HDTs empower decision-makers to respond swiftly to disruptions and adapt to dynamic conditions by providing insights into both monitored and unmonitored parts of the system, supporting a proactive and transparent decision-making process. This transparency, essential for accountability and trust, is vital in sectors where decisions have significant economic and safety impacts.

This integrated approach allows decision-makers to develop a scalable framework, which is adaptable across dimensions such as asset size and degrees of freedom, interdependency, and throughout the life cycle of assets. Adaptability refers to the capacity of the framework to remain effective whether applied to a single asset or when scaled up to encompass an entire network of assets, and its potential to be consistently implemented throughout all phases, from design and construction to operation and end-of-life management. During the manufacturing and construction phase, HDT technology facilitates the integration of real-time data and model-based predictive analytics, allowing for the optimization of design processes and the embedding of resilience measures tailored to anticipated operational challenges. As assets transition into the operational phase, HDT technology continuously learns operational strategies in real time to effectively manage emerging risks and minimize downtime, especially under extreme conditions. Finally, in the decommissioning phase, HDT technology provides a data-rich basis for executing cost-effective strategies by leveraging the comprehensive historical data accumulated over the operational lifetime of the asset. An HDT embodies a closed-loop, dynamic, possibly real-time, data-driven approach to asset management that not only accounts for complex interdependencies and curbs assessment uncertainty but also operates based on the current state of the system rather than its initial deployment conditions.

Despite the clear advantages of the use of DTs and, in particular, HDTs in the context of infrastructure management and resilience, their adoption has been slow in practice. This reluctance often stems from the diverse interpretations and lack of clarity surrounding the definition and applicability of a DT/HDT, as well as the relative lack of standards and protocols for formally framing the use of such tools. This statement paper aims to clarify the definition and potential use of HDTs within the domain of smart infrastructures, exploring the need to enhance their utility and maximize their uptake.

3. Hybrid digital twins—HDTs

The implementation of digital twins presents its own set of challenges. Data integration, modeling complexity, transparency, communication among agents, and ethical concerns relating to automated decision-making are significant challenges that must be addressed to ensure an actionable application. However, the first step is to propose a framework for cross-disciplinary understanding that sets the foundation for any future development.

3.1. Definition and interpretation of digital twins

The concept of *digital twin* (DT) finds its roots in NASA's Apollo XIII project, where digital simulators and a physical replica were connected to the real spaceship to receive information from it to update its operating condition and propose mission rules based on its state, especially in critical conditions (Shafto et al., 2010). As reported in this document, this was the case with the explosion of the oxygen tanks that damaged the engine during the mission, a situation in which the simulators helped to evaluate damage and solutions to perform informed crisis management.

With the surge of Industry 4.o, DTs became a go-to term in several fields; however, the definition of the term may still appear blurred and unclear (Wright and Davidson, 2020). Certain sources ((Alam and Saddik, 2017; Hughes, 2018; Platenius-Mohr et al., 2020) to name a few) define DTs as models, simulators, replicas of existing phenomena, i.e., digital replicas of real assets. Although partially correct, this definition lacks an essential element, namely the interaction with the physical asset. More recent frameworks within the engineering context describe a DT as a process that defines a closed loop between the physical entity and the digital replica (AIAA, 2020; McClellan et al., 2022). This requires a digital workflow of information, parametrized models, diagnostic and prognostic algorithms, and control tools, often aggregated in a visualization layer, which generates value for the user and facilitates decisions.

The origin of the DT concept may be traced back to a presentation by Michael Grieves at the University of Michigan in 2002, which aimed to establish the so-called Product Lifecycle Management (PLM) framework (Grieves, 2002). However, the first known definition for the DT is considered to be the one published by NASA in (Shafto et al., 2010). In this definition, a DT is claimed to be *an integrated multiphysics, multiscale, probabilistic simulation that uses the best available physical models, sensor updates, fleet history*, etc.*, to mirror the life of its flying twin* for *recommending changes in mission profile to increase both the life span and the probability of mission success*, already signifying the key aspect of two-way interaction between the physical and digital counterpart.

Following this spirit, similar descriptions have been assigned to DTs (Glaessgen and Stargel, 2012; Saddik, 2018; Xu et al., 2019; Liu et al., 2021; Kenett and Bortman, 2022). The recent AIAA position paper (AIAA, 2020) defines a digital twin as:

> A set of virtual information constructs that mimics the structure, context and behaviour of an individual/unique physical asset, or a group of physical assets, is dynamically updated with data from its physical twin throughout its life cycle and informs decisions that realise value.

We discern three main characteristics of a DT in the various definitions offered:

- A physical asset from which information is extracted, implying the presence of a monitoring system.
- A digital (virtual) representation of the physical element, represented by a model that captures the behavior of the physical counterpart. Here we distinguish four levels of description: component, asset, system, and process.
- A one- or two-way information flow process, depending on the application, that links the digital and physical counterparts to ensure continuous tracking of the behavior of the physical asset. This is used to update the status of the digital replica, offering valuable augmented information on the state of the system, and allows for acting on it with improved confidence margins. A one-way process is also called a "digital shadow" (Bergs et al., 2021).

https://doi.org/10.1017/dce.2025.10015 Published online by Cambridge University Press

Dynamic Data-Driven Application Systems (DDDAS) (Blasch et al., 2013), is proposed as a framework for the dynamic update of simulators (models) with data obtained from sensor networks and monitoring devices. Although this framework focuses on the aspect of updating a digital mirror (essentially) of the operating physical system, the purpose of DTs extends beyond computational modeling and updating to include performance and condition assessment, analysis, and optimization of physical assets throughout their life cycle.

In the life cycle of infrastructure systems, we can distinguish five main phases: design, construction, operation, maintenance, and decommissioning. Each of these phases can be coupled with digital twins, accompanying the evolution of the system and enhancing its management and optimization throughout its life cycle. Following (Grieves and Vickers, 2017), in this work, we define DTs using a classification in three essential categories (classes), according to the purpose served by the twin throughout the life cycle:

- the *Digital Twin Prototype* (DTP)
- the *Digital Twin Instance* (DTI)
- the *Digital Twin Aggregate* (DTA)

The first DT class we refer to here is the *Digital Twin Prototype* (DTP), which reflects a virtual representation of a physical object, encompassing the essential information sets needed to characterize and fabricate a physical counterpart (for instance, requirements, 3D models, lists of materials, processes, services, and disposal procedures). This class is typically used during the design phase and is closely associated with the features and goals of Building Information Modeling (BIM) (Definition, 2014).

In the work of Grieves and Vickers (2017), a *Digital Twin Instance* (DTI) is described as a specific physical asset to which a digital counterpart remains linked throughout the life of that physical product. Here, we adopt the interpretation of McClellan et al. (2022) in relation to the notion of an instance and define a DTI as the DT of an individual instance of the product, once it is manufactured and equipped with sensors that generate data. This implies that the DTI embodies the notion of information flow between the physical and digital counterparts.

The *Digital Twin Aggregate* (DTA) (Grieves and Vickers, 2017; McClellan et al., 2022) is described as the aggregation and analysis of data from numerous DTIs, allowing for review and possible intervention regarding a set of assets. Essentially, it describes a computing construct that allows to gather and analyze data from various DTIs to gain insights with respect to a broader range of physical products or processes. A DTA can aggregate instances ranging from different DTIs of components comprising an assembly, to multiple instances from similar systems that have aggregated a collected behavior. In the latter, DTA relates to the concept of learning from fleets or populations (Worden et al., 2020), reflecting a more massive collection of data, which can enhance predictive and prognostic capabilities at the system level.

Each class of DTs will require different levels of depth, abstraction, and enrichment to properly accompany the original twin throughout various phases of the asset's life cycle. Figure 1 has now been revised to illustrate these DT classes, delineating the systematic application of DTPs, DTIs, and DTAs across various stages of physical assets. The figure employs the example use case of wind turbine operations: DTPs aid in the design phase by simulating and refining turbine structures. Multiple DTIs represent real-time operational units equipped with sensors, facilitating ongoing monitoring and immediate adjustments. The DTA synthesizes insights from individual DTIs to guide system-wide performance assessments and predictive maintenance strategies, enhancing overall operational efficiency and the longevity of the assets.

Based on the description for each DT and the needs specific to each phase of the life cycle, varying levels of detail, abstraction, and enhancement will be necessary to effectively accompany the original twin. This evolutionary spirit of DTs is reflected in Figure 2. In these definitions, information flow is assumed to be available throughout the asset's life. Models that do not continuously follow a physical asset are merely snapshots, not true DTs. In engineering, Real-Time Digital Twins (RTDTs) are digital representations updated online, in real or near real-time, as data become available.

https://doi.org/10.1017/dce.2025.10015 Published online by Cambridge University Press

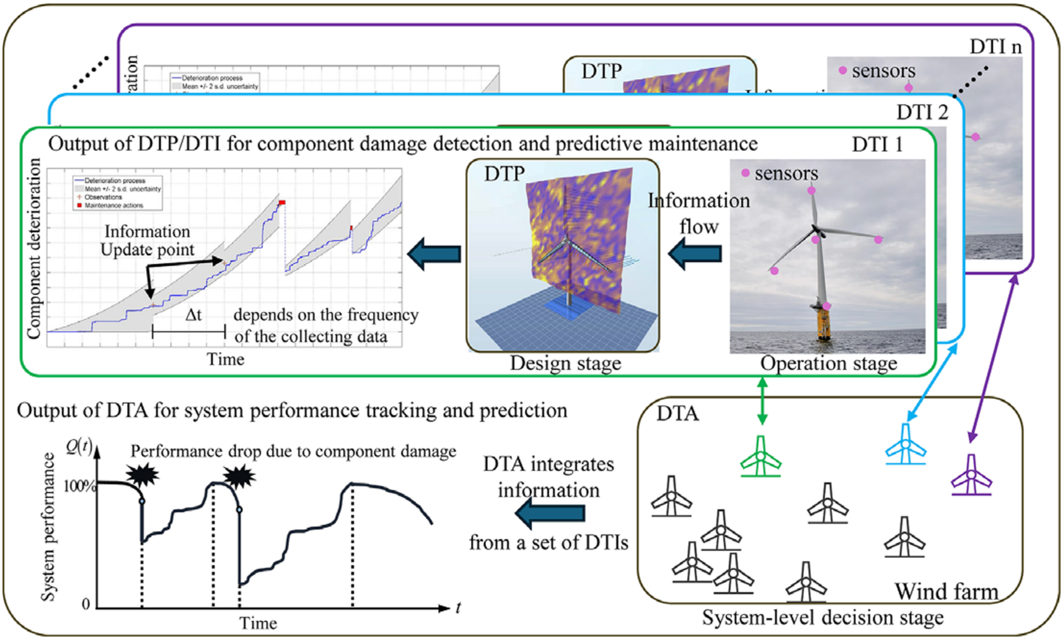

***Figure 1.** Life cycle integration of digital twin technologies for physical assets, using the example of wind farm management. DTPs aid in the design and decommissioning phases by simulating and optimizing turbine structures and the decommissioning process, while multiple DTIs represent real-time operational units equipped with sensors, facilitating ongoing monitoring and immediate adjustments. The DTA synthesizes insights from individual DTIs to guide system-wide performance assessments and predictive maintenance strategies, enhancing overall operational efficiency and longevity of the assets. DTI and DTA can evolve on a temporal scale depending on the frequency of the collecting data, where Real-Time Digital Twins (RTDTs) are specific DTs that are updated in a more frequent, real-time manner.*

DTs are powered by the use of simulators/models that provide representations of complex systems, processes, or phenomena of interest. Currently, BIM (Building Information Modeling) representations seem to prevail in terms of adoption in practice, despite them largely comprising geometric representations and metadata repositories of built objects. This observation is primarily evidenced by insights gathered from industry roundtables, where experienced practitioners emphasized the robustness and integration capabilities of BIM in the construction and engineering sectors. Whereas BIMs, as mainly adopted today, are closer to what one would define as "as-designed geometric models," effective DTs require more computational capabilities. Such more efficient models can be obtained via the use of structural (finite element) models and well-established formulations such as fluid mechanics, transient dynamics, and degradation models. To make such models actionable within a twinning framework, it is necessary to deliver reliable, yet reduced-order representations that can incorporate physics in a way that is manageable for the process at hand. Reduced Order Models (ROMs) significantly contribute by offering swift emulations of a monitored system with manageable computational expenses (Frangos et al., 2010; Chinesta et al., 2011; Amsallem et al., 2012; Farhat et al., 2018; Kapteyn et al., 2020; Vlachas et al., 2021; Agathos et al., 2022, 2024; Idrissi et al., 2022). ROMs are mathematical representations of complex systems that aim to provide simplified but accurate predictions of system behavior. When incorporating physics principles, such ROMs are often referred to as intrusive (Chinesta and Cueto, 2014). Although there are nonintrusive, that is, purely data-driven techniques that employ data from simulations or experiments to bypass physics (Ibáñez et al., 2018; Hernandez et al., 2021), the imposition of physics biases is often desirable to ensure interpretability (Vlachas et al., 2012; Bacsa et al., 2023; Liu et al., 2025).

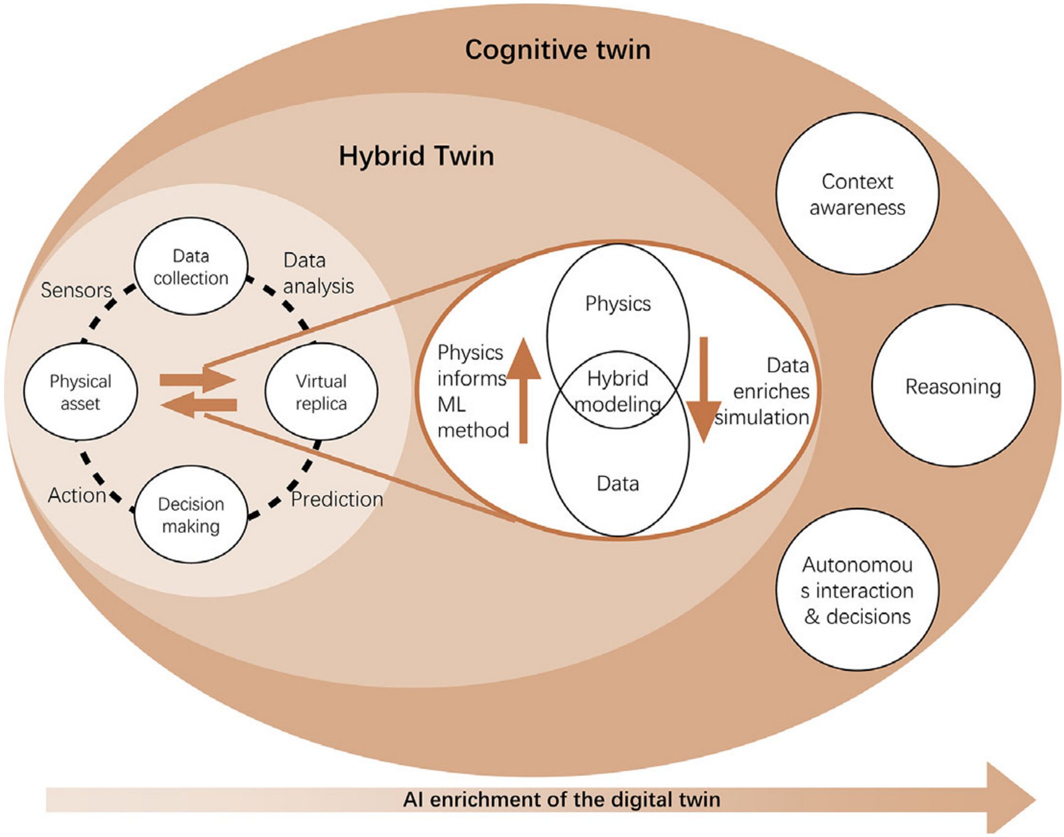

Figure 2. *Landscape of the DT paradigm. The HDT includes hybrid modeling to enrich simulations with aspects of physics and machine learning (ML) to accurately mimic the behavior of real systems. Such a construct offers higher interpretability. Finally, cognitive digital twin (CDT) would combine previous technologies with scene understanding and autonomous decision-making. As a result, the DT progressively increases in complexity and opportunities.*

Accompanying the real asset along its useful life requires the capacity of adaptation and re-engineering along its different phases, with flexible configurations that may have to respond to previously unseen conditions. In this regard, McClellan et al. (McClellan et al., 2022) also highlight the role of current developments such as artificial intelligence (AI), machine learning (ML), deep learning (DL), and data analytics to correctly fill the gap between the simulation model, usually defined by known physics, and the real behavior perceived as a manner to extend the capabilities of the original ROMs that reproduce the physics of the real asset.

AI-informed ROMs strongly depend on data quality and availability. To overcome this limitation, new techniques driven by physical knowledge may find patterns and reconstruct missing information. This involves embracing the smart data regime, which involves the right information, at the right moment, and right place. ML and DL can synergistically be combined with hybrid models, enhancing their explainability and predictive potential (Montáns et al., 2019; Champaney et al., 2022; Kenett, 2024). Such an instance has emerged in physics-enhanced or physics-informed modeling, which capitalizes on the fusion of physics principles, data, and ML, with this mixing assigning different weights to the mixed components, as explained in (Haywood-Alexander et al., 2023). Physics-informed digital twins (PIDT) are those digital twin representations that incorporate domain-specific knowledge of physics principles and laws, offering interpretable models that effectively capture the system's inherent dynamics (Kapteyn and

Willcox, 2020; Liu et al., 2025). While PIDTs require more development effort, they provide transparency and fidelity, making them well-suited for applications where understanding and certifiability are essential. The choice between these approaches depends on the specific requirements of the problem at hand, which balance predictive power with interpretability and reliability. Some versatile examples are those that employ known descriptions of the system, such as partial differential equations, or algorithms founded in known physical laws (Tatsis et al., 2022; Vlachas et al., 2022; Haywood-Alexander and Chatzi, 2023; Zhang and Zhao, 2023; Yang et al., 2024), such as those of thermodynamics (Hernandez et al., 2022; Cueto and Chinesta, 2023), and preservation of physical quantities (Kirchdoerfer and Ortiz, 2016; Bacsa et al., 2023).

Under this premise, we refer to *hybrid digital twins* (HDTs) as twin constructs that create a more comprehensive and accurate representation of a system or process. Here, accuracy reflects the ability of the digital twin to remain aligned with real-world behavior, including in previously unseen contexts or response to evolving loads and environments. As provided in Figure 2, HDTs integrate multiple modeling paradigms—combining physics-based (white-box) models that offer transparent insights into underlying physical mechanisms with data-driven ML (black-box) approaches that enhance predictive accuracy. The resulting grey-box models fuse interpretability with adaptability, enabling a richer and more robust digital representation of physical assets or systems. Specifically, HDTs may incorporate physics knowledge as a hard constraint(physics-guided or physics-encoded) by directly embedding differential equations within the neural network architecture, ensuring that predictions adhere to known physical laws. Alternatively, HDTs can treat physics knowledge as a soft constraint (physics-informed) by adding the residual of physics-based models to the loss function to guide the learning process or to refine the outputs of ML algorithms (Chinesta et al., 2020; Haywood-Alexander et al., 2023). This integration enhances both the explainability and transparency of the twins' outputs, while improving their capacity to adapt to varying loads and environments (Wagg et al., 2025). Furthermore, hybrid modeling allows interpretable diagnostics and generalization of their predictive ability of the twin, while maintaining computational efficiency. Purely physics-based models, while strong in interpretability, typically lack practical efficiency due to slower computational speeds required for precise simulations. HDTs thus present a compelling advantage by combining the strengths of both physics-based models and data-driven approaches to deliver more reliable predictions and enable real-time monitoring and decision support across a wide range of applications (Wagg et al., 2020).

In this paradigm, there is an incipient subclass of DTs that is expected to lead the next developments in the domain: the *cognitive digital twin* (CDT) (Abburu et al., 2020; Unal et al., 2022). Cognition refers to the set of abilities that encompass sensing, thinking, and reasoning (Bundy et al., 2023). Although research applications that mimic cognition are still limited (the most common use case being large language models), the appropriate design of algorithms can lead to the integration of some of these abilities. The emerging concept of cognitive, or smart, digital twins (CDT) refers to systems that can interact with both physical and virtual environments to autonomously make smarter decisions based on context (Abburu et al., 2020; Zheng et al., 2022). Although both HDTs and CDTs use ML to enrich themselves, HDTs tend to use data and ML to fill in gaps in the knowledge of the system. In contrast, CDTs use data for complex interpretation—also called perception (Moya et al., 2023)—reasoning (autonomously making decisions about their performance), automatic calibration for improved decision-making (Arcieri et al., 2021), and interaction with the user. Although one of the outcomes can be the enrichment of HDTs, we expect CDTs to more comprehensively capture the relationship between data and physics models. The expert in the loop complements the cognitive and interoperability requirements of CDTs (Niloofar et al., 2023). The incorporation of the human cognitive dimension within the digital twin paradigm leverages the expertise and experiential knowledge, serving as a crucial facilitator in understanding the underlying rationale of decisions and their appropriateness within a specific context. Consequently, the expert-in-the-loop paradigm underscores the significance of model explainability, a salient feature during various interaction phases within a Cognitive Digital Twin (CDT).

When extending prediction/estimation at the system level, DTs may require the incorporation of representations and simulations of interconnected systems or components (Heussen et al., 2011; Ouyang,

https://doi.org/10.1017/dce.2025.10015 Published online by Cambridge University Press

2014; Schluse et al., 2018; Liang and Xie, 2021). Such representations are defined as *System-Level Models.* For example, energy system network models (Heussen et al., 2011; Ouyang et al., 2017) provide a detailed understanding of how energy flows through various components, helping to optimize energy consumption and identify potential inefficiencies.

AR (augmented reality), VR (virtual reality), and DT technology connect the physical and digital worlds (Badías et al., 2019; Moya et al., 2022; Vettori et al., 2023), enhancing user interfaces to improve understanding, collaboration, and decision-making in various fields (Michalik et al., 2022).Specifically, AR allows users to overlay digital information onto the real world, enhancing the ability to understand complex systems and processes in situ. However, VR creates a completely immersive simulation environment that is ideal for training scenarios, safety drills, and visualization of scenarios that are either dangerous or impractical to replicate in the real world. Together, AR and VR enhance DTs by improving visualization, interaction, and simulation capabilities, allowing stakeholders to analyze potential outcomes in a controlled virtual setting, facilitating more informed decision-making. This proactive approach transforms industry practices in forecasting, troubleshooting, and optimizing operations, further establishing digital twins as essential in digital transformation.

Virtual environments often use virtual sensing to simulate the behavior of sensors that exist in the real world. Although remote sensing facilitates the creation of accurate DTs of infrastructure systems (Dorafshan et al., 2018; Phillips and Narasimhan, 2019; Bado et al., 2022; Kaartinen et al., 2022), there are still scenarios where it is impractical, expensive, or insufficient, such as the case of assessing the load and prediction of the performance of DTs of wind turbine blades (Vettori et al., 2022). These virtual sensors generate data within a virtual environment, which can then be used to simulate realistic scenarios, test algorithms for sensor data processing and analysis, and perform dynamic adaptation within virtual environments.

3.2. Role of Internet of Things, real-time data analytics

The Internet of Things (IoT) involves sensor selection, deployment, acquisition, and connectivity. IoT represents not only the deployed sensing network, but also the purpose of connecting and transferring information. Most of the information comes in the form of time series or image-based representations, collected via appropriate compression schemes. IoT regimes often involve multiple and heterogeneous or multimodal data sources. Hence, DTs must be designed to flexibly tackle diversified types of data input, which is usually tackled via the aspect of fusion. Even though some measurements (strains, pressure, temperature) can be directly correlated to quantities of interest, this is not true for other sources, which deliver indirect information (such as vibration-based ones). Physically infused hybrid modeling is required to extract physical insights from diverse and indirect data.

In this context, we revisit the previously introduced concept of RTDTs, which is based on *real-time* performance, reflecting a growing desire of the industry. It is important to properly define what real time implies in practice and to consider the appropriate time scale to assess the performance of the system and the required data flow rate. We define an RTDT as a digital twin that evolves synchronously to its physical counterpart, measuring and processing the changes that occur in the physical counterpart and correspondingly updating the virtual replica, and possibly implementing feedback (in the form of actions) to the physical asset, in an online fashion (Zipper and Diedrich, 2019). However, achieving perfectly synchronous, hard real-time response with minimal delays and high sampling rates can be inefficient, requiring excessive resources and infrastructure, and increasing risks of overhead and latency. Thus, "real-time" performance in a DT varies depending on its purpose, ranging from immediate to periodic updates, influenced by data collection rates and timing for related actions or decisions."

3.3. The smart data paradigm

The data collection process can pose challenges that require a comprehensive framework for intelligent data collection, processing, and use. Table 1 summarizes primary sources of data used in the construction of DTs. System loads and response data are critical because they provide real-time feedback on infrastructure performance and condition, forming the basis for operational digital twins; external

Table 1. *Summary of main sources of data for DTs*

Type	Description
System loads and response data	Time-series data on environmental sources (e.g., pressure, wind/wave velocity), and system response/condition data (e.g., acceleration, displacement, strain, power produced, acoustic emission signals, vision-based data on defects)
External environment data	Environmental conditions and stressors that may impact the asset or the associated processes (e.g., temperature, humidity, pollution, CO_2 concentration, precipitation)
Historical and domain knowledge	Time-stamped records of past operational and maintenance actions, which can be used for analyzing and identifying trends and patterns
Geospatial and connectivity data	Geographic features, coordinates, and spatial relationships of physical entities (e.g., GIS layers, satellite imagery) and relationships between different components within a system (e.g., network diagram, fault tree)

environment data help to understand how external factors influence infrastructure performance; historical and domain knowledge helps to identify patterns and trends that inform predictive maintenance and operational optimizations; geospatial and connectivity data are essential for simulating scenarios in digital twins and improving the accuracy of the interactions and dependencies modeled. In data acquisition and communication in DT, wireless technology plays a key role, and in the future prospects of this technology, 6G networks can be potential enablers in the commitment to synchronization-delay-accuracy (Bariah et al., 2023).

Early definitions of the incipient concept of smart data refer to the extraction of valuable information from Big Data to support decision-making (Iafrate, 2014; Lenk et al., 2015). However, this terminology has evolved to refer to the formulation of data practices that focus on answering four questions, as detailed in (Chinesta et al., 2020): (1) what data to collect, (2) where to deploy sensors to extract relevant information, (3) when and for how long to deploy the system, and (4) at what scale. As a result, the so-called *smart data* pipeline possesses some specific characteristics. A key trait is trustworthiness, ensuring reliability, accuracy, and credible sources through robust data collection, quality assurance, and adherence to governance standards (Bicevskis et al., 2017; Hong and Huang, 2017; Kirchen et al., 2017).

The smart data paradigm improves downstream tasks related to *cognitive capabilities* (advanced analysis, interpretation, and learning) (Abburu et al., 2020; Zheng et al., 2022). A very intuitive classification of digital representations in relation to their function is offered in (Wagg et al., 2020). Using techniques such as AI, ML, and natural language processing, cognitive data systems understand and derive insights from complex data sets to reach a desired characteristic, namely, interpretability. This is a pivotal characteristic for hybrid modeling (Champaney et al., 2022) and can typically be achieved through the appropriate exploitation of prior knowledge on the system and its behavior (Chinesta et al., 2020). Akin to the concept of gathering meaningful data is the concept of active learning, which allows for targeting maximal information extraction based on minimal data (Settles, 2009; Chabanet et al., 2022). Active learning makes use of human expertise (Khamesi et al., 2020) or ML schemes, allowing selective guidance on labeling specific unlabeled samples, optimizing resource use, and integrating human insights into the learning process.

However, an important challenge is the fact that not all required data can be measured. Internal variables, such as energy, entropy, and strain, cannot be directly measured, and some variables, such as stress and damage, are difficult to access accurately. Partial observations also occur in space and time, and it is important to understand where and when to measure, to optimize data collection efficiency and ensure data relevance (Bigoni et al., 2020; Di Lorenzo et al., 2023). Data completeness refers to the notion of

https://doi.org/10.1017/dce.2025.10015 Published online by Cambridge University Press

ensuring the availability of all relevant information for informing the digital asset, to enhance the reliability and applicability of the model prediction. With the appropriate data collected and a proper understanding of the system, hidden patterns and information can be recovered (Schöbi and Chatzi, 2016; Liang et al., 2020; Champaney et al., 2022; Moya et al., 2022; Bermejo-Barbanoj et al., 2024; Liu et al., 2025). Data quality and observation stochasticity also need to be considered in the hybrid modeling paradigm (Vettori et al., 2024; Liu et al., 2025), to propagate and evaluate uncertainty in the prediction and asses its value and trustworthiness.

3.4. Hybrid digital twin assessment

Evaluation of the digital twin in both the design and operation phases is essential for its real application. Through this study, we not only ensure the trustworthiness and usefulness of our proposal but also suggest a method for potential certification. For this purpose, Key Performance Indicators (KPI) may be defined to correctly evaluate and verify the validity of the twin (Papacharalampopoulos et al., 2020; Yang et al., 2022). In this work, we propose five main categories to develop such indicators:

- Accuracy, Reliability, and Robustness: It is imperative that the principal category indicators precisely assess how faithfully the DT corresponds to the real-world counterpart. Post-training, the predictive performance of HDT models can be appraised using established metrics, including accuracy, precision, recall, F1-score, and the confusion matrix. Such evaluations are crucial not only for confirming the validity of the approach during the design verification phase but also for ensuring the reliability and operational readiness of HDT designs and implementations in forecasting infrastructure failures and maintenance requirements. In this case, reliance on physics in the enrichment of the HDT could be crucial to achieve appropriate accuracy standards.
- Synchronization: As discussed in the previous section, RTDTs provide information that matches the correct time scale of the real twin system to correctly assess decisions using the information of the virtual replica. In this case, some important KPIs include synchronization latency, update frequency, and twin response time (Psarommatis and May, 2023).
- Scalability and flexibility: These terms pertain to the DT methodology and are independent of specific use cases. Assessing the flexibility of the DT is crucial for comparing various DT methodologies and for deriving significant insights through examining their flexibility (Psarommatis and May, 2023). This may also relate to the increasing complexity of infrastructure and the evolving behaviors. Hence, HDTs serve as a robust mechanism to meet the flexibility requirements, aligning with the state of the real twin throughout its entire life cycle.
- Interoperability with other Systems: Interoperability refers to the seamless cooperation and data exchange between different systems without manual intervention. For DT systems in infrastructure, it ensures effective functioning within a broad network of tools and technologies (Budiardjo and Migliori, 2021; Klar et al., 2023).
- Cost effectiveness: These KPIs assess the financial impact of implementing and maintaining the DT against potential savings in operations and maintenance. They include costs for sensor networks, computing infrastructure, and software development, usually represented by metrics such as the return on investment (ROI) (Chauhan, 2020; Bassey et al., 2024).

Recent developments have placed a growing emphasis on sustainable objectives. These goals seek to align with sustainable development goals and the needs of people and territories, ensuring that progress and innovations promote enduring ecological and societal balance (González et al., 2022).

4. Applications in management and resilience of smart infrastructures

The information generated and transformed by HDTs is expected to support long-term decision-making through the life cycle of an asset. What needs to be further highlighted is that these assets are usually

https://doi.org/10.1017/dce.2025.10015 Published online by Cambridge University Press

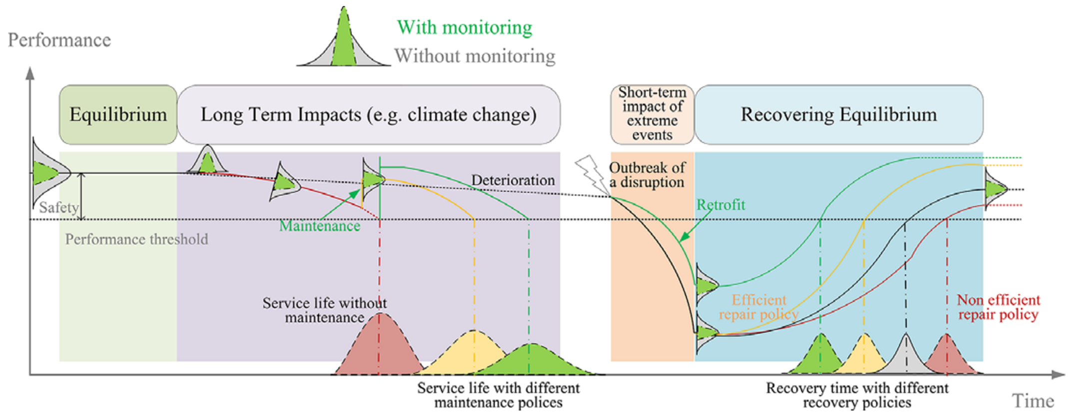

Figure 3. *Time-evolution resilience curve of component/asset/infrastructure network exposed to various environmental changes throughout their life cycle, with and without the monitoring system. Under long-term impacts of climate change, the performance degrades gradually: a red curve represents minimal maintenance leading to the lowest service life; a yellow curve signifies periodic maintenance misaligned with optimal timings, resulting in medium service life levels; a green curve indicates proactive maintenance based on health monitoring, which maximizes service life by predicting and addressing declines at critical thresholds. Under short-term impacts of extreme events, different strategies affect performance decline and recovery: a black curve represents typical scenarios; a red curve depicts poor repair sequencing that reduces efficiency; a yellow curve depicts optimized repairs for faster recovery; and a green curve shows how pre-disaster fortification minimizes damage and speeds up recovery.*

organized in an interdependent manner to supply specific service or functionality. Hence, hybrid twin–enhanced knowledge on components should be assembled and transferred onto the system-level for enabling informed and comprehensive decisions in support of infrastructure management and recovery from extremes, as mandated by the need for resilience.

The term *resilience* is commonly employed in infrastructure engineering to assess the capacity of a system to endure and bounce back from disturbances or disruptions (Bruneau et al., 2003; Ouyang et al., 2012; Labaka et al., 2016). For better understanding and visualization, Figure 3 depicts a time-evolution resilience curve in terms of performance/functionality of an infrastructure system, under the impact of both long-term effects (e.g., climate change/ aging/ corrosion/ fatigue/ deflection) and short-term extreme events (e.g., earthquake/ flood/ high gusts) throughout its life cycle. Infrastructure resilience is commonly quantified using metrics and indicators (e.g., residual functionality, downtime, and recovery time) that can be computed from actual data or simulated based on corresponding resilience curves (Poulin and Kane, 2021). Notably, under normal circumstances, the loss of functionality in an infrastructure system is typically not significant and takes a long time for performance to degrade below the performance threshold. This is attributed to the low probability of multiple component failures occurring simultaneously within the same infrastructure system. However, the situation changes under extreme conditions, where several components become more likely to fail. Consequently, the functionality of the network may experience a sudden and unexpected reduction below the predefined target threshold during such extreme conditions (Mohammadi and Taylor, 2021). This highlights the importance of considering and preparing for exceptional scenarios that could lead to simultaneous failures, ensuring the resilience of infrastructure systems under adverse circumstances (Francis and Bekera, 2014; Didier et al., 2018; Rehak et al., 2018; Fang and Sansavini, 2019; Blagojević and Stojadinović, 2022; Arcieri et al., 2023).

4.1. Benefits and status of DT-powered decision-making

DTs are becoming indispensable in the asset management process, offering substantial benefits in decision-making across various life cycle stages. Starting in the design phase, DTs facilitate rapid prototyping and testing, allowing for iterative refinement based on simulated outcomes rather than solely retrospective analyses. Traditional methods, often constrained by slower feedback loops and high costs of physical prototyping, are significantly outpaced by DT-enabled processes. As the project transitions into the construction phase, DTs seamlessly integrate real-time data from various sources, improving coordination across teams and technology systems. This integration helps predict and mitigate potential failures, reducing delays and associated costs (Medina and Hernandez, 2025). During the operational and maintenance phase, conventional methods that depend solely on historical data, such as past performance logs, maintenance records, and component failure rates, can limit predictive capabilities, leading to suboptimal policies that may not anticipate future challenges. In contrast, DTs utilize AI to blend historical data with real-time operational data, improving predictive capabilities and enabling proactive policies by predicting failures before they happen, unlike traditional methods that react to problems as they occur. This predictive capacity not only reduces downtime but also extends the asset's life expectancy. Additionally, limited data integration in conventional decision-making, involving disparate sources of information, hampers holistic decision-making, particularly for complex and interconnected infrastructure systems. This fragmentation increases the risk of infrastructure mismanagement and potential failures. On the contrary, DTs enable adaptation to evolving conditions, technological advancements, and infrastructure changes, enhancing system resilience. As assets approach the decommissioning phase, DTs contribute to sustainability by optimizing resource use and reducing emissions. They provide simulations that predict the environmental impacts of decommissioning processes, ensuring that the methods employed minimize waste and adhere to environmental standards.

To this end, the integration of hybrid digital twining in decision-making motivates a paradigm shift by providing proactive, on-time, and simulation-driven insights, promoting adaptability, and improving the overall understanding of the system compared to traditional decision-making frameworks (Makhoul et al., 2024). This evolution is particularly significant in complex and dynamic environments where a more responsive and accurate decision-making process is crucial. A so-called *smart decision* refers to a policy that informs the optimal sequence of actions that enhance the resilience at the system level at minimal cost, dictating which actions to take, along with the timing and location from a system-level perspective.

The growing recognition of the unparalleled efficacy of digital and hybrid twin models is manifesting in their escalating deployment within tangible infrastructure systems. As asset owners and managers increasingly acknowledge the transformative impact these models exert, there is a discernible trend toward incorporating DTs in diverse sectors of real-world infrastructure (Kuo et al., 2021; Zhao et al., 2022). This surge in adoption is a testament to the significant advantages these models confer in terms of predictive maintenance capabilities, operational efficiency improvement, smart city planning, and overall resilience improvement in the face of dynamic challenges. This trend is expected to continue and expand as DT technologies continue to evolve, offering innovative solutions to complex problems within the realm of infrastructure sustainability and emergency management.

4.2. Use cases

This section aims to elucidate the transformative impact of DT applications on strategic decision frameworks and the overall enhancement of infrastructure system resilience.

Predictive Maintenance stands as a primary use case for DT technology. Interactive digital representations allow for continuous monitoring, analysis, and intervention on infrastructure components. The integration of sensor and historical data with predictive models empowers decision-makers to optimize system performance and anticipate failure. This facilitates proactive scheduling of maintenance activities, minimizing risk, and enhancing the reliability and longevity. Recent representative case studies include the condition-based maintenance planning of a railway system based on the geometric measurement of track recorded periodically by a mobile sensing system on the train (Arcieri et al., 2023); diagnostics and prognostics of wind turbine structure health based on time-series environmental measured data, vibration data (Bogoevska et al., 2017), and supervisory control and data acquisition (SCADA) data (Schlechtingen et al., 2013; Urmeneta et al., 2023); fault diagnosis and condition based maintenance of overhead power

https://doi.org/10.1017/dce.2025.10015 Published online by Cambridge University Press

transmission lines utilizing the Cablewalker robotic system consisting of a laser scanner, a stereo camera, or a magnetic scanner (Tajnsek et al., 2011; Gitelman et al., 2020); predictive maintenance of manufacturing facility by monitoring parameters from sensors embedded within equipment, such as real-time temperature, vibration, and lubricant condition of the motors, bearings, and gearboxes (Olivotti et al., 2019; Yu et al., 2019); autonomous flaws detection of bridge based on images collected through an inspection robot or unmanned aerial systems (Dorafshan et al., 2018; Galdelli et al., 2022); BIM augmented models based on drone-imaged damage detection enhanced with AI (To et al., 2021); temperature prediction from the the building scale (BIM buildings) to city scale (CityGML) taking into consideration major anthropogenic heat sources and wind fluid dynamics through the Virtual Singapore digital twin (VSdt) (Gobeawan et al., 2018; Ignatius et al., 2019).

Operation Optimization in the context of logistics and supply chain management, DT simulation based on distributed agents can be performed by integrating real-time logistics data, trends of external needs, and optimization algorithms, helping to streamline operations and optimize inventory (Park et al., 2021). In smart manufacturing, real-time manufacturing data, historical performance metrics, and dynamic simulation models can be integrated into the deep reinforcement learning (DRL)-based digital model to identify bottlenecks and refine manufacturing practices, leading to increased efficiency and cost savings (Xia et al., 2021). For building energy management, digital twin–based methods can use building sensor networks and heating/ cooling data to optimize energy design, improve user satisfaction, and reduce energy costs (Bortolini et al., 2022). In the context of traffic management, the DL algorithm can be used using real-time traffic data and dynamic simulation models to optimize signal timings under disturbance and reduce congestion (Rasheed et al., 2020).

Urban Planning undergoes a revolutionary transformation with the application of digital twin technology, particularly in the realm of Smart and Green City Development (Deng et al., 2021; Caprari et al., 2022). DTs can be used to create virtual representations of entire cities by incorporating weather conditions, geospatial data, traffic flow simulations, building structure, and infrastructure models, to ensure a more sustainable and efficient urban environment. Recent representative case studies underscore the imperative of reevaluating urban planning in light of climate change repercussions (as observed in Dublin DT (White et al., 2021)), evolving energy needs (exemplified by research in Cambridge DT (Nochta et al., 2021)), biodiversity preservation initiatives (as evidenced in Singapore DT (Gobeawan et al., 2018; Ignatius et al., 2019)), governance frameworks (as analyzed in studies focused on Cambridge, Singapore, and Zurich DTs (Ignatius et al., 2019; Schrotter and Hürzeler, 2020; Nochta et al., 2021)), land allocation dynamics and social equity considerations (as exemplified in Herrenberg, Nigeria, and Zurich DTs (Dembski et al., 2020; Schrotter and Hürzeler, 2020; Enoguanbhor et al., 2021)), and environmental quality assessments (as illustrated in Nigeria and Helsinki DTs (Enoguanbhor et al., 2021; Hämäläinen, 2021)). These studies advocate for urban planning strategies that prioritize flexibility, adaptability, and incremental adjustments to effectively address the multifaceted challenges facing modern cities.

Extreme event handling is receiving growing interest given the increasingly frequent extreme events (e.g., earthquake, tornado, wildfire) that we have recently experienced. DTs can play a crucial role in supporting decision-making by reducing the uncertainty of condition assessment and, in turn, facilitating the efficiency of emergency response (Makhoul et al., 2024). Use cases include developing HDTs (Dabrowski et al., 2023) that can simulate and predict the spread of wildfires in real time by enhancing the physics-based fire characteristic model (Spark) (Miller et al., 2015) with spatial and forcing as well as weather information in a hybrid modeling structure, allowing decision-makers to efficiently plan evacuation routes, deploy firefighting resources strategically, and communicate timely warnings to the community (Zhong et al., 2023); developing a deep reinforcement learning (RL)-based decision framework to make rational decisions for transportation management under hurricanes based on the monitoring of weather information and traffic flow (Li and Wu, 2022); introducing a spatial–temporal graph DL model that uses heterogeneous community features (physics-based data and human-sensed data), to predict urban flooding in real time. This model improves risk mapping for better situational awareness and response strategies, verified using 2017 Hurricane Harvey in Harris County (Farahmand et al., 2023).

The common thread across these applications is the ability of DT to provide a dynamic and data-driven foundation for informed decision-making. In essence, the combination of robust data, advanced modeling, and diverse use cases exemplifies the multifaceted impact and potential of DT to revolutionize decision-making processes.

5. Future outlook

5.1. Future goals

As distilled in the analysis, two main objectives have been identified for future DTs. First, it is imperative to develop future-proof systems that not only draw insights from previous experience but also anticipate and adapt to forthcoming changes. This capability would enable proactive adjustment and resilience in unpredictable circumstances. Additionally, DTs are expected to work on multiple cross-connected levels, including infrastructure components, assets, individual systems, and system of systems. These levels reflect a hierarchical and integrated approach, where DTs not only replicate individual components but also encompass broader systemic interactions and dependencies, providing a scalable framework for proactive adjustments and resilience.

To set the foundation to achieve these goals, it is necessary to first work on a common language, yet equally essential is implementing frameworks to effectively organize the vast array of metadata and model information. This is where knowledge basis emerges as an indispensable tool for housing vital information, insights, and models (Marykovskiy et al., 2024). By leveraging knowledge bases and establishing uniform data models and vocabularies, organizations can promote smooth communication and cooperation within digital twin ecosystems. This common language not only encourages standardization and coherence for models but also fosters cooperation among stakeholders from different fields and sectors. In essence, it sets a solid foundation for more efficient and flexible digital twin solutions that can address complex real-world problems. This idea could also be expanded by having a high-fidelity repository of assets (BIM, visual platforms) across domains.

Next, it would be necessary to create a basis for actionably implementing hybrid modeling techniques and intelligent algorithms within a DT framework that can cater to creating value for assets. To this end, DTs must evolve toward decision support, with a focus on analysis tasks, such as independently analyzing data, evaluating scenarios, and recommending actions with or without direct human intervention. A profound and interpretable use of AI, ML algorithms, and online data streams will allow DT to independently evaluate the present condition of a system, forecast future results, and recommend the best course of action to attain pre-established goals.

All actions being considered, a final goal in the development of DTs for smart infrastructures will be quantifying the ROI. Modeling the long-term benefits of DTs involves assessing both tangible and intangible factors over an extended period. The ultimate aim would be to optimize the strategies of the stakeholders for DTs to consolidate their implementation, develop future opportunities, and create value. To this end, a number of approaches for quantifying the Value of Information have been recently put forth and serve as foundational work (Memarzadeh and Pozzi, 2016; Kamariotis et al., 2022; Zhang et al., 2022; Saifullah et al., 2023).

5.2. Challenges

Driven by industrial demands on technological readiness and maturity, formal frameworks for the exploitation of DTs are coming forth. Nevertheless, challenges persist in rendering DTs practical for use in real-world applications, as discussed below.

Adaptation to changing climates. Climate-related data, such as future weather patterns and extreme events, often involves uncertainties and may be incomplete. Inaccurate or insufficient data can compromise the reliability of digital twin prediction. Also, the amount and rate of data produced by sensors and IoT devices can exceed current infrastructure capabilities (Mashaly, 2021), necessitating scalable strategies to handle and analyze the data flow to reduce latency in the response.

Open data exchange. Challenges in open data exchange include ambiguous data ownership, data privacy concerns (Wang et al., 2023), data quality and consistency variability, leading to potential disputes and limiting the availability of relevant data for digital twin systems.

Security and trustworthiness of algorithms/data. Data may be corrupted, tampered with, or manipulated; algorithms used in DTs may exhibit bias and may not undergo thorough validation processes; the explainability of AI models is often limited. All these can lead to inaccurate representations and flawed decision-making outcomes (Amerirad et al., 2023).

Standardization and certification of DT. Current digital twin standards, including the IFC and ISO series (ISO.ISO/TR 24464-2020; ISO.ISO 23247-2021; ISO.ISO 19650-1:2018; ISO.ISO 37100-2016; ISO.ISO/IEC AWI 30173; ISO.ISO/IEC AWI 30172), IEEE series (IEEE.IEEE SA-P2806.1; IEEE.IEEE SA-P3144), IEC series (IEC.IEC 61850-2024; IEC.IEC 62832-2020) and ITU series (ITU.ITU-TY.3090; Interoperability framework of digital twin systems in smart cities and communities), encounter limitations hindering their widespread adoption and effectiveness. One notable challenge is the lack of comprehensive coverage across industries and application domains, leading to interoperability issues. Additionally, the rapid evolution of digital twin technologies outpaces standard development, resulting in outdated guidance for emerging use cases. Achieving consensus among stakeholders and allocating resources for compliance also pose significant challenges, especially for smaller organizations or those with legacy systems (Bicevskis et al., 2017; Hong and Huang, 2017; Kirchen et al., 2017; Burns et al., 2019).

Dealing with false positives/ responsibility for the decision. In a legal context, the attribution of responsibility becomes a crucial aspect, as stakeholders may question accountability for any adverse effects resulting from false positives or erroneous decisions. This challenge is exacerbated by the evolving nature of digital twin technologies, making it essential to navigate legal frameworks that may not have caught up with the rapid advancements.

Human element/ ethics to alleviate dangers from automation. Balancing the advantages of automation with ethical considerations, such as fairness, accountability, and transparency, is essential to prevent dangers stemming from unchecked automation, and a robust framework is needed for the integration of human expertise and ethical guidelines into automated decision-making in DTs to mitigate risks and build trust. In addition, training users to understand and work with the twin is crucial for the appropriate interpretation and use of its information.

Addressing these challenges requires collaborative efforts from stakeholders across industries, involving policymakers, standards organizations, technology providers, and end-users, to develop frameworks, standards, and best practices that promote the responsible and effective use of DTs for decision-making in a rapidly evolving technological landscape.

5.3. Opportunities

Recent perspective papers have highlighted the limitations of current digital twin tools in urban planning, particularly regarding their focus on short-term goals versus the long-term focus of city planning policies (Batty, 2024; Bettencourt, 2024). They note issues such as staticity, limited aggregation capacity, and a primary focus on visualization. Emphasizing the need for improvement, they advocate for modeling multilevel and multidomain as well as multi-spatiotemporal scale networks better to capture interactions and the dynamic nature of urban environments facing various stressors. Furthermore, these papers underscore the importance of robust verification, validation, and uncertainty quantification methods to enhance the reliability and accuracy of digital twin models. In addition, authors in (Mohammadi and Taylor, 2021) discuss the importance of utilizing Smart City DT for disaster decision-making in cities facing various stressors. They emphasize the integration of fast and slow modes in decision-making processes and highlight the need for capturing, predicting, and adapting to urban dynamics at varying paces to effectively manage disaster-related mortality and economic losses.

The ongoing standardization of DTs presents numerous opportunities for industries and stakeholders. Standardized frameworks and protocols facilitate seamless interoperability and integration, fostering collaboration and innovation while reducing implementation costs and risks through clear guidelines and best practices. In addition, standardized data formats and communication protocols enhance data quality, consistency, and security, building trust and confidence.

Finally, the demand for open platforms that integrate existing technologies is growing in the fast-changing tech landscape. (Robles et al., 2023). These platforms are designed to facilitate the integration of various data sources, sensors, devices, and applications within a smart city environment. Platforms like iTwinJS (Incorporated Bentley Systems) and Opentwins (Robles et al., 2023) exemplify the pivotal role of openness in fostering collaboration, innovation, and interoperability within the digital realm. Another example is the Digital Twin Platform (DTCC Platform), developed at the Digital Twin Cities Centre, that incorporates a DTCC builder (Logg et al., 2023) (Somanath et al., 2023), model and simulation, and visualization. An example of the implementation of the project is that of the city of Gothenburg (Gonzalez-Caceres et al., 2024).

The study of automation may result in the replacement of human labor in a positive sense. Although human expertise is pivotal in the digital twin cycle, the proposed new technology can intervene to automate fast decision-making in crucial scenarios and improve the efficiency, safety, and well-being of potential human users.

DTs must be built to empower the human, not the machine. The exploitation of AR, VR, or virtual spaces (metaverse) as facilitators can democratize access to information and insights, enabling a broader audience, including stakeholders with varying levels of technical expertise, to interact with and understand complex systems and data. This fosters cross-functional collaboration, accelerates decision-making processes, and improves the overall effectiveness of digital twin initiatives.

6. Conclusion

This statement paper aims to set the foundations for the development of next-generation DTs and their application to smart infrastructures. We have identified challenges in the data acquisition and simulation that could be addressed through the so-called *smart paradigms.* The smart use of data enhances data collection and processing efficiency by selecting what, when, where, and at what scale to avoid problems derived from big data. This, combined with analytics enriched with physics, improves the interpretation and quality of the results. Additionally, hybrid modeling provides an effective strategy for integrating diverse modeling methodologies, including physics-based and data-driven approaches, thereby improving the precision, adaptability, and effectiveness in simulating complex real-world systems.

Our analysis highlights the need to unify languages to improve communication among platforms and stakeholders handling various types of data. Furthermore, we advocate for exploring the integration of elements and agents within the digital twin framework to fully account for operational interactions and connections at different levels. Lastly, we recommend further investigation into the development of the smart digital twin framework to facilitate automation and intelligent decision-making processes that would enhance reaction to unpredictable, and possibly crucial, new scenarios.

We advocate for a paradigm shift from traditional decision-making practices in infrastructure management towards more proactive, data-driven approaches. We propose developing digital twin–enabled decision-making frameworks throughout the project's life cycle and discuss advanced applications including autonomous management, predictive maintenance, adaptive behavior, and resilience enhancement. Furthermore, we outline the future outlook for augmenting such digital twin–enabled decision-making frameworks by applying expert-guided paradigms, forming system-level perspectives, and considering unexpected extreme events, to make more informed and comprehensive decisions in support of infrastructure resilience.

Acknowledgments. This position paper has been developed as part of a roundtable session on the theme of Digital Twinning and Decision Support for Asset Management. The roundtable was held in the context of joint collaboration between the Future Resilient Systems (FRS) of the Singapore-ETH Centre and the DESCARTES interdisciplinary program of excellence by CNRS@CREATE. All involved sector stakeholders, including TÜV SÜD, ARUP, MEINHARDT, CETIM-Matcor, NAVAL Group, Ministry of National Development (MND), Land Transport Authority (LTA), and GOVTECH, are acknowledged for their participation and active feedback.

Author contribution. Conceptualization: H.L; B.M; F.C; E.C. Methodology: H.L; B.M; F.C; E.C. Project administration: F.C; E. C; D.B; J.J. Data curation: H.L; B.M; F.C; E.C. Resources: E.S; A.W; X.Z; F.C; E.C. Data visualization: H.L; B.M; E.C. Writing original draft: H.L; B.M. Supervision: F.C; E.C. Writing – review/editing: H.L; B.M; E.S; A.W; D.B; J.J; X.Z; F.C; E.C. All authors approved the final submitted draft.

Competing interests. None.

Data availability statement. In this manuscript, no data were produced or used to pursue the research stated.

Funding statement. The research was conducted at the Singapore-ETH Centre, which was established collaboratively between ETH Zurich and the National Research Foundation Singapore, and CNRS@CREATE through the DESCARTES program; both research programs supported by the National Research Foundation, Prime Minister's Office, Singapore under its Campus for Research Excellence and Technological Enterprise (CREATE) programme. E. Chatzi would also like to acknowledge the support of the InBlanc project, titled "INdustrialisation of Building Lifecycle data Accumulation, Numeracy and Capitalisation," funded under the Horizon Europe programme with the Grant Agreement ID 101147225. B. Moya acknowledges support from the French government, managed by the National Research Agency (ANR), under the CPJ ITTI.

Ethical standards. The research meets all ethical guidelines, including adherence to the legal requirements of the study country.

References

Abburu S, **Berre AJ**, **Jacoby M**, **Roman D**, **Stojanovic L and Stojanovic N** (2020) Cognitive digital twins for the process industry. In *Proceedings of the the Twelfth International Conference on Advanced Cognitive Technologies and Applications (COGNITIVE 2020), Nice, France*, pp. 25–29.

Abburu S, **Berre AJ**, **Jacoby M**, **Roman D**, **Stojanović L and Stojanovic N**. (2020) Cognitwin – hybrid and cognitive digital twins for the process industry. In *2020 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC)*, pp. 1–8. https://api.semanticscholar.org/CorpusID:221846414.

Agathos K, **Tatsis KE**, **Vlachas K and Chatzi E** (2022) Parametric reduced order models for output-only vibration-based crack detection in shell structures. *Mechanical Systems and Signal Processing 162*, 108051.

Agathos K, **Vlachas K**, **Garland A and Chatzi E** (2024) Accelerating structural dynamics simulations with localised phenomena through matrix compression and projection-based model order reduction. *International Journal for Numerical Methods in Engineering 125*, e7445.

AIAA (2020) *AIAA Digital Engineering Integration Committee Et al. Digital Twin: Definition & Value—An AIAA and AIA Position Paper.* Reston, VA: AIAA.

Alam KM and Saddik AE (2017) C2ps: A digital twin architecture reference model for the cloud-based cyber-physical systems. *IEEE Access 5*, 2050–2062.

Amerirad B, **Cattaneo M**, **Kenett RS and Luciano E** (2023) Adversarial artificial intelligence in insurance: From an example to some potential remedies. *Risks 11*(1), 20.

Amsallem D, **Zahr MJ and Farhat C** (2012) Nonlinear model order reduction based on local reduced-order bases. *International Journal for Numerical Methods in Engineering 92*(10), 891–916.

Arcieri G, **Wölfle D and Chatzi E** (2021) Which model to trust: Assessing the influence of models on the performance of reinforcement learning algorithms for continuous control tasks. *arXiv preprint arXiv:2110.13079*.

Arcieri G, **Hoelzl C**, **Schwery O**, **Straub D**, **Papakonstantinou KG and Chatzi E** (2023) Bridging POMDPs and Bayesian decision making for robust maintenance planning under model uncertainty: An application to railway systems. *Reliability Engineering & System Safety 239*, 109496.

Argyroudis SA, **Mitoulis SA**, **Chatzi E**, **Baker JW**, **Brilakis I**, **Gkoumas K**, **Vousdoukas M**, **Hynes W**, **Carluccio S**, **Keou O**, **Frangopol DM and Linkov I** (2022) Digital technologies can enhance climate resilience of critical infrastructure. *Climate Risk Management 35*, 100387.

Bacsa K, **Lai Z**, **Liu W**, **Todd M and Chatzi E** (2023) Symplectic encoders for physics-constrained variational dynamics inference. *Scientific Reports 13*(1), 2643.

Badías A, **Curtit S**, **González D**, **Alfaro I**, **Chinesta F and Cueto E** (2019) An augmented reality platform for interactive aerodynamic design and analysis. *International Journal for Numerical Methods in Engineering 120*(1), 125–138.

Bado MF, **Tonelli D**, **Poli F**, **Zonta D and Casas JR** (2022) Digital twin for civil engineering systems: An exploratory review for distributed sensing updating. *Sensors 22*(9), 3168.

Bariah L, **Sari H and Debbah M** (2023) Digital twin-empowered communications: A new frontier of wireless networks. *IEEE Communications Magazine 61*(12), 24–36.

Bassey KE, **Opoku-Boateng J**, **Antwi BO and Ntiakoh A** (2024) Economic impact of digital twins on renewable energy investments. *Engineering Science & Technology Journal 5*(7), 2232–2247.

Batty M (2024) Digital twins in city planning. *Nature Computational Science*, *4*(3), 192–199. https://doi.org/10.1038/s43588-024-00606-7.

Bergs T, **Gierlings S**, **Auerbach T**, **Klink A**, **Schraknepper D and Augspurger T** (2021) The concept of digital twin and digital shadow in manufacturing. *Procedia CIRP 101*, 81–84.

Bermejo-Barbanoj C, **Moya B**, **Badías A**, **Chinesta F and Cueto E** (2024) Thermodynamics-informed super-resolution of scarce temporal dynamics data. *arXiv preprint arXiv:2402.17506*.

Bettencourt LMA (2024) Recent achievements and conceptual challenges for urban digital twins. *Nature Computational Science 4*(3), 150–153. https://doi.org/10.1038/s43588-024-00604-9.

Bicevskis J, **Bicevska Z and Karnitis G** (2017) Executable data quality models. *Procedia Computer Science 104*, 138–145.

Bigoni C, **Zhang Z and Hesthaven JS** (2020) Systematic sensor placement for structural anomaly detection in the absence of damaged states. *Computer Methods in Applied Mechanics and Engineering 371*, 113315.

Blagojević N and Stojadinović B (2022) A demand-supply framework for evaluating the effect of resource and service constraints on community disaster resilience. *Resilient Cities and Structures 1*(1), 13–32.

Blagojević N, **Hefti F**, **Henken J**, **Didier M and Stojadinović B** (2023) Quantifying disaster resilience of a community with interdependent civil infrastructure systems. *Structure and Infrastructure Engineering 19*(12), 1696–1710.

Blasch E, **Seetharaman G and Reinhardt K** (2013) Dynamic data driven applications system concept for information fusion. *Procedia Computer Science 18*, 1999–2007.

Bogoevska S, **Spiridonakos M**, **Chatzi E**, **Dumova-Jovanoska E and Höffer R** (2017) A data-driven diagnostic framework for wind turbine structures: A holistic approach. *Sensors 17*(4), 720.

Bortolini R, **Rodrigues R**, **Alavi H**, **Vecchia LFD and Forcada N** (2022) Digital twins' applications for building energy efficiency: A review. *Energies 15*(19), 7002.

Bruneau M, **Chang SE**, **Eguchi RT**, **Lee GC**, **D O'Rourke T**, **Reinhorn AM**, **Shinozuka M**, **Tierney K**, **Wallace WA and Von Winterfeldt D** (2003) A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake Spectra 19*(4), 733–752.

Budiardjo A and Migliori D (2021) Digital Twin System Interoperability Framework. Technical report, Tech. rep. Digital Twin Consortium, East Lansing, Michigan.

Bundy A, **Chater N and Muggleton S** (2023) Introduction to 'cognitive artificial intelligence'. *Philosophical Transactions of the Royal Society A 381*. *2251*: 20220051.

Burns T, **Cosgrove J and Doyle F** (2019) A review of interoperability standards for industry 4.0. *Procedia Manufacturing 38*, 646–653.

Caprari G, **Castelli G**, **Montuori M**, **Camardelli M and Malvezzi R** (2022) Digital twin for urban planning in the green deal era: A state of the art and future perspectives. *Sustainability 14*(10), 6263.

Chabanet S, **El-Haouzi HB and Thomas P** (2022) Toward a self-adaptive digital twin based active learning method: An application to the lumber industry. *IFAC-PapersOnLine 55*(2), 378–383.

Champaney V, **Amores VJ**, **Garois S**, **Irastorza-Valera L**, **Ghnatios C**, **Montáns FJ**, **Cueto E and Chinesta F** (2022) Modeling systems from partial observations. *Frontiers in Materials 9*, 970970.

Champaney V, **Chinesta F and Cueto E** (2022) Engineering empowered by physics-based and data-driven hybrid models: A methodological overview. *International Journal of Material Forming 15*(3), 31.

Chauhan N (2020) Digital twins: Details of implementation. *ASHRAE Journal 62*(10), 20–24.

Chinesta F and Cueto E (2014) *PGD-Based Modeling of Materials, Structures and Processes*. Switzerland: Springer International Publishing.

Chinesta F, **Ladeveze P and Cueto E** (2011) A short review on model order reduction based on proper generalized decomposition. *Archives of Computational Methods in Engineering 18*(4), 395–404.

Chinesta F, **Cueto E**, **Abisset-Chavanne E**, **Duval JL and Khaldi FE** (2020) Virtual, digital and hybrid twins: A new paradigm in data-based engineering and engineered data. *Archives of Computational Methods in Engineering 27*, 105–134.

Cimellaro GP, **Renschler C**, **Reinhorn AM and Arendt L** (2016) Peoples: A framework for evaluating resilience. *Journal of Structural Engineering 142*(10), 04016063.

Cueto E and Chinesta F (2023) Thermodynamics of learning physical phenomena. *Archives of Computational Methods in Engineering 30*(8), 4653–4666.

Dabrowski JJ, **Pagendam DE**, **Hilton J**, **Sanderson C**, **MacKinlay D**, **Huston C**, **Bolt A and Kuhnert P** (2023) Bayesian physics informed neural networks for data assimilation and spatio-temporal modelling of wildfires. *Spatial Statistics 55*, 100746.

Definition BIM (2014) Frequently asked questions about the national BIM standard-United States-national BIM standard-United States. Nationalbimstandard.org. Archived from the original on 16 October 2014.

Dembski F, **Wössner U**, **Letzgus M**, **Ruddat M and Yamu C** (2020) Urban digital twins for smart cities and citizens: The case study of Herrenberg, Germany. *Sustainability 12*(6), 2307.

Deng T, **Zhang K and Shen Z-JM** (2021) A systematic review of a digital twin city: A new pattern of urban governance toward smart cities. *Journal of Management Science and Engineering 6*(2), 125–134.

Dhar TK and Khirfan L (2017) A multi-scale and multi-dimensional framework for enhancing the resilience of urban form to climate change. *Urban Climate 19*, 72–91.

Di Lorenzo D, **Champaney V**, **Marzin JY**, **Farhat C and Chinesta F** (2023) Physics informed and data-based augmented learning in structural health diagnosis. *Computer Methods in Applied Mechanics and Engineering 414*, 116186.

Didier M, **Broccardo M**, **Esposito S and Stojadinovic B** (2018) A compositional demand/supply framework to quantify the resilience of civil infrastructure systems (re-codes). *Sustainable and Resilient Infrastructure 3*(2), 86–102.

Digital Twin Cities Centre. https://github.com/dtcc-platform. [Online].
Dorafshan S, **Thomas RJ and Maguire M** (2018) Fatigue crack detection using unmanned aerial systems in fracture critical inspection of steel bridges. *Journal of Bridge Engineering 23*(10), 04018078.
Enoguanbhor EC, **Gollnow F**, **Walker BB**, **Nielsen JO and Lakes T** (2021) Key challenges for land use planning and its environmental assessments in the Abuja city-region, Nigeria. *Land 10*(5), 443.
Fang Y-P and Sansavini G (2019) Optimum post-disruption restoration under uncertainty for enhancing critical infrastructure resilience. *Reliability Engineering & System Safety 185*, 1–11.
Farahmand H, **Xu Y and Mostafavi A** (2023) A spatial–temporal graph deep learning model for urban flood nowcasting leveraging heterogeneous community features. *Scientific Reports 13*(1), 6768.
Farhat C, **Bos A**, **Avery P and Soize C** (2018) Modeling and quantification of model-form uncertainties in eigenvalue computations using a stochastic reduced model. *AIAA Journal 56*(3), 1198–1210.
Francis R and Bekera B (2014) A metric and frameworks for resilience analysis of engineered and infrastructure systems. *Reliability Engineering & System Safety 121*, 90–103.
Frangos M, **Marzouk Y and Willcox K** (2010) Surrogate and reduced-order modeling: A comparison of approaches for large-scale statistical inverse problems. In *Large-Scale Inverse Problems and Quantification of Uncertainty.* Wiley Online Library, pp. 123–149.
Galdelli A, **D'Imperio M**, **Marchello G**, **Mancini A**, **Scaccia M**, **Sasso M**, **Frontoni E and Cannella F** (2022) A novel remote visual inspection system for bridge predictive maintenance. *Remote Sensing 14*(9), 2248.
Gitelman LD, **Kozhevnikov MV and Kaplin DD** (2020) Asset management in grid companies using integrated diagnostic devices. *Energy Resources and Policies for Sustainability*, 211.
Glaessgen E and Stargel D (2012) The digital twin paradigm for future nasa and us air force vehicles. In *53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference 20th AIAA/ASME/AHS Adaptive Structures Conference 14th AIAA*, pp. 1818. IAAA.
Gobeawan L, **Lin ES**, **Tandon A**, **Yee ATK**, **Khoo VHS**, **Teo SN**, **Yi S**, **Lim CW**, **Wong ST**, **Wise DJ**, **Cheng P**, **Liew SC**, **Huang X**, **Li QH**, **Teo LS**, **Fekete GS and Poto MT** (2018) Modeling trees for virtual Singapore: From data acquisition to CityGML models. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences 42*, 55–62.
González Chávez CA, **Bärring M**, **Frantzén M**, **Annepavar A**, **Gopalakrishnan D and Johansson B**. 2022. Achieving sustainable manufacturing by embedding sustainability KPIs in digital twins. In *2022 Winter Simulation Conference (WSC)*, pp. 1683–1694. IEEE.
Gonzalez-Caceres A, **Hunger F**, **Forssén J**, **Somanath S**, **Mark A**, **Naserentin V**, **Bohlin J**, **Logg A**, **Wästberg B**, **Komisarczyk D**, **Edelvik F and Hollberg A** (2024) Towards digital twinning for multi-domain simulation workflows in urban design: A case study in Gothenburg. *Journal of Building Performance Simulation*, 1–22.
Grieves M (2002) Conceptual ideal for PLM. In *Presentation for the Product Lifecycle Management (PLM) Center*, University of Michigan.
Grieves M and Vickers J (2017) Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In J. Kahlen, S. Flumerfelt and A. Alves (eds), *Transdisciplinary Perspectives on Complex Systems: New Findings and Approaches*, Cham: Springer, pp. 85–113.
Hämäläinen M (2021) Urban development with dynamic digital twins in Helsinki city. *IET Smart Cities 3*(4), 201–210.
Haywood-Alexander M and Chatzi E (2023) Physics-informed neural networks for one-step-ahead prediction of dynamical systems. In *14th International Workshop on Structural Health Monitoring (IWSHM 2023)*. Lancaster, PA: DEStech Publications, pp. 2253–2262.
Haywood-Alexander M, **Liu W**, **Bacsa K**, **Lai Z and Chatzi E** (2023) Discussing the spectra of physics-enhanced machine learning via a survey on structural mechanics applications. *arXiv preprint arXiv:2310.20425.*
Hernandez Q, **Badias A**, **Chinesta F and Cueto E** (2022) Thermodynamics-informed graph neural networks. In *IEEE Transactions on Artificial Intelligence.* IEEE.
Hernandez Q, **Badias A**, **Gonzalez D**, **Chinesta F and Cueto E** (2021) Deep learning of thermodynamics-aware reduced-order models from data. *Computer Methods in Applied Mechanics and Engineering 379*, 113763.
Heussen K, **Koch S**, **Ulbig A and Andersson G** (2011) Unified system-level modeling of intermittent renewable energy sources and energy storage for power system operation. *IEEE Systems Journal 6*(1), 140–151.
Hong J-H and Huang M-L (2017) Enabling smart data selection based on data completeness measures: A quality-aware approach. *International Journal of Geographical Information Science 31*(6), 1178–1197.
Hughes A (2018) *Forging the Digital Twin in Discrete Manufacturing, a Vision for Unity in the Virtual and Real Worlds*. LNS Research e-book
Iafrate F (2014) A journey from big data to smart data. In *Digital Enterprise Design & Management: Proceedings of the Second International Conference on Digital Enterprise Design and Management DED&M 2014*, pp. 25–33. Springer.
Ibáñez R, **Abisset-Chavanne E**, **Ammar A**, **González D**, **Cueto E**, **Huerta A**, **Duval JL and Chinesta F** (2018) A multidimensional data-driven sparse identification technique: The sparse proper generalized decomposition. *Complexity 2018*(1), 5608286.
Idrissi MEF, **Praud F**, **Champaney V**, **Chinesta F and Meraghni F** (2022) Multiparametric modeling of composite materials based on non-intrusive pgd informed by multiscale analyses: Application for real-time stiffness prediction of woven composites. *Composite Structures 302*, 116228.

IEC.IEC 61850-2024. Communication protocols for intelligent electronic devices at electrical substations. https://webstore.iec.ch/publication/6028. [Online].
IEC.IEC 62832-2020. Industrial-process measurement, control and automation-Digital factory framework. https://webstore.iec.ch/publication/65858. [Online].
IEEE.IEEE SA-P2806.1. Standard for Connectivity Requirements of Digital Representation for Physical Objects in Factory Environments. https://standards. ieee.org/ieee/2806.1/10370/. [Online].
IEEE.IEEE SA-P3144. Standard for Digital Twin Maturity Model and Assessment Methodology in Industry. https://https://standards.ieee.org/ieee/3144/10837/. [Online].
Ignatius M, **Wong NH**, **Martin M and Chen S** (2019) Virtual Singapore integration with energy simulation and canopy modelling for climate assessment. In *IOP Conference Series: Earth and Environmental Science, volume 294*, pp. 012018. IOP Publishing.
Incorporated Bentley Systems. iTwin.js. https://www.itwinjs.org. [Online].
Interoperability framework of digital twin systems in smart cities and communities. https://www.itu.int/ITU-T/workprog/wp_item.aspx? [Online].
ISO.ISO 19650-1:2018. Organization and digitization of information about buildings and civil engineering works, including building information modelling (BIM) - Information management using building information modelling - Part 1: Concepts and principles. https://www.bsigroup.com. [Online].
ISO.ISO 23247-2021. Automation system and integration-Digital twin framework for manufacturing. https://www.iso.org/standard/75066.html. [Online].
ISO.ISO 37100-2016. Sustainable cities and communities - Vocabulary. .https://standards.iteh.ai/catalog/standards/sist/0d35f35d-85e7-467e-b8ed-984fa9a66590/iso-37100-2016. [Online].
ISO.ISO/IEC AWI 30172. Digital Twin-Use cases. https://www.iso.org/standard/81578.html. [Online].
ISO.ISO/IEC AWI 30173. Digital twin-Concepts and terminology. https://www.iso.org/standard/81442.html. [Online].
ISO.ISO/TR 24464-2020. Automation systems and integration- – Industrial data-Visualization elements of digital twins. https://www.iso.org/standard/78836.html. [Online].
ITU.ITU-TY.3090. Digital twin network-Requirements and architecture. https://www.itu.int/rec/T-REC-Y.3090-202202-I/en. [Online].
Kaartinen E, **Dunphy K and Sadhu A** (2022) Lidar-based structural health monitoring: Applications in civil infrastructure systems. *Sensors 22*(12), 4610.
Kamariotis A, **Chatzi E and Straub D** (2022) Value of information from vibration-based structural health monitoring extracted via bayesian model updating. *Mechanical Systems and Signal Processing 166*, 108465.
Kamariotis A, **Chatzi E**, **Straub D**, **Dervilis N**, **Goebel K**, **Hughes AJ**, **Lombaert G**, **Papadimitriou C**, **Papakonstantinou KG**, **Pozzi M**, **Todd M and Worden K** (2024) Monitoring-supported value generation for managing structures and infrastructure systems. *arXiv preprint arXiv:2402.00021*.
Kapteyn MG and Willcox KE (2020) From physics-based models to predictive digital twins via interpretable machine learning. *arXiv preprint arXiv:2004.11356*.
Kapteyn MG, **Knezevic DJ and Willcox K** (2020) Toward predictive digital twins via component-based reduced-order models and interpretable machine learning. In *AIAA Scitech 2020 Forum*, pp. 0418.
Kenett RS (2024) Engineering, emulators, digital twins, and performance engineering. *Electronics 13*(10), 1829.
Kenett RS and Bortman J (2022) The digital twin in industry 4.0: A wide-angle perspective. *Quality and Reliability Engineering International 38*(3), 1357–1366.
Khamesi AR, **Shin E and Silvestri S** (*2020*) Machine learning in the wild: The case of user-centered learning in cyber physical systems. In *2020 International Conference on COMmunication Systems & NETworkS (COMSNETS)*, pp. 275–281. IEEE.
Kirchdoerfer T and Ortiz M (2016) Data-driven computational mechanics. *Computer Methods in Applied Mechanics and Engineering 304*, 81–101.
Kirchen I, **Schütz D**, **Folmer J and Vogel-Heuser B** (2017) Metrics for the evaluation of data quality of signal data in industrial processes. In *2017 IEEE 15th International Conference on Industrial Informatics (INDIN)*, pp. 819–826. IEEE.
Klar R, **Arvidsson N and Angelakis V** (2023) Digital twins' maturity: The need for interoperability. *IEEE Systems Journal 18*(1), 713–724.
Koliou M, **van de Lindt JW**, **McAllister TP**, **Ellingwood BR**, **Dillard M and Cutler H** (2020) State of the research in community resilience: Progress and challenges. *Sustainable and Resilient Infrastructure 5*(3), 131–151.
Kuo Y-H, **Pilati F**, **Qu T and Huang GQ** (2021) Digital twin-enabled smart industrial systems: Recent developments and future perspectives. *International Journal of Computer Integrated Manufacturing 34*(7–8), 685–689.
Labaka L, **Hernantes J and Sarriegi JM** (2016) A holistic framework for building critical infrastructure resilience. *Technological Forecasting and Social Change 103*, 21–33.
Lenk A, **Bonorden L**, **Hellmanns A**, **Roedder N and Jaehnichen S** (2015) Towards a taxonomy of standards in smart data. In *2015 IEEE International Conference on Big Data (Big Data)*, pp. 1749–1754, . http://doi.org/10.1109/BigData.2015.7363946.
Li S and Wu T (2022) Deep reinforcement learning-based decision support system for transportation infrastructure management under hurricane events. *Structural Safety 99*, 102254.
Liang H and Xie Q (2021) System vulnerability analysis simulation model for substation subjected to earthquakes. *IEEE Transactions on Power Delivery 37*(4), 2684–2692.

Liang G, Liu G, Zhao J, Liu Y, Gu J, Sun G and Dong Z (2020) Super resolution perception for improving data completeness in smart grid state estimation. *Engineering 6*(7), 789–800.
Liang H, Blagojević N, Xie Q and Stojadinović B (2023) Seismic resilience assessment and improvement framework for electrical substations. *Earthquake Engineering & Structural Dynamics 52*(4), 1040–1058.
Liu M, Fang S, Dong H and Xu C (2021) Review of digital twin about concepts, technologies, and industrial applications. *Journal of Manufacturing Systems 58*, 346–361.
Liu W, Lai Z, Bacsa K and Chatzi E (2022) Physics-guided deep markov models for learning nonlinear dynamical systems with uncertainty. *Mechanical Systems and Signal Processing 178*, 109276.
Liu W, Lai Z, Stoura CD, Bacsa K and Chatzi E (2025) Model-based unknown input estimation via partially observable markov decision processes. *Mechanical Systems and Signal Processing 225*, 112233. https://doi.org/10.1016/j.ymssp.2024.112233.
Logg A, Naserentin V and Wästberg D (2023) DTCC builder: A mesh generator for automatic, efficient, and robust mesh generation for large-scale city modeling and simulation. *Journal of Open Source Software 8*(86), 4928.
Makhoul N, Roohi M, van de Lindt JW, Sousa H, Santos LO, Argyroudis S, Barbosa A, Derras B, Gardoni P, Lee JS, *et al.* (2024) Seismic resilience of interdependent built environment for integrating structural health monitoring and emerging technologies in decision-making. *Structural Engineering International 34*(1), 19–33.
Marykovskiy Y, Clark T, Day J, Wiens M, Henderson C, Quick J, Abdallah I, Sempreviva AM, Calbimonte J-P, Chatzi E, *et al.* (2024) Knowledge engineering for wind energy. *Wind Energy Science 9*(4), 883–917.
Mashaly M (2021) Connecting the twins: A review on digital twin technology & its networking requirements. *Procedia Computer Science 184*, 299–305.
McClellan A, Lorenzetti J, Pavone M and Farhat C (2022) A physics-based digital twin for model predictive control of autonomous unmanned aerial vehicle landing. *Philosophical Transactions of the Royal Society A 380*(2229), 20210204.
Medina FG and Hernandez VM (2025) Product digital twins: An umbrella review and research agenda for understanding their value. *Computers in Industry 164*, 104181.
Memarzadeh M and Pozzi M (2016) Value of information in sequential decision making: Component inspection, permanent monitoring and system-level scheduling. *Reliability Engineering & System Safety 154*, 137–151.
Michalik D, Kohl P and Kummert A (2022) Smart cities and innovations: Addressing user acceptance with virtual reality and digital twin city. *IET Smart Cities 4*(4), 292–307.
Miller C, Hilton J, Sullivan A and Prakash M (2015) Spark–a bushfire spread prediction tool. In *Environmental Software Systems. Infrastructures, Services and Applications: 11th IFIP WG 5.11 International Symposium, ISESS 2015, Melbourne, VIC, Australia, March 25–27, 2015. Proceedings 11*, pp. 262–271. Springer.
Mohammadi N and Taylor JE (2021) Thinking fast and slow in disaster decision-making with smart city digital twins. *Nature Computational Science 1*(12), 771–773.
Montáns FJ, Chinesta F, Gómez-Bombarelli R and Kutz JN (2019) Data-driven modeling and learning in science and engineering. *Comptes Rendus Mécanique 347*(11), 845–855.
Moya B, Badías A, Alfaro I, Chinesta F and Cueto E (2022) Digital twins that learn and correct themselves. *International Journal for Numerical Methods in Engineering 123*(13), 3034–3044.
Moya B, Badias A, Gonzalez D, Chinesta F and Cueto E (2022) Physics perception in sloshing scenes with guaranteed thermodynamic consistency. *IEEE Transactions on Pattern Analysis and Machine Intelligence 45*(2), 2136–2150.
Moya B, Badías A, González D, Chinesta F and Cueto E (2023) A thermodynamics-informed active learning approach to perception and reasoning about fluids. *Computational Mechanics 72*(3), 577–591.
Niloofar P, Lazarova-Molnar S, Omitaomu F, Xu H and Li X (2023) A general framework for human-in-the-loop cognitive digital twins. In *2023 Winter Simulation Conference (WSC)*, pp. 3202–3213. IEEE.
Nochta T, Wan L, Schooling JM and Parlikad AK (2021) A socio-technical perspective on urban analytics: The case of city-scale digital twins. *Journal of Urban Technology 28*(1–2), 263–287.
Olivotti D, Dreyer S, Lebek B and Breitner MH (2019) Creating the foundation for digital twins in the manufacturing industry: An integrated installed base management system. *Information Systems and e-Business Management 17*, 89–116.
Ouyang M (2014) Review on modeling and simulation of interdependent critical infrastructure systems. *Reliability Engineering & System Safety 121*, 43–60.
Ouyang M, Dueñas-Osorio L and Min X (2012) A three-stage resilience analysis framework for urban infrastructure systems. *Structural Safety 36*, 23–31.
Ouyang M, Xu M, Zhang C and Huang S (2017) Mitigating electric power system vulnerability to worst-case spatially localized attacks. *Reliability Engineering & System Safety 165*, 144–154.
Oztemel E and Gursev S (2020) Literature review of industry 4.0 and related technologies. *Journal of Intelligent Manufacturing 31*, 127–182.
Papacharalampopoulos A, Giannoulis C, Stavropoulos P and Mourtzis D (2020) A digital twin for automated root-cause search of production alarms based on KPIs aggregated from IoT. *Applied Sciences 10*(7), 2377.
Papatheou E, Tatsis KE, Battu RS, Agathos K, Haywood-Alexander M, Chatzi E, Dervilis N and Worden K (2023) Virtual sensing for shm: A comparison between kalman filters and gaussian processes. In *Proceedings of ISMA2022 Including USD2022*, pp. 3792–3803.
Park KT, Son YH and Noh SD (2021) The architectural framework of a cyber physical logistics system for digital-twin-based supply chain control. *International Journal of Production Research 59*(19), 5721–5742.

Phillips S and Narasimhan S (2019) Automating data collection for robotic bridge inspections. *Journal of Bridge Engineering 24*(8), 04019075.

Platenius-Mohr M, **Malakuti S**, **Grüner S**, **Schmitt J and Goldschmidt T** (2020) File-and API-based interoperability of digital twins by model transformation: An IIoT case study using asset administration shell. *Future Generation Computer Systems 113*, 94–105.

Poulin C and Kane MB (2021) Infrastructure resilience curves: Performance measures and summary metrics. *Reliability Engineering & System Safety 216*, 107926.

Psarommatis F and May G (2023) A standardized approach for measuring the performance and flexibility of digital twins. *International Journal of Production Research 61*(20), 6923–6938.

Rasheed F, **Yau K-LA and Low Y-C** (2020) Deep reinforcement learning for traffic signal control under disturbances: A case study on Sunway City, Malaysia. *Future Generation Computer Systems 109*, 431–445.

Rehak D, **Senovsky P and Slivkova S** (2018) Resilience of critical infrastructure elements and its main factors. *Systems 6*(2), 21.

Robles J, **Martín C and Díaz M** (2023) Opentwins: An open-source framework for the development of next-gen compositional digital twins. *Computers in Industry 152*, 104007.

Sacks R, **Girolami M and Brilakis I** (2020) Building information modelling, artificial intelligence and construction tech. *Developments in the Built Environment 4*, 100011.

Saddik AE (2018) Digital twins: The convergence of multimedia technologies. *IEEE Multimedia 25*(2), 87–92.

Saifullah M, **Andriotis C and Papakonstantinou KG** (2023) The role of value of information in multi-agent deep reinforcement learning for optimal decision-making under uncertainty. In *14th International Conference on Applications of Statistics and Probability in Civil Engineering 2023.* Dublin, Ireland.

Schlechtingen M, **Santos IF and Achiche S** (2013) Wind turbine condition monitoring based on SCADA data using normal behavior models. Part 1: System description. *Applied Soft Computing 13*(1), 259–270.

Schluse M, **Priggemeyer M**, **Atorf L and Rossmann J** (2018) Experimentable digital twins—Streamlining simulation-based systems engineering for industry 4.0. *IEEE Transactions on Industrial Informatics 14*(4), 1722–1731.

Schöbi R and Chatzi EN (2016) Maintenance planning using continuous-state partially observable Markov decision processes and non-linear action models. *Structure and Infrastructure Engineering 12*(8), 977–994.

Schrotter G and Hürzeler C (2020) The digital twin of the city of Zurich for urban planning. *PFG–Journal of Photogrammetry, Remote Sensing and Geoinformation Science 88*(1), 99–112.

Settles B (2009) *Active Learning Literature Survey*. University of Wisconsin-Madison.

Shafto M, **Conroy M**, **Doyle R**, **Glaessgen E**, **Kemp C**, **LeMoigne J and Wang L** (2010) Draft modeling, simulation, information technology & processing roadmap. *Technology Area 11*, 1–32.

Somanath S, **Naserentin V**, **Eleftheriou O**, **Sjölie D**, **Wästberg BS and Logg A** (2023) On procedural urban digital twin generation and visualization of large scale data. *arXiv preprint arXiv:2305.02242.*

Tajnsek V, **Pihler J and Roser M** (2011) Advanced logistical systems for the maintenance of overhead distribution lines through dcc with the use of laser monitoring. *IEEE Transactions on Power Delivery 26*(3), 1337–1343.

Tatsis KE, **Agathos K**, **Chatzi EN and Dertimanis VK** (2022) A hierarchical output-only bayesian approach for online vibration-based crack detection using parametric reduced-order models. *Mechanical Systems and Signal Processing 167*, 108558.

To A, **Liu M**, **Bin Muhammad Hairul MH**, **Davis JG**, **Lee JSA**, **Hesse H and Nguyen HD** (2021) Drone-based Ai and 3D reconstruction for digital twin augmentation. In *International Conference on Human-Computer Interaction*, pp. 511–529. Springer.

Unal P, **Albayrak O**, **Jomâa M and Berre AJ** (2022) Data-driven artificial intelligence and predictive analytics for the maintenance of industrial machinery with hybrid and cognitive digital twins. In *Technologies and Applications for Big Data Value*, pp. 299–319. Springer.

Urmeneta J, **Izquierdo J and Leturiondo U** (2023) A methodology for performance assessment at system level—Identification of operating regimes and anomaly detection in wind turbines. *Renewable Energy 205*, 281–292.

Vettori S, **DiLorenzo E**, **Peeters B and Chatzi E** (2022) Virtual sensing for wind turbine blade full field response estimation in operational modal analysis. In *Model Validation and Uncertainty Quantification, Volume 3: Proceedings of the 39th IMAC, A Conference and Exposition on Structural Dynamics 2021*, pp. 49–52. Springer.

Vettori S, **Gomes G**, **Di Lorenzo E**, **Peeters B and Chatzi E** (2023) Influence of the input model for virtual sensing of wind turbine blades. *Proceedings of ISMA2022 Including USD2022*, 4537–4550.

Vettori S, **Di Lorenzo E**, **Peeters B and Chatzi E** (2024) Assessment of alternative covariance functions for joint input-state estimation via Gaussian process latent force models in structural dynamics. *Mechanical Systems and Signal Processing 213*, 111303.

Vlachas K, **Tatsis K**, **Agathos K**, **Brink AR**, **Quinn D and Chatzi E** (2022) On the coupling of reduced order modeling with substructuring of structural systems with component nonlinearities. In *Dynamic Substructures, Volume 4: Proceedings of the 39th IMAC, a Conference and Exposition on Structural Dynamics 2021*, pp. 35–43. Springer.

Vlachas K, **Najera-Flores D**, **Martinez C**, **Brink AR and Chatzi E** (2012) A physics-based reduced order model with machine learning-boosted hyper-reduction. In *Topics in Modal Analysis & Parameter Identification, Volume 8: Proceedings of the 40th IMAC, A Conference and Exposition on Structural Dynamics 2022*, pp. 131–139. Springer.

Vlachas K, **Tatsis K**, **Agathos K**, **Brink AR and Chatzi E** (2021) A local basis approximation approach for nonlinear parametric model order reduction. *Journal of Sound and Vibration 502*, 116055.

https://doi.org/10.1017/dce.2025.10015 Published online by Cambridge University Press

Wagg DJ, **Worden K**, **Barthorpe RJ and Gardner P** (2020) Digital twins: State-of-the-art and future directions for Modeling and simulation in engineering dynamics applications. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering*, *6*(3), 030901, 2332–9017. https://doi.org/10.1115/1.4046739.

Wagg DJ, **Keith Worden and Gardner P** (2020) Digital twins: State-of-the-art and future directions for modeling and simulation in engineering dynamics applications. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering 6*(3), 030901.

Wagg DJ, **Burr C**, **Shepherd J**, **Conti ZX**, **Enzer M and Niederer S** (2025) The philosophical foundations of digital twinning. *Data-Centric Engineering 6*, e12.

Wang Y, **Su Z**, **Guo S**, **Dai M**, **Luan TH and Liu Y** (2023) A survey on digital twins: architecture, enabling technologies, security and privacy, and future prospects. *IEEE Internet of Things Journal 10*(17), 14965–14987.

White G, **Zink A**, **Codecá L and Clarke S** (2021) A digital twin smart city for citizen feedback. *Cities 110*, 103064.

Worden K, **Bull LA**, **Gardner P**, **Gosliga J**, **Rogers TJ**, **Cross EJ**, **Papatheou E**, **Lin W and Dervilis N** (2020) A brief introduction to recent developments in population-based structural health monitoring. *Frontiers in Built Environment 6*, 146.

Wright L and Davidson S (2020) How to tell the difference between a model and a digital twin. *Advanced Modeling and Simulation in Engineering Sciences 7*(1), 1–13.

Xia K, **Sacco C**, **Kirkpatrick M**, **Saidy C**, **Nguyen L**, **Kircaliali A and Harik R** (2021) A digital twin to train deep reinforcement learning agent for smart manufacturing plants: Environment, interfaces and intelligence. *Journal of Manufacturing Systems 58*, 210–230.

Xu Y, **Sun Y**, **Liu X and Zheng Y** (2019) A digital-twin-assisted fault diagnosis using deep transfer learning. *IEEE Access 7*, 19990–19999.

Yang J, **Langley RS and Andrade L** (2022) Digital twins for design in the presence of uncertainties. *Mechanical Systems and Signal Processing 179*, 109338.

Yang S, **Kim H**, **Hong Y**, **Yee K**, **Maulik R and Kang N** (2024) Data-driven physics-informed neural networks: A digital twin perspective. *arXiv preprint arXiv:2401.08667*.

Yu W, **Dillon T**, **Mostafa F**, **Rahayu W and Liu Y** (2019) A global manufacturing big data ecosystem for fault detection in predictive maintenance. *IEEE Transactions on Industrial Informatics 16*(1), 183–192.

Zhang J and Zhao X (2023) Digital twin of wind farms via physics-informed deep learning. *Energy Conversion and Management 293*, 117507.

Zhang W-H, **Qin J**, **Lu D-G**, **Thöns S and Faber MH** (2022) Voi-informed decision-making for shm system arrangement. *Structural Health Monitoring 21*(1), 37–58.

Zhao J, **Feng H**, **Chen Q and de Soto BG** (2022) Developing a conceptual framework for the application of digital twin technologies to revamp building operation and maintenance processes. *Journal of Building Engineering 49*, 104028.

Zheng X, **Lu J and Kiritsis D** (2022) The emergence of cognitive digital twin: Vision, challenges and opportunities. *International Journal of Production Research 60*(24), 7610–7632.

Zhong C, **Cheng S**, **Kasoar M and Arcucci R** (2023) Reduced-order digital twin and latent data assimilation for global wildfire prediction. *Natural Hazards and Earth System Sciences 23*(5), 1755–1768.

Zipper H and Diedrich C (2019) Synchronization of industrial plant and digital twin. In *2019 24th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*, pp. 1678–1681. IEEE.

Cite this article: Liang H, Moya B, Seah E, Ng Kwok Weng A, Baillargeat D, Joerin J, Zhang X, Chinesta F and Chatzi E (2025). Harnessing hybrid digital twinning for decision-support in smart infrastructures. *Data-Centric Engineering*, 6, e43. doi:10.1017/dce.2025.10015