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Cross-domain comparative analysis of digital twins and universalised solutions

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A B S T R A C T

Digitalisation is transforming various economic sectors, with the digital twin (DT) being a key manifestation for complex systems. While numerous studies focus on sector-specific DTs, few offer comparative analyses across domains. This paper delivers three major contributions: (1) A six-dimensional characterisation framework that systematically captures DT development processes across conceptual (twinning objects, purposes, system architectures) and implementation (data, modelling, services) dimensions; (2) Cross-domain comparative analysis of DTs across five representative domains (agriculture, manufacturing, construction, healthcare, smart cities) using this framework, revealing universal commonalities in DIKW-based intelligence progression and identifying three key differentiators—digitalisation capability, cost-benefit dynamics, and socio-ethical risks—that explain domain-specific variations in DT maturity and adoption; and (3) A unified Digital Twin Platform-as-a-Service (DT-PaaS) solution that standardises common processes, tools, and applications while accommodating domain-specific variations through interoperable data models, reusable modelling libraries, and cross-domain service orchestration. A case study demonstrates that the proposed DT-PaaS framework enables connected DT ecosystems with capabilities for data synchronisation, co-simulation, collaborative learning, and coordinated decision-making across sectors. This research establishes the first systematic cross-domain DT comparison methodology and provides practical pathways for knowledge transfer between mature and emerging DT domains, ultimately supporting more efficient and interoperable digital transformation.

1. Introduction

Digitalisation, often regarded as the fourth major innovation cycle in human history, is transforming nearly every aspect of economic activities [1]. Among the key technological enablers—including artificial intelligence, Internet of Things and autonomous systems—DTs have emerged as powerful manifestations of data-centric approaches to system engineering. Digital twinning establishes a dynamic correspondence and continuous alignment between physical and virtual entities, enabling real-time monitoring, predictive analysis, and performance optimisation of engineering systems through their digital counterparts [2].

1.1. Digital twins evolution

The development of DT has been a cross-domain effort. The idea of DT was born at NASA in the 1960 s as a “living model” of the Apollo mission, where DTs allowed engineers on the ground to control vehicles in space [3]. The DT’s formal academic definition was first introduced in Michael Grieves’ work with NASA’s John Vickers in a 2003 lecture when they envisioned virtual models as foundations for product lifecycle management [4]. Later, Grieves expanded the concept to align with product lifecycles through four components [5]: DT Prototype (design phase), DT Instance (individual manufactured products), DT Aggregate (accumulation of instances), and DT Environment (virtual representation of the physical environment enabling simulation and evaluation). The modern DT framework was emphasised as a central vision for Industry 4.0 in manufacturing, supporting process optimisation and lifecycle management [6]. The adoption of DTs has since expanded into other industries and fields, including real-time urban mobility monitoring [7] and sustainable development [8] within smart cities, as well as medical resource management [9,10] and precision medicine [11] in healthcare. Though the physical object and context differ across domains, the core definition of DT remains consistent - they all describe real-time, bidirectional, data-driven virtual representations of physical entities that enable monitoring, prediction, and optimisation.

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1.2. Research gaps

Despite this widespread adoption and advancements in DT research, there are significant limitations that motivated this comparative study:

1.2.1. Restricted domain focus

Existing research on DT tends to focus on a specific domain, and these studies often benchmark DT applications against advanced domains such as manufacturing. For instance, [12] surveyed DT applications in smart cities against Industry 4.0, and [13] reviewed DT developments in manufacturing and maritime domains. [14] summarised features of manufacturing DT and discussed their applicability for the built environment. These one-to-one comparisons, while valuable, fall short of uncovering shared challenges and transferable insights.

1.2.2. Limited interdisciplinary insights

Existing studies on DT applications across domains often provide only brief and unstructured comparisons. For instance, [15] examined DT applications across various industries with a focus on construction, limiting the comparison to aspects such as usage and benefits. While some characterisation frameworks for DTs exist, they are typically confined to single domains, lacking cross-domain application or analysis of distinct characteristics from different fields. This narrow scope struggles to uncover deeper insights into the interdisciplinary potential of DTs.

1.2.3. Insufficient theoretical foundations

Most DT review studies primarily rely on existing DT literature [16–19], often neglecting to trace the origins of the terminology or explore the foundational principles. As a result, these studies tend to describe what DTs currently represent but fall short of explaining the origins of the concepts or the rationale behind the terminology used to define DTs.

1.2.4. Gap between high-level principles and implementation guidance

While the Gemini Principles [20] define high-level objectives for DTs (public good, value creation, insight, security, interoperability, federation, curation, evolution, and quality), but do not specify how these objectives should be operationalised across different domains. Similarly, existing analysis frameworks provide valuable contributions by proposing systematic approaches that focus on common functional characteristics for comparison, enabling the characterisation and comparison of different DTs through unified frameworks [21]. However, these frameworks primarily address functional requirements and comparison methodologies but lack implementation guidance, procedural details, and systematic approaches for identifying transferable insights. This paper argues that a comprehensive characterisation framework and its application in a structured cross-domain comparison are necessary to address these fundamental gaps and enable systematic knowledge transfer across domains.

1.3. Need for cross-domain analysis

The need for cross-domain DT analysis is driven by both theoretical foundations and practical urgency across multiple dimensions:

1.3.1. Interdisciplinary nature and global challenges

The interdisciplinary nature of digital twinning demands a more holistic approach. The advancement of DT has utilised concepts from various engineering fields - complex systems engineering, software engineering, modelling engineering, etc. This interdisciplinary foundation suggests that insights from one domain could benefit others, yet systematic cross-domain analysis remains unexplored. Furthermore, emerging global challenges—such as pandemic response, climate change mitigation, and sustainable development—require interconnected systems that span multiple domains. For instance, addressing urban sustainability requires coordination between energy supply systems, building performance and transportation networks. Such complex challenges cannot be addressed through isolated, domain-specific DTs.

1.3.2. Universal principles vs. domain fragmentation

Cross-domain DT research is critical because it reveals the universal principles hidden beneath apparent domain-specific differences, preventing the fragmentation of what is fundamentally a single, transformative technology, while current domain-specific approaches create differences in scholars' understanding of the same entity in different fields [22]. Without systematic cross-domain analysis, each sector continues to reinvent the wheel, leading to domain-specific development where applications might differ in requirements but unnecessarily duplicate data processing techniques and modelling capabilities [17].

1.3.3. Knowledge transfer and multi-domain integration

The cross-domain DT research could enable critical knowledge transfer from mature to emerging domains while addressing complex, multi-domain challenges that span multiple sectors. Agriculture represents the next stage of DT use after its application to the manufacturing industry [23], demonstrating how insights from mature domains can accelerate development in emerging ones. In addition, modern challenges require DT applied across healthcare, agriculture, retail, manufacturing, energy, and transportation working together as integrated solutions [24], which require DTs that can model not just individual entities but also the whole system where multiple domains interact [25].

Given the identified research gaps and importance of cross-domain DT analysis, this study divides the cross-domain comparison into two stages: **Stage 1**: Establishing a principle-based terminology characterisation DT framework. This framework should be grounded in principles that trace the historical and conceptual development of DTs, providing deeper insights into their evolution and underlying rationale. It should also capture the key procedures for DT implementation across various domains, ensuring a comprehensive understanding of their foundational aspects. **Stage 2**: Applying this framework to analyse DTs across multiple domains. This comparison would identify commonalities and domain-specific features, aiming to uncover the principles that universalise or differentiate DT applications, thereby enabling knowledge exchange and interdisciplinary collaboration.

The rest of this paper is organised as follows: Section 2 outlines the methodology of this study, including the rationale for domain selection and the synthesis of a six-dimensional DT comparative framework. Section 3 presents the selection of domains based on the Three Sector Model and academic publication analysis. Section 4 details the synthesis of the comparative framework, defining the six dimensions: twinning objects, twinning purposes, system architectures, data, modelling, and services. Section 5 applies the framework to analyse selected DT archetypes across the five domains (agriculture, manufacturing, construction, healthcare, and smart cities). Section 6 discusses cross-domain observations and insights that universalise or differentiate DT applications, as well as proposes a unified DT-PaaS solution for cross-domain DT development. Finally, conclusions and future research directions are drawn in Section 7.

2. Methodology

With the research gaps and research significance discussed in Section 1, the overall research objective – how to conduct a cross-domain DT comparison – has been broken down into a two-stage comparative analysis process, as reflected in the following research questions:

- RQ1: What are the most frequently discussed DT domains, and what domains are most suitable for comparative analysis?
- RQ2: How can a framework be developed to enable the comparison of DTs across various domains?

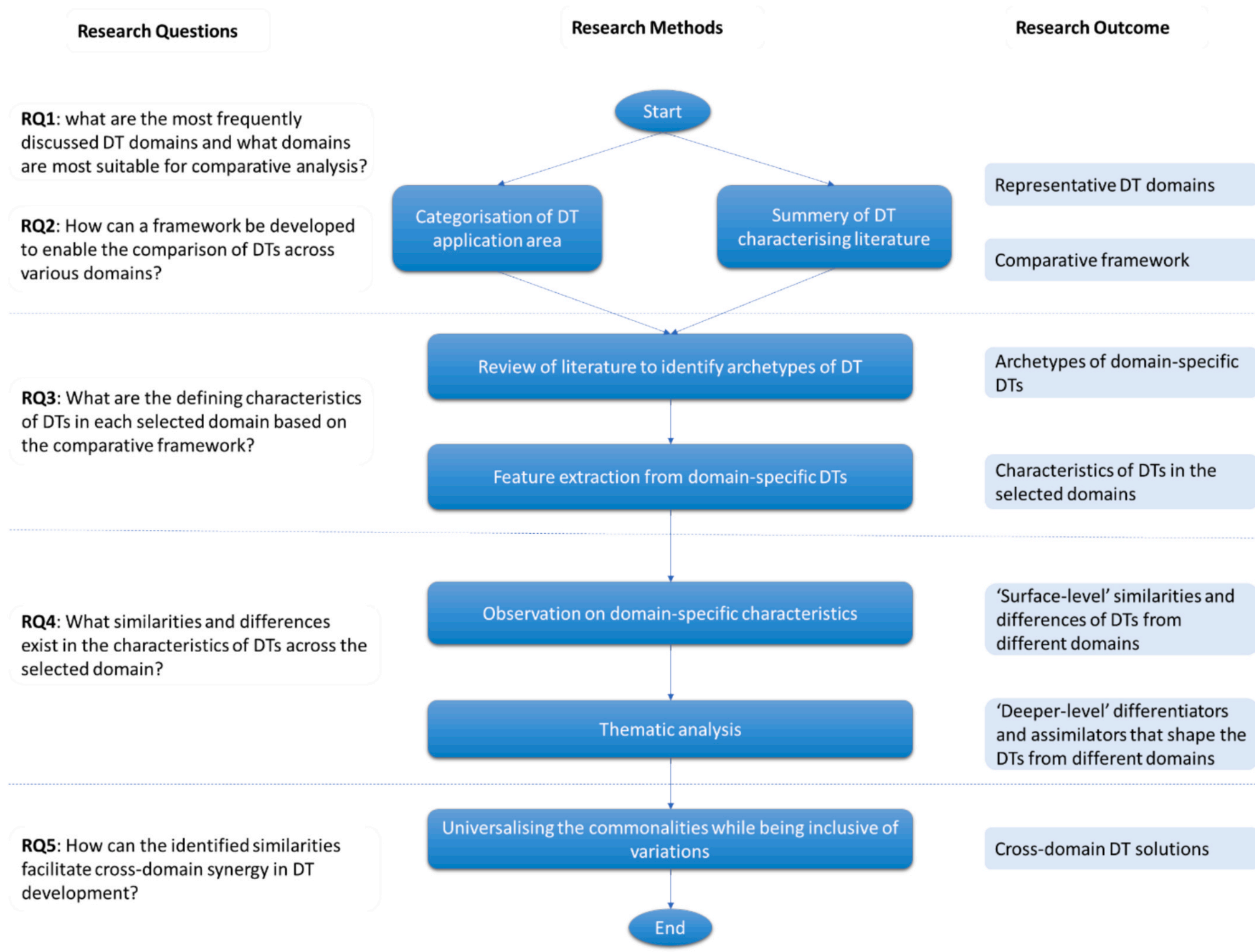

Fig. 1. Methodology diagram for comparative framework development.

- RQ3: What are the defining characteristics of DTs in each selected domain based on the comparative framework?
- RQ4: What similarities and differences exist in the characteristics of DTs across the selected domains?
- RQ5: How can the identified similarities facilitate cross-domain synergy in DT development?

Stage 1 addresses **RQ1 and RQ2**: For **RQ1**, the domains selected were required to be representative and encompass major DT applications. DT-related publications were sourced from Scopus and Web of Science and filtered into two subject lists – one for each database. The classic Three Sector Model was then leveraged to categorise and refine these subjects into three groups, from which one or two representative domains were selected for in-depth analysis and cross-domain comparison. For **RQ2**, existing DT characterisation frameworks from academic literature were systematically examined, and key DT attributes were conceptualised into three levels of categories to establish a principle-based six-dimensional characterisation framework grounded in DT historical and conceptual development principles. **Stage 2** encompasses **RQ3-RQ5**: For RQ3, representative DT use-cases from each selected domain were analysed using the comparative framework. The characteristics of these use-cases were extracted and linked to the underlying reasons for the observed phenomena, often reflecting the demands and nature of the domain. For RQ4, thematic analysis using the Principles of Variation and Universality [26] was conducted to summarise and explain the differences and similarities between DTs across domains. Finally, for RQ5, the insights gained from the six-dimensional framework and the explanatory theory were used to propose universal DT solutions. These solutions were integrated into a unified cross-domain DT-PaaS.

The five research questions of two stages, along with their corresponding research methods, are presented in the methodology illustrated in Fig. 1.

3. Selection of domains

To systematically select representative domains for cross-domain DT comparison, an appropriate classification framework is essential. While DT represents fundamentally an engineering technology, the ultimate goal of digitalisation and digital twinning is to improve efficiency in human economic activities, making economic frameworks suitable for domain selection. The selection criteria require a model that can capture and categorise all research areas of DT while being sufficiently simple for systematic analysis; therefore, widely acknowledged foundation theories are preferred.

In economics, the production chain is often used as an analytical tool to understand the production process. The Three Sector Model, developed by economists Fisher and Clark [27], categorises economic activities into three categories: 1) the primary industry, where raw material are extracted from natural resources; 2) the secondary industry, involving the transformation of raw materials into manufactured goods and constructed assets; and 3) the tertiary industry, which delivers

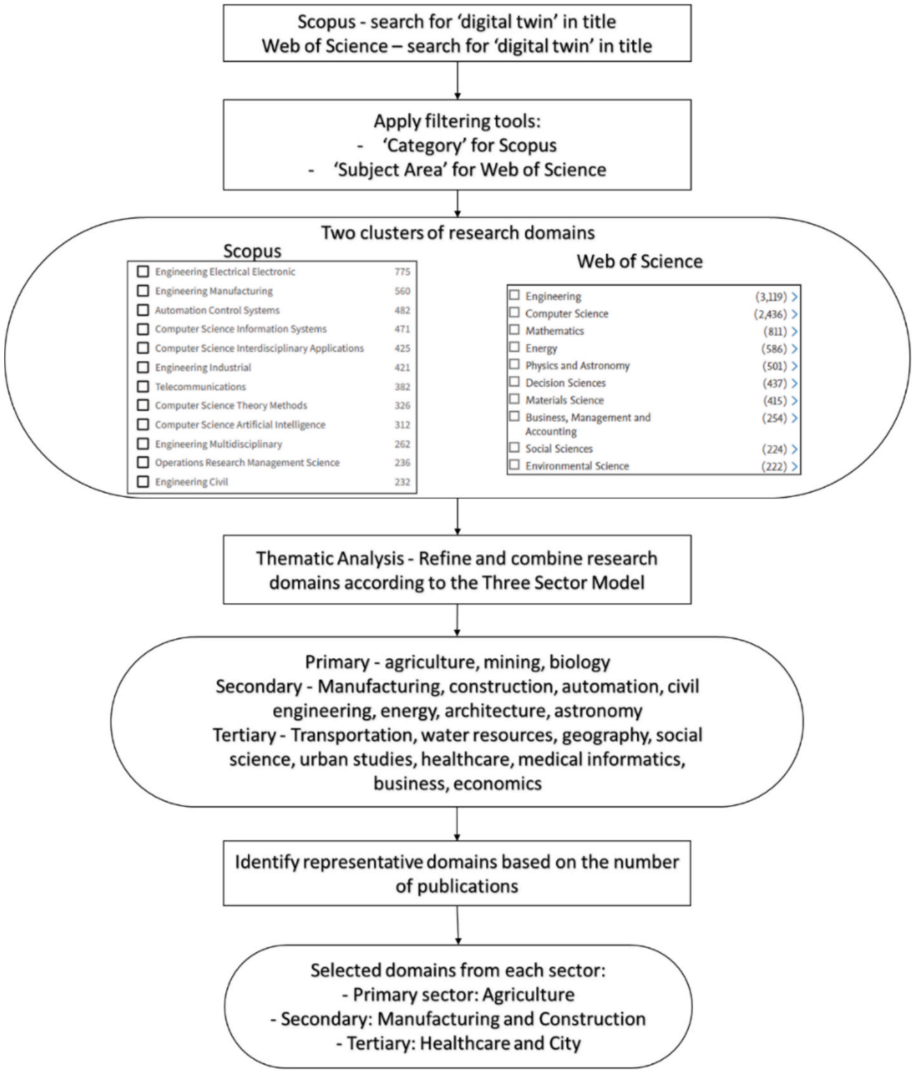

Fig. 2. Selection of digital twin domains for comparative study.

services to customers and end-users. This model provides a systematic framework for DT domain selection because it ensures comprehensive coverage across fundamental economic activities, enables structured comparison across different types of production processes, and allows for analysis of digitalisation patterns that may correlate with economic sector characteristics.

To assess the presence of DTs across economic sectors, a cluster of publications was retrieved with the search query “digital twin” from the academic databases Scopus and Web of Science, covering the period 2015–2023. The initial search yielded 10,600 papers from Scopus and 6411 papers from Web of Science. The two databases were selected as Scopus provides ’Subject Area’ filtering and Web of Science offers ’Category’ filtering, which align with economic sector categorisation and are essential for the domain selection methodology using the Three Sector Model. The filtering tools of these databases were then applied to classify the collected publications by subject area or category. Inclusion criteria comprised peer-reviewed articles and book chapters in English language, while exclusion criteria eliminated data papers, letters, notes or non-English papers.

The two clusters of research domains obtained were then manually picked up, assessed, refined, and combined through a thematic analysis process to ensure accurate domain categorisation and eliminate overlapping or ambiguous classifications. The refined research domains were subsequently mapped to the Three Sector Model, ranked by the number of publications, and selected based on their presence in the research literature.

Finally, representative sectors for each industry were selected for reviewing DT research and application, following the procedures illustrated in Fig. 2. From the primary sector, agriculture was selected based on publication volume and research activity. Manufacturing and construction were chosen from the secondary sector due to their prominent presence in DT literature and established research foundations. For the tertiary sector, multiple service domains were identified, including transportation, water, social science, healthcare, healthcare, business, and economics. These were consolidated into two clusters: the majority of them were grouped as “smart city” due to their spatial relationships, municipal governance, and infrastructure-centric nature; healthcare was kept separate due to its human-focused, individual-centric service delivery and distinct stakeholders. Business and economics were excluded as they are not engineering-related.

4. Synthesis of comparative framework

The comparison of DTs across multiple domains can be viewed as a form of comparative analysis. According to the methodology outlined in [26], the study aims to establish that every concept, implementation, and use case of DTs adheres to the same set of principles. To achieve this, a universal frame of reference must be developed based on the following

Table 1
Digital twin characterising frameworks.

Ref.	Domains	DT Characterising Frameworks	Comments on frameworks
[16]	Manufacturing, energy, aerospace, automotive, agriculture, healthcare	1) Industrial sector 2) Purpose 3) Physical reference object 4) Completeness 5) Creation time	• Provide perspective on the application scenarios of DT across industries • DT technical development details are not included
[28]	Multiple domains	1) Connection 2) Application context 3) Life-cycle phases 4) Functions 5) Architecture 6) Components/ technologies	• Defined where, when, why and how to develop a DT • Physical object and digital modelling are not addressed
[29]	Multiple domains	1) Goals 2) User focus 3) Life cycle focus 4) System focus 5) Data sources 6) Data integration level 7) Authenticity	• For application-oriented DT applications and universally valid in all DT related domains • All the key elements are covered, but lack details and the links on the elements
[2]	Manufacturing	1) Physical entity/ virtual twin 2) Physical/virtual environment 3) State 4) Metrology 5) Realisation 6) Twining rate 7) Physical-to-Virtual connection 8) Virtual-to-Physical connection 9) Physical/virtual processes	• A complete conceptual description of the DT • Some implementation tools and technology are described
[30]	Based on the Manufacturing domain	1) Purpose 2) Data input 3) Data link 4) Synchronisation 5) Interface	• Possible to be used as a reference to measure the DT development progress • Digital model and application/services are not introduced
[31]	Multiple domains	1) Scope of physical entity 2) Feature of a physical entity 3) Scope of virtual entity 4) Form of data communication 5) User-specific output/values	• For cross-industry classification and development of applications within the concept of the DT • Major DT elements are covered, and can be used as a basis for creating a more detailed framework
[32]	Multiple domains	1) Application areas 2) Federation 3) Layering 4) Spatial scale & resolution 5) Temporality & resolution 6) Lifecycle stage 7) DT actors & asset stakeholders	• Enable decision-makers to articulate the DT user requirements • involve the supply and delivery of a complex DT by multiple parties • Technical elements are not fully covered
[33]	For manufacturing systems	1) Physical entity 2) Virtual model 3) Service 4) Data 5) Connection	• Emphasis on functions and practice, clear causal links are presented between DT elements • Can be further extended for cross-domain comparison

criteria:

- Inclusivity: The framework should encompass all commonly agreed core elements of DTs.
- Causality: The elements should reveal underlying causal patterns.
- Universal Applicability: The framework should be applicable to DTs across all domains, scales, and use cases.
- Balanced Detail: It must provide sufficient detail for comprehensive analysis while remaining reasonably simplified to ensure the conciseness of the comparative study.

4.1. Evaluation of existing DT frameworks

Relevant work has been reviewed against the above criteria based on systematic literature analyses from academic research. The results are summarised in Table 1.

4.2. Framework synthesis methodology

Currently, there are no clearly defined criteria for comparing DTs across domains. A framework for comparison is therefore essential, with explicit parameters and criteria for measurement. Furthermore, since the appearance and behaviour of DTs are not directly measurable, a process of operationalisation is required to define the attributes for effective comparison. With this framework, features of typical DTs from selected domains can be extracted and compared. Consequently, the DT comparative framework is synthesised through the following steps:

- Conceptualisation of DT Attributes: Identifying and defining key attributes of existing DT frameworks.
- Characterisation of DT Attributes: Structuring the attributes into categories and sub-categories based on shared and domain-specific features.
- Operationalisation for Measurement: Establishing criteria and parameters to enable measurable and meaningful comparison.

By summarising the DT characterising frameworks in Table 1, it becomes evident that characteristics of DT can generally be divided into two broad groups: abstractions and concepts on one side, and implementation-focused tools and techniques on the other. Accordingly, it is proposed that the frame of reference shall be primarily divided into two categories – conceptualisation and implementation –to assess DTs across domains in terms of their conceptual and technical development.

Numerous publications [2,16]. [31,32] emphasise that the starting point of digital twining is the physical entity, and the purposes must be clearly defined in the beginning. This is consistent with the Gemini Principles [20]. The purposes of digital twinning encompass the objectives to be achieved [29], the values to be created [31] and the application to be realised [32].

To bridge the starting point and purposes, a bi-directional and synchronised data link [16]. [2]. [30,31] shall be introduced, alongside with some other elements (users [29–32], life-cycle stage [28,29,32], etc), to be packaged into the system architecture, as a presentation of the whole picture of the conceptualised DT.

After establishing the conceptual foundations of DTs, the next step addresses their implementation—how to transform these concepts into working systems using various technologies and methodologies. Three steps were identified for the technology-oriented implementation. To begin with, the behaviours of the physical entity are captured in the form of data via technologies such as sensors, cameras and scanners. To interpret the data, certain levels of computing power are required so the data is transmitted to another venue, normally the cloud. There might be a reduction in the complexity of data during the communication, but the nature of the data remains unchanged until the next step, where data is reconstructed to form models that can mimic the operation of the

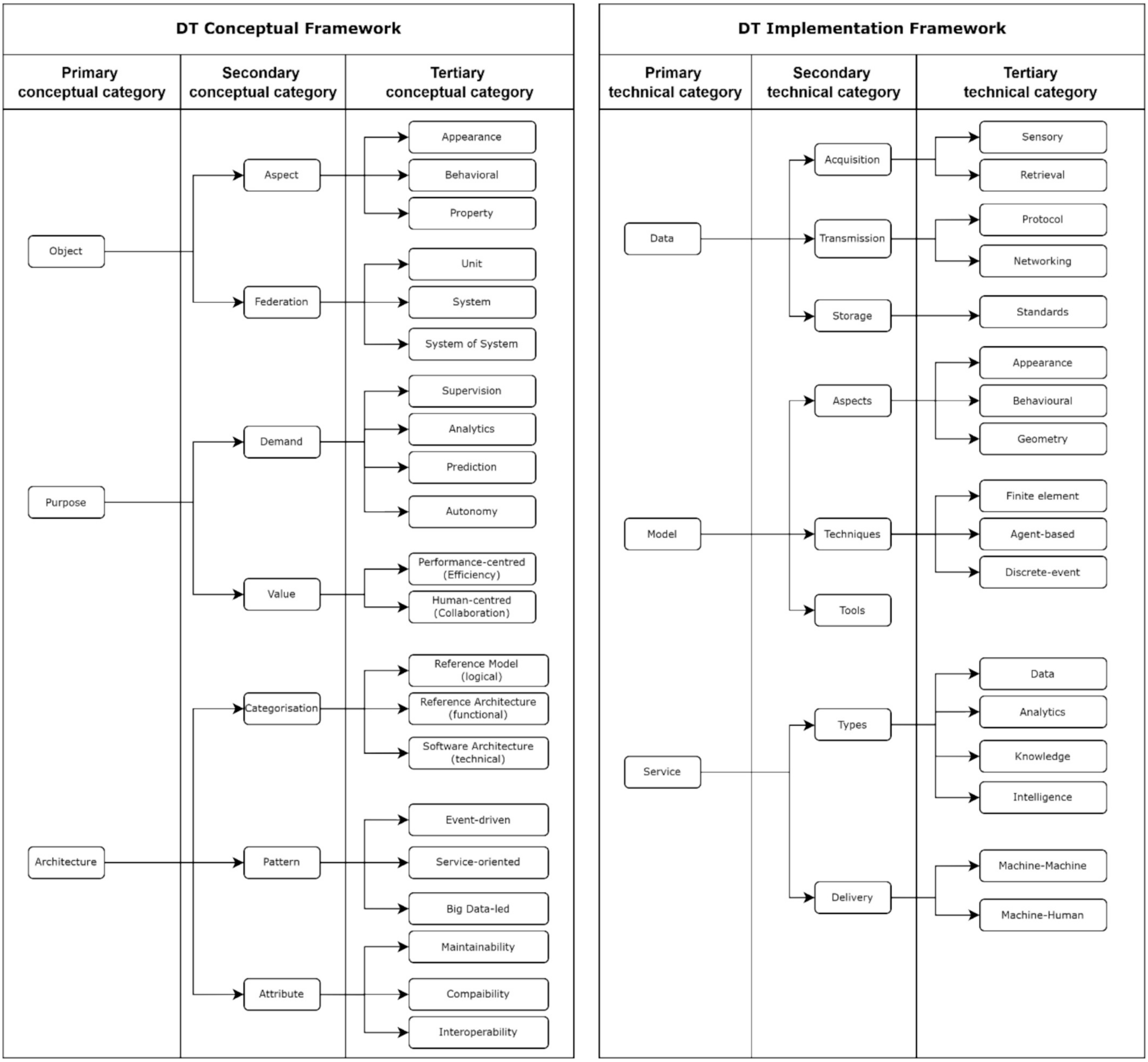

Fig. 3. Six-dimensional cross-domain digital twin comparative framework.

physical object. While setting up the modelling of the physical object might be a milestone, it is not the destination. As the final step, different levels of services are delivered to the users to meet their demands defined in the purposes.

To conclude, the six-dimensional framework was derived through a systematic analysis of the frameworks in Table 1. The synthesis process involved: (1) extracting common elements across frameworks (e.g., physical entity, purpose, data, services, etc.); (2) grouping similar elements into broader categories (e.g., "physical entity," "scope of physical entity," and "feature of physical entity" were consolidated into "twinning objects"); and (3) organising each dimension into sub-categories to accommodate domain-specific variations while maintaining universal applicability.

Thus, a six-dimensional comparative framework of DTs is shown in Fig. 3, it describes a DT from characteristics in the conceptual development and technical implementation. The framework synthesises insights from the existing frameworks (Table 1) into six core dimensions: three conceptual dimensions (twinning objects, twinning purposes, system architectures) and three implementation dimensions (data, modelling, services), with each dimension extended to multi-hierarchical to include representative categories and sub-categories based on the DT studies from different domains.

4.3. Framework specification

This section operationalises the six-dimensional comparative framework by establishing explicit parameters and criteria for measurement across domains. Since DT characteristics are not directly observable, each dimension requires detailed specification to enable systematic comparison. The following sub-sections define the scope, categories, and measurable attributes for twinning objects, purposes, system architectures, data, modelling, and services. This operationalisation transforms the abstract framework into a practical tool for extracting and comparing features from domain-specific DT

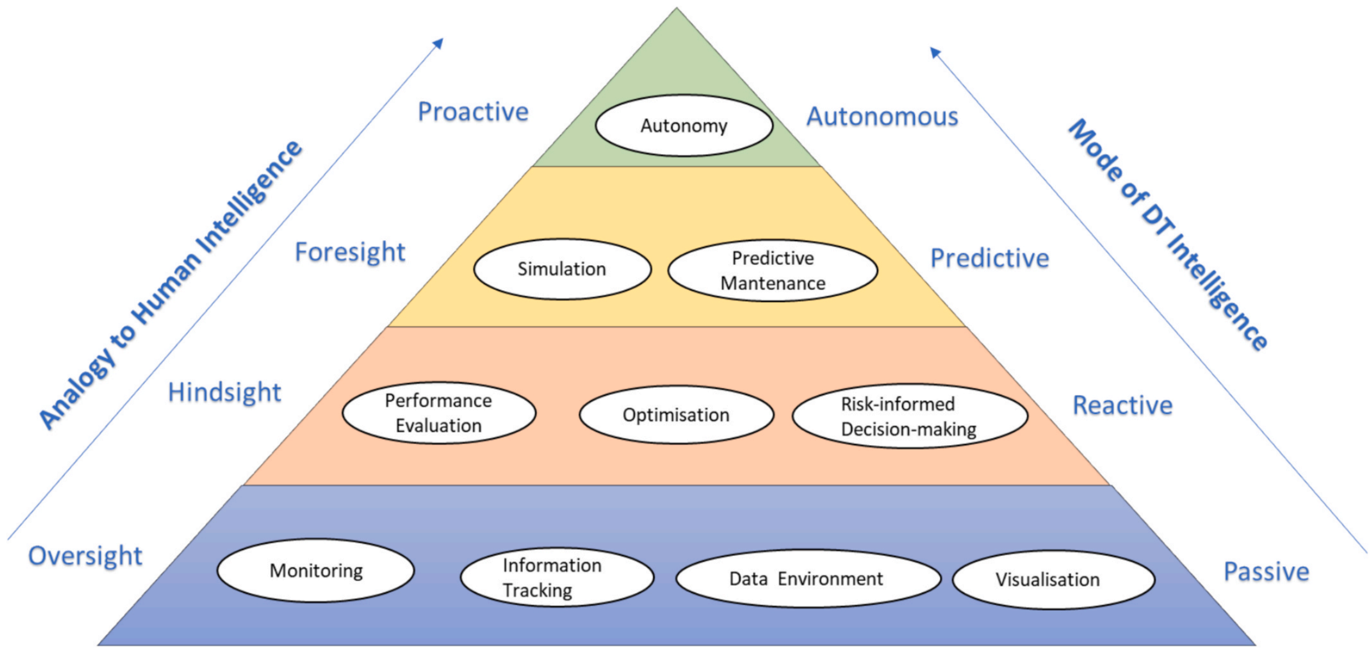

Fig. 4. Digital twin intelligence mode and analogy to human intelligence.

implementations in Section 5.

4.3.1. Twinning objects

A twinning object is the entity for which the DT is created, making its identification the first question to address when developing a DT. Analysis of twinning object patterns across relevant studies reveals three insights critical for cross-domain DT development and transferability.

Initially, twinning objects were predominantly physical, human-made entities, such as a product [34] or a factory [35]. More recently, interest has expanded to include natural entities such as animals [36], climate systems [37] and abstract entities like enterprise DTs, which replicate the operation of organisations that do not physically exist [38,39]. This progression from purely physical objects in early manufacturing studies to conceptual entities in recent healthcare and organisational research signals DT technology's maturation beyond its manufacturing origins and purely physical representations.

The commonality among these entities – whether physical products, natural systems, or abstract organisations- lies in their existence in the real world, either physically or conceptually, enabling them to be digitally twinned in cyberspace. Hence, though some papers refer to the twinning object as a "physical twin," this study adopts the term "twinning object" to reflect broader developments and applications.

On another dimension, twinning often focuses on specific **aspects** of an object, such as **geometry**, **materials**, or **behaviours**, depending on the information of interest to DT users. Therefore, it is crucial to consider which aspects of the object are twinned and how this selection impacts the twinning process.

Both industry and academia have proposed practices to characterise twinning objects. Siemens [40] categorises twinning objects based on the product lifecycle stage, identifying product twins for efficient design, production twins for production planning, and performance twins for capturing and analysing operational data. IBM [41] defines twinning objects in terms of magnification levels, ranging from component twins, which focus on individual parts, asset twins that study interactions between components, system twins representing entire functional systems, to process twins that reveal how systems collaborate.

The distinction between these categories primarily lies in their application areas. For instance, Whyte *et al.* [42], in a feasibility study for the Thames Tideway Tunnel scheme, proposed three levels of twinning for various subsystems: asset, project, and system of systems, each employing different modelling techniques. Similarly, Rosen, Boschert and Sohr [43] suggest that a production system can be twinned at three scales: product, process or system. Tao *et al.* [33] classify entities by function and structure into unit, system, and system of systems (SoS) levels. Al-Sehrawy, Kumar and Watson [32] further extend this framework to urban DTs, proposing a classification into sub-system, system, and system of systems to enable inter-organisational collaboration and address sectoral silos in infrastructure.

In conclusion, twinning objects can be broadly categorised according to their **federation/aggregation**: **units**, **systems**, or **systems of systems**. The selection of the twinning object depends on the research purpose and focus, with different objects dictating different modelling techniques.

4.3.2. Twinning purposes

The purposes of digital twinning define the rationale for creating a particular DT. They establish the critical link between the DT system and the applications, functions, or use cases the DT is intended to serve. DTs are developed for a variety of purposes, even when addressing the same physical twinning object. These purposes determine which aspects of the physical asset are digitised and the level of detail the DT should encompass relative to its physical counterpart [44]. Furthermore, the purposes influence other key DT components, including system architecture design [45], modelling fidelity and dynamics [46], and the services to be delivered [47]. Therefore, it is essential to define the purposes of a DT before proceeding with design, development, or implementation.

A significant body of cross-domain research has categorised DT purposes. In agriculture, Pylianidis *et al.* [48] categorised DT functions into four levels: (1) fundamental, with monitoring, user-interface, and analytics; (2) enhanced, including actuator components for control; (3) further enhanced, with simulation capabilities; and (4) the highest level, incorporating learning capabilities to uncover underlying system mechanisms. For manufacturing, Wagg *et al.* [46] proposed a five-level capability hierarchy: supervisory, operational, predictive, learning, and autonomous management. In the construction domain, Boje *et al.* [49] described a three-tier paradigm for DT platforms, ranging from monitoring platforms to intelligent semantic platforms, and finally, agent-driven socio-technical platforms, reflecting increasing levels of intelligence and lifecycle integration. In the city's domain, Al-Sehrawy *et al.* [32] developed a multi-dimensional classification framework for city DT uses, dividing them into four categories: information mirror, communication, analysis, and control. On a broader cross-industry scale, Enders & Hoßbach [16] summarised DT application purposes into three levels—monitoring, simulation, and control—based on a systematic literature review of major DT application domains.

Across different domains, the purposes of DTs share several commonalities, including real-time monitoring, fault analytics, simulation and prediction, and optimisation. These purposes are often classified based on capability and intelligence levels, which can be evaluated from two perspectives: (1) situational awareness and understanding, and (2) timeliness of response. Therefore, an analogy can be drawn as in Fig. 4 to match DT intelligence to human intelligence for clarity. Furthermore, a single DT can perform different levels of intelligence in applications; in other words, DTs may shift between modes depending on their purpose and application requirements. These modes correspond to the levels of DT intelligence and are analogous to how humans adopt different roles in their professional tasks.

The first level/mode, "passive(oversight)" involves monitoring the physical twin without influencing it while at the second "reactive (hindsight)", DTs at these levels may analyse data and understand situations, their performance is typically reactive, with delayed responses to take predefined actions based on changes in the physical twin or its environment. The "predictive (foresight)" level involves simulation-based predictions of future scenarios, enabling pre-planning and targeted optimisation, though human intervention is still required to close the control loop. At the highest level, "proactive" and "autonomous" DTs achieve a degree of autonomy by influencing their physical twins through actuators, facilitating lifecycle management with minimal human involvement. This hierarchy can be applied as a universal scale for assessing the purposes of digital twinning. This purpose intelligence hierarchy (from passive to autonomous) represents the decision-making autonomy of the DT system, which is distinct from but related to the cognitive sophistication of services delivered (DIKW framework discussed in Section 4.3.6). Purpose intelligence addresses decision-making authority and timing, while service sophistication addresses cognitive processing complexity.

Notably, while the emergence of agentic AI represents a potential advancement in DT capabilities, its integration with DT systems presents both opportunities and significant challenges. AI agents can theoretically be positioned at the wisdom level of the DIKW hierarchy due to their autonomous decision-making and proactive action capabilities [50], yet current implementations often struggle with reliability, explainability, and contextual understanding in complex real-world environments. Agentic AI-equipped DTs incorporate autonomous agents that can independently analyse situations and execute actions without human intervention [51], though concerns remain regarding decision transparency and accountability in critical applications [52].

On top of the basic demands, the values that DTs will create for organisations and society also motivate the adoption of this technology. The Gemini Principles [20] for DTs of the built environment emphasise public good, openness and trustworthiness as foundational values. Current DT applications are often motivated by two primary value drivers: performance-centric and human-centric goals. **Performance-centric** DT intelligence, such as optimisation, predictive maintenance, and autonomy, focuses on efficiency and effectiveness. However, human-centric DT design is increasingly discussed. For example, Schrotter and Hürzeler [53] introduced the DT of the City of Zurich for collaboration on urban planning and public awareness on climate change. Longo, Nicoletti and Padovano [28] proposed a **human-centric** paradigm, where manufacturing employees are integral to the system, empowered with knowledge of manufacturing processes to enhance both production and business outcomes.

Excessive automation enabled by DTs could introduce societal challenges, such as unemployment. As Elon Musk [54] argued, closing the manufacturing control loop without human involvement could erode buying power and weaken business performance. Hence, while performance improvement is often the primary goal, human-centric design remains vital to achieving long-term benefits for organisations and society.

4.3.3. System architectures

The identification of twinning objects and purposes is often a straightforward process, but mapping them to a coherent system architecture can present significant challenges. However, established concepts and practices from other fields offer valuable insights to address this issue. In system and software engineering, once the starting point (i.e., the twinning object) and the objective (i.e., the twinning purpose) are identified, the next step in conceptualisation is to compose a system architecture that enables the system's expected functionalities [55]. To conceptualise DT architectures further, the academic community has developed reference models [56,57], reference architectures [47,58] and architectural styles such as multi-layered [59] and service-oriented [60] approaches tailored to DT systems.

This taxonomy is well-described by Len Bass and Paul Clements (2003) in the book Software Architecture in Practice, where the completeness of a software system's architecture is defined across three levels: reference model, reference architecture, and software architecture. Architectural styles are linked to system quality attributes and act as the foundation for attribute-driven architecture design.

Building on these terminologies, researchers have worked to extract DT architectural features and develop classification frameworks. Eindhoven and Version [61] described a method to classify architecture frameworks for automotive software systems based on the level of abstraction, starting from logical architecture to functional architecture and finally implementation architecture. Tekinerdogan and Verdouw [62] proposed a pattern-oriented approach for architecting DT-based agricultural systems, featuring a catalogue of nine distinct architectural design patterns tailored to various use cases (e.g., model, matching, proxy, monitor, control, autonomy). These patterns primarily employ multi-layered architectures, where each layer performs specific tasks, and additional layers accommodate higher levels of intelligence and complexity.

Similarly, Ghita, Siham and Hicham [63] presented a DT reference architecture inspired by RAMI 4.0 (Reference Architecture Model for Industry 4.0) and its variants. These architectures were designed for diverse industrial ecosystems, including industrial IoT, complex system engineering, and cloud services. They consist of two primary layers, each housing distinct functional elements. These elements provide variable performance across contexts such as data management, multi-agent interoperability, security management, and functional suitability. Ferko, Bucaioni and Behnam [45] conducted a systematic mapping of DT proposals in the literature, aligning them with architectural solutions, patterns, and quality attributes. Their study concluded that most DT architectures combine layered and service-oriented patterns to address attributes such as maintainability, performance efficiency, and compatibility.

Multi-layered architectures are widely referenced in DT implementations. This approach organises modules or components with similar functionalities into horizontal layers, each performing a specific role [64]. In the manufacturing domain, DT architectures often share conceptual foundations with cyber-physical systems (CPS), both addressing physical-cyber integration challenges. While CPS emphasises real-time control and system automation, DT focuses on virtual representation and predictive capabilities [33]. However, it is important to note that the relationship between CPS and DT varies across implementations and researchers' perspectives. While some view DT as a specific realisation of CPS concepts [33], others position DT as a complementary technology that can operate within or alongside CPS architectures [65]. Many manufacturing implementations combine both approaches, leveraging CPS infrastructure while providing additional capabilities for predictive modelling and virtual experimentation.

CPS, a core concept of Industry 4.0. CPS is based on the ISA-95 architecture, has evolved into the 5C architecture, which comprises five layers: connection, conversion, cyber, cognition, and configuration. Component-based or module-based architectures are prevalent in manufacturing for constructing CPSs [66]. Meanwhile, service-oriented architectures, drawn from advances in computer engineering, have been applied to multi-service-based DT implementations. For instance, [67] proposed a software-intensive DT architecture to achieve contextual-awareness and automatic self-management.

It is important to note that DT architectures differ from pure software system architectures because they include physical twins and a range of hardware components for data acquisition, processing, and delivery. In conclusion, the system architectures of DTs should be evaluated based on their levels of completeness, architectural patterns, and quality attributes in a comparative framework.

4.3.4. Data

Data acquisition and communication form the foundational layer for DT implementation, capturing behaviours of twinning objects and enabling the transformation from physical reality to digital representation. It is widely recognised that the foundation of DTs lies in data [29], with data quality and accessibility directly determining DT capabilities [65] and service sophistication [68].

Data approaches reflect varying domain constraints, revealing systematic patterns of technology adoption and adaptation. Manufacturing utilises advanced industrial IoT with standardised protocols (OPC UA, MQTT) and established formats (STEP, AutomationML) for precision control applications [69,70]. Agriculture employs resource-constrained approaches using low-power sensors with seasonal sampling frequencies matching biological growth cycles. Construction relies on high-fidelity reality capture technologies (laser scanning, photogrammetry) and IFC standards, though requiring significant enhancements for dynamic operational applications [49]. Healthcare implements privacy-preserving wearable devices with wireless communication (Bluetooth) while managing sensitive personal data. Cities integrate complex heterogeneous multi-source data streams through hybrid communication systems (NFC, Wi-Fi, NB-IoT, fibre optics) and geographic standards (GML) [71]. The domain-specific patterns reveal maturity gaps, as manufacturing benefits from decades of industrial automation investment, while agriculture and healthcare face fundamental economic and regulatory barriers that limit sophisticated data infrastructure deployment.

The first step in DT implementation is to acquire data capable of describing the conditions of the twinning object. The most common method is automated real-time data collection via sensors, including physical phenomenon detection and visual capture, such as cameras. Sensors are generally classified by mechanism (e.g., mechanical, electronic, chemical, and biosensors) and integrated into systems for reliable data collection. In some applications, retrieving historical or external data from databases is also required. For example, Newbery describes a chemical process, DT that receives live data from sensors attached to physical assets, historical data from external databases, and weather data (e.g., humidity and temperature) from national weather services.

Data acquisition is typically conducted through sensor networks deployed in various scenarios, such as cities, construction sites, farmland, factories, or even personal applications. These networks employ versatile sensors like gauges, high-resolution cameras, scanners, QR tags, and readers, selected based on the DT services required. Sampling frequency, highly tied to the timeliness of the digital representation of the physical entity, is determined by domain-specific characteristics. For instance, agriculture DTs do not require high sampling frequencies due to the slow growth process of crops, whereas manufacturing applications, such as 3D printing DTs, demand high sampling rates to reflect rapid manufacturing processes and ensure product quality.

Another critical factor is sensor placement, including the quantity and location of sensors, which directly impacts the accuracy and granularity of the DT. Optimal sensor placement remains a key research focus, as it varies significantly across domains. For example, accelerometer placement for structural health monitoring (SHM) considers structural elements, material, geometry, and algorithms, while wearable sensor placement in healthcare depends on medical knowledge and patient conditions. Sensor energy management is another research hotspot, as a stable power supply remains challenging in many scenarios. Research focuses on three main solutions: renewable energy sources (e.g., wind, solar) for sensor nodes, ultra-low-power sensors capable of running for years on batteries, and self-powered or energy-harvesting sensors (e.g., vibration energy harvesters and self-powered biosensors).

Data transmission can use wired or wireless communication. While wired networks offer greater data volume capabilities, wireless communication enables monitoring in previously inaccessible areas. For example, wearable devices require wireless communication, such as Bluetooth, for mobility. Wireless communication is classified by range (short, medium, or long) or topology (cellular or non-cellular). The choice of communication technology depends on factors like data rates and delays. Low data rates may cause communication congestion when managing massive heterogeneous data, while high delays hinder DT synchronisation. DT communication systems often employ hybrid technologies; for instance, in smart cities, NFC handles resident identification, open Wi-Fi supports public communication, NB-IoT or LTE-M monitors infrastructure, and optical fibre connects gateways to cloud servers. In industries with advanced digitisation, standard protocols include OPC UA for industrial telecommunication, Ethernet/IP for industrial networks, TCP/IP for network interconnection, UDP for low-latency communication, and MQTT for lightweight publish-subscribe messaging.

Data storage represents the third critical component, encompassing the infrastructure and technologies for persistent data management. DT implementations utilise diverse storage approaches ranging from edge computing for real-time processing to cloud-based data warehouses for historical analysis. Storage requirements vary significantly across domains: manufacturing requires high-performance time-series databases for real-time control, agriculture needs cost-effective long-term storage for seasonal data, healthcare demands secure, compliant storage for sensitive patient information, while cities require scalable distributed storage for massive heterogeneous datasets.

Unlike widely applicable transmission protocols, data formats and standards are domain-specific. In manufacturing, formats like STEP store lifecycle product information, while AutomationML manages production monitoring data for DT services [69,70]. These high-level models enable data exchange but rely on middleware for data extraction. In the city domain, Geography Markup Language (GML) supports geographic information modelling, transport, and storage for infrastructure and civil engineering activities [71]. However, GML lacks asset management capabilities needed for dynamic DT applications. Similarly, the Industry Foundation Class (IFC), widely used in construction, requires enhancements to transition from static data models to dynamic information-sharing paradigms [49]. Efforts like [72,73] have extended IFC models to include semantic structural descriptions and dynamic time-series sensor data. Overall, domain-specific data standards still face challenges in interoperability between interconnected DTs, while cross-domain efforts are addressing these limitations through initiatives like FIWARE Smart Data Models [74] serving as interoperable middleware and CDBB foundational data models [75] providing top-level ontologies. Data acquisition, transmission, and storage constitute the primary characteristics distinguishing DT data implementations across domains. Cross-domain analysis reveals systematic differences driven by domain constraints, with standardisation efforts facing ongoing interoperability challenges due to domain-specific requirements.

4.3.5. Modelling

DT modelling represents the core differentiator of DT systems from conventional data-driven approaches [4], as virtual models enable the transformation of raw data into predictive insights and autonomous decision-making capabilities [65]. DT modelling replicates key aspects of the twinning object, such as physical geometries, properties, and behaviours. The model must be constructed at an appropriate level of abstraction using suitable modelling techniques [76]. Without robust virtual models, DT services may not significantly differ from traditional monitoring systems [2], making model construction and integration critical to DT functionality [77].

Literature review of DT modelling reveals three primary virtual model construction approaches, each addressing different system characteristics and requirements. Physics-based modelling, as suggested by [65], remains central during design and construction phases, categorised into observed physics, modelled physics, and resolved physics based on the level of understanding of physical phenomena. These can be combined with data-driven modelling to reduce complexity while maintaining interpretability [78]. Hybrid approaches integrate both methodologies to create flexible frameworks for rapid adaptation while preserving predictive accuracy.

Broader frameworks were proposed by Qi et al. [68] and Liu et al. [77], both emphasising that a DT model integrates four sub-model types—**geometry**, **physics**, **behaviour**, and **rules**—each serving distinct functions. Model integration is key to resolving the contradiction between simplified virtual models and the complex behaviour of twinning objects. For instance, Liu et al. [79] implemented model fusion through a mimic modelling method, merging geometric, behaviour, and context models to enable holistic information monitoring during machining processes.

In terms of domain-specific model construction, the observed patterns reflect varying requirements for accuracy, real-time performance, and interpretability. Manufacturing utilises physics-based CPS models with high precision for control applications [33], agriculture employs empirical models based on environmental relationships for seasonal predictions [48], construction integrates BIM with physics-based structural models [49], healthcare applies data-driven models for complex physiological monitoring [11], and cities use agent-based models to capture complex socio-technical interactions [80].

Virtual model integration with DT services enables the DIKW progression from passive data collection to autonomous decision-making [68]. Models serve as computational engines that transform sensor data into Information-level insights through pattern recognition, Knowledge-level understanding through simulation and reasoning, and Wisdom-level capabilities through predictive optimisation and autonomous control [46]. This integration distinguishes DTs from conventional data systems by providing dynamic, predictive virtual representations rather than static data repositories [5]. Certain modelling techniques have been identified for their suitability in DT applications:

- Finite Element Analysis (FEA): A physics-based technique for assessing the behaviour of assemblies under physical effects.
- Agent-Based Modelling: Applied in complex systems where multiple parts interact and influence each other.
- Discrete Event Modelling: Suitable for systems decomposable into autonomous processes that progress through time [81].

Modelling is typically performed using desktop-based tools, although web-based tools are gaining traction due to their lightweight, open-source nature and better interoperability with other systems. Examples include Xeokit for building information modelling and Cesium for geographic information modelling. These tools also serve as management platforms for model evaluation and verification tasks. From a model engineering perspective, Zhang, Zhou and Horn [82] propose metrics to assess the "rightness" of DT models across their lifecycle, including model construction, evaluation, and management. Similarly, Tao *et al.* [83] performed multi-aspect analysis of the DT modelling via model construction, assembly, fusion, verification and modification. Model maintenance and updating represent ongoing challenges, particularly in operational environments where virtual models must continuously synchronise with evolving physical systems while maintaining accuracy and reliability.

While other aspects of DT modelling are discussed in the literature, the types of models, modelling techniques, and tools constitute the primary characteristics that distinguish DT modelling.

4.3.6. Services

Once the model of the twinning object is complete, the final stage of DT implementation is to leverage the DT model and integrate it with domain-specific knowledge to provide service benefits to users. In this study, service benefits refer to the functions derived from the purposes of digital twinning that fulfil the potential of the DT data and modelling. Williams, Chatterjee and Rossi [84] identified key design dimensions that distinguish digital services. Two of these dimensions—service resource and service delivery—are particularly relevant to DT services. From the perspective of servitisation, Meierhofer *et al.* [85] considered DT as an enabler for the servitisation of manufacturing, hinged on its role in the value creation. The services, generated through data analytics or simulation, are delivered to the system actors, such as production lines, products, or users. Both studies highlight the origin of the service (resource) and its destination (delivery).

Comprehensive dimensions for DT services have also been derived from software engineering. Qi, Tao and Nee [86] analysed the workflow of DT services, identifying steps such as service request, resource collection, service encapsulation, and service delivery. Aheleroff *et al.* [47] proposed Digital Twin as a Service (DTaaS) paradigm on the basis of Everything-as-a-service (XaaS) – a general category of applications enabled by cloud computing. DTaaS delivers four categories of DT services: data transformation using the DIKW hierarchy (data, information, knowledge, wisdom), integration of human workforce and cyberspace to enhance efficiency and accuracy, retrieval of semantic content across assets, and autonomous decision-making enabled by real-time connectivity.

The first main element of DT services is the resources from which the service is generated. These resources also indicate the service's maturity level, which can be rated using the DIKW based on the extent of data value extraction. The DIKW framework provides an appropriate classification system because it captures both the cognitive sophistication and technical implementation requirements that determine service value and complexity. This alignment is evidenced by Qi *et al.* [68] who summarised enabling technologies for DT services as platform services, resource services, knowledge services and application services, directly reflecting DIKW progression. In addition, the DIKW framework aligns with the purposes and processes of digital twinning, where services evolve from basic data management to autonomous decision-making capabilities.

Based on the DIKW model, DT service maturity is categorised as follows:

- **Data service** where the presentation of data is the priority, while processing data is set as a minimum requirement. Examples are a common data environment, data storage and retrieval, etc.
- **Information service** to provide semantics sourced from pattern recognition and statistical analysis, such as threshold-based diagnostics, visualisation of the current status of the system, etc.
- **Knowledge service** based on the construction of domain-specific modelling and behavioural analysis for problem investigation, examples are rule-mining, decision tree, expert system, etc.
- **Wisdom service** characterised by autonomous decision-making capabilities that integrate system knowledge with real-time adaptation. Examples include self-optimising control systems based on

performance feedback and predictive maintenance systems that autonomously schedule interventions.

It is important to note that the complexity of analysis does not automatically determine DIKW classification. For example, fault diagnostics can be simple threshold-based detection, as in Information services, while behavioural modelling for fault diagnosis represents knowledge services. Similar to simulation, basic trend extrapolation may be Information-level, while autonomous optimisation through simulation represents wisdom-level services. The classification depends on the degree of autonomous decision-making and system integration rather than purely on analytical sophistication.

The second key characteristic of DT services is service delivery, which defines the gateways through which data and information exit the DT. Technologically, DT services can be divided into machine-to-human and machine-to-machine [30].

- **Machine-to-human** services present outcomes to users visually, using tools like augmented reality and dashboards.
- **Machine-to-machine** services transmit actionable intelligence to autonomous machines that can communicate and share critical information required for asset operations [87].

5. Domain-specific DT analysis

In this section, thematic analysis was conducted on literature of each selected domain to identify archetypes of the domain-specific DT use-cases. Consequently, several collections of DT instances were compiled. The description of DT instances adheres to the dimensions defined in the synthesised comparative framework, aiming to present a detailed outline of DTs in each domain, which are used as groundings for the cross-domain comparison in Section 6.

5.1. Agriculture

As a process for cultivating soil to grow crops and rearing animals to provide food, agricultural DT could realise a sophisticated management system to maximise productivity while reducing labour requirements, energy usage, and losses. A similar concept—precision agriculture—was introduced before agricultural DTs, both focusing on a more timely understanding of farmland and livestock for optimised farming management.

The most discussed twinning object in the literature is farmland, which consists of crops and the environment. Services of agricultural DT emphasise visible and automated management of irrigation scheduling, fertiliser application, and the detection of infectious disease [88]. The implementation of the system architecture tends to utilise established platforms. A typical example is an irrigation DT implemented by, where they applied low-cost sensors designed by Sensing Change, an IoT platform built in the SWAMP project, and a data subscription service developed by FIWARE Foundation.

One distinctive characteristic of agriculture DTs is the direct involvement of living systems, including animals [36] and plants. Unlike human DTs in healthcare, agricultural processes tend to evolve relatively slowly in the temporal dimension, so high-frequency interaction between the physical object and the DT is not as vigorously required [48]. This feature can affect the technical development of agriculture DTs, as data acquisition relies on IoT monitoring solutions featuring low power and long-range communication. The modelling of farming environments could be based on empirical equations [89], and the service level mostly remains at sensing and basic analytics. More advanced services, usually in controlled environments where parameters are more manageable [90], include prediction and automation of nutrient application [91].

5.2. Manufacturing

As a sector diligently pursuing production efficiency, manufacturing has been at the heart of industrial revolutions, starting from industrialisation to electrification, then automation and now digitalisation. Industry 4.0 has provided numerous enablers for manufacturing DTs, including Internet of Things (IoT) for data acquisition, cloud computing for processing capabilities, artificial intelligence for analytics, and CPS concepts for physical-digital integration frameworks.

The digital twinning object in the manufacturing domain could be any of the following: product at the unit level [92], production line at the system level [93,94], or network of operational products at the System of Systems (SoS) level [35]. A product DT describes the geometry, properties, and functional information of a product in the design, manufacturing, and use phases to monitor its status over the entire life cycle, for prognostic health management.

The integration of multiple unit-level DTs constitutes a system-level production DT, which could represent a manufacturing line, shop floor, or factory. The goals are to optimise the allocation of manufacturing resources and improve production efficiency through semi-automation, such as human-robot collaboration, and full automation based on the closed-loop cycle of sensing-analysis-decision-execution [33]. The proposed system architectures have evolved to a relatively mature level, with a technical architecture and established architectural patterns.

Data collection benefits from developed technologies, including CPS and Industrial Internet of Things (IIoT), where data formats (e.g. STEP [69]) have been standardised. Blockchain also plays an important role by enabling the decentralised data storage for life-cycle product information [92]. Services for a product DT range from web-based visual simulation to present the model construction at the design stage, data dashboards at the usage stage and predictive maintenance at the operational stage.

5.3. Construction

Digital twinning has been found to offer several applications in the design, construction, operation, and maintenance of assets in the construction domain. While many researchers [73,95,96] have proposed combining DT and Building Information Modelling (BIM), which provides various digitised information of the physical assets, such as dimensions, material, and structural connections, contemporary perspectives emphasise that construction DTs represent fundamentally different paradigms from static BIM structures. Rather than positioning BIM as the foundation, emerging frameworks conceptualise building DTs as dynamic, operational models that enable real-time data and information exchange between physical and virtual building systems [97]. These systems function as closed-loop control mechanisms that continuously monitor, analyse, and respond to operational conditions, moving beyond BIM's primary role in design and construction documentation [98]. Data for construction DTs mainly reflect the operational status of the structure or facility, which is acquired via IoT sensors or reality capture technologies, such as laser scanning and photogrammetry. The modelling approach is typically a combination of the conventional structural model, BIM model, and machine learning algorithms to create dynamic operational representations. Industry Foundation Classes (IFC) provide data exchange standards, though enhanced frameworks are required to support the dynamic, time-series data requirements of operational DTs [15,99].

Construction involves a wide range of high-hazard activities, so addressing health and safety (H&S) is one of the main purposes of applying DT. Augmented Reality (AR) and Virtual Reality (VR) are crucial DT service delivery technologies to tackle H&S issues and can also improve collaboration among multiple stakeholders [100].

The system architecture of construction DT implementations demonstrates evolution from conceptual frameworks(functional-level) toward operational deployment(technical-level), though significant gaps

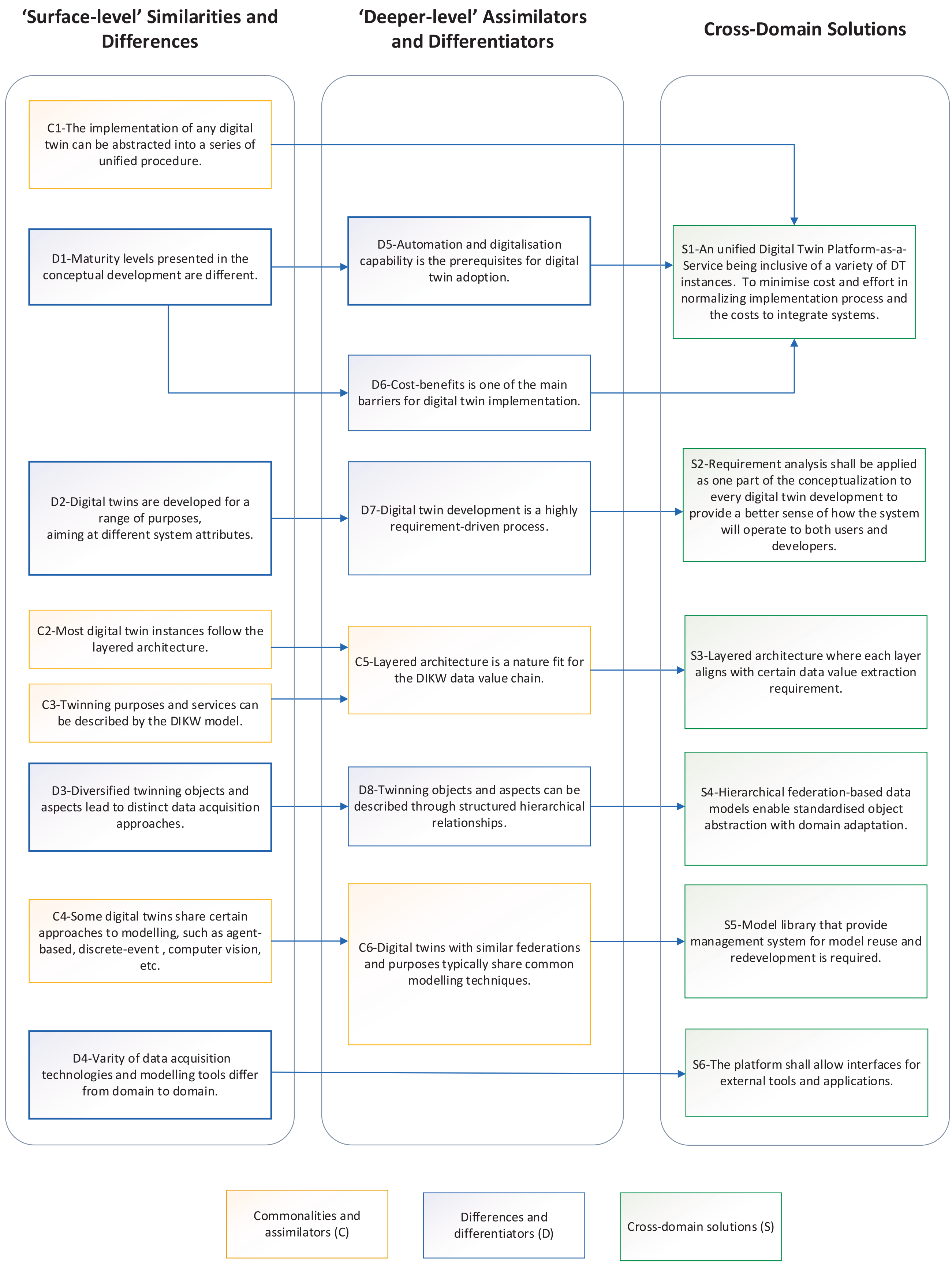

Fig. 5. Derivation of cross-domains DT solutions.

remain between research prototypes and industry-scale implementation. Current efforts focus on developing interoperable platforms that can integrate diverse data sources while providing actionable insights for construction and facility management stakeholders.

5.4. Healthcare

Existing DT applications in the healthcare domain primarily focus on precision medicine and healthcare services management. Twinning objects in precision medicine are mainly organs and the human body, used for analysing and developing predictions to provide clinical advice for patients [11,101]. Real-time supervision of healthcare services [9] aims to characterise health service delivery processes for effective demand management. The most proposed healthcare DT architecture is reference model, which suggests that DT applications generally remain at the conceptual level.

DT for patients relies on wearable devices to collect data, so wireless data communication (e.g., Bluetooth, Machine-to-Machine, etc.) is typically required. Data privacy and security are more sensitive in the healthcare domain, which can make it difficult to obtain patient data for validation of modelling and prediction [102].

DT modelling in the healthcare domain shares methodologies across disciplines, such as data-driven [11], discrete-time events [101], and agent-based [10]. DT in this domain is believed to be more challenging due to the high level of uncertainty. For example, the mechanism of human behaviour in a socio-technical system like an ICU is largely unknown [9], which makes quantitative modelling of clinical decision-making difficult. As a result, approximate behavioural models are more feasible, even if this means fidelity may be compromised [102]. For similar reasons, full automation may not be favoured when the consequences of system errors are intolerable, so human-in-the-loop services are essential for healthcare DT [10].

5.5. City

A city-level DT encompasses several components, including one or multiple systems such as transportation, environment, and energy. When city-level DTs are integrated, they are often referred to as a “smart city.” A smart city assembles individual city-level DTs and their interdependencies through a federated system, enabling a coordinated approach to planning, predicting, and managing the city. City digital twinning is sometimes confused with construction DT due to overlaps in their twinning objects, such as buildings and infrastructure. However, the two domains diverge in their focus. Construction DTs address the design and building processes of physical structures, whereas city DTs focus on the socio-economic impacts of urban infrastructure.

The purposes of city DTs include monitoring the current state of the urban environment, providing rapid and effective responses to emergencies, conducting efficient design and planning assessments, and predicting situational developments. The potential value/benefits include optimising resource use, reducing service disruptions, increasing resilience, and improving the quality of life for citizens [80]. Contemporary frameworks increasingly emphasise structured datasets, particularly energy usage data, for AI-enhanced policy decision-making that supports carbon–neutral strategies and energy efficiency initiatives [103]. However, effectively materialising these benefits through policy-making remains a significant challenge [104]. Compared to other domains, city DTs are more likely to rely on graphic visualisation data for acquiring information, as sensor-based reality information may be insufficient to provide dynamic spatiotemporal details about physical vulnerabilities [105]. The physical form of the city can represent the operational status of twinning objects in applications such as road traffic control. Visual data collected from the city environment is fed into machine learning-based computer vision models [106], requiring high-quality video transmission. Cabled internet connections (e.g., broadband, fibre optics) are typically prerequisites for smart city DTs. However, wireless telemetry may be applied in cases with relatively low data volumes, such as machine-to-machine(M2M) communication for harvesting energy usage data or billing customers for utilities.

The referenced twinning objects of city DTs are typically systems, and it is widely believed that achieving a large-scale, dynamic, and highly complex city-wide DT is the ultimate goal [80]. As a result, city DTs often employ systems engineering principles. Agent-based simulations are commonly used for resource application modelling, where large systems consist of autonomous and interacting individuals. Geographic information system (GIS) modelling is extensively applied as the base layer for city DTs, with the topography, environment, and spatial structure of the city surveyed and mapped into GIS-based databases.

5.6. Cross-domain digital twin implementation summary

Table 7 summarises the key characteristics of DT implementations across all five domains using the six-dimensional framework, demonstrating how each dimension manifests differently while revealing universal patterns. It validates that all domains follow similar six-dimensional development procedures with layered architectures, DIKW service progression, and IoT-based data acquisition. However, domain variations show different service sophistication levels, with manufacturing achieving the most advanced implementations while agriculture and healthcare focus on foundational monitoring capabilities. Cities and construction demonstrate intermediate complexity in system requirements and stakeholder coordination needs.

The analysis also reveals a clear maturity hierarchy correlated with environmental controllability. Manufacturing benefits from controlled production environments, enabling autonomous operations, while agriculture faces uncontrolled natural systems limiting advancement. The comparison also shows architecture-purpose alignment across the Three Sector Model: primary sectors (agriculture) prioritise monitoring with simple layered architectures, secondary sectors (manufacturing) achieve optimisation through sophisticated CPS-based designs, and tertiary sectors require federated architectures for multi-stakeholder coordination.

These patterns and variations provide the foundation for identifying universal principles that can be standardised across domains, as well as key differentiators that explain implementation challenges and opportunities. Section 6 examines these cross-domain insights to develop unified solutions for DT development and interoperability.

6. Cross-domain analysis and unified implementation framework

As illustrated in Fig. 5, this section of the study starts from the observed ‘surface-level’ similarities and differences from domain-specific DTs, then commits to investigating ‘deeper-level’ correlations that assimilate or differentiate the DTs of different domains, to provide explanations on why DTs are the way they are. Finally, based on the commonalities shared across the domains, unified approaches to conceptualise and implement DTs are proposed, where the differences of a variety of DT instances are encompassed in the cross-domain solutions.

The derivation of cross-domain DT solutions follows a systematic analysis of commonalities and differentiators identified through the six-dimensional framework. As shown in Fig. 5, the first pipeline starts from commonality analysis (C1), where framework application across five domains demonstrates that DT implementations follow unified procedures: object identification, purpose definition, architecture design, data acquisition, modelling, and service delivery. This procedural universality suggests standardisation opportunities across domains. On the other hand, differentiator analysis (D1 to D5 and D6) shows that maturity variations correlate with digitalisation capability and cost-benefit constraints, while tool diversity analysis reveals that the variety of data acquisition technologies and modelling tools differ from domain to domain (D4). High-capability domains (manufacturing) show advanced maturity, while cost-constrained domains (agriculture) demonstrate slower adoption despite technical feasibility. Both pipelines lead to solutions where the combination of procedural universality (C1) with identified constraint patterns (D5, D6) suggests that a unified platform approach can address both standardisation opportunities and constraint barriers (S1), while tool diversity requirements indicate that platforms must allow interfaces for external tools and applications (S6) to accommodate existing domain-specific infrastructures.

6.1. Commonalities for universal development principles

6.1.1. Requirement-driven digital Twin conceptualisation

Analysis from Section 5 demonstrates that the purposes of DTs within different domains are common, including real-time monitoring, integration tool, fault analysis, prediction, optimisation, etc. The classification of the purposes is mainly based on the level of capability. Though DTs could potentially provide greater benefits by advancing through the DIKW hierarchy, this involves increased system complexity and development costs [107]. Therefore, instead of pursuing higher levels of maturity and sophistication, the DT users and developers shall develop systems to meet the specific needs and purposes.

With guidance from the comparative framework described in Section 4, requirements for DT frameworks can be derived from object conceptual models, twinning purpose and system architectures. The object conceptual model may include any design related to the nature of the object, such as the federation and aspects that suggest appropriate modelling techniques [12]. Purpose specification identifying demands and values shall establish foundations and boundaries for developing DTs [20]. Architecture specification is closely linked to system quality attributes such as reusability, extensibility, interchangeability and maintainability across the entire DT lifecycle [45]. Requirements developed from the conceptualisation process set the baseline framework, and all the aspects of these requirements shall be addressed in the DT development [108].

Requirement-driven development emerges as critical for DT success across domains. Cross-domain analysis reveals that DTs are developed for a range of purposes, aiming at different system attributes (D2), even when addressing identical physical objects. Process analysis demonstrates that DT development is a highly requirement-driven process (D7), where purpose definition determines all subsequent design decisions. Therefore, requirement analysis shall be applied as one part of the conceptualisation to every DT development to provide a better sense of how the system will operate to both users and developers (S2).

6.1.2. Reusable and interoperable data model and modelling library

The case studies in Section 5 reveal that neither raw DT data nor modelling data formats adhere to universal standards. Raw data formats are typically determined by their sources, which may include unstructured data (e.g., sensor data), semi-structured data (e.g., JSON), and structured data (e.g., spreadsheets). In contrast, modelling data formats are often domain-specific, such as IFC for the construction sector, GML for the city domain, and STEP/AutomationML for manufacturing applications. It can also be seen that diversified twinning objects and aspects lead to distinct data acquisition approaches (D3), where manufacturing emphasises geometric precision, healthcare focuses on behavioural dynamics, and cities require spatial–temporal integration. Despite this diversity, examination of twinning object categorisation patterns across domains shows that twinning objects and aspects can be described through structured hierarchical relationships (D8), enabling hierarchical decomposition and federated representation.

Cross-domain analysis also reveals modelling reuse opportunities. Certain modelling techniques appear across multiple domains: agent-based modelling in both healthcare (ICU management) and cities (traffic systems), discrete-event modelling in manufacturing (production lines) and healthcare (patient flow), and computer vision in agriculture (crop monitoring) and cities (infrastructure monitoring) (C4). This indicates that DTs with similar federations and purposes typically employ common modelling approaches (C6), demonstrating predictable patterns in technique selection. Raw data formats are domain-specific and heavily influenced by the types of sensors, actuators, and communication requirements. However, the potential for standardisation exists within the cyber layer of DT systems) intermediate data models converting raw data from various sources to standard formats that DT engines can understand; 2) generalised DT models (e.g. agent-based, discrete event, image processing, etc) which are scalable and extensible according to service requirements.

The case studies in Section 5 also highlight that the primary focus of digital twinning typically lies in the operational status of the twinned object. This status can be assessed through visual data (e.g., camera or video feeds) or performance indicators captured by sensors. This operational focus creates a common data requirement pattern across domains, where status representation involves similar core properties (state, behaviour, performance metrics) despite domain-specific variations in measurement methods and data sources. Given this commonality in operational focus combined with the hierarchical object relationships identified across domains (D8), a hierarchical federation-based approach to data modelling would allow DT developers to select specific aspects relevant to their twinning purposes, supporting data semantics storage and streamlining modelling processes [109]. Similarly, since modelling technique patterns emerge across domains with similar purposes and federations (C6), DT model libraries could store reusable model collections, enabling users to select and adapt models based on specific objectives [82]. Efforts to develop interoperable and reusable DT data models and libraries are already underway, including Smart Data Models and Foundation Data Models (Section 4.3.4), IBM Industry Data Models [41], semantic mediation solutions [110], reusable discrete event simulation models [111], and implemented frameworks like Mesa [112].

Therefore, cross-domain analysis reveals systematic solutions for data and modelling standardisation challenges. Hierarchical federation-based data models enable standardised object abstraction with domain adaptation (S4), while model libraries providing management systems for model reuse and redevelopment are required (S5) to capitalise on identified commonalities and reduce duplicated development efforts. Despite progress, achieving true interoperability and reusability across domains remains challenging, requiring universal data formats and exchange protocols that balance domain-specific needs with cross-domain compatibility.

6.1.3. Dikw-based service architecture and value progression

Cross-domain architectural analysis reveals systematic patterns supporting service implementation. Analysis across domains demonstrates that most DT instances follow a layered architecture (C2), consisting of three fundamental layers: the physical space, the digital space, and the connections between them [68]. The physical space may include an edge layer to address local computing demands, while the digital/cyber layer often encompasses cloud and application layers for data storage, processing, and functionality. Examination of purpose-service relationships shows that twinning purposes and services can be effectively described by the DIKW model (C3), creating consistent classification across diverse applications. This architectural convergence occurs because layered architecture is a natural fit for the DIKW data value chain (C5), where each processing layer corresponds to different levels of cognitive sophistication. Therefore, it is concluded that a layered architecture where each layer aligns with certain data value extraction requirements (S3) provides the optimal structural foundation for implementing DIKW-based services across domains.

Particularly, the cyber space's architectural patterns can vary depending on the intended services, such as event-driven, service-oriented, or big data-led designs. As summarised in Section 4.3.3, architectural classifications—reference models (logical), reference

Table 2
Instances of agriculture DTs in the comparative framework.

Ref.	Object	Purpose	Architecture	Data	Model	Service
[36]	Environmental factors of a pig farm	– Discover the best environmental conditions for growth – Improve animal welfare and minimise the unnecessary cost due to disease	Layered reference model based on commercial DT platforms (e.g. GE Predix, Eclipse Ditto, IBM Watson IoT)	Sensors for measuring environmental factors (i.e., temperature, NH3, CO2, humidity, dust, etc.), which can affect the growth of livestock	Optimal environmental condition is determined via a big data model	– Simulation to suggest optimal temperature and CO2 for livestock farms, and then operate fans and open windows as an execution – Visualise data and analysis results in a user-friendly way using 2D/3D
[89]	Watershed's water balance and Irrigation of farmland	– Present different aspects and parameters that impact the farm's behaviour, yield production and resource consumption – Enable farmers to make better decisions and to decrease the environmental impact on water, land and soil resources	Five-layered reference model based on the SWAMP project with various hardware and software tools	Data collection via LPWAN sensors developed by Sensing Change to monitor soil, air and light. Including a Raspberry Pi-based monitoring Station and a smartphone application to view the real-time field data.	Watershed's water balance is modelled based on–Penman-Monteith equation to calculate optimal soil moisture and control the irrigation based on the environment.	– IoT data visualised on the SWAMP environment – Data queries and subscription services via the FIWARE platform
[90]	Controlled environment of a greenhouse	Optimise yields and quality of crops with the energy consumption of the greenhouse	Layered structure with functional hardware and software	– Temperature and humidity sensors, operation status of the exhaust fan and submersible pump. – Data storage in MySQL on server.	– Data-driven modelling based on a historical dataset in Energyplus.net – Crop growing modelling based on Soil–Plant–Atmosphere dynamics in Dssat.net	– Python-based CDE for data processing – Simulation of behaviour of heating and ventilation systems with EnergyPlus.net – Simulation of growth and yield of crops for agricultural decision support with DSSAT.net
[91]	Field state and corp health condition of the farm	– Monitor soil parameters – Automate the optimisation process of irrigation and fertilisation activities	Reference model showing the logical connection of system elements	–Images of plant leaves are captured by a drone and uploaded to a cloud server –Soil parameters are measured by WSN and sent to the cloud via LoRaWAN	– Images of plant leaves are processed by computer vision (e.g. MobileNet CNN) to detect disease and nutrient deficiency. – Correlation of the The result of the image processing is analysed with the data gathered from the WSN.	– Remote access to view the status of farmlands in near real-time – Automated detection of crop diseases based on images Recommends optimal irrigation and fertilisation strategies

architectures (functional), and software architectures (technical)—are key indicators of maturity. Publications before 2020 mostly proposed simpler architectures, such as reference models, whereas more recent works increasingly describe reference architectures that map system elements to functionalities, reflecting a step-up in the maturity of implementation.

Architectural maturity also varies across domains. Manufacturing DTs exhibit more advanced architectural solutions, evidenced by a higher prevalence of reference architectures. Conversely, city DTs, as systems of systems, demand interoperability, scalability for progressive subsystem integration, and often employ service-oriented architectures. Healthcare DTs, particularly medical systems, are largely event-driven to ensure responsiveness.

The Gemini Principles set the purpose of DTs as to provide determinable insight into the built environment. It is noted that the DT architecture and services are structured following the DIKW model, a hierarchical framework that can enable the extraction of insights and value from data, regardless of the domains. As a result, the services/applications generated by the DT system could be classified based on the DIKW model, as described in Section 4.3.6.

Table 8 validates the six-dimensional framework's universal applicability by demonstrating systematic alignment between DIKW concepts and all framework dimensions. The mapping shows that twinning purposes naturally progress from passive monitoring to proactive management, system architectures evolve from basic data acquisition to sophisticated service engines, and delivered services advance from simple storage to autonomous decision-making. This consistent alignment across purposes, architecture, and services dimensions confirms that the proposed framework captures fundamental DT development patterns regardless of domain.

The presented DIKW-framework correspondence reveals universal commonalities underlying domain diversity. All domains follow the same progression pathway: establishing data foundations, developing information processing capabilities, building knowledge through modelling, and achieving wisdom via integrated services. This universality validates the framework's cross-domain applicability and provides a standardised development pathway that domains can follow.

Table 3
Instances of manufacturing DTs in the comparative framework.

Ref.	Object	Purpose	Architecture	Data	Model	Service
[35]	Cyber-physical production system (CPPS)	– To achieve information symmetry between the CPPS and manufacturing employees – Implement 'human-in-the-loop' perspective for better production performance	Service-oriented architectural pattern, Technological reference architecture	Data collection via IIoT in CoAP, data delivered to users in JASON	Ontology-based knowledge structure to map data generated by the CPPS.	– Augmented reality combined with a vocal interaction system to deliver manufacturing knowledge – Remote terminal units to serve as gateways to the knowledge model
[92]	Life cycle operational data of all the manufactured turbine products.	To address the difficulty in the management of product lifecycle data, many participants constructing a complicated network with enormous data volume.	Service-oriented blockchain-structured data management architecture	Sensor data indicating the dynamic product profile of the turbines is stored in a specific block and chained in a peer-to-peer network	Not included	– The data management platform can be accessed through a mobile device to monitor the states of the turbine – The entire blockchain can be presented on the platform, where a specific block can be explored through the search function – Performance optimisation and design improvements of the new turbine
[93]	Operating status, including production elements and production processes, of the shop floor	– By continuously monitoring the status of the production process, shop-floor managers can make decisions timely manner – Accelerate response to production problems	A layered functional shop-floor data management model is constructed to indicate data flow among system components	Location of logistics, equipment start and stop signal, motion data of equipment sent to the data centre.	Discrete events modelling (i.e. ESHLEP-N) builds the operation logic of the shopfloor. Markov chain is used in the modelling of deduction rules.	– A 3D virtual scene of the shopfloor is shown in Unity3D – Prediction of shop-floor operating status using Markov chain to assist managers to identify bottlenecks and optimise the production processes
[94]	Robotic operation of a micro smart factory	– To solve inefficiency in the current Factory-as-a-service paradigm – Real-time monitoring of the present, tracking information from the past, and operational decision-making support for the future	Conceptual-level four-layered interoperability-context system architecture.	Information exchange in JSON format. RESTful API is used as the network architecture for the IIoT network layer.	External (e.g. Mworks) robotics simulation engine.	Web-based communication environment for event handling and synchronisation.

6.2. *Differentiators for readiness levels and perspectives*

While cross-domain analysis reveals universal DT development principles (Section 6.1), examination of domain-specific implementations identifies three critical differentiators that explain maturity variations and adoption barriers. Analysis shows that maturity levels presented in conceptual development differ significantly across domains (D1), requiring investigation of underlying constraints that create these variations.

From the conceptualisation perspective, the primary difference observed is the purposes of digital twinning, which is also the fundamental defined in Gemini Principles [20]. These variations correlate with the Three Sector Model categorisation. Primary sectors (agriculture) face uncontrolled natural environments and prioritise production monitoring due to their dependence on extracting products from nature. Secondary sectors (manufacturing) benefit from controlled production environments (factories, shop floors), enabling demands for smarter management and autonomous operation. Construction concerns the full lifecycle of buildings from design to operation, requiring both real-time services and optimisation capabilities. Healthcare seeks precise and personalised services, while city DTs aim to enhance governance and cross-department collaboration. These variations come from the distinct value-creation goals of each sector.

Moreover, from the perspective of the twinning object, each domain requires DTs' operation from the unit level to the system level. Unit-level DT monitor individual components, while system-level DTs ensure overall performance optimisation. Analysis indicates that differences at the conceptual level often correlate with the maturity and development of DTs in each domain, as evidenced by the implementation patterns in Tables 2–6.

The following sections identify and discuss three key differentiators influencing current readiness levels and future development of DTs, to explain why universal development principles manifest differently across domains.

6.2.1. *Digitalisation capability and controllability*

Cross-domain analysis reveals that automation and digitalisation capability serve as a prerequisite for DT adoption (D5). The readiness level of DTs across domains depends significantly on their digitalisation capability and controllability. Digitalisation involves converting physical objects into digital models that computers can process. These models enable computers to predict, optimise, and, through actuators, intervene in physical objects. Two core procedures—digitising and intervening—are critical to this process and vary significantly across domains.

DTs are easier to implement in domains where twinning objects are relatively static, which use simpler data structures and fewer parameters, such as equipment monitoring [92] or simple system optimisation [94] in manufacturing. These models involve fewer variables and hence require less computational effort for predictions and simulations. In contrast, modelling a human body is far more complex due to constant molecular and physiological changes, making precise data extraction

Table 4
Instances of construction DTs in the comparative framework.

Ref.	Object	Purpose	Architecture	Data	Model	Service
[44]	Geometric and semantic information of the electrical and fire-safety equipment of the building	Acquiring information about the electrical and fire-safety equipment of the building	Reference model showing the components of the workflow	Capture 2D information from images and 3D information from laser-scanned point clouds	– Semantic information on the devices is extracted by AI-based image segmentation – Geometry of the devices is reconstructed using Structure-from-Motion (SfM) and Multi-View Stereo (MVS) software	The geometric and semantic information of electrical and fire-safety equipment is mapped to the 3D model of the building.
[72]	Operation and maintenance (O&M) of buildings	Predicting a building's O&M status and ensuring that the buildings work normally, as well as reducing the damage caused by functional errors.	Layered and component-based architecture with proposed implementation tools	– The surrounding environment recorded by sensors such as cameras, humidity, smoke, etc. – Building entity, stress sensors, strain sensors, n Equipment information such as water volume, electricity usage	Architectural structure model, building equipment model, energy consumption model, geometric model, physical model, machine learning (Neural Network)	Operating system development, status prediction, life prediction, disease analysis and risk analysis
[100]	Construction environment and onsite-worker behaviour	Monitoring the construction environment for safety purposes	Reference architecture displaying the workflow	Recording video and a motion detection sensor	– Computer vision algorithm to detect unsafe factors and worker behaviours – 4D BIM simulation for construction activity	– Issue a warning for unsafe behaviours – Record the occurrence of misconduct to generate a knowledge base and training programs
[113]	Structural behaviour of a railway bridge	Monitoring the structural health of the bridge Creating a collaborative environment for stakeholders at various stages of the project	No provided	Strain/stress data collected by fibre optic sensor networks	Integrating both a physics-based finite element analysis model and a data-driven machine learning model	Real-time sensor data and associated bridge behaviour are visualised in a BIM software.
[114]	Decision analysis framework for the O&M OF tunnels	Guiding and optimising the O&M management	Layered and service-oriented architecture with technical implementation details	Physical data from real-time sensor monitoring and semantic data extracted from manual inspection, construction and maintenance activities in IFC format.	– Physical rule-based structural model – Knowledge retrieval model – The visualisation model uses BIM	The extended COBie standard-based organisation, the semantic mapping-based ontological expression and the rule- based semantic reasoning of the tunnel

and modelling exceptionally challenging [117].

Similarly, implementing DTs for systems with numerous interacting factors, such as healthcare or smart cities, involves managing high-dimensional, complex, and dynamic data. This requires advanced modelling techniques, substantial computational resources, and robust data-handling capabilities. By contrast, system-level DTs in environments with predictable causal links, such as greenhouses or built environments, are comparatively easier to develop than those in domains exposed to uncontrollable factors, like natural ecosystems [118].

Controllability also plays an important role in DT readiness level. For example, in manufacturing, production machines and products often feature bi-directional, automated connections to industrial IoT, enabling near real-time control [16]. Conversely, in construction, DTs rely on complex management tools to bridge the digital and physical environments. These tools often depend on human decision-making and manual intervention, complicating DT implementation [119].

Additionally, both digitalisation and controllability are tied to potential misrepresentations in DTs. Small errors in data or models can amplify through interactive algorithms and cascading interactions, especially in systems or systems of systems [120].

6.2.2. *Cost-benefit analysis*

Systematic examination demonstrates that cost-benefits represent one of the main barriers for DT implementation (D6). Deploying sensors, communication networks, and software platforms involves substantial upfront investment, which varies depending on sector-specific resources and digital infrastructure availability [121].

Key factors to assess cost-benefit include integration level, granularity (detail and accuracy), and complexity (resource requirements) to balance the cost of creating DTs against their potential business value [47]. For example, the large scale and the volatile nature of the sector make adopting DT in the construction industry a difficult task [15].

Sector-specific ecosystems and organisational structures further shape investment decisions. Domains like agriculture, manufacturing, and healthcare often have less inter-party collaboration, easing implementation. In contrast, construction and urban management require coordination among multiple stakeholders during design, operation, and maintenance phases. In such ecosystems, the initial costs of creating a DT often do not align with the immediate benefits for those tasked with collecting operational data. As a result, reaching collective agreements on DT implementation can be more challenging in these domains [122,123].

6.2.3. *Socio-ethical risks*

Beyond the technical and economic differentiators, socio-ethical challenges can also hinder the adoption of DTs in some domains.

In labour-intensive sectors, such as agriculture and manufacturing, psychological and skill-related barriers of producers could deter the implementation of DT. In agriculture, low-skilled workers on small-scale farms may resist the introduction of DTs, perceiving them as disruptive or difficult to adapt to [118]. In manufacturing, working alongside complex technological systems requires industrial workers to develop new competencies, necessitating additional training and learning [124]. While these challenges are notable, their impacts are often short-term

Table 5
Instances of healthcare DTs in the comparative framework.

Ref.	Object	Purpose	Architecture	Data	Model	Service
[9]	Operation of ICU (Intensive Care Unit)	– Improve critical care delivery by effectively managing demand surge and alleviating physician burnout. – Evaluation of ICU capacity and data generation during extreme scenarios. – Optimisation of ICU services aligned with the priorities of all stakeholders.	Reference and functional architecture	Hospitalisation data, bed location data, and medication data, IoT sensors monitor the processes within the ICU.	A hybrid simulation model to simulate care delivery processes as discrete-time Events, combined with behaviours of clinicians and patients in the same simulation environment, to capture their interactions under a variety of ICU production conditions.	It is proposed that the services can be delivered by integrating the simulation with the hospital information system (e.g. EHR)
[10]	Physiology of individual elderly patients and local medical resources	– Real-time supervision and accuracy of crisis warning for the elderly in healthcare services – Prediction and optimisation of medical resources for seasonal diseases.	Layered reference architecture compromising – Healthcare resource layer – Perception layer – Virtualisation layer – Service layer – User interface layer – Application and user layer	–Wearable monitoring equipment for real-time physiological data –Digital healthcare records from institutions	– Iterative optimisation model to recommend dosage and frequency of medication – Disease incidence prediction model based on historical data for pre-arranged healthcare equipment and personnel	– Real-time supervision for medication reminder and health physiotherapy – Crisis early warning (emergency, first-aid) – Medical resource scheduling and optimisation (bed planning, clinicians' allocation)
[11]	Cardiology of patients	– Treatment and prevention of cardiovascular disease based on accurate predictions of the underlying causes of disease	Reference model with conceptual system design	Combined data resources from mobile health monitor, clinical reports, and medical images	Combining induction using statistical models learnt from data, and deduction, through mechanistic modelling and simulation, integrating multiscale knowledge and data.	Guide clinical decision-making
[101]	Heart rhythms of patients	– Monitor health status and early detect abnormal situations – Enable healthcare professionals to prescribe suitable treatments and test them in a safe environment	Reference model with functional data flow chart	Heart rhythms are captured by IoT wearable sensors and transferred to a cloud database.	Data-driven classifiers and predictive models to detect anomalies and future conditions.	– Patents' access to the cloud database where the machine learning models' results are stored. – Healthcare professionals correct based on diagnosis – Healthcare professionals can compare similar cases for more advanced and accurate decisions.

and not significantly prohibitive.

Whereas in domains involving human lives and sensitive data, such as precision healthcare and urban management, ethical and governance challenges can pose significant barriers to the adoption of DTs. In precision healthcare, robust governance is critical to address ethical concerns, including data privacy, inequality arising from limited accessibility [125], and the potential misuse of sensitive personal information [126]. Similarly, city-scale DTs, which handle private data and influence governance decisions, must meet relevant security standards [12] while ensuring transparency and accountability before deployment [120].

Therefore, to manage socio-ethical risks while supporting DT advancement, targeted strategies are essential. For labour-intensive sectors, overcoming resistance through targeted training and an upskilling programme can help workers adapt to new technologies. In domains involving human data and impacts on human lives, establishing robust governance, transparency, and accessibility measures can mitigate concerns while enabling progress. These tailored approaches can help to address both technical and socio-ethical barriers, enabling smoother adoption of DT technologies across diverse fields while supporting the universal development principles identified in Section 6.1.

6.3. Solutions for unified cross-domain implementation

Most DTs described in academic publications remain at the conceptual or prototyping level. Successful implementation requires developers to not only understand user requirements and domain-specific knowledge but also possess expertise in emerging ICT technologies such as the IoT, web development, and machine learning.

The proposed cross-domain implementation solutions directly address the universal principles and domain-specific constraints identified through systematic analysis. Building on the unified procedures and standardisation opportunities (S1), requirements-driven development needs (S2), layered architecture alignment (S3), federated data models (S4), model library management (S5), and external tool integration capabilities (S6), a comprehensive DT-PaaS approach emerges as the optimal solution for cross-domain DT development.

While adoption of DTs faces domain-specific challenges, shared principles exist in their conceptualisation and implementation across sectors. This creates opportunities to standardise processes and system components, integrating them into a unified framework to support researchers and practitioners while enabling knowledge transfer from investment-rich domains to those with lower investment incentives.

Current implementation approaches typically follow domain-specific pathways: sectors independently develop conceptualisation

Table 6
Instances of city DTs in the comparative framework.

Ref.	Object	Purpose	Architecture	Data	Model	Service
[7]	Objects on the road that may affect the driving conditions of vehicles	To monitor the road conditions and enable the self-driving function of vehicles	A flow chart indicating the data interpretation process and the technical-oriented platform setup	Camera images of Vehicles and persons, including when and where an object appeared.	Machine learning models in JSON format (Single-Shot Detector and deep learning) model for car and person recognition, fused with GPS GPS-coordinated 3D road model.	– Citizens can view the 360° live streams of the road on the web page. – Authorities can be alerted to dangerous object and generate automatic statistical reports to optimise traffic planning
[8]	Sustainable urban road planning	To provide a functional, economic, people-friendly, and eco-friendly urban road planning scheme, considering new road construction and existing old road widening to alleviate traffic congestion	Logical, functional and technical, layered and service-oriented	Geographic information, traffic information and environmental information	Multi-criteria decision making and GIS	Focuses on interpreting various data from multiple sources in the physical world into a digital expression
[95]	Energy generation system (EGS) running status of the wind farm	– To develop energy-saving procedures and strategies – To integrate production systems from EGS	Logical, functional and technical layered and service-oriented	Wind and smart city data collection by IoT	Integration DT Model (BIM and GIS-based) and LEDs	– Provide energy-saving strategies – Optimising maintenance processes and energy efficiency in ports
[105]	Distant objects in the city that may lead to hazards in extreme weather events	Effective risk-informed decision-making for better disaster risk management	A logically structured flowchart showing the data and process	Mapping and updating vulnerable objects rely on citizen reporting through 2D map-based enquiry or participatory sensing and crowdsourced visual data analytics	A model update based on unstructured crowdsourced visual data analytics to understand the spatio-temporal information of physical vulnerabilities concerning neighbouring critical infrastructure	The public can access interactive 3D visualisation in a computer-aided virtual environment to view the vulnerable objects in their neighbourhood and the likelihood of affecting critical infrastructure during extreme weather events.
[115]	Traffic loads of bridges in a regional transportation infrastructure network	Monitoring the traffic loads on physical bridge Evaluating the working status of physical bridges	Reference model, consisting of hardware and software	Information fusion of weigh-in-motion (WIM) and multi-source machine vision	– Statistical models to analyse bridge response – Machine learning model to identify traffic flow via machine vision	Issue a safety warning when damages are detected
[116]	Flooding levels of rivers in the city and tidal levels near the coast	Monitoring flooding of rivers caused by rain and high tides, and quickly assess shelter requirements when a disaster occurs	Technical data flow chart centred on NEC's Data Utilisation platform service	Real-time water and tide level sensors at the observation points. Rainfall data provided on the weather forecast website.	Not introduced.	– Visualisation of disaster management data – Services developed based on FIWARE that can provide free access and use of public data services to citizens and businesses, and the government

frameworks, select technologies without cross-domain reference, adopt sector-specific standards and protocols, and deploy solutions within organisational boundaries. This creates a fundamental disconnect between the aspirational vision of interoperable, federated DTs and the practical reality of fragmented, domain-isolated implementations. The absence of systematic implementation guidance that bridges high-level principles with operational requirements across domains represents a critical barrier to achieving the cross-domain potential that DT technology promises.

6.3.1. *Limitations of current DT software and platforms*

Early adopters of DTs, such as GE Predix, Bentley iTwin, and Microsoft Azure DT, have leveraged their expertise to offer software and platforms. However, these commercial solutions face the following limitations:

1) Modelling Scope: Current platforms primarily focus on geometric and GIS-based modelling. For instance, Bentley's iTwin can be integrated with Azure Digital Twins to enhance civil infrastructure design and operations, emphasising geometric modelling and real-time sensor data integration [127]. However, support for mechanism-based modelling—simulating the underlying physical processes of systems—is less prominent. Additionally, while data-driven modelling methods are emerging, their integration into these platforms is still developing.
2) Service Capabilities: The services offered often centre on data visualisation and basic semantic information. For example, GE Predix provides threshold-based alarms, while Microsoft Azure DT supports ontology creation in JSON format and links it to telemetry data [128].

Despite these limitations, Azure Digital Twins demonstrates promising potential due to its openness through the Command Line Interface, which enables integration with IoT data, modelling tools, and service delivery hardware (e.g., mixed reality headsets).

Currently, most DT platforms focus on integrating IoT services with GIS/CAD-based modelling. However, advancements in openness and interoperability are expected, driven by the growing availability of open-source modelling tools. While these platforms have established a strong foundation for digital twin technology, further development is needed to support more complex modelling capabilities and advanced analytical services.

6.3.2. *Proposed cross-domain DT-PaaS*

Another key motivation for a cross-domain DT platform is the need for interconnected DTs to understand and predict complex systems.

Table 7
Cross-domain digital twin implementation summary.

	Agriculture	Manufacturing	Construction	Healthcare	Cities
Twinning Objects	Farmland, crops, livestock	Products, production lines, factories	Buildings, infrastructure	Patients, ICU systems	Transportation, environment, energy systems
Twinning Purposes	Environmental monitoring, yield optimisation	Process optimisation, predictive maintenance	Safety monitoring, lifecycle management	Precision medicine, resource management	Urban planning, emergency response
System Architecture	Layered reference models with IoT platforms	CPS-based, component architectures, industry-scale implementation	BIM-integrated layered systems, operational deployment	Reference models, research prototypes and conceptual frameworks	Federated systems of systems, small-scale deployment
Data	Environmental sensors, drone imagery	Industrial IoT, equipment sensors	IoT sensors, laser scanning	Wearable devices, clinical records	Cameras, satellite data, municipal sensors
Modelling	Empirical equations, computer vision	Physics-based, discrete event	BIM models, physics-based, computer vision	Data-driven, agent-based	GIS-based, agent-based simulation
Service	Data – Environmental monitoring; Information – Disease detection; Knowledge – Yield prediction; Wisdom – Limited services	Data – Equipment monitoring; Information – Fault diagnostics(threshold); Knowledge – Process optimisation; Wisdom – Autonomous control	Data – Structural monitoring; Information – Safety alerts; Knowledge – Performance modelling; Wisdom – Limited services	Data – Vital sign monitoring; Information – Health analysis; Knowledge – Treatment modelling; Wisdom – Limited services	Data – Infrastructure monitoring; Information – Traffic analysis; Knowledge – Urban planning models; Traffic optimisation Wisdom – Limited services

Table 8
DIKW-based Digital Twin Architecture and Services.

DIKW Level	Reflection on six-dimensional framework		
	Purposes	Architecture	Services
Data	Passive monitoring	Data acquisition in physical space	– Common data environment – Data storage and retrieval
Information	Reactive analytics	Semantic information extracted from data via the data engine	– Visualisation and/or notification of current system status – Threshold-based fault diagnostics
Knowledge	Prediction of future status	Modelling engine to assist investigation of the reasons for certain system behaviours	– System behaviour modelling to provide reasoning via ontologies, etc. – An expert system that uses databases of expert knowledge to offer advice
Wisdom	Proactive management	Service engine to generate user-required service based on data, information and knowledge	– Prediction of system behaviour on the basis of data and models – Decision-making based on multi-objective optimisation

When two DTs interoperate with each other, we need to define their relationship to address global issues, such as pandemics and climate change. For instance, the National Digital Twin program initiated by the Centre for Digital Built Britain envisions an ecosystem of connected DTs, including building DTs, transport DTs, and healthcare DTs, to deliver cost savings and societal benefits for stakeholders [75].

Based on the six-dimensional comparative framework and insights from the comparative study, a proposed DT-PaaS illustrated in Fig. 6 integrates all derived solutions: unified procedures (S1), requirement-driven development (S2), layered architecture (S3), federated data models (S4), model libraries (S5), and external tool interfaces (S6). This platform is designed to provide standardised solutions for data models, modelling libraries, and various service applications to streamline and simplify DT development. In addition, it aims to enable multiple DTs, which are built upon similar procedures and standards, to work together seamlessly, exchanging data and coordinating actions.

1) Conceptualisation: Prospective DT users begin by clarifying requirements, defining the twinning purpose, conceptualising the twinning object, and specifying the system architecture.
2) Solution Development: Requirements are refined with input from domain practitioners and translated into application-specific data and modelling solutions. These are then fed into the corresponding engines on the DT-PaaS platform.
3) Utilisation of the standard solutions: The DT-PaaS platform supports the development process through three primary engines—Data Engine, Modelling Engine, and Service Engine—each offering standardised solutions along with peripheral functions, such as data storage, modelling management, service encapsulation, etc. DT instance can be created from standardised data models, modelling libraries and pre-defined services.
4) Security and Access Control: As multiple stakeholders and data contributors are involved, a robust security module that ensures authorised access and protects sensitive data during interoperation is needed.
5) Interoperation of DTs: DTs built on the DT-PaaS platform follow standardised procedures and data models, allowing them to interoperate seamlessly. Examples of cross-twin interoperation include:

- Data Synchronisation: Sharing real-time and/or historical data across DTs.

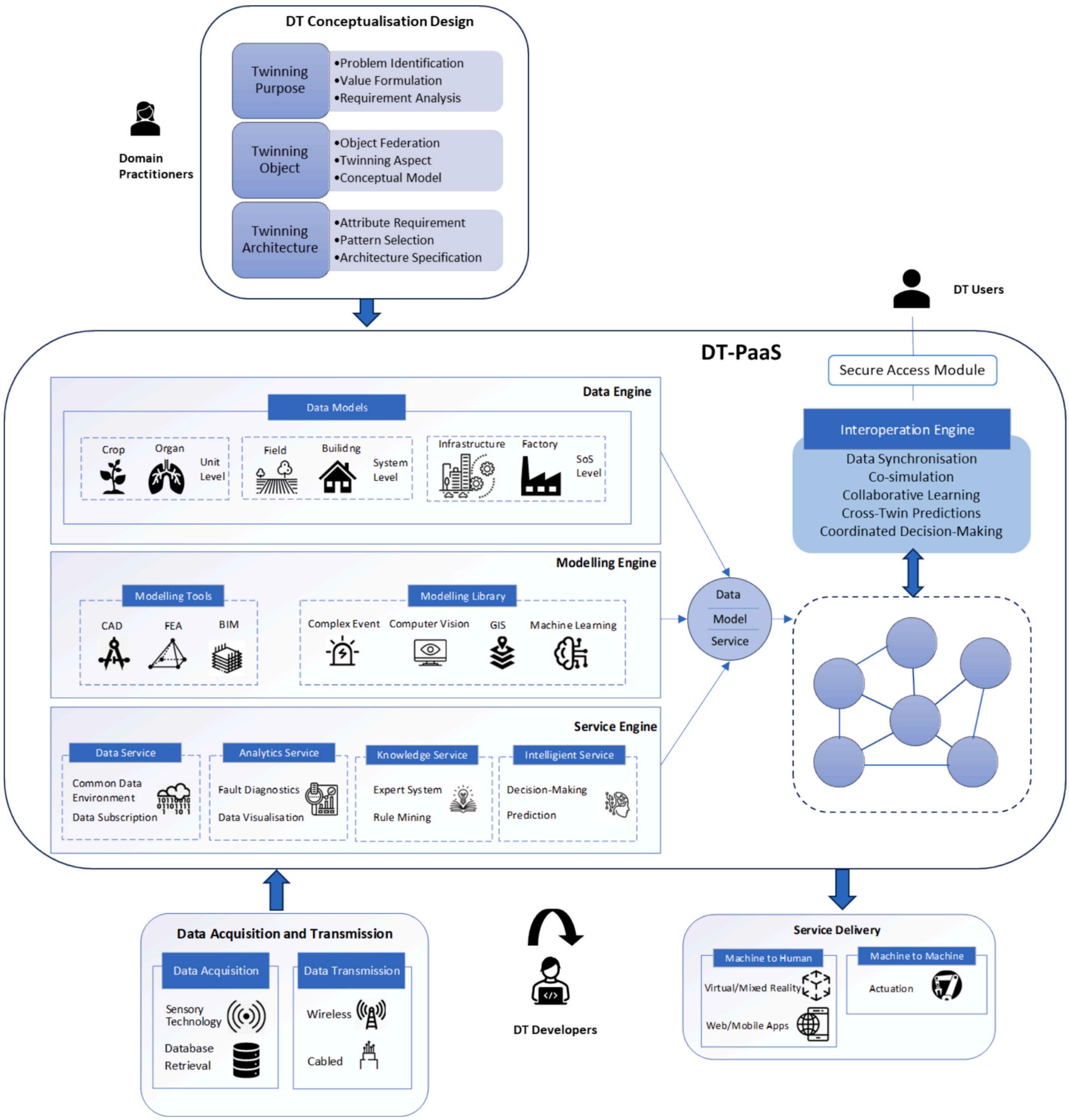

Fig. 6. Illustration of DT-PaaS.

- Co-simulation: Simultaneous simulation of interconnected systems.
- Collaborative Learning: Sharing insights and improving algorithms collectively.
- Cross-Twin Predictions: Leveraging aggregated data for predictive analysis.
- Coordinated Decision-Making: Enabling joint optimisation and decision processes.

The DT-PaaS platform simplifies DT development and fosters the creation of a robust DT ecosystem by promoting interoperability. This aligns with the Levels of Conceptual Interoperability Model (LCIM), which defines seven levels of interoperability: technical, syntactic, semantic, pragmatic, dynamic, conceptual, and organisational. Theoretical foundations from LCIM and prior research ([129–131]) emphasise that higher-level interoperation (e.g., model exchange, service requests) is essential for realising advanced DT applications.

The DT-PaaS platform envisions a future where digitalisation removes technological barriers between domains. Standardised tools empower developers to build interoperable DTs, while domain practitioners remain essential for integrating physical objects through tasks like data acquisition, simulation, and actuation control.

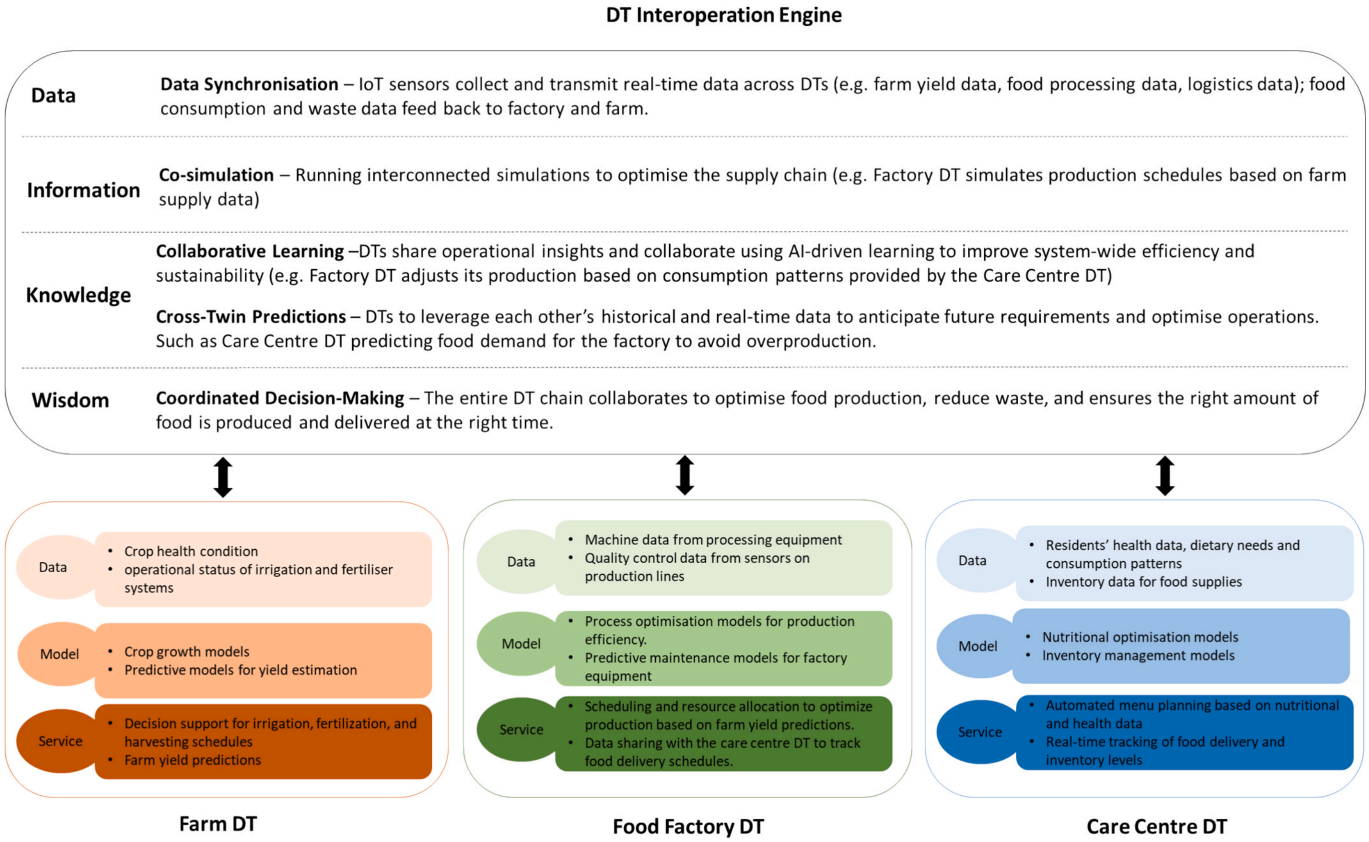

Fig. 7. Case study on the interoperation of connected digital twins.

6.3.3. *Case study on DTs interoperation*

As per the Three Sector Model, the primary forms of human economic activity can be categorised into harvesting, production, and consumption. To validate the proposed framework, an example of interoperable DTs representing these three stages of economic activity—a Farm DT, a Food Factory DT, and a Care Centre DT—is presented in Fig. 7.

For each DT, the twinning purpose, object, and architecture have been conceptualised to define the necessary data, models, and services. By implementing these three DT instances, an interoperability engine is formed to facilitate data exchange and interaction across the interconnected ecosystem. This engine serves as the backbone of the DT network, enabling them to operate collectively as part of a larger, intelligent system.

Similar to single DT services, cross-twin services can also be categorised using the DIKW Model, reflecting the levels of intelligence achieved by the applications delivered through the DT ecosystem. By integrating their data, models, and services, the DTs of the farm, food factory, and care centre create a smart, adaptive supply chain that enhances efficiency, promotes sustainability, and improves the well-being of care centre residents.

7. Conclusion

A comprehensive literature review was conducted, encompassing both academic publications and industry reports from relevant companies and organisations (i.e., FIWARE, Siemens, Digital Twin Consortium, Centre for Digital Built Britain). Given the rapid evolution of all aspects of DT technology, there is an urgent need for methodologies to identify and refine common principles across diverse DT systems.

This paper three primary contributions to the DT research community:

1. A six-dimensional DT framework: Grounded in established research and engineering principles, this framework captures the universal development process across domains. It serves as both a descriptive tool and a comparative metric.
2. Framework validation through cross-domain use-cases: The proposed framework was validated through multiple DT use cases, systematically analysing similarities and differences. This led to an explanatory theory of variations in DT implementations across domains.
3. Proposal and case study for DT-PaaS: Leveraging cross-domain insights, this paradigm standardised processes and tools while supporting DT interoperability.

The comparative framework (Fig. 3) a practical guide for developing a DT from raw ideas through conceptualisation to implementation, regardless of the domain. The systematic analysis key differentiators (digitalisation capability, cost-benefit dynamics, socio-ethical risks) and universal principles (DIKW progression, layered architecture, federated data models) that shape DT development across sectors, forming a theoretical basis to underpin DT systems requirements, workflow, and real-world applications.

This study had several limitations that should be acknowledged. First, domain bias may have been present in the Section 5 analysis, with more examples from high-resource sectors like manufacturing, while fewer were available from resource-constrained domains such as agriculture. Second, the current snapshots of DT development may not have captured the dynamics of rapid advancement, requiring periodic updates to maintain validity. Third, while Fig. 6 the conceptual architecture for the DT-PaaS platform, detailed technical specifications for data model management and inter-engine communication represent important areas for future implementation research.

This study the field by framing future DT use-cases within a cross-domain framework. Future research should address the detailed technical implementation of the DT-PaaS architecture, including data model federation mechanisms, inter-engine communication protocols, and service orchestration frameworks identified in the conceptual proposal. Additionally, interoperability standards should be prioritised to enable data exchange between DTs, facilitating knowledge-sharing across sectors. Another future direction involves designing for wider societal value and wellbeing, including human-centric, resilient and sustainable approaches that align with Industry 5.0 [132], such as human-robot collaborative assembly [133] and embedding lifecycle and carbon footprint assessment metrics into DT decision loops.

8. Declaration of generative AI and AI-assisted technologies

During the preparation of this work, the author(s) used ChatGPT3.5 and Claude AI to improve readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

CRediT authorship contribution statement

Guanyu Xiong: Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Haijiang Li:** Supervision, Conceptualization. **Yan Gao:** Validation, Methodology.

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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Data availability

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

References

[1] L. Floridi, The fourth revolution: how the infosphere is reshaping human reality, (2014). https://philpapers.org/rec/FLOTFR-3 (accessed October 3, 2022).
[2] D. Jones, C. Snider, A. Nassehi, J. Yon, B. Hicks, Characterising the digital twin: a systematic literature review, CIRP J. Manuf. Sci. Technol. 29 (2020) 36–52, https://doi.org/10.1016/j.cirpj.2020.02.002.
[3] M. Shafto, M. Conroy, R. Doyle, E. Glaessgen, C. Kemp, J. LeMoigne, L. Wang, DRAFT Modelling, simulation, information technology & processing roadmap - technology area 11, Natl. Aeronaut. Sp. Adm. (2010) 27. https://www.nasa.gov/pdf/501321main_TA11-MSITP-DRAFT-Nov2010-A1.pdf.
[4] Grieves: Digital twin: manufacturing excellence through... - Google Scholar, (n. d.). https://scholar.google.com/scholar_lookup?title=Digital twin%3A manufacturing excellence through virtual factory replication &publication_year=2014&author=M. Grieves (accessed May 29, 2025).
[5] M. Grieves, J. Vickers, Digital Twin: mitigating unpredictable, undesirable emergent behaviour in complex systems, transdiscipl, Perspect. Complex Syst. New Find. Approaches. (2017) 85–113, https://doi.org/10.1007/978-3-319-38756-7_4.
[6] W. Kritzinger, M. Karner, G. Traar, J. Henjes, W. Sihn, Digital twin in manufacturing: a categorical literature review and classification, IFAC-PapersOnLine 51 (2018) 1016–1022, https://doi.org/10.1016/j.ifacol.2018.08.474.
[7] O. El Marai, T. Taleb, J. Song, Roads infrastructure digital twin: a step toward smarter cities realization, IEEE Netw. 35 (2021) 136–143, https://doi.org/10.1109/MNET.011.2000398.
[8] F. Jiang, L. Ma, T. Broyd, W. Chen, H. Luo, Digital twin enabled sustainable urban road planning, Sustain. Cities Soc. 78 (2022) 103645, https://doi.org/10.1016/J.SCS.2021.103645.
[9] X. Zhong, F. Babaie Sarijaloo, A. Prakash, J. Park, C. Huang, A. Barwise, V. Herasevich, O. Gajic, B. Pickering, Y. Dong, A multidisciplinary approach to the development of digital twin models of critical care delivery in intensive care units, 60, 2022:4197–4213. doi: 10.1080/00207543.2021.2022235.
[10] Y. Liu, L. Zhang, Y. Yang, L. Zhou, L. Ren, F. Wang, R. Liu, Z. Pang, M.J. Deen, A novel cloud-based framework for the elderly healthcare services using digital twin, IEEE Access 7 (2019) 49088–49101, https://doi.org/10.1109/ACCESS.2019.2909828.
[11] J. Corral-Acero, F. Margara, M. Marciniak, C. Rodero, F. Loncaric, Y. Feng, A. Gilbert, J.F. Fernandes, H.A. Bukhari, A. Wajdan, M.V. Martinez, M.S. Santos, M. Shamohammdi, H. Luo, P. Westphal, P. Leeson, P. DiAchille, V. Gurev, M. Mayr, L. Geris, P. Pathmanathan, T. Morrison, R. Cornelussen, F. Prinzen, T. Delhaas, A. Doltra, M. Sitges, E.J. Vigmond, E. Zacur, V. Grau, B. Rodriguez, E. W. Remme, S. Niederer, P. Mortier, K. McLeod, M. Potse, E. Pueyo, A. Bueno-Orovio, P. Lamata, The "digital twin" to enable the vision of precision cardiology, Eur. Heart J. 41 (2020) 4556–4564B, https://doi.org/10.1093/eurheartj/ehaa159.
[12] G. Mylonas, A. Kalogeras, G. Kalogeras, C. Anagnostopoulos, C. Alexakos, L. Munoz, Digital twins from smart manufacturing to smart cities: a survey, IEEE Access 9 (2021) 143222–143249, https://doi.org/10.1109/ACCESS.2021.3120843.
[13] N. Taylor, C. Human, K. Kruger, A. Bekker, A. Basson, Comparison of digital twin development in manufacturing and maritime domains, Stud. Comput. Intell. 853 (2020) 158–170, https://doi.org/10.1007/978-3-030-27477-1_12.
[14] J.M. Davila Delgado, L. Oyedele, Digital twins for the built environment: learning from conceptual and process models in manufacturing, Adv. Eng. Inform. 49 (2021) 101332, https://doi.org/10.1016/j.aei.2021.101332.
[15] O.C. Madubuike, C.J. Anumba, R. Khallaf, A review of digital twin applications in construction, J. Inf. Technol. Constr. 27 (2022) 145–172, https://doi.org/10.36680/j.itcon.2022.008.
[16] M.R. Enders, N. Hoßbach, Dimensions of digital twin applications - a literature review, 25th Am Conf. Inf. Syst. AMCIS 2019 (2019).
[17] D.M. Botín-Sanabria, S. Mihaita, R.E. Peimbert-García, M.A. Ramírez-Moreno, R. A. Ramírez-Mendoza, J. D.J. Lozoya-Santos, Digital twin technology challenges and applications: a comprehensive review, Remote Sens. 14 (2022) 1335, https://doi.org/10.3390/RS14061335.
[18] M. Singh, E. Fuenmayor, E.P. Hinchy, Y. Qiao, N. Murray, D. Devine, Digital twin: origin to future, Appl. Syst. Innov. 4 (2021) 36, https://doi.org/10.3390/ASI4020036.
[19] E. VanDerHorn, S. Mahadevan, Digital Twin: generalization, characterization and implementation, Decis. Support Syst. 145 (2021) 113524, https://doi.org/10.1016/J.DSS.2021.113524.
[20] A. Bolton, L. Butler, I. Dabson, M. Enzer, M. Evans, T. Fenemore, F. Harradence, E. Keaney, A. Kemp, A. Luck, N. Pawsey, S. Saville, J. Schooling, M. Sharp, T. Smith, J. Tennison, J. Whyte, A. Wilson, C. Makri, Gemini Principles (2018), https://doi.org/10.17863/CAM.32260.
[21] H. Boyes, T. Watson, Digital twins: an analysis framework and open issues, Comput. Ind. 143 (2022) 103763, https://doi.org/10.1016/J.COMPIND.2022.103763.
[22] J.F. Yao, Y. Yang, X.C. Wang, X.P. Zhang, Systematic review of digital twin technology and applications, Vis. Comput. Ind. Biomed. 61 (61) (2023) 20, https://doi.org/10.1186/S42492-023-00137-4.
[23] M. Escribà-Gelonch, S. Liang, P. van Schalkwyk, I. Fisk, N.V.D. Long, V. Hessel, Digital twins in agriculture: orchestration and applications, J. Agric. Food Chem. 72 (2024) 10737, https://doi.org/10.1021/ACS.JAFC.4C01934.
[24] N.L. Rane, S. Shirke, Digital twin for healthcare, finance, agriculture, retail, manufacturing, energy, and transportation industry 4.0, 5.0, and society 5.0, Artif. Intell. Ind. Soc. 5 (2024), https://doi.org/10.70593/978-81-981271-1-2_3.
[25] Z. Wang, R. Gupta, K. Han, H. Wang, A. Ganlath, N. Ammar, P. Tiwari, Mobility digital twin: concept architecture, case study, and future challenges, IEEE Internet Things J. 9 (2022) 17452–17467, https://doi.org/10.1109/JIOT.2022.3156028.
[26] C.G. Pickvance, Four varieties of comparative analysis, J. Hous. Built Environ. 16 (2001) 7–28, https://doi.org/10.1023/A:1011533211521.
[27] A.G.B. Fisher, A.G.B. Fisher, Production, primary, secondary and tertiary, Econ. Rec. 15 (1939) 24–38, https://doi.org/10.1111/J.1475-4932.1939.TB01015.X.
[28] C. Semeraro, M. Lezoche, H. Panetto, M. Dassisti, Digital twin paradigm: a systematic literature review, Comput. Ind. 130 (2021), https://doi.org/10.1016/j.compind.2021.103469.
[29] J.F. Uhlenkamp, K. Hribernik, S. Wellsandt, K.D. Thoben, Digital twin applications: a first systemization of their dimensions, Proc. - 2019 IEEE Int. Conf. Eng. Technol. Innov. ICE/ITMC (2019), https://doi.org/10.1109/ICE.2019.8792579.
[30] H. van der Valk, H. Haße, F. Möller, B. Otto, Archetypes of Digital Twins, Bus. Inf. Syst. Eng. 64 (2021) 375–391, https://doi.org/10.1007/s12599-021-00727-7.
[31] S.R. Newrzella, D.W. Franklin, S. Haider, 5-dimension cross-industry digital twin applications model and analysis of digital twin classification terms and models, IEEE Access 9 (2021) 131306–131321, https://doi.org/10.1109/ACCESS.2021.3115055.
[32] R. Al-Sehrawy, B. Kumar, R. Watson, A digital twin uses classification system for urban planning & city infrastructure management, J. Inf. Technol. Constr. 26 (2021) 832–862, https://doi.org/10.36680/J.ITCON.2021.045.
[33] F. Tao, Q. Qi, L. Wang, A.Y.C. Nee, Digital twins and cyber–physical systems toward smart manufacturing and industry 4.0: correlation and comparison, Engineering 5 (2019) 653–661, https://doi.org/10.1016/j.eng.2019.01.014.
[34] D. Shangguan, L. Chen, J. Ding, A hierarchical digital twin model framework for dynamic cyber-physical system design, PervasiveHealth Pervasive Comput. Technol. Healthc. Part F 1476 (2019) 123–129, https://doi.org/10.1145/3314493.3314504.
[35] F. Longo, L. Nicoletti, A. Padovano, Ubiquitous knowledge empowers the smart factory: the impacts of a service-oriented digital twin on enterprises'

performance, Annu. Rev. Control 47 (2019) 221–236, https://doi.org/10.1016/j.arcontrol.2019.01.001.
[36] S.K. Jo, D.H. Park, H. Park, S.H. Kim, Smart livestock farms using digital twin: feasibility study, 9th Int Conf. Inf. Commun. Technol. Converg. ICT Converg. Powered by Smart Intell. ICTC (2018) 1461–1463, https://doi.org/10.1109/ICTC.2018.8539516.
[37] T. Savage, J. Akroyd, S. Mosbach, N. Krdzavac, M. Hillman, M. Kraft, Universal digital twin: integration of national-scale energy systems and climate data, Data-Centric Eng. 3 (2022), https://doi.org/10.1017/dce.2022.22.
[38] M. Dietz, G. Pernul, Digital twin: empowering enterprises towards a system-of-systems approach, Bus. Inf. Syst. Eng. 62 (2020) 179–184, https://doi.org/10.1007/S12599-019-00624-0/FIGURES/2.
[39] R. Parmar, A. Leiponen, L.D.W. Thomas, Building an organizational digital twin, Bus. Horiz. 63 (2020) 725–736, https://doi.org/10.1016/J.BUSHOR.2020.08.001.
[40] Siemens, No Title, Siemens Digit. Ind. Softw. (2022). https://www.plm.automation.siemens.com/global/en/our-story/glossary/digital-twin/24465 (accessed December 1, 2022).
[41] IBM, What is a digital twin? | IBM, (2022). https://www.ibm.com/uk-en/topics/what-is-a-digital-twin#anchor–1523106008 (accessed December 5, 2022).
[42] J. Whyte, D. Coca, J. Fitzgerald, M. Mayfield, K. Pierce, N. Shah, L. Chen, C. Gamble, C. Genes, F. Babovic, A. Pedro, Analysing systems interdependencies using a digital twin, General Prioject (2019).
[43] R. Rosen, S. Boschert, A. Sohr, Next generation digital twin, Atp. Mag. 60 (2018) 86–96, https://doi.org/10.17560/atp.v60i10.2371.
[44] I. Brilakis, Y. Pan, A. Borrmann, H.-G. Mayer, Built Environment Digital Twinning, 2019. https://www.ias.tum.de/ias/research-areas/advanced-computation-and-modeling/built-environment-digital-twinning/.
[45] E. Ferko, A. Bucaioni, M. Behnam, Architecting digital twins, IEEE Access 10 (2022) 50335–50350, https://doi.org/10.1109/ACCESS.2022.3172964.
[46] D.J. Wagg, K. Worden, R.J. Barthorpe, P. Gardner, Digital twins: state-of-the-art and future directions for modeling and simulation in engineering dynamics applications, ASCE-ASME J. Risk Uncertain. Eng. Syst. Part B Mech. Eng. 6 (2020), https://doi.org/10.1115/1.4046739.
[47] S. Aheleroff, X. Xu, R.Y. Zhong, Y. Lu, Digital twin as a service (DTaaS) in industry 4.0: an architecture reference model, Adv. Eng. Informatics. 47 (2021) 101225, https://doi.org/10.1016/j.aei.2020.101225.
[48] C. Pylianidis, S. Osinga, I.N. Athanasiadis, Introducing digital twins to agriculture, Comput. Electron. Agric. 184 (2021) 105942, https://doi.org/10.1016/j.compag.2020.105942.
[49] C. Boje, A. Guerriero, S. Kubicki, Y. Rezgui, Towards a semantic construction digital twin: directions for future research, Autom. Constr. 114 (2020), https://doi.org/10.1016/j.autcon.2020.103179.
[50] T. Kreuzer, P. Papapetrou, J. Zdravkovic, Artificial intelligence in digital twins—a systematic literature review, Data Knowl. Eng. 151 (2024) 102304, https://doi.org/10.1016/J.DATAK.2024.102304.
[51] S. Yoon, J. Song, J. Li, Ontology-enabled AI agent-driven intelligent digital twins for building operations and maintenance, J. Build. Eng. 108 (2025) 112802, https://doi.org/10.1016/J.JOBE.2025.112802.
[52] A. Barredo Arrieta, N. Díaz-Rodríguez, J. Del Ser, A. Bennetot, S. Tabik, A. Barbado, S. Garcia, S. Gil-Lopez, D. Molina, R. Benjamins, R. Chatila, F. Herrera, Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI, Inf. Fusion 58 (2020) 82–115, https://doi.org/10.1016/J.INFFUS.2019.12.012.
[53] G. Schrotter, C. Hürzeler, The digital twin of the city of zurich for urban planning, PFG - J. Photogramm. Remote Sens. Geoinf. Sci. 88 (2020) 99–112, https://doi.org/10.1007/S41064-020-00092-2/FIGURES/14.
[54] Elon Musk, Elon Musk on Twitter, Twitter. (2018). https://twitter.com/elonmusk/status/984882630947753984 (accessed January 8, 2023).
[55] F. Oquendo, Software architecture challenges and emerging research in software-intensive systems-of-systems, in: Lect. Notes Comput. Sci. (Including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics), LNCS, 2016, pp. 3–21, https://doi.org/10.1007/978-3-319-48992-6_1/TABLES/3.
[56] K.M. Alam, A. El Saddik, C2PS: a digital twin architecture reference model for the cloud-based cyber-physical systems, IEEE Access 5 (2017) 2050–2062, https://doi.org/10.1109/ACCESS.2017.2657006.
[57] Y. Lu, C. Liu, K.I.K. Wang, H. Huang, X. Xu, Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues, Robot. Comput. Integr. Manuf. 61 (2020) 101837, https://doi.org/10.1016/j.rcim.2019.101837.
[58] A.J.H. Redelinghuys, A.H. Basson, K. Kruger, A six-layer architecture for the digital twin: a manufacturing case study implementation, J. Intell. Manuf. 31 (2020) 1383–1402, https://doi.org/10.1007/s10845-019-01516-6.
[59] Y. Zheng, S. Yang, H. Cheng, An application framework of digital twin and its case study, J. Ambient. Intell. Humaniz. Comput. 10 (2019) 1141–1153, https://doi.org/10.1007/S12652-018-0911-3/FIGURES/10.
[60] F. Schnicke, T. Kuhn, P.O. Antonino, Enabling industry 4.0 service-oriented architecture through digital twins, Commun. Comput. Inf. Sci. 1269 (2020) 490–503, https://doi.org/10.1007/978-3-030-59155-7_35/FIGURES/2.
[61] T.U. Eindhoven, D. Version, On the design of an architecture framework and quality evaluation for automotive software systems On the Design of an Architecture Framework and, 2020.
[62] B. Tekinerdogan, C. Verdouw, Systems architecture design pattern catalog for developing digital twins, Sensors (Switzerland). 20 (2020) 1–20, https://doi.org/10.3390/s20185103.
[63] M. Ghita, B. Siham, M. Hicham, Digital twins development architectures and deployment technologies: Moroccan use case, Int. J. Adv. Comput. Sci. Appl. 11 (2020) 468–478, https://doi.org/10.14569/ijacsa.2020.0110260.
[64] M. Richards, Software Architecture Patterns - Understanding Common Architecture Patterns and When to Use Them, Encycl. Database Syst. (2015) 1601–1601. https://www.oreilly.com/library/view/software-architecture-patterns/9781491971437/ (accessed November 28, 2022).
[65] A. Rasheed, O. San, T. Kvamsdal, Digital twin: values, challenges and enablers from a modelling perspective, IEEE Access 8 (2020) 21980–22012, https://doi.org/10.1109/ACCESS.2020.2970143.
[66] S.H. Ahmed, G. Kim, D. Kim, Cyber physical system: architecture, applications and research challenges, IFIP Wirel. Days. (2013) 4, https://doi.org/10.1109/WD.2013.6686528.
[67] L.F. Rivera, M. Jiménez, N.M. Villegas, G. Tamura, Toward intensive digital twin systems, IEEE Softw. (2022).
[68] Q. Qi, F. Tao, T. Hu, N. Anwer, A. Liu, Y. Wei, L. Wang, A.Y.C. Nee, Enabling technologies and tools for digital twin, J. Manuf. Syst. 58 (2021) 3–21, https://doi.org/10.1016/j.jmsy.2019.10.001.
[69] R. Anderl, S. Haag, K. Schützer, E. Zancul, Digital twin technology-an approach for Industrie 4.0 vertical and horizontal lifecycle integration, IT – Inf. Technol. 60 (2021) 125–132, https://doi.org/10.1515/ITIT-2017-0038/MACHINEREADABLECITATION/RIS.
[70] G.N. Schroeder, C. Steinmetz, C.E. Pereira, D.B. Espindola, Digital twin data modeling with automationml and a communication methodology for data exchange, IFAC-PapersOnLine 49 (2016) 12–17, https://doi.org/10.1016/J.IFACOL.2016.11.115.
[71] T. Ruohomaki, E. Airaksinen, P. Huuska, O. Kesaniemi, M. Martikka, J. Suomisto, Smart city platform enabling digital twin, in: 9th Int. Conf. Intell. Syst. 2018 Theory, Res. Innov. Appl. IS 2018 - Proc., 2018, pp. 155–161, https://doi.org/10.1109/IS.2018.8710517.
[72] C. Wang, B. Lee, S. Shirowzhan, Y. Zhao, N. Wang, Z. Liu, E. Mu, Construction theory for a building intelligent operation and maintenance system based on digital twins and machine learning, Build. 12 (2022) 87, https://doi.org/10.3390/BUILDINGS12020087.
[73] T. Wang, V.J.L. Gan, D. Hu, H. Liu, Digital twin-enabled built environment sensing and monitoring through semantic enrichment of BIM with SensorML, Autom. Constr. 144 (2022), https://doi.org/10.1016/J.AUTCON.2022.104625.
[74] FIWARE, Smart Data Models, (2021). https://www.fiware.org/smart-data-models/ (accessed February 13, 2023).
[75] CDBB, National Digital Twin Programme, Cent. Digit. Built Britain. (2020). https://www.cdbb.cam.ac.uk/what-we-did/national-digital-twin-programme (accessed March 7, 2023).
[76] H. Seaton, S.M.E. Sepasgozar, Digital twins from design to handover of constructed assets, R. Inst. Chart. Surv. (2022). www.rics.org (accessed December 14, 2022).
[77] M. Liu, S. Fang, H. Dong, C. Xu, Review of digital twin about concepts, technologies, and industrial applications, J. Manuf. Syst. 58 (2021) 346–361, https://doi.org/10.1016/j.jmsy.2020.06.017.
[78] M.G. Kapteyn, D.J. Knezevic, K.E. Willcox, Toward predictive digital twins via component-based reduced-order models and interpretable machine learning, AIAA Scitech 2020 Forum 1 Part F (2020), https://doi.org/10.2514/6.2020-0418.
[79] S. Liu, J. Bao, Y. Lu, J. Li, S. Lu, X. Sun, Digital twin modelling method based on biomimicry for machining aerospace components, J. Manuf. Syst. 58 (2021) 180–195, https://doi.org/10.1016/J.JMSY.2020.04.014.
[80] E. Shahat, C.T. Hyun, C. Yeom, City digital twin potentials: a review and research agenda, Sustain 13 (2021) 1–20, https://doi.org/10.3390/su13063386.
[81] D.R. Gunasegaram, I. Steinbach, Modelling of microstructure formation in metal additive manufacturing: recent progress, research gaps and perspectives, Met. 11 (2021) 1425, https://doi.org/10.3390/MET11091425.
[82] L. Zhang, L. Zhou, B.K.P. Horn, Building a right digital twin with model engineering, J. Manuf. Syst. 59 (2021) 151–164, https://doi.org/10.1016/j.jmsy.2021.02.009.
[83] F. Tao, B. Xiao, Q. Qi, J. Cheng, P. Ji, Digital twin modelling, J. Manuf. Syst. 64 (2022) 372–389, https://doi.org/10.1016/J.JMSY.2022.06.015.
[84] K. Williams, S. Chatterjee, M. Rossi, Design of emerging digital services: a taxonomy, Eur. J. Inf. Syst. 17 (2008) 505–517, https://doi.org/10.1057/EJIS.2008.38.
[85] J. Meierhofer, S. West, M. Rapaccini, C. Barbieri, The Digital Twin as a Service Enabler: From the Service Ecosystem to the Simulation Model, (2020). Doi: 10.1007/978-3-030-38724-2_25.
[86] Q. Qi, F. Tao, A.Y.C. Nee, From service to digital twin service, Digit. Twin Driven Serv. (2022) 1–31, https://doi.org/10.1016/B978-0-323-91300-3.00006-1.
[87] S. Leminen, M. Rajahonka, R. Wendelin, M. Westerlund, Industrial internet of things business models in the machine-to-machine context, Ind. Mark. Manag. 84 (2020) 298–311, https://doi.org/10.1016/J.INDMARMAN.2019.08.008.
[88] L.S. Pereira, Water, agriculture and food: challenges and issues, Water Resour. Manag. 31 (2017) 2985–2999, https://doi.org/10.1007/S11269-017-1664-Z/FIGURES/2.
[89] R.G. Alves, G. Souza, R.F. Maia, A.L.H. Tran, C. Kamienski, J.P. Soininen, P. T. Aquino, F. Lima, A digital twin for smart farming, 2019 IEEE Glob, Humanit. Technol. Conf. GHTC 2019 (2019) 2019–2022, https://doi.org/10.1109/GHTC46095.2019.9033075.
[90] J.D. Chaux, D. Sanchez-Londono, G. Barbieri, A digital twin architecture to optimize productivity within controlled environment agriculture, Appl. Sci. 11 (2021), https://doi.org/10.3390/app11198875.

[91] P. Angin, M.H. Anisi, F. Göksel, C. Gürsoy, A. Büyükgülcü, Agrilora: A digital twin framework for smart agriculture, J. Wirel. Mob. Networks, Ubiquitous Comput. Dependable Appl. 11 (2020) 77–96, https://doi.org/10.22667/JOWUA.2020.12.31.077.
[92] S. Huang, G. Wang, Y. Yan, X. Fang, Blockchain-based data management for digital twin of product, J. Manuf. Syst. 54 (2020) 361–371, https://doi.org/10.1016/J.JMSY.2020.01.009.
[93] C. Zhuang, J. Liu, H. Xiong, Digital twin-based smart production management and control framework for the complex product assembly shop-floor, Int. J. Adv. Manuf. Technol. 96 (2018) 1149–1163, https://doi.org/10.1007/S00170-018-1617-6/METRICS.
[94] K.T. Park, Y.W. Nam, H.S. Lee, S.J. Im, S. Do Noh, J.Y. Son, H. Kim, Design and implementation of a digital twin application for a connected micro smart factory, Int. J. Comput. Integr. Manuf. 32 (2019) 596–614, https://doi.org/10.1080/0951192X.2019.1599439.
[95] S. Agostinelli, F. Cumo, M.M. Nezhad, G. Orsini, G. Piras, Renewable energy system controlled by open-source tools and digital twin model: zero energy port area in Italy, Energies 15 (2022), https://doi.org/10.3390/EN15051817.
[96] R. Sacks, I. Brilakis, E. Pikas, H.S. Xie, M. Girolami, Construction with digital twin information systems, Data-Centric Eng. 1 (2020), https://doi.org/10.1017/dce.2020.16.
[97] S. Yoon, J. Lee, J. Li, P. Wang, Virtual in-situ modelling between digital twin and BIM for advanced building operations and maintenance, Autom. Constr. 168 (2024) 105823, https://doi.org/10.1016/J.AUTCON.2024.105823.
[98] J. Koo, S. Yoon, Virtual in-situ calibration for digital twin-synchronized building operations, Energy Build. 340 (2025) 115760, https://doi.org/10.1016/J.ENBUILD.2025.115760.
[99] D.G.J. Opoku, S. Perera, R. Osei-Kyei, M. Rashidi, Digital twin application in the construction industry: a literature review, J. Build. Eng. 40 (2021) 102726, https://doi.org/10.1016/j.jobe.2021.102726.
[100] L. Hou, S. Wu, G.K. Zhang, Y. Tan, X. Wang, Literature review of digital twins applications in constructionworkforce safety, Appl. Sci. 11 (2021) 1–21, https://doi.org/10.3390/app11010339.
[101] H. Elayan, M. Aloqaily, M. Guizani, Digital twin for intelligent context-aware IoT healthcare systems, IEEE Internet Things J. 8 (2021) 16749–16757, https://doi.org/10.1109/JIOT.2021.3051158.
[102] K.P. Venkatesh, M.M. Raza, J.C. Kvedar, Health digital twins as tools for precision medicine: considerations for computation, implementation, and regulation, Npj Digit. Med. 51 (5) (2022) 1–2, https://doi.org/10.1038/s41746-022-00694-7.
[103] S. Choi, S. Yoon, AI agent-based intelligent urban digital twin (I-UDT): concept, methodology, and case studies, Smart Cities 8 (28) (2025), https://doi.org/10.3390/SMARTCITIES8010028.
[104] L. Wan, T. Nochta, J.M. Schooling, Developing a city-level digital twin - Propositions and a case study, Int. Conf. Smart Infrastruct. Constr. 2019, ICSIC 2019 Driv. Data-Informed Decis. (2019) 187–193. Doi: 10.1680/ICSIC.64669.187/ASSET/IMAGES/SMALL/ICSIC.64669.187.F6.GIF.
[105] Y. Ham, A.M. Asce, J. Kim, S.M. Asce, Participatory sensing and digital twin city: updating virtual city models for enhanced risk-informed decision-making, J. Manag. Eng. 36 (2020), https://doi.org/10.1061/(ASCE)ME.1943-5479.0000748.
[106] A. Zahra, M. Ghafoor, K. Munir, A. Ullah, Z., Ul Abideen, Application of region-based video surveillance in smart cities using deep learning, Multimed. Tools Appl. (2021) 1–26, https://doi.org/10.1007/S11042-021-11468-W/FIGURES/9.
[107] G. Lay, Servitization in industry, Servitization Ind. 9783319069357 (2014) 1–349. Doi: 10.1007/978-3-319-06935-7/COVER.
[108] J. Moyne, Y. Qamsane, E.C. Balta, I. Kovalenko, J. Faris, K. Barton, D.M. Tilbury, A requirements driven digital twin framework: specification and opportunities, IEEE Access 8 (2020) 107781–107801, https://doi.org/10.1109/ACCESS.2020.3000437.
[109] S. Muralidharan, B. Yoo, H. Ko, Designing a semantic digital twin model for IoT, Dig. Tech. Pap. - IEEE Int. Conf. Consum. Electron. (2020), https://doi.org/10.1109/ICCE46568.2020.9043088.
[110] U. Shani, H. Broodney, Reuse in model-based systems engineering, 9th Annu, IEEE Int. Syst. Conf. Syscon 2015 - Proc. (2015) 77–83, https://doi.org/10.1109/SYSCON.2015.7116732.
[111] L. Boyle, M. Mackay, A Reusable Discrete Event Simulation Model for Improving Orthopedic Waiting Lists, (2023) 973–984. Doi: 10.1109/WSC57314.2022.10015512.
[112] J. Kazil, D. Masad, A. Crooks, Utilizing Python for Agent-Based Modeling: The Mesa Framework, Lect. Notes Comput. Sci. (Including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics). 12268 LNCS (2020) 308–317. Doi: 10.1007/978-3-030-61255-9_30/FIGURES/3.
[113] C. Ye, L. Butler, B. Calka, M. Iangurazov, Q. Lu, A. Gregory, M. Girolami, C. Middleton, A digital twin of bridges for structural health monitoring, Struct. Heal. Monit. 2019 Enabling Intell. Life-Cycle Heal. Manag. Ind. Internet Things - Proc. 12th Int. Work. Struct. Heal. Monit. 1 (2019) 1619–1626. Doi: 10.12783/shm2019/32287.
[114] G. Yu, Y. Wang, Z. Mao, M. Hu, V. Sugumaran, Y.K. Wang, A digital twin-based decision analysis framework for operation and maintenance of tunnels, Tunn. Undergr. Sp. Technol. 116 (2021), https://doi.org/10.1016/J.TUST.2021.104125.
[115] D. Dan, Y. Ying, L. Ge, Digital twin system of bridges group based on machine vision fusion monitoring of bridge traffic load, IEEE Trans. Intell. Transp. Syst. (2021) 1–16, https://doi.org/10.1109/TITS.2021.3130025.
[116] I. Kazuhiko, Y. Atsushi, Building a common smart city platform utilizing FIWARE (case study of Takamatsu City), NEC Tech. J. 13 (1) (2018) 28.
[117] M. Segovia, J. Garcia-Alfaro, Design, modelling and implementation of digital twins, Sensors 22 (2022) 5396, https://doi.org/10.3390/S22145396.
[118] E.D. Lioutas, C. Charatsari, M. De Rosa, Digitalization of agriculture: a way to solve the food problem or a trolley dilemma? Technol. Soc. 67 (2021) 101744 https://doi.org/10.1016/j.techsoc.2021.101744.
[119] M. Chiachío, M. Megía, J. Chiachío, J. Fernandez, M.L. Jalón, Structural digital twin framework: formulation and technology integration, Autom. Constr. 140 (2022) 104333, https://doi.org/10.1016/J.AUTCON.2022.104333.
[120] D. Helbing, J. Argota Sánchez-Vaquerizo, Digital twins: potentials, ethical issues, and limitations, SSRN Electron. J. (2022), https://doi.org/10.2139/SSRN.4167963.
[121] McKinsey, Digital twins: How to build the first twin, (2022). https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/digital-twins-how-to-build-the-first-twin (accessed December 14, 2024).
[122] WSP, How Digital Twin technology will improve engagement with stakeholders and communities, (2021). https://www.wsp.com/en-us/insights/digital-twins-improve-engagement (accessed December 14, 2024).
[123] 12dsynergy, Digital Twins Explained: A Guide for the Built Environment - 12d Synergy, (2022). https://www.12dsynergy.com/innovation-showcase/digital-twins-explained/ (accessed December 14, 2024).
[124] E. Ras, F. Wild, C. Stahl, A. Baudet, Bridging the skills gap of workers in industry 4.0 by human performance augmentation tools - challenges and roadmap, ACM Int Conf. Proceeding Ser. Part F 128530 (2017) 428–432, https://doi.org/10.1145/3056540.3076192.
[125] E.O. Popa, M. van Hilten, E. Oosterkamp, M.J. Bogaardt, The use of digital twins in healthcare: socio-ethical benefits and socio-ethical risks, Life Sci. Soc Policy 17 (2021) 1–25, https://doi.org/10.1186/s40504-021-00113-x.
[126] M.M. Helms, R. Moore, M. Ahmadi, Information technology (IT) and the healthcare industry: a SWOT analysis, Int. J. Healthc. Inf. Syst. Inform. 3 (2008) 75–92, https://doi.org/10.4018/jhisi.2008010105.
[127] Microsoft, Bentley iTwin and iModel.js Integration with Azure Digital Twins | Microsoft Learn, (2022). https://learn.microsoft.com/en-us/shows/internet-of-things-show/bentley-itwin-and-imodeljs-integration-with-azure-digital-twins?utm_source=chatgpt.com (accessed December 17, 2024).
[128] Microsoft, Azure Digital Twins | Microsoft, Microsoft 2023. (2023). https://learn.microsoft.com/en-us/azure/digital-twins/concepts-models (accessed March 17, 2023).
[129] A. Tolk, J. Muguira, The Levels of Conceptual Interoperability Model, (2003).
[130] L. Esterle, C. Gomes, M. Frasheri, H. Ejersbo, S. Tomforde, P.G. Larsen, Digital twins for collaboration and self-integration, Proc. - 2021 IEEE Int. Conf. Auton. Comput. Self-Organizing Syst. Companion, ACSOS-C 2021. (2021) 172–177. Doi: 10.1109/ACSOS-C52956.2021.00040.
[131] I. David, G. Shao, C. Gomes, D. Tilbury, B. Zarkout, Interoperability of Digital Twins: Challenges, Success Factors, and Future Research Directions, (2025) 27–46. Doi: 10.1007/978-3-031-75390-9_3.
[132] Industry 5.0 - European Commission, (n.d.). https://research-and-innovation.ec.europa.eu/research-area/industrial-research-and-innovation/industry-50_en (accessed May 28, 2025).
[133] B. Wang, P. Zheng, Y. Yin, A. Shih, L. Wang, Toward human-centric smart manufacturing: a human-cyber-physical systems (HCPS) perspective, J. Manuf. Syst. 63 (2022) 471–490, https://doi.org/10.1016/J.JMSY.2022.05.005.