Harnessing Hybrid Digital Twinning for Decision-Support in Smart Infrastructures

A Preprint

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August 7, 2024

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 Digital Twinning 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 modelling as a seminal tool for facilitating twinning applications. Hybrid modelling refers to the synergistic use of data with models that carry engineering or empirical intuition on the system's behaviour. 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's behaviour. We thus propose Hybrid Digital Twins (HDT) as the main enabler of smart and resilient infrastructures.

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Keywords hybrid digital twin · decision making · smart infrastructures · resilience support

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 development of next-generation digital twins for smart infrastructures. This study summarises the insights gained from a round-table discussion on Decision Support for Infrastructural Asset Management, which was held as a joint initiative of the Future Resilient Systems (FRS) program at the Singapore-ETH Centre and the DESCARTES interdisciplinary program of excellence 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 digitisation has been more broadly applied in the context of manufacturing and production technologies and the handling of industrial assets, it remains still less exploited in the context of large-scale built environments, i.e., in the context of infrastructures. There, the field has been dominated by the advent on Building Information Models (BIM) which, however, remain more of static images of a system, finding application primarily during the phase of design and construction Sacks et al. [2020]. Nevertheless, also at this scale, the concept of Digital Twinning has the potential not only to deliver information on the state of the system "as-is", but to further inform decision support frameworks that 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 eventually the decommissioning phase. In generating value, DT representations ought to allow for a closed loop exchange between the digital and physical asset, by extracting information garnered from operating physical systems (e.g. by means of monitoring), distilling this information via use of the digital representation, and finally exploiting this analysis for acting onto the physical asset with a view to protecting critical infrastructure and guaranteeing its resilience Argyroudis et al. [2022].

Infrastructure resilience is here employed as a main criterion on the basis of which strategic decision making can be accomplished. It can be defined as the capability of anticipating, preparing for, and adapting to environmental changes as well as coping with, responding to, and recovering 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. Such studies put forth resilience quantification and enhancement frameworks across scales, extending from the component, to the asset, and further to the interconnected networks level Ouyang et al. [2012], Cimellaro et al. [2016], Dhar and Khirfan [2017], Koliou et al. [2020], Liang et al. [2023], Blagojević et al. [2023]. Such an analysis is typically conducted in the pre-incident phase on the basis of simulated scenarios that employ stochastic deterioration/fragility models and restoration models, without thus accounting for information that is gathered from the actual system over time. Here, we concern ourselves primarily with decision making in the context of the *during-incident* and *post-incident* phases that usually require fast (sometimes even real-time) decision making. The premise for such an investigation lies in the assumption of availability of data from such infrastructural assets and systems. This is nowadays justified by the information that is increasingly becoming available, not only in terms of digitised logs that contain inspection information on structural systems, but also due to adoption of sensing technologies for monitoring such systems on both a periodic (e.g. Non Destructive Evaluation) and continuous (e.g. Structural Health Monitoring) basis Kamariotis et al. [2024]. Currently, no integrated framework exists for quantifying and enhancing infrastructural resilience based on the fusion of such data within digital twinning (DT) techniques.

In this context, 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 to, finally, highlight the associated challenges and opportunities in this respect.

2 Motivation for integrating HDTs in Infrastructural Management

The integration of digital twinning techniques into the management of infrastructures can reshape the process of strategic planning for operation, maintenance and resilience enhancement by offering decision-makers unprecedented, and often real-time, insights into the status and behaviour of physical assets, which refer to any physical object, system, or infrastructure holding economic value to an organisation (e.g. building, bridge, wind energy structures). Unlike traditional periodical and reactive decision-making methods, the real-time dynamic insights provided by hybrid digital twinning (HDT) empowers decision-makers to attain a more comprehensive understanding of the overall exposure to risks and hazards. It is reminded that the term hybrid implies exploitation of a model of the system, which in turn implies amplified predictive potential, including tasks that relate to virtual sensing Vettori et al. [2023] Papatheou et al. [2023], meaning prediction of the response of the system in critical positions that lie beyond the positions of sensor observations/measurements. This allows for prompt response to - and recovery from - emerging disruptions and strategic adaptation to changing conditions and requirements (e.g. increase of operational loads of transport infrastructure assets). The integration of digital twining introduces predictive analytics, which are informed on the basis of evidence collected from the operating physical asset. This forecasting potential supports system readiness and thereby resilience, by providing decision-makers with the tools to navigate uncertainties with greater confidence and, if required, proactively plan system repair and intervention in both a short-term, e.g. in the face an impending hazard, and long-term horizon, e.g. when planning for maintenance policies under slow evolving deterioration effects. In this sense, a DT framework with extended predictive abilities, can not only fortify operational resilience but also foster a proactive and adaptive approach to infrastructure management. A main element of DTs, and HDTs, lies in the exploitation of telemetry and remote operation and control features, which allow to oversee and manage assets remotely, i.e., without the need for physical access. This functionality allows to streamline decision-making in challenging environments such as inaccessible (e.g. offshore) locations, enhancing operational efficiency and adaptability.

In the context of resilience enhancement, such an integrated approach allows decision-makers to develop a scalable framework that can proactively plan and optimize the entire life performance of assets, contributing to long-term sustainability and adaptability. HDT embodies a data-driven, dynamic, possibly real-time, and closed-loop approach to asset management, allowing to account for complex interdependencies, curb assessment uncertainty, and operate on the basis of assessment of the system as-is and not as-deployed. In spite of the benefits in the use of DTs within the context of infrastructure management and resilience, the uptake has been slow in practice. A reason for this is associated with the diverse interpretations and lack of clarity surrounding the definition and applicability of a DT, 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 DTs within the domain of smart infrastructures and explore potential needs for expanding their usefulness and maximising their uptake.

3 Hybrid Digital Twins - HDTs

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

3.1 Definition and Interpretation of Digital Twins

The concept of a *Digital Twin* (DTs) 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, such 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 across several fields, however, the definition of the term may still appear blurred and unclear Wright and Davidson [2020]. Certain sources (Hughes [2018], Alam and El Saddik [2017], Platenius-Mohr et al. [2020] to name a few) define digital twins 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 framings within the engineering context, describe a DT as a process that defines a closed loop between the physical entity and the digital replica Committee et al. [2020], McClellan et al. [2022]. This necessitates a digital workflow of information, parameterized models, diagnostic and prognostic algorithms and control tools, often aggregated in a visualisation 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 Life-cycle Management (PLM) framework Grieves [2002]. However, the first known definition for 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 multi-physics, multi-scale, 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], El Saddik [2018], Liu et al. [2021], Xu et al. [2019]. The recent AIAA position paper Committee et al. [2020] defines a digital twin as:

"A set of virtual information constructs that mimics the structure, context and behavior 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 realize value."

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

- A physical asset from which information is extracted, implying presence of a monitoring system.
- A digital (virtual) representation of the physical element, represented by a model that captures the behaviour 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 counterpart to ensure continuous tracking of the behaviour 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 to act on it with improved confidence margins. A one-way process is also referred to as a "digital shadow". Bergs et al. [2021].

At this point, it is worth referring to the definition of *Dynamic Data-Driven Application Systems* (DDDAS) in the work of Blasch et al. [2013], who propose this as a framework for dynamic updating of simulators (models) with data obtained from sensor networks and monitoring devices. While this framework focuses on the aspect of updating of a digital mirror (essentially) of the operating physical system, the purpose of DTs extends beyond computational modelling and updating to include performance and condition assessment, analysis, and optimisation of physical assets throughout their lifecycle. Following Grieves and Vickers [2017], in this work we define DTs along a classification in three essential categories (classes), according to the purpose served by the twin:

- 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 characterise and fabricate a physical counterpart (for instance requirements, 3D models, lists of materials, processes, services, and disposal procedures). This type, is usually established at design stage and is strongly linked to the characteristics and objectives of BIM (Building Information Modelling) Definition [2014].

In the work of Grieves and Vickers [2017], a *Digital Twin Instance (DTI)*, is described as a specific corresponding physical product that an individual DT remains linked to throughout the life of that physical product. We here, 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 counterpart.

Finally, the *Digital Twin Aggregate (DTA)* Grieves and Vickers [2017], McClellan et al. [2022] can be defined as the collection and processing of data from multiple instances of DT (DTIs), for interrogation of and possible action on a collection of assets. Essentially, it describes a computing construct that allows to gather and analyse data from various DTIs to gain insights with respect to a broader range of physical products or processes. A 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.

In these definitions, it is important to note that the information flow is assumed to be available throughout the life of the asset. This implies that individual instances of updated models, which do not continually follow a physical asset may be merely viewed as snapshots of a twin and not actual DTs. On the other hand, in the context of engineering, it is further helpful to define the notion of Real-Time Digital twins (RTDTs), signifying digital representations that are updated in an online fashion, i.e., on the fly (in real- or near real-time) as data is attained.

Accompanying the real asset along its useful life requires 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. [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.

Under this premise, we refer to *Hybrid Digital Twins (HDT)* as twin constructs that adopt a hybrid modelling approach. Such an approach combines different modelling techniques or methodologies to create a more comprehensive and accurate representation of a system or process. In the context of DT, hybrid modelling involves integrating various modelling schemes, such as physics-based models, data-driven models, and ML algorithms, to create an accurate representation of a physical asset or system that goes beyond the available knowledge. HDT extend this concept to digital twin technology Chinesta et al. [2020], Haywood-Alexander et al. [2023]. Hybrid models typically entail incorporation of physics into the simulation process allowing for interpretable diagnostics and generalisation in their predictive ability. By combining physics-based models with data-driven approaches, hybrid digital twins can provide more accurate predictions, real-time monitoring, and decision support across a wide range of applications Wagg et al. [2020b].

In this paradigm, there is an incipient sub-class of DTs that is expected to lead next developments in the domain: the *cognitive digital twin* (CDT) Abburu et al. [2020b], 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 (CDTs) refers to systems that can interact with both physical and virtual environments to autonomously make smarter decisions based on the context Zheng et al. [2022], Abburu et al. [2020a]. Although both HDTs and CDTs use machine learning 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 its performance), automatic recalibration for enhanced decision making Arcieri et al. [2021], and interactivity 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 comprehending 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).

At their core, DTs are powered by use of simulators/models that provide representations of complex systems, processes, or phenomena of interest. In spite of the continuous growth of tools for data-driven modelling, there is still a remarkable prevalence of trust in BIM (Building Information Modeling) representations, or purely simulation- and physics-based models that are cross-validated across industries. Such models rely on finite elements and well established formulations such as fluid mechanics, transient dynamics, and degradation models. In order to make such models actionable within a twinning framework, it is necessary to deliver reliable, yet reduced order representations, which can incorporate physics in a way that is manageable for the process at hand. This is where Reduced Order Models (ROMs) present a salient contribution, in that they deliver accelerated emulators of a monitored system at reasonable computational costs Chinesta et al. [2011], Amsallem et al. [2012], Farhat et al. [2018], Agathos et al. [2022], Vlachas et al. [2021], Agathos et al. [2024], Idrissi et al. [2022], Frangos et al. [2010], Kapteyn et al. [2020]. ROMs are mathematical representations of complex systems that aim to provide simplified but accurate predictions of system behaviour. When incorporating physics principles, such ROMs are often referred to as intrusive Chinesta and Cueto [2014]. While non-intrusive, i.e., purely data-driven techniques do exist and employ data from simulations or experiments to bypass physics Hernandez et al. [2021], Ibáñez et al. [2018], the imposition of physics biases is often desirable to ensure interpretability Vlachas et al. [2012], Liu et al. [2022a], Bacsa et al. [2023].

When extending prediction/estimation at the system level, the DT may require the incorporation of representations and simulations of interconnected systems or components Heussen et al. [2011], Ouyang [2014], Schluse et al. [2018], Liang and Xie [2021]. Such representations are defined as *System-Level Models*. For instance, energy system network models Heussen et al. [2011], Ouyang et al. [2017] provide a detailed understanding of how energy flows through various components, aiding in the optimisation of energy consumption and the identification of potential inefficiencies.

Once models have been selected, AR, VR, and DT technology create a bridge between the physical and digital realms Moya et al. [2022a], Badías et al. [2019], Vettori et al. [2023] and augment the user interface, fostering an enhanced comprehension, collaboration, and decision-making process across diverse domains Michalik et al. [2022].

Virtual environments often use virtual sensing to simulate the behaviour of sensors that exist in the real world. Although remote sensing facilitates the creation of accurate DT of infrastructure systems Bado et al. [2022], Kaartinen et al. [2022],

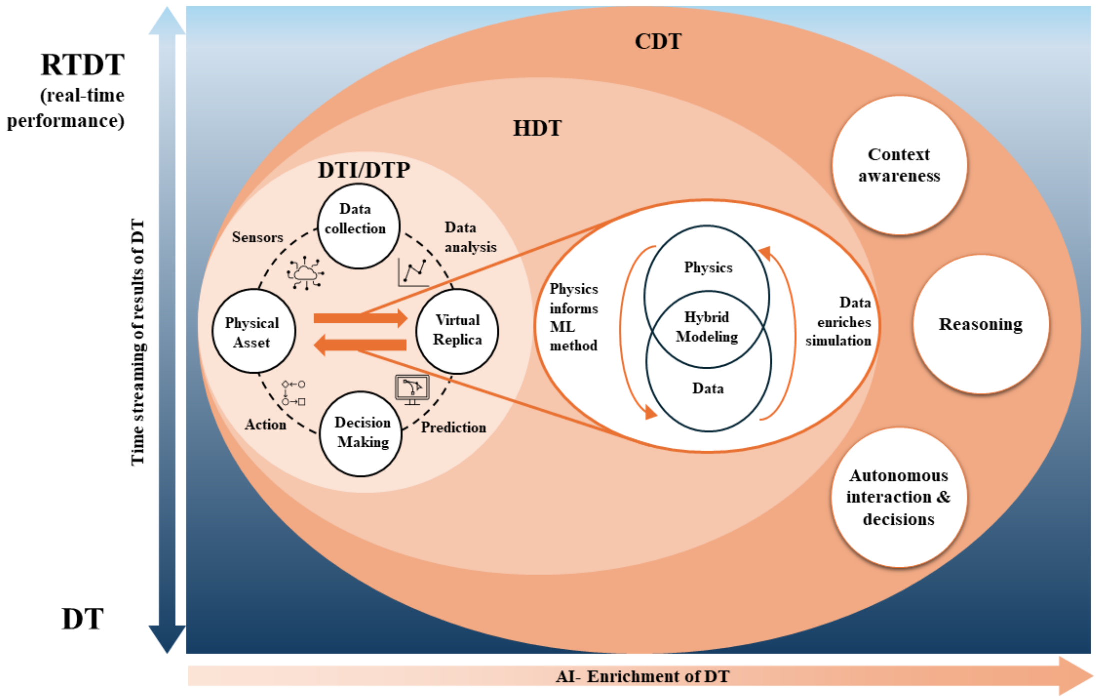

Figure 1: Landscape of the DT paradigm. DTPs and DTIs reflect the basic characteristics of the twinning technology in design and operation respectively. The HDT includes hybrid modelling to enrich simulations with aspects of physics and ML to accurately mimic the behavior of real systems. Such a construct offers higher interpretability. Finally, CDT would combine previous technologies with scene understanding and autonomous decision-making. As a result, the DT progressively increases in complexity and opportunities. DTs can also evolve on a temporal scale, where RTDTs are specific DTs that are updated in a more frequent, real-time, manner.

Dorafshan et al. [2018], Phillips and Narasimhan [2019], there are still scenarios where it is impractical, expensive, or insufficient, such as the case of the evaluation of 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 Tings, Real-time Data Analytics, and Artificial Intelligence

The concept of Internet of Things (IoT) touches on the aspects of sensor selection, deployment, use/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 entail multiple and, thus, heterogeneous or multi-modal data sources. Hence, DT must be designed to flexibly tackle diversified types of data inputs, which is usually tackled via the aspect of fusion. Moreover, 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). In order to derive physical insights from a collection of heterogeneous and often indirect observables, it is necessary to resort to physically-infused hybrid modelling.

In this context, we revisit the previously introduced concept of RTDTs, which focus on *real-time* performance, reflecting a growing desire of the industry. It is important to properly define what real-time implies in practice and consider the appropriate time scale of system performance assessment and require rate of data flow. We define an RTDT as a digital twin which evolves synchronously to the physical counterpart, by measuring and processing 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, a perfectly synchronous response, in the sense of hard real-time, implying minimal delays and alignment at a high sampling rate, could be inefficient in practice, involving disproportional allocation of resources and infrastructure and risks of overhead and latency. Thus, the meaning of "real-time" performance in a digital twin is used in a flexible context and will differ

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 produces, 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, CO2 concentration, precipitation)
Historical and domain knowledge	Time-stamped records of past operational and maintenance actions, which can be used for analysing 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)

Table 1: Summary of main sources of data for DTs

based on the DT purpose, ranging from instantaneous to periodic updates, based on the rate of data collection and time restrictions in assuming corresponding action/decisions.

Machine learning and deep learning can synergistically be combined with hybrid models, enhancing their explainability and predictive potential Montáns et al. [2019], Champaney et al. [2022b]. Such an instance has emerged in physics-enhanced or physics-informed modelling, which capitalises 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]. In this context, one can refer to physics-informed digital twins (PIDT) as those DT representations that integrate domain-specific knowledge of physical laws and principles, providing interpretable models that capture the underlying system dynamics Kapteyn and Willcox [2020], Liu et al. [2022a]. Although these may require more effort to develop and calibrate, PIDTs offer transparency and fidelity, rendering these well-suited for applications where understanding and certifiability are crucial. Ultimately, the choice between these approaches depends on the specific requirements of the problem at hand, balancing 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 HAYWOOD-ALEXANDER and CHATZI [2023], Zhang and Zhao [2023], Yang et al. [2024], Vlachas et al. [2022], Tatsis et al. [2022], such as those of thermodynamics Cueto and Chinesta [2023], Hernandez et al. [2022], and preservation of physical quantities Kirchdoerfer and Ortiz [2016], Bacsa et al. [2023].

AI strongly depends 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, in the right moment, and right place.

3.3 The smart data paradigm

Data collection process can pose challenges that require a comprehensive framework for intelligent data collection, processing, and use. Table 1 summarizes main sources of data in DTs. In this context, wireless technology plays a pivotal role in data acquisition and communication in DTs. in the future prospects of this technology, 6G networks can be potential enablers in the synchronisation-delay-accuracy commitment Bariah et al. [2023].

Some early definitions on the incipient concept of smart data refer to the extraction of valuable information from Big Data to support decision making [Lenk et al., 2015, Iafrate, 2014]. However, this terminology has evolved to refer to the formulation of data practises that focus on answering four questions as detailed in Chinesta et al. [2020]: (1) what data to collect, (2) where to deploy sensors for extracting relevant information, (3) when and for how long to deploy the system, and (4) at which scale. As a result, the so-called *smart data* pipeline possesses some specific characteristics. A main trait pertains to trustworthiness, i.e., the extent to which reliability and accuracy is ensured, and whether credible sources are used. This trust is established through robust data collection methods, quality assurance processes, and adherence to data governance standards Kirchen et al. [2017], Bicevskis et al. [2017], Hong and Huang [2017].

The smart data paradigm is also linked to the extent to which it facilitates downstream tasks, usually linked to the concept of *cognitive capabilities*, which refer to advanced analysis, interpretation, and learning Abburu et al. [2020a], Zheng et al. [2022]. A very intuitive classification of digital representations in relation to their function is offered in Wagg et al. [2020a]. 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 modelling Champaney et al. [2022b] and can typically be achieved through appropriate exploitation of prior knowledge on the system and its behaviour Chinesta et al. [2020]. Akin to the concept of gathering meaningful data is the concept of active learning, which allows to target maximal information extraction on the basis of minimal data Settles [2009], Chabanet et al. [2022]. Active learning makes use of either human expertise Khamesi et al. [2020] or ML schemes, allowing for selective guidance on labelling specific unlabelled samples, optimising resource utilisation 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, with a view to optimising data collection efficiency and ensure data relevance Di Lorenzo et al. [2023], Bigoni et al. [2020]. Data completeness refers to the notion of ensuring availability of all relevant information for informing the digital asset, with a view to enhancing 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 Champaney et al. [2022a], Moya et al. [2022b], Schöbi and Chatzi [2016], Liu et al. [2022b], Liang et al. [2020], Bermejo-Barbanoj et al. [2024]. Data quality and observation stochasticity need also be considered in the hybrid modelling paradigm Liu et al. [2022a], Vettori et al. [2024], to propagate and evaluate uncertainty in the prediction and asses its value and trustworthiness.

4 Applications in Management and Resilience of Smart Infrastructures

The information generated and transformed by the HDT is expected to support long-term decision making through an asset's life cycle. What needs to be further highlighted is that these assets are usually organised in an interdependent manner so as 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 system's capacity to endure and bounce back from disturbances or disruptions Bruneau et al. [2003], Labaka et al. [2016], Ouyang et al. [2012]. For better understanding and visualisation, Fig. 2 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/ ageing/ 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]. Noteworthy, 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 a number of components becomes 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 Arcieri et al. [2023], Fang and Sansavini [2019], Didier et al. [2018], Blagojević and Stojadinović [2022], Rehak et al. [2018], Francis and Bekera [2014].

4.1 Benefits and Status of DT-powered Decision Making

As mentioned DTs are increasingly entering the asset management process, rendering several benefits. A first advantage pertains to the reaction time, allowing for rapid response and alleviating the delays associated to non DT-informed approaches that are necessarily of reactive nature, often resulting in increased downtime and increased maintenance costs. Moreover, the pure reliance on historical data limits predictive capabilities, leading to suboptimal policies that may not anticipate future challenges. In terms of resource allocation, conventional practices may suffer lack of real-time insights, reliance on subjective schemes that are prone to human error (e.g. inspection practices), potentially yielding inaccurate assessment. 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, the use of a DT allows to adapt to changing conditions, technological advancements, and shifts in infrastructure requirements, thus, favouring the resilience of infrastructure systems.

To this end, the integration of hybrid digital twinning in decision-making motivates a paradigm shift by providing proactive, on-time, and simulation-driven insights, promoting adaptability, and enhancing overall system understanding compared to traditional decision-making frameworks Makhoul et al. [2024]. This evolution is particularly significant

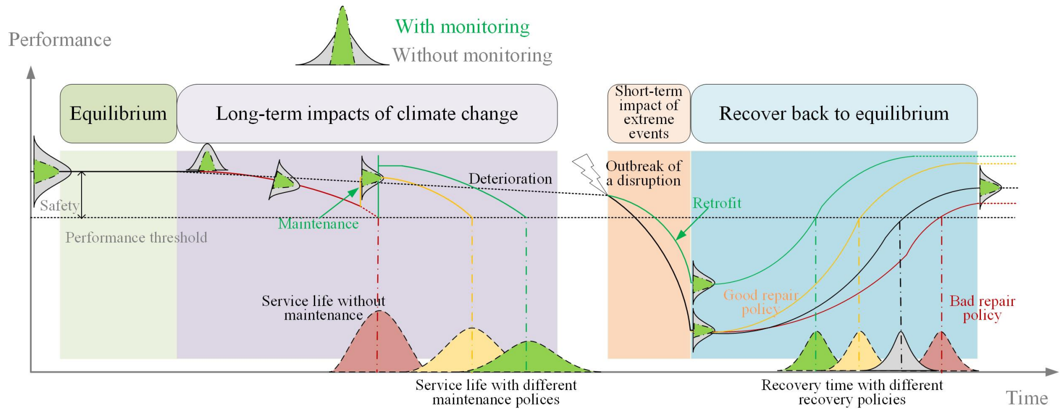

Figure 2: Time-evolution resilience curve of component/asset/infrastructure network exposed to various environmental changes throughout their life-cycle with and without the monitoring system

in complex and dynamic environments where a more responsive and accurate decision-making process is crucial. In this manner, a so-called *smart decision* would be achieved, referring to the policy that can inform sequential actions to maximise resilience with minimum cost, by dictating what actions should be taken, when and where to take that action 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 wield, there is a discernible trend towards incorporating DT across diverse sectors of real-world infrastructure Zhao et al. [2022], Kuo et al. [2021]. This surge in adoption is a testament to the significant advantages these models confer in terms of predictive maintenance capabilities, operational efficiency enhancing, smart cities planning, and overall resilience improvement in the face of dynamic challenges. This trend is expected to persist 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 that allow for continuous monitoring, analysis and intervention on infrastructure components. The integration of sensor and historical data with predictive models empowers decision-makers to optimise system performance and anticipate failure. This facilitates proactive scheduling of maintenance activities, minimising 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 SCADA data Urmeneta et al. [2023], Schlechtingen et al. [2013]; fault diagnosis and condition based maintenance of overhead power transmission lines utilizing the Cablewalker robotic system consisted of a laser scanner, a stereo camera, or a magnetic scanner Tajnsek et al. [2011], Gitelman et al. [2019]; 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) Ignatius et al. [2019], Gobeawan et al. [2018].

Operation Optimisation, in the context of logistics and supply chain management, distributed agent-based DT simulation can be performed by integrating real-time logistics data, external need trends, and optimisation algorithms, assisting in streamlining operations and optimising inventory Park et al. [2021]. In smart manufacturing, real-time manufacturing data, historical performance metrics, and dynamic simulation models cab be integrated into the 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 utilise building sensor networks and heating/ cooling data to optimise energy design, improve users' satisfaction, and reduce energy costs Bortolini et al. [2022]. In the context of traffic management, DL algorithm can be employed by utilising real-time traffic data and dynamic simulation models to optimise 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]. In this context, 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, etc. with the aim of ensuring 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 Nochta et al. [2021], Ignatius et al. [2019], Schrotter and Hürzeler [2020]), land allocation dynamics and social equity considerations (as exemplified in Herrenberg, Nigeria, and Zurich DTs Dembski et al. [2020], Enoguanbhor et al. [2021], Schrotter and Hürzeler [2020]), 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 multifaceted challenges confronting modern cities.

Extreme event handling receives growing interest given the increasingly frequent extreme events (e.g., earthquake, tornado, wildfire) we have experienced recently. DTs can play a crucial role in supporting decision-making by reducing uncertainty of condition assessment and in turn, facilitating the efficiency of emergency react Makhoul et al. [2024]. Use cases include developing DTs that can simulate and predict the spread of wildfires, allowing decision makers to plan evacuation routes, deploy firefighting resources strategically, and communicate timely warnings to community Zhong et al. [2023]; developing deep RL-based decision framework to make rational decisions for transportation management under hurricanes based on the monitoring 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 enhances risk mapping for better situational awareness and response strategies, verified using the 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, data-driven foundation for informed decision-making. In essence, the combination of robust data, advanced modelling, and diverse use cases exemplifies the multifaceted impact and potential of DT in revolutionising decision-making processes.

5 Future Outlook

5.1 Future Goals

As distilled in the analysis exposed, two main objectives have been identified for future DTs. First, it is imperative to develop future-proof systems, that do 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, DT are expected to work on multiple cross-connected levels in which the twins operate in reality.

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 indispensable tool for housing vital information, insights, and models Marykovskiy et al. [2024]. By leveraging knowledge bases, establishment of uniform data models and vocabularies, organisations can promote smooth communication and cooperation within digital twin ecosystems. This common language not only encourages standardisation 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 modelling techniques and intelligent algorithms within a DT framework that can cater to creating value for assets. To this end, DTs must evolve towards decision support, with a focus on analysis tasks, such as independently analysing 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 return on investment (ROI), and modelling the long-term benefits of DT involves assessing both tangible and intangible factors over an extended period. The ultimate aim would be to optimise the strategies of the stakeholders for DT 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 Kamariotis et al. [2022], Zhang et al. [2022], Memarzadeh and Pozzi [2016], Saifullah et al. [2023].

5.2 Challenges

Driven by industrial demands on technological readiness and maturity, formal frameworks on 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 analyse the data flow to reduce latency in the response.

Open data exchange. challenges in open data exchange include ambiguous data ownership, data privacy concern 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 DT may exhibit bias and may not under go thorough validation processes; explainability of AI models is often limited; all these can lead to inaccurate representations and flawed decision-making outcomes.

Standardisation and certification of DT. Lack of universally accepted standards hampers interoperability and poses challenges in assessing digital twin quality and reliability Burns et al. [2019], Kirchen et al. [2017], Bicevskis et al. [2017], Hong and Huang [2017].

Dealing with false positives/ responsibility for 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 integration of human expertise and ethical guidelines into automated decision-making in DT 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 organisations, technology providers, and end-users, to develop frameworks, standards, and best practices that promote the responsible and effective use of DT 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 visualisation. Emphasising the need for improvement, they advocate for modelling 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 utilising Smart City DT for disaster decision-making in cities facing various stressors. They emphasise 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 standardisation 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. Moreover, standardized data formats and communication protocols enhance data quality, consistency, and security, building trust and confidence. Despite these benefits, current digital twin standards, including the IFC and ISO series 19650-1:2018, 23247-2021, 24464-2020, 30172, 30173, 37100-2016, IEEE series SA-P2806.1, SA-P3144, IEC series 61850-2024, 62832-2020 and ITU series Y.3090, ITU, 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 organisations or those with legacy systems. Overcoming these limitations is essential for advancing digital twin standardisation and realising its full potential across industries.

Last but not least, in the rapidly evolving landscape of technology, the demand for open platforms that incorporate previous technologies has become increasingly apparent 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 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 Centre, that incorporates a DTCC builder Logg et al. [2023] Somanath et al. [2023], model and simulation, and visualisation. 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 labour 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.

DT must be built to empower the human, not the machine. The exploitation of AR, VR, or virtual spaces (metaverse) as facilitators can democratise 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 which 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 modelling provides an effective strategy for integrating diverse modelling 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 unpredicted, 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 projects' life cycle and discuss advanced applications including autonomous management, predictive maintenance, adaptive behaviour, 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, in order to make more informed and comprehensive decisions in support of infrastructure resilience.

Acknowledgements 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.

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 supported by the National Research Foundation, Prime Minister's Office, Singapore under its Campus for Research Excellence and Technological Enterprise (CREATE) programme.

Competing Interests None

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

Author Contributions 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 visualisation: 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.

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