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A framework to define, design and construct digital twins in the mining industry

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ABSTRACT

The mining industry is set to increasingly use technological innovations surrounding digitalisation, particularly in the context of the fourth industrial revolution, to address current productivity challenges and safety concerns. Digital twins serve as an enabling technology for many digitalisation-based technological innovations. However, there is currently a lack of a comprehensive understanding of the digital twin concept within the mining industry. This paper presents a framework customised to mining which delineates various dimensions, model types and properties associated with a digital twin. The framework establishes a shared understanding of the concept, serving as a blueprint for the development of future digital twin works in the mining industry. The framework is enriched by accompanying model selection tools which could aid new users in developing digital twins within the proposed framework. Two case studies depicting existing mining digital twins are presented and deconstructed within the proposed framework. These case studies illustrate the framework's ability to effectively identify various digital twin types, instilling confidence in the framework's ability to thoroughly deconstruct existing works whilst simultaneously serving as an effective tool to construct future digital twins.

1. Introduction

The mining industry must explore technological innovations to increase productivity amidst fluctuating metal prices and increasingly scarce ore resources. Simultaneously, a drive towards increased safety in mining has further prompted the need for technological innovation. With the advent of the fourth industrial revolution, products and systems have become more intelligent, amassing larger volumes of data (Singh et al., 2022). The fourth industrial revolution encompasses a proliferation of technologies and digital advances that integrate physical and digital worlds (Javaid et al., 2023). The mining industry is embracing these digital technologies to advance production and safety objectives (Barnewold & Lottermoser, 2020; Grehl et al., 2017). Digitalisation encompasses the utilisation of computerised or digital devices, methods, systems and digitised data to reduce costs, improve business productivity and safety and transform mining practices (Barnewold & Lottermoser, 2020).

Barnewold and Lottermoser (2020) identify multiple digital technologies pertinent to the mining operations at various production scales, including automation, robotics, internet of things, big data, real-time data, machine learning, 3D printing and artificial intelligence. Many of these concepts are encapsulated within the broader concept of a digital twin Javaid et al. (2023). Digital twinning therefore represents a promising technology for driving digitalisation (Plavšić & Mišković, 2022; Singh et al., 2022) and is expected to facilitate the transition into the fourth industrial revolution (Ghobakhloo, 2020).

Previously, digital twins were often overlooked due to limitations in the Internet of Things (IoT) and data processing technologies. However, with these technologies now maturing and with COVID19 having emphasised vulnerabilities in the supply of labour and a necessity for remote operations (Singh et al., 2022), digital twin research is poised to experience rapid growth (Yao et al., 2023). Digital twins present mining companies with the potential to effectively utilise the vast amount of data available to them through the fourth industrial revolution (4IR) (PwC, 2023), converting it into actionable and interpretable insights (Tao et al., 2019). Yao et al. (2023) indicate that recent digital twin literature reflects a readiness to penetrate industry, with global players introducing policies regarding digital twins. Moreover, standardisation organisations such as the International Organisation for Standardisation (ISO), the Institute of Electrical and Electronics Engineers (IEEE), the International Electrotechnical Commission (IEC), and the International Telecommunication Union (ITU) are introducing industry standards related to digital twins. From 2017 to 2019, Gartner Consulting listed digital twins as one of the top ten strategic technologies. The German Information Technology and New Media Association (BITKOM) suggest that the expected value of digital twins

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in the manufacturing market alone will exceed 78 billion euros by 2025 (Wu et al., 2020). The mining industry is also beginning to recognise the value of digital twin technologies, with (Singh et al., 2022) reporting that 70% of mining companies are expected to invest in digital twin technology in the coming years.

While the manufacturing industry is anticipated to lead the trend in deploying digital twins (Dihan et al., 2024; Singh et al., 2022), a recent literature review by Singh et al. (2022) illustrates that the mining industry publishes a third of the volume of digital twin literature compared to manufacturing. Plavšić and Mišković (2022) note that as of 2022, only 32 mining case studies of digital twins were available. These findings suggest that while the mining industry recognises the value of digital twins, the concept is still in its infancy in this industry. Plavšić and Mišković (2022) suggest that the current dearth of published case studies may be attributed to mining companies' uncertainty in applying digital twin technologies to their industry-specific needs. Digital technologies are often ambiguously defined and poorly understood, causing a failure in digital technology implementation (Barnewold & Lottermoser, 2020).

Consequently, numerous digital twin definitions with overlapping concepts have been proposed. Recent works have proposed digital twin frameworks to consolidate these overlapping similarities (Sjarov et al., 2020). Some notable frameworks include (Grieves, 2014), credited with coining the term "digital twin", who introduced a foundational three-dimensional framework depicting a real and virtual domain with connections bridging these domains. Tao et al. (2018) expanded the framework by introducing two additional dimensions related to services and digital twin data. Stark and Damerau (2019) developed a more expansive framework delineating eight crucial dimensions of a digital twin, each with varying maturity levels. Thelen et al. (2022a) added additional communication and model optimisation dimensions to the three dimensions proposed by Grieves (2014).

One of the continual considerations in the mining industry is a transition to more mechanised operations for increased productivity (Willis et al., 2004). However, human involvement remains significant (PwC, 2023), and many modern frameworks do not adequately address this scenario (Agrawal et al., 2023). Such misalignment can hinder the practical adoption of digital twins in mining.

Therefore, we propose a novel digital twin framework that consolidates, aligns, and expands recent works with reported industry needs, creating a shared understanding between literature and industrial definitions of digital twins. Such a shared understanding is anticipated to cultivate an environment conducive to recognising the potential value of digital twins, preventing duplication of efforts, and facilitating the positioning of various existing works within the framework to help identify future twinning opportunities. Crucially, model selection tools are included with the proposed framework to assist newcomers in identifying the necessary models for developing a digital twin within the proposed framework.

Furthermore, while the framework is customised to address the potential uncertainty around digital technologies in mining (Plavšić & Mišković, 2022), it is readily extendable to similar industries where humans play a significant role in a mechanised environment. This adaptability ensures the proposed framework can have broader applications beyond mining, benefiting other sectors with similar operational characteristics and uncertainty around digital technology implementation.

To demonstrate the proposed framework's comprehensive yet succinct nature, two case studies are provided where existing digital twins from the mining industry are positioned within the proposed framework. This effort showcases the ability of the proposed framework to effectively deconstruct vastly different digital twins into their constituent parts within the framework, instilling confidence in the framework's ability to thoroughly describe existing works and serve as a tool for the development of future digital twins.

The principal contributions of this work can be summarised as follows:

1. A comprehensive overview of existing digital twin literature with key concepts relevant to the global mining industry being highlighted.
2. Formulation of a comprehensive digital twin framework customised to the mining industry.
3. Provision of various model selection tools to assist newcomers to digital twins in identifying the requisite models to construct a digital twin within the proposed framework.
4. A presentation of two case studies depicting existing digital twins in the mining industry positioned within the proposed framework, demonstrating its capacity to effectively capture the core aspects of diverse digital twins in a comprehensive yet concise manner.

The following section summarises various intricacies associated with digital twin definitions and discusses common properties associated with digital twins. Section 3 presents the newly proposed framework and details each element of the proposed framework. Section 4 positions two digital twin case studies within the proposed framework, showcasing the framework's ability to identify the essential elements of a digital twin. Finally, conclusions and recommendations are presented in Section 5.

2. A broad overview of digital twins

The mining industry is seeing increased interest in digital technologies and by extension digital twins (Singh et al., 2022). Despite this interest, Plavšić and Mišković (2022) report a dearth of published digital twin case studies in the mining industry, which is attributed to uncertainty around the concept. Schweiger and Barth (2023) emphasise that digital twins have various properties and characteristics and therefore each digital twin is essentially unique, explaining why a single definition remains elusive. Tao et al. (2017) note that the absence of a universal digital twin definition has prompted researchers to simplify digital twins into broad concepts, to accommodate varied perspectives. This section provides a comprehensive overview of existing digital twin works to identify and synthesise key concepts related to digital twins for the mining industry. These concepts will be used in the following section to construct a novel digital twin framework, specifically customised to reduce the uncertainty around the concept in the mining industry.

2.1. Digital twin definitions

Digital twin definitions vary over time (Yao et al., 2023), lifecycle phase (Thelen et al., 2022a), industry (Schweiger & Barth, 2023), and capability (Autodesk, 2022; Kritzinger et al., 2018). The following sub-sections briefly explore the reasons for these variations.

2.1.1. Variation across time

The definition of digital twins can be traced back to concepts introduced by NASA in 1970, and evolved significantly over time until Professor Michael Grieves formalised it in 2003 (Yao et al., 2023). At that time, the definition comprised three components: a physical product, a virtual product, and their interconnections (Tao et al., 2019). Grieves and Vickers coined the term "digital twin" in 2011. Subsequently, NASA formalised the definition of a digital twin as an "integrated multi-physics, multi-scale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history etc., to mirror the life of its corresponding flying twin" (Glaessgen & Stargel, 2012). This definition was aerospace-specific but was widely adopted beyond aerospace applications (Thelen et al., 2022a).

As more researchers entered the field, updated digital twin definitions proliferated further. Definitions evolved to include concepts such as simulation in the virtual space, high model fidelity across micro- and macroscopic scales, the notion of control to influence the physical reality, modelling over entire asset lifecycles and the use of multi-dimensional, multi-physical and multi-temporal approaches (Yao et al., 2023). Evolving technological (Grieves, 2014) and digital (Singh et al., 2022) advancements have changed the capabilities of digital twins and consequently evolved the definition of a digital twin as the enabling technologies improved (Grieves & Vickers, 2017). These perspectives are especially relevant to the mining industry where elements of mechanisation (Willis et al., 2004) and digitalisation (PwC, 2023) are being adopted across various operational and time scales. Therefore, evolving mining digital twin capabilities need to be considered when designing the proposed framework.

2.1.2. Variation across context

Digital twin definitions vary according to context, such as asset life-cycle phase or application (Stark & Damerau, 2019; Tao et al., 2019; Thelen et al., 2022a). Thelen et al. (2022a) identify three distinct life-cycle phases in which digital twins may be applied, namely the design phase, the manufacturing phase and the service phase. These phases have parallels in the mining industry, namely the exploration and mine planning, mine development and ore extraction phases.

Groeneveld et al. (2019) (production planning) and Savolainen and Urbani (2021) (operations and maintenance optimisation) serve as noteworthy examples from the exploration and planning phase. Path planning (Declercq et al., 2021), mine support optimisation (Jiao et al., 2022) and mine ventilation optimisation (Kychkin & Nikolaev, 2020) are examples of works from the mine development phase. Finally, rock cutting (Zhang et al., 2024), equipment diagnosis and prognosis (Patil et al., 2021), equipment design optimisation (Guan et al., 2018) and path planning (Rubio-Sierra et al., 2020) all represent digital twins in the ore extraction phase.

These varied works emphasise the importance of both the application type and life-cycle phase as differentiating factors when describing a digital twin in the mining industry.

2.1.3. Variation across twin maturity

Many definitions mention a digital counterpart to physical reality. Kritzinger et al. (2018) argue that misinterpretation of the relationship between these elements has caused various related models to be labelled as digital twins when they are not. A clear distinction between digital models, digital shadows and digital twins is made, all of which are related but ultimately differ by their levels of data integration and hence maturity. Fig. 1 illustrates this concept, with a digital twin ultimately being defined by a bi-directional, automatic data flow. Kritzinger et al. (2018) identified that 82% of research papers misclassified digital models or shadows as digital twins. Looking at two mining examples: (Insight Australia, 2024) states, "*A Digital Twin for Mining is a virtual representation of the physical world, stored in a representative structure on a cloud data platform.*". MineRP (2019) state "*the digital twin of a mining operation is the real time digital copy representing, in 3D, the state and status of the sum, and the parts of the operation and its assets over time*". In the first instance, a digital model is being described, and in the second, a digital shadow. Both definitions illustrate the misunderstanding of the digital twin concept in the mining industry, which is characterised by bi-directional data integration.

Autodesk (2022) identify five levels of digital twin maturity based on function. These functions are labelled as descriptive twins, informative twins, predictive twins, comprehensive twins and autonomous twins. Agrawal et al. (2023) distinguish digital twin maturity based on the ability to improve model performance by observing the world (learning) and the ability to complete functions independently (autonomy). Consequently, models with a greater ability to learn and act in dynamic environments are classified as being more mature.

By comparing these works, it is clear that a combined perspective is more useful, where it is understood that digital twins may be initialised with only a few capabilities and improve these capabilities over time. The mining environment contains both mechanised (Willis et al., 2004) and digitalised (PwC, 2023) aspects and therefore considerations of digital twin maturity based on autonomy should be incorporated into the proposed framework.

2.2. Digital twin properties

While digital twin definitions offer valuable insights, they often oversimplify the complexities of the digital twin concept. Therefore, deconstructing digital twins into their fundamental properties provides a more comprehensive understanding. Despite evolving digital twin definitions, themes of a physical reality, digital counterpart and interconnections between these two persist. This section highlights prevalent properties throughout recent literature across each theme, with parallels relevant to the mining industry being emphasised. Many of these properties are inspired by those presented in the comprehensive work from Schweiger and Barth (2023).

2.2.1. Physical reality

Digital twins typically emulate some physical counterpart, originally focused on tangible products but now recognised to encompass a broader range of entities with distinct value-generating potential (Grieves, 2014). Singh et al. (2021) highlight that these entities should be easily identifiable and are hierarchical, being modelled at multiple scales and across multiple disciplines. Thelen et al. (2022a) suggest that a single digital twin may not adequately represent a component, as multiple failure modes may require different twins for modelling. Therefore, digital twins may represent a single failure mechanism on a component or various levels of integration, reflecting different application scopes. In the context of mining, this flexibility for various scopes is especially relevant, with anything from component failure prediction to mine-wide optimisation being feasible areas for digital twinning, as highlighted by the examples from Section 2.1.2.

Data collection is another fundamental property associated with digital twins. Data sources vary and data do not originate from sensors alone. Schweiger and Barth (2023) indicate that data may be extracted from systems related to product data management (PDM), enterprise resource planning (ERP) and customer relationship management (CRM) as well as programs like computer-aided design (CAD). Data may also originate from third-party systems such as weather services. Schweiger and Barth (2023) identify three distinct sources of data, namely sensors, internal systems, and external systems, each of which is also relevant to mining operations.

2.2.2. Digital counterpart

Model fidelity is often described as an important distinguishing factor for digital twins. Grieves (2014) and Singh et al. (2021) mention a high-fidelity model as a requirement for a digital twin. However, Schweiger and Barth (2023) argue that for many industrial applications, this requirement may be impractical or altogether impossible. Consequently, a model with "sufficient fidelity" is proposed to be an adequate digital twin property. This term arises from the Industrial Internet Consortium definition: "[a] digital representation, sufficient to meet the requirements of a set of use cases". Stark and Damerau (2019) highlight a similar sufficient fidelity property. Modern requirements of digital model fidelity are therefore more relaxed and are ultimately determined by the use case. The scope of possible digital twins in the mining industry is broad and therefore model fidelity should feature in the proposed framework.

Model capability is another important distinguishing factor for a digital twin. Schweiger and Barth (2023) identify simulation, optimisation, prediction, detection, prevention and automation as important factors. Singh et al. (2022) present a similar list comprising simulation, monitoring, control, design, validation, customisation, optimisation, prediction and maintenance. In other frameworks, such as the one proposed by Tao et al. (2018), these capabilities are often labelled

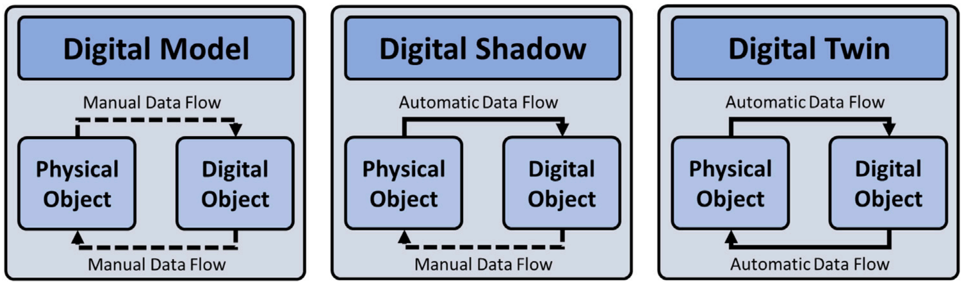


Fig. 1. The distinction between a digital model, digital shadow and digital twin according to Kritzinger et al. (2018). A digital model is characterised by manual data flow from the physical object to the digital object and vice-versa. A digital shadow requires automatic data flow from the physical object but retains manual data flow from the digital object. A digital twin is therefore characterised by automatic data flow between the physical and digital object.

as services. Digital twins in mining are expected to possess a wide range of capabilities, and therefore the framework should include this distinguishing factor.

Schweiger and Barth (2023) identify that although many digital twins are developed for a specific purpose, they generally improve some aspect of the overall equipment effectiveness (OEE). The OEE is a function of performance, availability and quality. It is therefore argued that many digital twins will have a recognisable property of increasing one of the three elements of OEE. Barnewold and Lottermoser (2020) and Grehl et al. (2017) highlight the use of digital twins for safety aspects in mining and therefore this may be seen as an additional purpose of a digital twin which is especially relevant to mining.

2.2.3. The connection between physical and digital counterparts

Synchronisation between the physical and digital domains of a digital twin is deemed crucial, often emphasised as "real-time" in many definitions. However, Schweiger and Barth (2023) argue that the synchronisation frequency varies depending on the specific use case, suggesting that near real-time or periodic synchronisation may suffice in certain scenarios. Stark and Damerau (2019) propose a more rigid delineation with four levels of synchronisation, namely weekly, daily, hourly and immediate or event-driven, which presumably refers to a digital twin acting on the sub-hour scale. These considerations are especially relevant in underground mining, where network connections may be sporadic, leading to varying synchronisation frequencies.

Another omnipresent property of digital twins is the interconnection between the digital model and the physical reality, referred to as the data link. Many authors emphasise the necessity of bi-directional connectivity for a digital twin, ensuring continuous information exchange (Kritzinger et al., 2018). Schweiger and Barth (2023) suggest that in certain industrial applications, uni-directional communication from the physical entity to the digital model is sufficient, especially when the digital model's output is actionable by humans, contrasting with earlier classifications that categorised uni-directional links as characteristics of digital shadows (Kritzinger et al., 2018). Thelen et al. (2022a) provide additional insights into this contradiction, highlighting scenarios where a uni-directional link may meet the requirements of digital twin applications, particularly in contexts where human intervention is involved in decision-making processes, such as predictive maintenance. They argue that the context dictates whether a uni-directional connection aligns with a digital shadow or a full-fledged digital twin.

A related property to the data link is the actioning interface responsible for enforcing the derived insights of the digital model. Schweiger and Barth (2023) identify two categories, namely human-to-machine or machine-to-machine interaction. Stark and Damerau (2019) highlight related properties termed "cyber–physical intelligence" and "human interaction". Cyber-physical intelligence refers to the intelligence of the digital twin, with the lowest level using humans, and the highest level indicating full autonomous behaviour. Agrawal et al. (2023) support this classification, outlining five levels of twin-human interaction, ranging from manual labour to fully autonomous behaviour. Barn (2022) emphasises that the twin-human interaction results in a socio-technical system which is inherently complex, due to humans' complex nature. The human's role in a digital twin must therefore be considered during the design phase, with full transparency and equity in mind. Camara Dit Pinto et al. (2024) propose a structured framework of human-in-the-loop digital twin design which ensures that over the long term, digital twin outputs are optimised for human interaction, aiding rather than frustrating users.

The mining environment is by no means completely mechanised or automated (Cucuzza, 2021). Humans are consequently expected to play an important role in the proposed mining digital twin framework. Humans will action digital twin insights in certain circumstances, and their role must therefore be considered in the proposed framework.

3. Proposed digital twin framework for mechanised mining

Mining operations are becoming more digitalised (PwC, 2023) and are expected to benefit greatly from digital twin applications. However, digital technologies are often ambiguously defined (Barnewold & Lottermoser, 2020) which can cause uncertainty around the digital twin concept, leading to poor adoption (Plavšić & Mišković, 2022).

This paper proposes a novel dimension-type-property (DTP) digital twin framework (see Fig. 2) with accompanying model selection tools to help clarify the concept, reduce uncertainty and consequently increase the likelihood of digital twin adoption across the mining industry. The proposed framework and selection tools are strongly influenced by the insights gathered from Section 2, which sought to identify the key developments, definitions and properties of digital twins against the backdrop of the mining industry.

Although digital twin frameworks have previously been proposed (Sjarov et al., 2020), they may be too general to address mine-specific factors. Factors such as mechanised operations, underground operations where communication is limited or non-existent, unique safety concerns and fluctuating commodity prices justify a framework specifically customised to the mining industry.

The proposed DTP framework comprises five dimensions (D) with various model types (T) and seven properties (P). The five dimensions are inspired by the framework proposed by Thelen et al. (2022a) because they strike a good balance between complexity and comprehensiveness. The five dimensions of the proposed framework are:

1. A physical entity (PE).
2. A digital model (DM).
3. Physical-to-digital (P2D) updating method.
4. Digital-to-physical (D2P) updating method.
5. Continual optimisation (OPT) across all dimensions.

The proposed framework may be used to construct a digital twin definition from the digital twin dimensions (words in **bold**) and properties (words in *italics*):

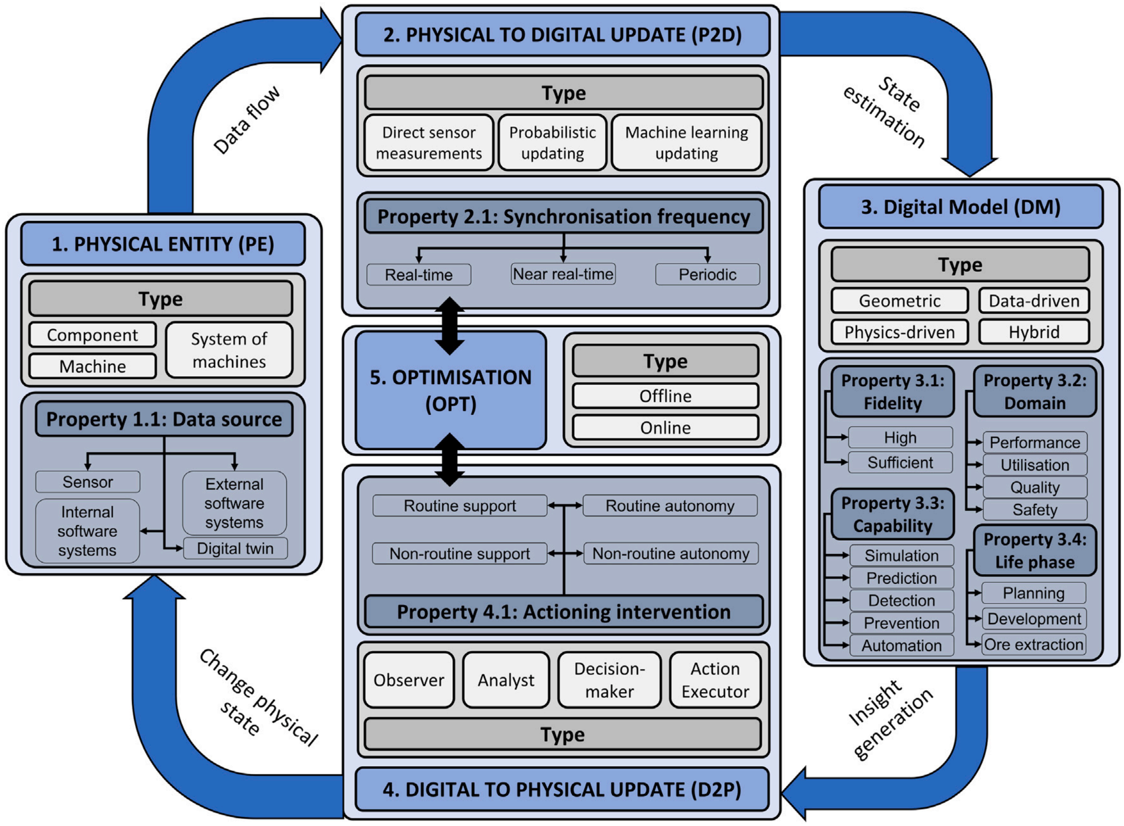


Fig. 2. The physical entity refers to the physical counterpart (a component, machine, or system of machines) being twinned. The P2D dimension converts data generated from the physical entity from a physical state to a digital model state. The digital model optimises some aspects of the digital state and generates valuable insights that can be acted upon to enact the corresponding change to the physical state. The D2P dimension enforces these insights through a human or machine actioning intervention. Optimisation affects all dimensions of the digital twin, being used to optimise data acquisition of the physical entity, parameter and state estimations and the interaction of humans with the digital twin through the D2P dimension. OPT can further be split into offline and online elements.

A digital twin is a tool for driving **optimisation** across a physical entity. Comprising a **digital model**, **physical counterpart**, and **connections** between the two, it embodies a *synchronised* flow of *data* between the physical entity and the digital model, facilitating continual estimation of the entity's state. The digital model, characterised by its *fidelity* and optimisation *capabilities*, serves as the cornerstone for enhancing various application *domains* throughout the physical entity's *life-cycle*. Crucially, the digital twin's defining feature lies in its ability to create *actionable interventions* to enforce the proposed optimisation actions on the physical entity.

The authors recognise that this framework may be sufficiently general for applications beyond mining, however, the framework terminology, explanation and focus will be developed with the mining industry at the forefront. The following sections illuminate the proposed DTP framework by describing the role of each dimension along with their associated model types and properties. Each section is accompanied by a tool to aid newcomers to digital twinning in selecting the relevant model types for each dimension. Appendices A and B present a summary of model types per dimension and a description of the interplay between properties, respectively.

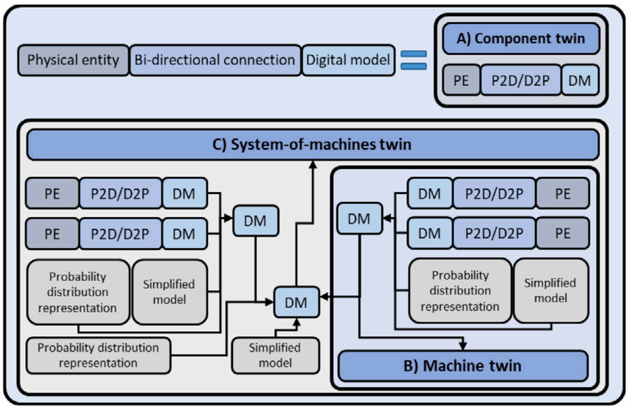
3.1. Physical entity

The proposed framework refers to the digital model's counterpart as the physical entity. This terminology specifically focuses digital twin applications on their likely counterparts in a mining environment, namely tangible assets. This terminology is deemed more specific and applicable to the mining industry, as opposed to the broader and more abstract definition of a "real entity" described by Schweiger and Barth (2023).

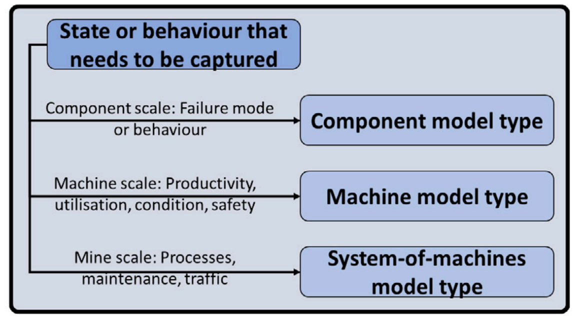
The physical entity possesses a dynamic state, and the goal of any digital twin is to capture this state such that it can optimise some aspect of the physical entity and apply the necessary action to achieve this goal (Singh et al., 2021). Three distinct physical entity types are specified within the proposed framework: components, machines and systems of machines. These are analogous to definitions of twins of singular entities (Thelen et al., 2022a), systems (Juarez et al., 2021) or systems-of-systems (Yao et al., 2023). The distinction and relationship between these physical entity types are shown in Fig. 3(a).

The component model type is used where the intention is to capture the state of a mining asset's component or its accompanying behaviour and failure modes, as considered in Thelen et al. (2022a). A machine (system) model type refers to scenarios where the intention is to capture the state of the larger mining asset. At this scale, components are modelled at the required fidelity (high fidelity or probability distributions) to capture the physical state. A system of machines (or system-of-systems) model type indicates a use case where the state of a mining process, reliant on multiple mining assets, is captured. This model type captures the behaviour of a part or entirety of a mine. At this level, machines may be modelled by high-fidelity digital twins, or be replaced by simpler alternatives such as probabilistic models. The selection criteria to determine which physical entity model one requires, are fairly simple and are outlined in Fig. 3(b).

A single accompanying property is assigned to the physical entity, namely the data source. Sensors are the most common data source (Thelen et al., 2022a), however, other data sources may also be utilised to inform digital twin decision-making. These sources include internal software systems (e.g. a mine resource or maintenance planner), external third-party systems (e.g. weather data) or outputs from other related digital twins. The physical entity may have multiple



(a) Illustration of the scale of mining digital twins. A) A twin of a single component. B) A twin of multiple components - a machine twin. C) A twin of multiple machines - a system of machines twin.



(b) A simplified selection process to determine the correct physical entity model type. If the behaviour or state being captured relates to component behaviour or failures, a component model type is applicable. If machine-based behaviour or states such as productivity, utilisation, condition or safety considerations need modelling, a machine-scale model type is applicable. If mine-scale applications are required, such as process optimisation, maintenance scheduling and traffic management, a system-of-machines model type is applicable.

Fig. 3. (a) Illustration of the various scales of digital twins and (b) how to select the relevant model for an application.

data sources and therefore the data source properties are not mutually exclusive.

Further considerations surrounding data such as real-time data capturing and updating (Juarez et al., 2021; Khalid et al., 2023), data quality (Yao et al., 2023), data fusion (Tao et al., 2019), cloud and edge computing (Macchi et al., 2018; Wu et al., 2023), communication networks (Yassin et al., 2023), cyber security (Somers et al., 2023) and integration platforms are all relevant to the physical entity. These concepts see continued development and are not considered directly within the proposed DTP framework. These elements are assumed to be considered in conjunction with the framework or have already been developed before framework usage.

3.2. Digital model

The digital model is a virtual representation of the physical counterpart and is the core component of any digital twin Wu et al. (2023). The digital model contains a set of internal states and parameters, which is used to estimate the true state of the physical system (Thelen et al., 2022a). These states and parameters are optimised to achieve a specific objective in the physical domain. The proposed framework delineates four broad but distinct digital model types that are relevant to mining and are commonly used to achieve these objectives. These encompass geometric, physics-driven, and data-driven models, with hybrid models – often referred to as physics-informed machine learning models (Karniadakis et al., 2021) – serving as an amalgamation of data-driven and physics-driven approaches.

Geometric models refer to virtual representations of reality in some geometric form. These model types refer to solid models, laser scans, virtual reality (VR), augmented reality (AR) and mixed reality (MR) applications.

Physics-based models model the fundamental laws governing the real world, and often rely on partial differential equations. They can broadly be grouped into solid body models (finite or discrete element methods), thermal and fluid flow models (computerised fluid dynamic models), kinematic and dynamic models (multi-body dynamics) and multi-physics models (an amalgamation of multiple physics-based models).

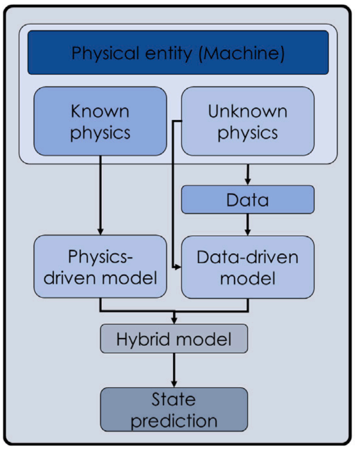
Data-driven models capture complex relationships between a set of inputs and outputs. They are particularly efficient at predicting digital states for real-time control and optimisation applications and tend to excel where physics-based approaches face challenges, either due to complex or poorly understood physics or practical computational limitations (Thelen et al., 2022a). The proposed framework outlines four data-driven model types: Statistical, machine learning, deep learning and knowledge-based models.

Statistical models typically extract hand-crafted features from data. These features are often designed from expert knowledge. Machine learning models aim to automatically learn important features from data without expert knowledge (Lei et al., 2020). Deep learning models are a subset of machine learning models with multi-layer, end-to-end model architectures (Jia et al., 2016) allowing for much richer features to be extracted and classified automatically (Lei et al., 2020). Knowledge-based models rely on historical data and computational techniques to extract and apply knowledge in the form of rules, facts or cases. These models include rule-based, case-based and fuzzy knowledge-based models (Montero Jimenez et al., 2020). Although knowledge-based models may be classified separately from data-driven models (Montero Jimenez et al., 2020), we follow the classification of Lei et al. (2018), which classify these models as a subset of data-driven models. However, it is important to recognise varied perspectives and include knowledge-based systems as a separate digital model type in future versions of the framework, should future literature converge on a single classification.

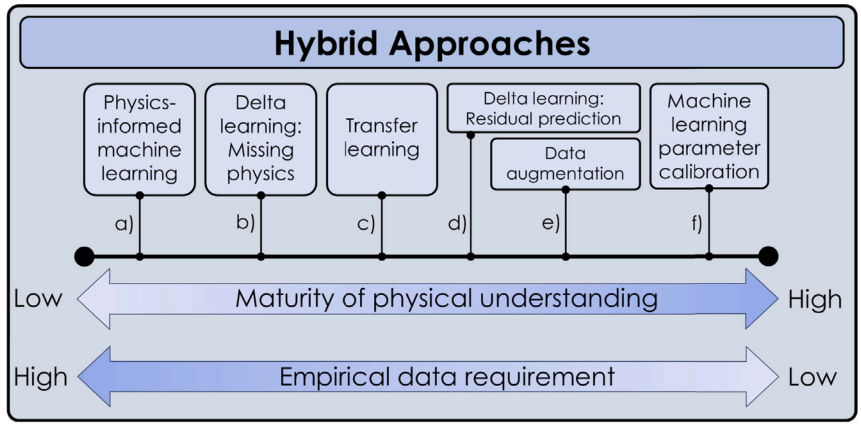
The choice of data- or physics-driven model is often made based on data availability, physical knowledge of the asset, computational efficiency and the importance of model interpretability. Physics-based models do not incorporate online data, require good physical knowledge of the asset, and are less computationally efficient but are inherently interpretable. Data-driven models generally use online data, do not require physical understanding of the problem, are more computationally efficient but are not inherently interpretable, often being described as "black box" models (Thelen et al., 2022a). In light of these complications, hybrid methods, the fourth model type, are useful. Hybrid methods combine physics-based and data-driven approaches to extract knowledge from both methods. An illustration of this concept is given in Fig. 4(a).

Six distinct hybrid modelling methods are described by the proposed framework, namely physics-informed machine learning, delta learning for missing physics, transfer learning, delta learning for residual prediction, data augmentation and machine learning for parameter calibration. Interested readers are referred to Thelen et al. (2022a) for a more detailed description of these models. A hybrid approach spectrum has been constructed to distinguish these models according to their dependence on data and necessary maturity of physical understanding, as illustrated in Fig. 4(b).

Although the selection of an applicable digital model is unique for each use-case, a guideline is constructed (Fig. 5) to aid users in identifying the most appropriate model for a specific use case.



(a) The physical reality contains both known and unknown physics. Physics-driven models capture the known physics from the physical reality. However, due to unknown unknowns or certain constraints, some physics will not be captured in the physics-driven model (unknown physics). When measuring data from physical reality, the assumption is that both known and unknown physics are measured, implying that a data-driven model may extract some unknown physics to complement the known physics from the physics-driven model. This results in a hybrid approach for physical state prediction.



(b) The applicability of different hybrid approaches is based on the required physical understanding and subsequent data requirement for each method. These interpretations merely serve as simplifications and may not be applicable in every scenario. The left side of the spectrum involves models which do not have a strong physical understanding, and therefore likely require more data. On the opposite side, the physical knowledge is high, and less data is required to train the model. a) Physics-informed machine learning methods are applicable in cases where the relevant differential quantities of the problem are understood, but the detailed relationship between these quantities is not. Therefore, these models are labelled as requiring a low maturity of physical understanding, but large amounts of data. b) Delta learning for missing physics approaches inherently assumes missing physics and therefore a less mature physics-based understanding is required for application. Consequently, a relatively large amount of data is required to use this technique. c) Transfer learning approaches also assume incomplete physical understanding and are therefore applicable when partially understood/modelled physics and some measured data is available. d) Delta learning for residual prediction methods requires the majority of underlying physics to be captured, and therefore this approach requires a good maturity of physical understanding and hence less empirical data. e) Data augmentation approaches are applicable in cases where good agreement between simulated and real data exists, requiring a higher level of physical understanding maturity and hence less empirical data. f) Machine learning parameter calibration methods inherently assume perfectly modelled physics, and require a small amount of empirical data to calibrate the parameters of the physics-based models.

Fig. 4. (a) Demonstration of the benefits of a hybrid approach and (b) an illustration of various hybrid models according to their physical understanding maturity and empirical data requirement.

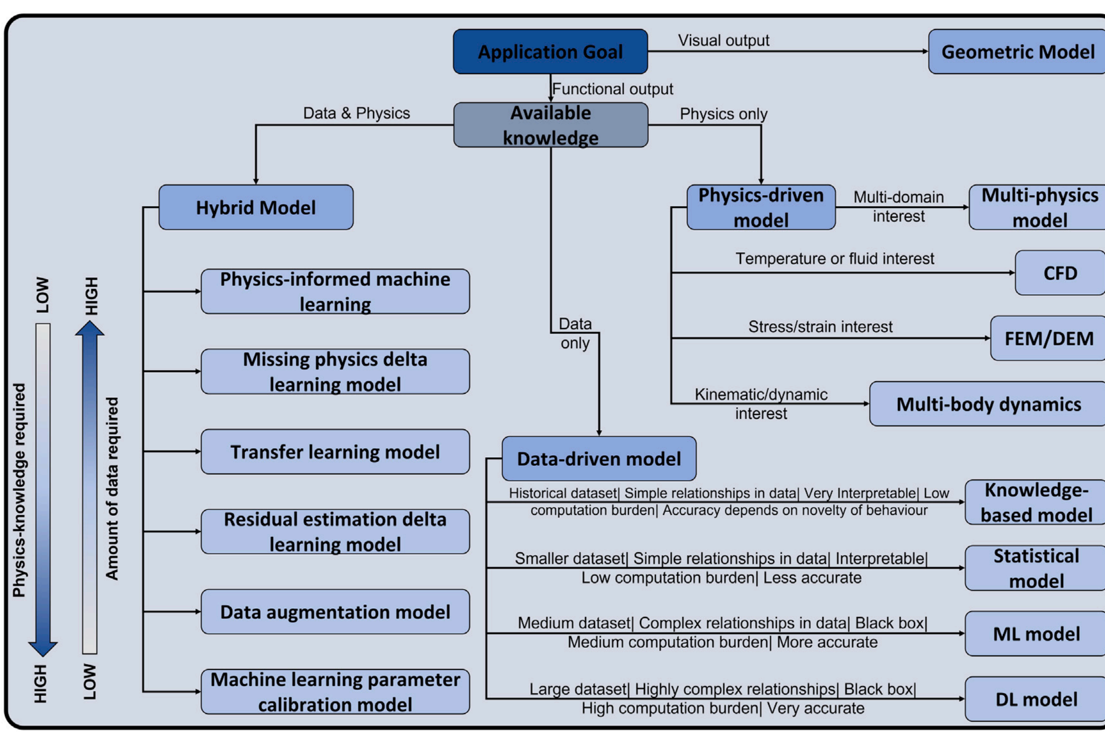


Fig. 5. A decision diagram to aid in choosing the correct digital model for a digital twinning application. Four broad domains of models are possible, namely geometric, physics-driven, data-driven or hybrid models. The main distinction between each domain is the purpose (visual or functional), and the amount of physical knowledge and available data for the use case.

Four properties are associated with the digital model, namely model fidelity, application domain, model capability, and life cycle. Model fidelity refers to the level of complexity employed in modelling the physical entity, recognising that computational constraints within the mining environment may necessitate variations in fidelity levels (Thelen et al., 2022a). Such constraints become especially relevant when considering underground mining, where edge computing may be required when network infrastructure is not reliable or altogether missing. Therefore, a digital model is said to be a high-fidelity or sufficient-fidelity (Stark & Damerau, 2019) replica of reality depending on computational constraints in the mining environment.

Half of the digital twin case studies across all industries have capabilities which optimise reliability and operational efficiency (Plavšić & Mišković, 2022). Therefore, a model capability property should be aligned with the overall equipment effectiveness (OEE), which comprises elements of performance, availability (utilisation) and quality (Schweiger & Barth, 2023). Although OEE is expected to be a strong motivation for digital twin applications in mining, safety is also expected to play a large role in mining industries (Barnewold & Lottermoser, 2020; Grehl et al., 2017). In the framework's context, safety does not refer to elements such as personal protective equipment (PPE), but rather systems or processes that are employed to increase mine worker safety. Collision prevention systems (CPS) are one such example (Bissert et al., 2016). In certain circumstances, increased mine safety has come at the cost of decreased OEE metrics (Trudel et al., 2014) and therefore safety is a relevant factor directly affecting OEE. Consequently, four model capabilities need to be considered, namely performance, utilisation, quality and safety.

Mining applications are expected to require various digital model capabilities, and therefore a model capability property may be adopted. This property groups model capabilities into simulation, prediction, detection, prevention and automation classifications, similar to Schweiger and Barth (2023).

The final property, inspired by Thelen et al. (2022a), pertains to the life cycle phase during which the digital model is applied. This categorisation distinguishes the application across the exploration and mine planning, mine development and ore extraction phases of a mine's lifecycle.

3.3. Physical-to-digital updating

The P2D updating dimension refers to the process which continually converts the inferred physical state from the physical entity into a digital state within the digital model. The P2D updating process is required due to the time-varying physical state. The proposed DTP framework identifies four relevant types of P2D updating, jointly inspired by Thelen et al. (2022a) and Montero Jimenez et al. (2020). These include updating from historical data, direct sensor measurements, probabilistic updating and machine learning updating. The choice of updating mechanism is not arbitrary and is often guided by the choice of digital model. To determine the relevant P2D updating mechanism, simplified selection criteria from Fig. 6 may be used.

When the digital model states are physically meaningful, these states can be updated directly through sensor measurements or expert knowledge. Geometric, knowledge-based, physics-driven or hybrid digital models with physically meaningful parameters will likely use this updating form. It is however important to consider the maturity of the communication networks involved in the mining process (Javaid et al., 2023), with underground mines potentially lacking a robust communication network necessary for live applications. If the digital model state is not physically meaningful (for example a state of charge or health state of an asset), or large measurement uncertainty exists, probabilistic model updating methods are better suited (Thelen et al., 2022a). In applications where machine learning models are used for digital modelling, machine learning updating is applicable. Machine learning models largely rely on pre-training and are only updated once model drift is detected (Thelen et al., 2022a).

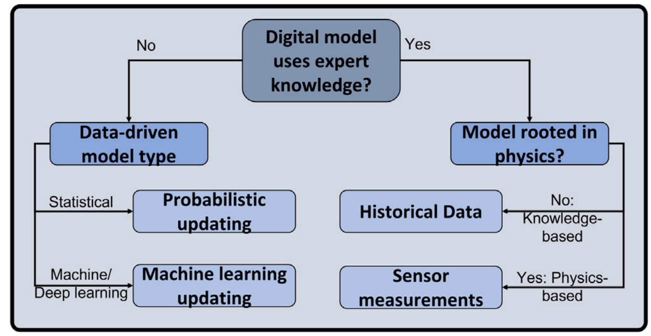


Fig. 6. Selection criteria to determine whether historical data, sensor measurements, probabilistic updating or machine learning updating is required for the digital twin application. When expert knowledge is used to construct the digital twin, and the digital model contains physically measurable state variables, which are common in geometric, physics-based and some hybrid approaches, sensor measurements are required. If human intellect is rather used (knowledge-based methods), historical data/experience is more likely. If the digital model does not use expert knowledge, it is likely to be data-driven. If the data-driven model is based on a statistical model and has abstract state variables, probabilistic updating methods are likely. If the digital model is based on machine learning (deep learning included), machine learning updating methods are more applicable.

The only property associated with the P2D dimension is that of synchronisation frequency. This property is deemed relevant to mining operations where bandwidth and application scope need to be considered. In certain scenarios, like underground mining, communication bandwidth may be constrained, and therefore synchronisation frequency will need to dynamically change depending on available network bandwidth. Furthermore, depending on the digital twin's scale of operation, various synchronisation frequencies may be applicable. For example, a rock-cutting digital twin will require sub-second feedback, whereas a maintenance or resource-planning digital twin is only required to generate feedback at an hourly or daily frequency. Taking these scenarios into account, three periods are distinguished, namely real-time (sub-second), near real-time (sub-hour) and periodic (periods longer than an hour).

3.4. Digital-to-physical updating

The D2P dimension converts a digital state into a corresponding action required to alter the physical state. Consequently, the property of an actioning intervention is assigned to the D2P connection (see Fig. 2). Although many works consider machines or control systems as the actioning intervention of a digital twin, Agrawal et al. (2023) emphasise that humans are often present in the actioning process and should therefore be considered. This observation is especially relevant for the mining industry, where issues such as lack of interoperability and retrofitting of old equipment are delaying the potential for fully autonomous mining operations, and consequently will require humans for the foreseeable future (Cucuzza, 2021). The role of humans is therefore explicitly included in the proposed framework as a property of the D2P updating. Barn (2022) states that where digital twins are used to support or enhance human activities, unintended consequences may follow due to the uncertainty associated with human actions. Therefore, it is paramount that the humans involved in the digital twin are consulted in the design process to ensure an equitable, trustworthy and well-interfacing digital twin. Camara Dit Pinto et al. (2024) recommend a method of user task analysis, prototype implementation and human-in-the-loop validation to converge on a sensible digital twin solution after multiple iterations of these three steps.

The actioning intervention's level of autonomy and learning ability may be used as a sensible measure of human involvement. A revised

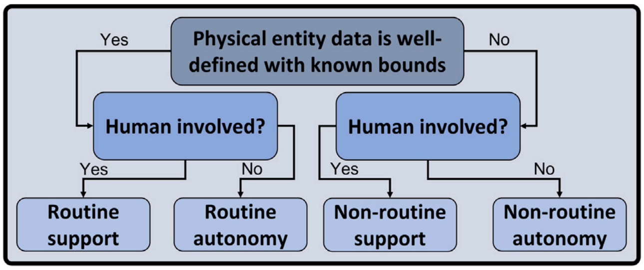


Fig. 7. Selection criteria to determine which D2P property is relevant to the application. If the problem has complex, dynamically changing input data, non-routine autonomy or support is relevant. If the problem is well-defined with known inputs, routine autonomy or support is relevant. The distinction between autonomy and support is determined by whether a human is involved in the action intervention process.

Table 1
An adapted broad classification of various D2P model types from Agrawal et al. (2023). These types are grouped according to the sequence needed to complete a task.

Observer	Analyst	Decision Maker	Action Executor
Sensing	Analysis	Optimisation	Physical (human) action
Representation	Pattern recognition	Simulation	Actuation
Description	Prediction	Forecasting	Communication
Visualisation	Interpretation	Prescription	Control
Retrieval	Perception	Planning	
Manipulation	Diagnosis	Prognosis	
Monitoring			

delineation given by Agrawal et al. (2023) is included in the proposed framework where human involvement is inversely proportional to digital twin maturity. At the lowest level of maturity, routine support is relevant where digital model insights are used to support human decision-making, but can only be used in cases where input data does not dynamically change. At the next level of maturity, non-routine support is present, where digital model insights can be generated in dynamic environments, but still require humans to action the insight. The penultimate level of maturity is denoted by routine autonomy, where humans are not required, but digital model insights are restricted to domains which do not dynamically change. At the final level of maturity, non-routine autonomy is relevant, where the twin can act in dynamic environments without the need for human intervention. A decision mechanism to identify the correct D2P is illustrated in Fig. 7.

Digital to physical state conversion can be achieved through various D2P model types. The proposed framework uses the delineation given by Agrawal et al. (2023), which groups D2P model types according to the usual order required to complete a task: Observation, analysis, decision-making and action execution. These D2P types are broad groupings of more specific digital twin functions and a list for each type is shown in Table 1. Note that these model types are illustrative, not exhaustive.

Observation models gather, process and communicate data from the physical entity. Analysis models further interpret this data to assess the state of the physical entity to inform decision-making. Decision-making models use the analysed information to make rational decisions to achieve the best outcome for a specific application. Finally, action execution models implement the aforementioned decisions using humans or machines to achieve the desired digital twin outcome.

A digital twin application may address one or more of these model types, each with a differing level of maturity. For example, a fully autonomous solution will observe, analyse, make decisions and execute actions automatically, and therefore the only applicable model type to report would be the action-executor. However, if this digital twin displays a summary dashboard, it simultaneously possesses an observation model type. Therefore, the delineation of model types is determined by considering whether the given D2P model type generates outputs for an end-user or machine.

Due to the inclusion of humans in the proposed framework, manual data flow (human intervention) may be required when converting digital states to physical states (D2P). Although this contrasts many digital twin definitions that require completely automatic data flow, it is well-aligned with the industrial view of digital twins reported by Schweiger and Barth (2023). The actioning intervention property is therefore tightly linked with the P2D property of synchronisation frequency, as the actioning intervention, human or machine, may guide the possible synchronisation frequencies.

3.5. Optimisation

The optimisation dimension affects all dimensions of the digital twin and is the key differentiating element of a digital twin from a control system or stand-alone mathematical model (Singh et al., 2022). The essence of a digital twin lies in the continual optimisation of the twinned physical entity by continually updating digital model parameters with new data (Singh et al., 2021).

The optimisation dimension does not have distinct properties and shares the properties related to the P2D and D2P dimensions, namely model synchronisation frequency and actioning intervention. The speed of synchronisation drives the type of optimisation algorithm, and in turn, drives the necessary actioning intervention.

Two types of optimisation are distinguished in the proposed model, namely offline and online optimisation. Offline optimisation activities involve the initial calibration and optimisation of digital twin elements before the twin's application. Experimental or historical data is relevant for this type of optimisation. Online optimisation refers to calibration activities during digital twin deployment. In this setting, real-time data calibrates and optimises the digital twin dimensions.

Fig. 2 shows the interaction of the optimisation dimension with the other four dimensions. The physical entity benefits from optimisation in scenarios such as sensor placement optimisation or design of experiments (Thelen et al., 2022b). The P2D dimension initially estimates the state and model parameters that optimally describe the physical entity's true state from historical data or expert knowledge. During operation, re-calibration (optimisation) of model states and parameters may be necessary. The digital model optimises some aspects of the physical entity in the digital realm. Finally, the D2P dimension determines the optimal approach to achieve the optimal physical state from the optimised digital state. If humans are involved in this process, iterative optimisation of digital twin interaction with the human will be required (Barn, 2022; Camara Dit Pinto et al., 2024). In summary, the optimisation dimension drives the other four digital twin dimensions and ultimately drives the physical entity to a more optimal state.

4. Case studies: An illustration of the framework's digital twin classification ability

To demonstrate the value of the proposed framework, two case studies of mining digital twins are presented. In these case studies, the works are summarised and deconstructed into their dimensions, types and properties within the proposed framework. This process demonstrates the utility of the framework to capture essential parts of existing digital twin works from the mining industry comprehensively and concisely.

The two case studies represent completely different production scales in mining, with the first case study considering a model of a single mining machine, and the second case study the operations and maintenance of an entire mine. They also represent two twins at the extremes of a mine's lifecycle, with one twin occurring during the planning phase and the other during the ore extraction phase. These case studies were purposefully selected at different production scales and life-cycle phases to illustrate the ability of the proposed framework to capture the essence of a broad range of digital twins in mining.

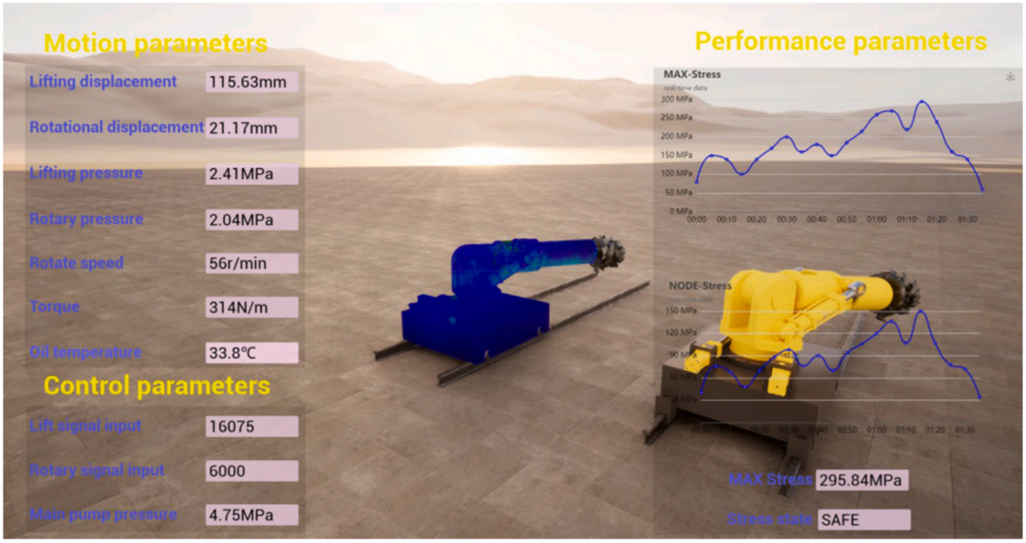


Fig. 8. Visual interface of the road header digital twin developed by Zhang et al. (2024).

Table 2
Deconstructed digital twin from Zhang et al. (2024).

Dimension	Type	Property
1. Physical entity	Machine	P1.1 - Data Source: Sensors
2. Physical to digital update	Machine learning updating	P2.1 - Synchronisation: Real-time
3. Digital model	Hybrid	P3.1 - Fidelity: High & sufficient P3.2 - Domain: Performance P3.3 - Capability: Prediction & automation P3.4 - Life phase: Ore extraction
4. Digital to physical update	Observer	P4.1 - Actioning intervention: Routine autonomy
	Action executor	P4.1 - Actioning intervention: Routine autonomy
5. Optimisation	Online & offline	Linked to P2 and P7

4.1. Case study 1: Road header digital twin

4.1.1. Description of work

The first case study investigates a digital twin developed by Zhang et al. (2024) for real-time monitoring and control of the mechanical performance of a road header. By inputting multi-sensor data into the digital twin, the system can predict the cutting-induced stress on the structure of the road header arm almost in real-time (0.3s between predictions). This stress prediction is used to adjust the swing speed of the cutting arm to ensure the arm is not over-stressed. By controlling the swing speed, the system can prevent overload conditions and optimise the cutting efficiency of the road header.

Although this functionality is sufficient to qualify as a digital twin, Zhang et al. (2024) further utilise physical rendering engines, databases, and 3D modelling tools to visualise the movement, performance, and control parameters of the road header in real-time, providing a comprehensive overview of the road header's state in real-time. An illustration of the visual portion of the digital twin is given in Fig. 8.

4.1.2. Deconstruction of digital twin into dimensions, types and properties

The case study is deconstructed according to the dimensions, types and properties outlined in the proposed framework in Table 2.

The physical entity in this case study is identifiable as the road header, which is a machine comprising multiple components. The type is therefore selected as a machine (system-level) with components such as a cutting head, boom arm and hydraulic actuator. The physical entity utilises sensors as the only form of data input, comprising vibration, displacement, pressure, speed and torque sensors.

Two digital models are used in this study, namely a physics-based finite element (FE) model, and a data-driven machine learning model in the form of a neural network. The FE model determines the stress field over the road header for multiple sensor inputs. This creates a dataset which is used to train the machine learning model to predict the stress field given the same set of sensor inputs. This digital model uses both physics-driven and data-driven approaches constituting a hybrid method, specifically transfer learning, where simulated (FEM) and real sensor data are fused into a machine learning model. The digital model fidelity is high for the FE model, but sufficient for the machine learning model, which acts as a surrogate to the FE model. However, the FE model is only used during offline calibration and the machine learning model during online calibration. Therefore, during operation, only sufficient fidelity is observed. The application domain of the twin is performance optimisation, as boom speed is optimised to maximise the amount of rock that can be cut within the boom's stress envelope. The digital model uses capabilities of prediction and automation to achieve this goal. Finally, the digital model's life cycle phase is readily identified as the ore-extraction phase.

The connection from the physical to digital domain is characterised by machine learning updating because the stress prediction machine learning model will continually convert sensor readings into stress predictions, and will only need to be updated if a drift in input data is detected. This connection has the property of real-time synchronisation due to the use of a machine learning model for fast inference. In the inverse direction, two model types are present, namely an observation model (dashboard) and an action executor (control system) model. These models update and act autonomously in a routine environment. Although the machine learning model adapts to dynamically changing stress values, the road header needs to be positioned and programmed within certain bounds and speeds to operate. Furthermore, the road header would need the ability to adapt to different rock types and anomalies encountered during the cutting process. These limitations, therefore, classify the digital to physical updating process as autonomous, but routine.

Finally, the optimisation dimension is seen to have both offline and online elements, with offline optimisation used to pre-train the machine learning model from FEM data, and online optimisation used to continually optimise the road header control parameters.

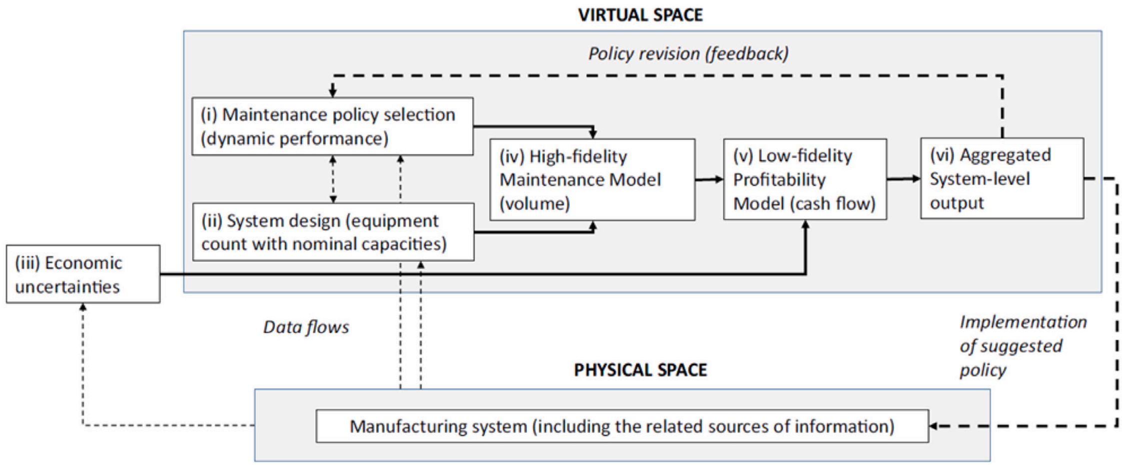


Fig. 9. Mine operations and maintenance digital twin layout developed by Savolainen and Urbani (2021).

Table 3
Deconstructed digital twin from Savolainen and Urbani (2021).

Dimension	Type	Property
1. Physical entity	System of machines	P1.1 - Data Source: Internal & external software systems
2. Physical to digital update	Probabilistic updating	P2.1 - Synchronisation: Periodic
3. Digital model	Hybrid	P3.1 - Fidelity: Sufficient P3.2 - Domain: Performance & utilisation P3.3 - Capability: Simulation P3.4 - Life phase: Mine planning phase
4. Digital to physical update	Decision maker	P4 - Actioning intervention: Non-routine support
5. Optimisation	Offline	Linked to P2 and P7

4.2. Case study 2: Mine operations and maintenance digital twin

4.2.1. Description of work

The second case study considers a digital twin described by Savolainen and Urbani (2021), which optimises mine operations and maintenance (O&M). The digital twin simulates various mine fleet combinations and selects the combination that maximises the mine's cash flow. Multiple facets of the mine are simultaneously simulated. Firstly, an O&M module is used to simulate the interactions between shovels, trucks, dumpsites and workshops. Shovels extract ore, which needs to be hauled by trucks to dump sites. Shovels and trucks are subject to breakdowns and therefore each item has an associated maintenance policy within the simulation model. The second facet is a cash-flow module, which accounts for factors such as the current commodity price and various operational costs associated with maintenance labour, leasing of machines etc. Fig. 9 illustrates the digital twin structure according to Savolainen and Urbani (2021) and the relationships between the various models.

The simulation model contains multiple variables which may be changed to evaluate various fleet selections. These include the predictive maintenance schedule, number of trucks, shovels and workshops and the effect of the commodity price. The optimal set of variables is reported to management for human decision-making.

4.2.2. Deconstruction of digital twin into dimensions, types and properties

The case study is deconstructed according to the dimensions, types and properties outlined in the proposed framework in Table 3 below.

The physical entity in this case study is the entire mine. The type of physical entity is therefore identified as a system-of-machines (system-of-systems). Due to the global nature of the twin, the physical entity has two data source properties, namely internal software systems (maintenance and operations systems) and external systems (commodity prices).

This twin comprises two digital models, namely an O&M model and a cash-flow model. Both models are data-driven, focusing on statistical modelling methods. The digital model has the property of sufficient fidelity because simplifying assumptions are made during digital model construction. The model is simultaneously applied to the domains of performance and utilisation and uses simulation capabilities for this purpose. The twin is applied during the planning phase of the mine, but may certainly be applied during the service phase as well.

The connection from the physical to digital domains is achieved by probabilistic updating methods, using internal and external software systems to calibrate the statistical digital model. Due to the global scale of the digital twin, requiring management input, synchronisation frequency is expected to be slow, leading to a property of periodic synchronisation. For the inverse connection from the digital model to the physical entity, a decision-maker model type is identified, due to the digital twin simulating optimal decisions that will maximise cash flow. This model has the property of acting in a non-routine support role because the model accounts for dynamically changing commodity prices along with varying numbers of fleet elements. Therefore, as the input data dynamically changes, so too do the optimal decisions that the digital twin delivers as output to management decision-makers.

For this application, the optimisation dimension is only intended to occur during the planning phase and is therefore indicated as the offline optimisation type. However, should the twin be used during actual production, online updating will become relevant.

5. Conclusion and recommendations

The mining industry is set to increasingly use digital technologies to improve production and safety targets, with digital twins expected to serve as the enabler for many of these technologies. However, the digital twin concept is widely misunderstood across multiple industries (Kritzinger et al., 2018), with two mine-specific examples given in Section 2.1.3. This widespread misunderstanding underscores the need for reference language to clarify the concept for mining practitioners and researchers alike.

This work presents a novel framework to create a common understanding around the concept and serves as a reference for future digital twin works in the mining industry, which has unique challenges that existing frameworks have not previously addressed. The proposed framework describes five core dimensions of digital twins, namely a physical entity, a digital model, a physical-to-digital updating mechanism, a digital-to-physical updating mechanism and optimisation across these dimensions. This framework expands the framework by incorporating seven properties which are specifically customised to the mining industry. These are data source, synchronisation frequency, model fidelity, application domain, model capability, mine life phase and actioning intervention. The proposed framework further outlines common model types within each dimension and presents corresponding tools for selecting the relevant model for various use cases.

To demonstrate the proposed framework's ability to capture the essential parts of a mining digital twin, two different digital twin types are presented as case studies. The first case study considers a road header digital twin, which was successfully deconstructed into the core components within the framework. The second case study showcases a mine operations and maintenance planning digital twin, which encompasses a digital twin example at a much larger scale. The proposed framework similarly deconstructed the twin into the core components without losing any clarity. These case studies underscore the proposed framework's ability to succinctly describe vastly different digital twins within the mining industry. This framework therefore acts as a useful reference for the mining industry as it can capture the essential components of many possible digital twins.

The proposed framework is valuable beyond simply clarifying the concept of a digital twin, but also serves as a blueprint for designing future digital twins. By using the accompanying model selection and property relationship tools presented in this work, users can readily identify the necessary technologies to implement a digital twin.

The framework currently assumes that data capturing, processing, transmission, storage and security considerations have been developed before framework implementation. However, in some instances, this may not be the case and therefore future work may focus on incorporating these considerations into the physical entity dimension to further aid users in building a digital twin. Furthermore, consensus surrounding the categorisation of knowledge-based models has not been reached and future versions of the framework must reflect the state-of-the-art consensus.

To further showcase the framework's utility, future work will focus on developing a digital twin for a mining application using the given model selection tools. During the literature research stage, works on underground mining digital twins were scarce, with no digital twin works on drilling and blasting. Therefore, the future focus is to demonstrate a digital twin in this unexplored domain of mining extraction.

CRediT authorship contribution statement

Luke van Eyk: Writing – original draft, Visualization, Methodology, Investigation, Conceptualization. **P. Stephan Heyns:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Summary of the applicable models for each twin dimension

Fig. A.10 presents a summary of the various model types in the proposed DTP framework. This serves as a useful reference when trying to identify the relevant model for each dimension in the DTP framework. The physical entity model type is chosen based on the scale of the twinning application, distinguishing between component-level, machine-level and system of machines level. The digital model is split into geometric, physics-based, data-driven and hybrid model types. Geometric models refer to solid geometry models, laser scans and virtual, augmented and mixed-reality applications. Physics-based models include solid body models, thermodynamic and fluid-dynamic models, kinematic and dynamic models and multi-physics models.

The connection from the physical to digital domains can be facilitated by direct sensor updates, probabilistic updates or machine learning updates, all of which are largely dictated by the choice of digital model for the application. The connection back to the physical entity from the digital model is mainly distinguished by the level of involvement of the digital twin in solving a given problem, ranging from observing physical states, analysing these states, making decisions based on these states or at full involvement, directly acting to optimise the measured states. The optimisation model types are discerned according to the period during which optimisation is relevant, namely before twin application (offline), or during twin application (online).

Appendix B. Relationship between the twin properties

The DTP framework couples properties to their respective dimensions. However, it is useful to recognise that the selection of properties is not uncoupled and that certain properties exclude the selection of other properties. These relationships are illustrated in Fig. B.11.

Depending on the chosen level of twinning (component, machine or systems-of-machines level), different data sources may be relevant. For example, component-level twins will likely rely on sensors but will have little use for internal or external systems. Conversely, system-of-machines twins will likely incorporate a large array of data sources.

After defining the data source property of the physical entity, the connections between this entity and the digital model need to be specified. The synchronisation period is application-specific, with real-time applications likely using direct sensor measurements and perhaps inputs from other digital twins. Internal and external software systems may be too slow for real-time applications. However, for longer synchronisation periods, these software systems may be applicable. Depending on the synchronisation frequency, four actioning interventions are relevant. For real-time decision-making, actuators are the only sensible option and will therefore complete the digital twin loop through autonomy (routine or non-routine). However, for applications where periodic updating is sufficient (like condition-based maintenance), a human will likely be the applicable acting mechanism to complete the cycle, leading to routine or non-routine support operations. For near real-time applications, either option should be sufficient.

Finally, four digital model properties need to be specified. In cases where model fidelity is high, one would likely not be able to have a real-time control system action and therefore this link is not shown to autonomous solutions. For these applications, models of lower but sufficient fidelity are likely required. This limitation is, however, subject to future computational advancements. For slower, human support applications, both high or sufficient-fidelity models may suffice. The application domain of the digital model is not affected by fidelity considerations and can be used with any capability of the digital twin. However, not all capabilities are necessarily applicable to the life cycle phase of the physical entity. For the planning phase, simulation models will most likely be used to optimise the twinned object before manufacturing. For the development phase, we expect any capability to be applicable, except prevention. For the ore extraction phase, any capability of the digital model is relevant.

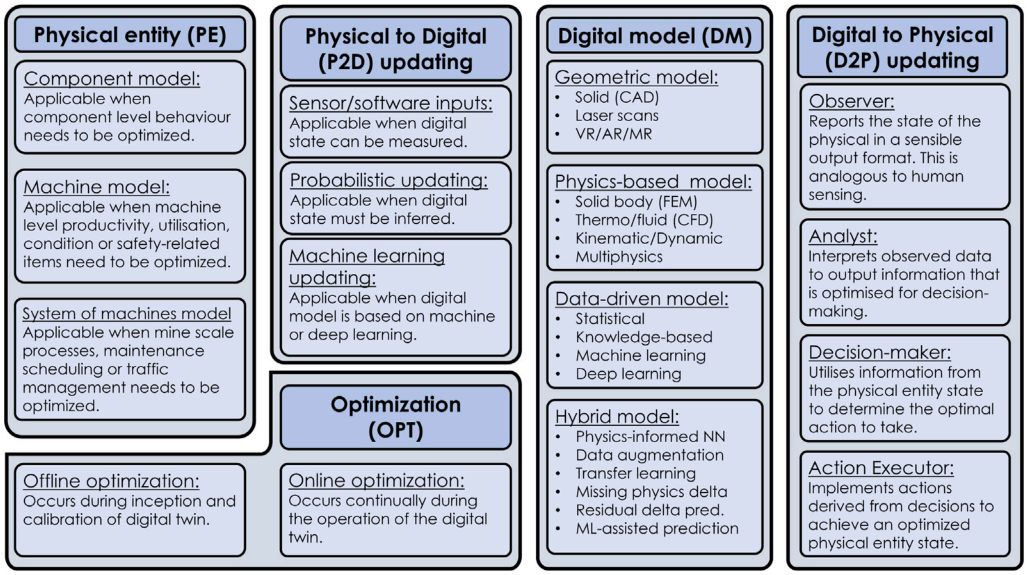

Fig. A.10. A summary of various model types and mechanisms that are present in a digital twin. The physical entity may be a component, machine or system of machines. The physical-to-digital updating process may rely on raw sensor measurements, probabilistic model updating or machine learning model updating techniques to handle input data to the digital model. Digital models can broadly be classified as geometric, physics-based, data-driven or hybrid models. These models optimise the physical entity they are modelling via D2P models. The D2P models are chosen based on the level of involvement of the twin in the problem-solving process, reaching from observing data to executing actions on data. A digital twin is calibrated (optimised) during inception, which is an offline process and can be continually updated during operation, which is an online process.

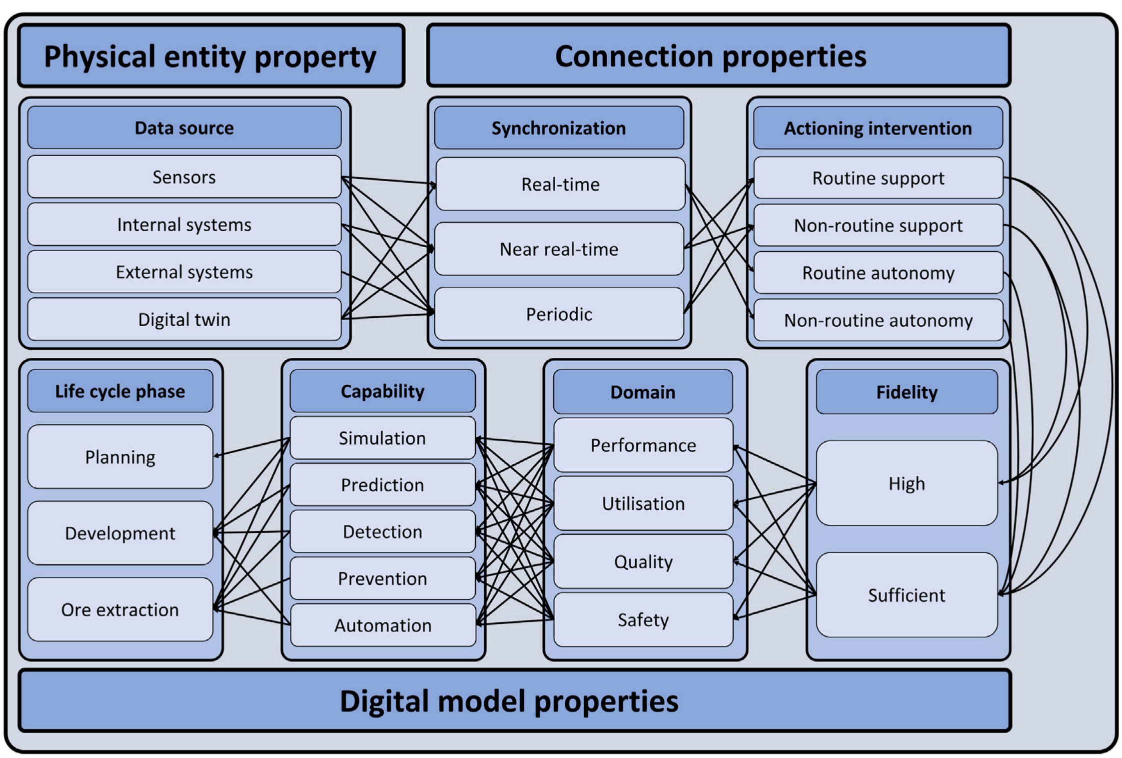

Fig. B.11. The relationship between various properties of the proposed digital twin. The data source associated with the physical entity is determined by the application. These data sources limit the synchronisation frequency within the digital twin, which determines which actioning intervention is most useful for the digital twin application. The actioning intervention determines whether high-fidelity models are possible, or whether simpler, sufficient-fidelity models need to be used. The varying fidelity models apply to any application domain and in turn rely on a range of capabilities to fulfil the digital twin goal. These capabilities are largely restricted by the life cycle phase of the twinned entity.

Data availability

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

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