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Review Article

Digital Twins in Engineering Informatics: Architectures, Maturity, and Emerging Intelligent Capabilities

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ABSTRACT Digital twins have emerged as a central paradigm in engineering informatics, enabling the dynamic integration of physical systems with their digital representations. Despite rapid growth in both research and industrial adoption, the conceptualisation, implementation, and evaluation of digital twins remain highly heterogeneous across domains. This paper presents a comprehensive review of digital twin systems from an engineering informatics perspective, focusing on their architectures, levels of maturity, and integration with emerging intelligent capabilities. We synthesise existing literature to identify common architectural components, including data acquisition, synchronisation mechanisms, semantic integration, and analytical modules. A maturity framework is proposed to categorise digital twin systems based on their degree of real-time coupling, autonomy, and decision support capability. The review further examines the role of artificial intelligence in enhancing digital twins, particularly in predictive modelling, anomaly detection, and the integration of Large Language Models (LLMs) and World Models for autonomous decision-making. In addition, we analyse lifecycle applications of digital twins across design, construction, manufacturing, and operation and maintenance phases. Key challenges are identified, including interoperability, data consistency, validation, and scalability. The paper concludes with a discussion of future research directions toward intelligent, autonomous, and lifecycle-integrated digital twin systems.

Keywords: Digital Twins, Maturity, Lifecycle Management, Knowledge Graphs, Large Language Models, World Models

1. Introduction

Digital twins (DTs) have become one of the most visible paradigms at the intersection of cyber-physical systems, industrial informatics, and lifecycle engineering. The concept is commonly traced to product lifecycle thinking and aerospace health management, where a digital counterpart was expected to mirror the state and behaviour of a physical asset over time [1, 2]. Since then, DT research has expanded rapidly across manufacturing, buildings, civil infrastructure, energy, mobility, and smart-city systems [3–5]. At the same time, conceptual ambiguity has also expanded. In both academic and industrial discourse, the label "digital twin" is frequently applied to systems that differ substantially in fidelity, coupling, autonomy, and lifecycle scope [6, 7].

From an engineering informatics perspective, this ambiguity is not a minor terminological issue. Engineering informatics is fundamentally concerned with how information about engineered assets is structured, exchanged, interpreted, and operationalised across the lifecycle. A DT therefore should not be reduced to a three-dimensional model or dashboard. It should instead be understood as an operational information system that integrates sensing, synchronization, semantics, simulation, analytics, and decision support in a way that is useful for engineering action [7–9]. This distinction matters because many implementation failures arise not from insufficient visualization, but from weak data integration, inadequate semantics, poor validation, or the absence of actionable feedback loops.

Recent reviews confirm both the vibrancy and the fragmentation of the field. Broad surveys have catalogued enabling technologies and application domains [3–5], while sectoral reviews in the built environment, manufacturing, and infrastructure have shown that DT practice remains uneven across lifecycle phases and organisational contexts [10–14]. In parallel, a new wave of AI-oriented literature is pushing DTs beyond conventional predictive analytics toward cognitive interaction, in-context adaptation, and world-model-driven autonomy [15–18]. These developments create a need for a review that does not merely catalogue use cases, but synthesizes the field around a coherent engineering-informatics logic.

This paper therefore makes four contributions. First, it clarifies the conceptual foundations of DTs and adopts a stricter operational distinction among digital model, digital shadow, and digital twin. Second, it synthesizes a reference architecture for DT systems, highlighting the importance of semantic integration and hybrid analytics. Third, it proposes a practical five-level maturity synthesis that can be used to characterise DT capability in engineering settings. Fourth, it examines how AI—especially LLMs and emerging world-model approaches—may transform DT systems from data-rich mirrors into adaptive decision systems. The discussion spans the asset lifecycle and concludes with an assessment of the field's major unresolved challenges.

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2. Conceptual Foundations of Digital Twins

2.1. Digital model, digital shadow, and digital twin

A useful starting point is the distinction among digital model, digital shadow, and digital twin. Kritzinger et al. provide one of the clearest operational classifications: a digital model is a digital representation that is manually updated; a digital shadow incorporates automated one-way data flow from physical to digital; and a digital twin adds bi-directional coupling or at least persistent synchronization mechanisms that support feedback and intervention [6]. While different sectors interpret these categories with varying strictness, the underlying distinction remains valuable because it separates mere representation from operational cyber-physical integration.

In this review, a DT is treated as more than a virtual copy. It is a fit-for-purpose digital representation that remains synchronized with an observable physical system and supports engineering decisions across time. This interpretation aligns with the manufacturing-oriented ISO 23247 framework, which formalises DTs around synchronized representations, observable elements, and structured interfaces [8, 19]. Not every DT must be fully autonomous; however, a system that never moves beyond manual updates and descriptive visualization is better understood as a digital model or, at most, a digital shadow.

2.2. Core characteristics

Despite definitional diversity, several core characteristics recur across the literature. First, DTs require *representation fidelity*: the virtual side must encode relevant structural, behavioural, and contextual features of the physical asset. Second, they require *temporal continuity*: state updates must be timely enough for the intended use case. Third, they require *service orientation*: the DT must support engineering tasks such as diagnosis, prediction, optimization, or scenario testing. Fourth, they require *lifecycle continuity*: DT value increases when design data, operational data, maintenance records, and simulation results are connected rather than isolated [4, 5, 9].

The widely cited five-dimensional abstractions of DTs—typically involving physical entity, virtual entity, connection, data, and service/application dimensions—remain useful as conceptual guides [20]. Their continuing relevance lies not in imposing a rigid ontology, but in reminding researchers that a DT is not only a model, nor only a dataset, nor only a user interface. It is an organized integration of all three.

2.3. Role in engineering informatics

Engineering informatics provides an especially productive lens because it foregrounds information continuity across lifecycle phases. In conventional practice, design files, sensor streams, maintenance reports, enterprise data, and simulation models are often siloed. A well-designed DT can instead act as a digital thread: design intent informs operation, operational observations inform redesign, and lifecycle decisions become traceable over time [7, 9, 21]. In this sense, DTs are not simply computational mirrors of assets; they are knowledge-bearing infrastructures for engineering action.

3. Architectures of Digital Twin Systems

DT systems are best understood as layered architectures rather than monolithic platforms. Although implementations vary by sector, a broadly transferable architecture can be synthesized around four major layers: sensing and connectivity, semantic integration, analytics, and interaction.

3.1. Sensing and connectivity

The first architectural requirement is the ability to capture and transport state information from the physical system. In industrial settings this includes industrial IoT devices, PLCs, machine-vision systems, robotics interfaces, and shop-floor communication standards. In buildings and infrastructure, it includes sensor networks, building management systems, UAV-based capture, laser scanning, and structural health monitoring streams [11, 12, 22]. ISO-oriented manufacturing literature further emphasises structured interfaces and machine-observable elements as prerequisites for robust DT deployment [8, 19].

A major recent trend is the shift from purely cloud-centric architectures toward cloud-edge collaboration. Edge-centric frameworks can reduce latency, localise pre-processing, and improve resilience under bandwidth constraints, especially where DTs are expected to support near-real-time operational decisions [23]. This architectural shift is important because the viability of many DT use cases depends not only on model quality but also on whether synchronization can be sustained at the required timescale.

3.2. Semantic integration and knowledge representation

Raw connectivity does not solve the central informatics problem: heterogeneous data still need to be interpreted consistently across tools, teams, and lifecycle phases. This is why semantic modelling and ontology-based integration are increasingly central to DT research. In the built environment, ontology and semantic-web approaches are being used to connect BIM, operational sensor data, and management information that were previously stored in incompatible silos [24, 25]. Similar logic appears in aviation and condition-based maintenance, where ontology-based DTs can formalise system structure, health states, and reasoning pathways for maintenance support [26].

Semantic integration matters for at least three reasons. First, it improves interoperability by giving shared meaning to heterogeneous data. Second, it supports explainability by making relationships explicit rather than buried in ad hoc interfaces. Third, it enables reasoning across levels of abstraction, from component state to system service impact. For engineering informatics, this semantic layer is often the difference between a data-rich platform and a knowledge-rich DT.

3.3. Analytics and hybrid intelligence

Analytics form the operational core of DT systems. Here the literature increasingly converges on hybrid approaches that combine physics-based models, data-driven learning, and optimization. Review evidence from manufacturing shows that DT analytics are most mature in prediction, anomaly detection, process optimization, and quality control [22, 27]. Broad surveys similarly highlight surrogate modelling, time-series forecasting, diagnostics, and decision support as central DT functions [4, 5].

Hybridization is critical. Purely physics-based models often struggle with computational cost and incomplete observability, while purely data-driven models can be brittle outside the training distribution. DT architectures therefore increasingly rely on mixed model ecosystems in which mechanistic understanding constrains or complements data-driven adaptation. This is especially important in safety-critical domains where predictive performance alone is not enough; explanations, consistency, and constraint-awareness also matter.

3.4. Human interaction and operational interfaces

The final layer concerns how humans interact with DTs. Traditional dashboards remain important, but recent work points toward more interactive and cognitively supportive interfaces. Digital-twin-enabled cockpit concepts, for example, treat the DT not only as a monitoring system but also as a coordinated interaction environment for testing, management, and decision support [28]. In manufacturing, emerging LLM-based interfaces aim to turn fragmented operational data into conversational decision support, allowing users to query the DT in natural language [29].

This interaction layer is not merely cosmetic. In practice, DTs fail when decision makers cannot understand, trust, or effectively query the system. Human-centered interaction design is therefore part of DT architecture, not an optional add-on.

4. Maturity of Digital Twin Systems

The maturity of DTs is frequently discussed but not uniformly defined. Existing maturity models differ by domain and evaluation purpose, and some focus on organizational readiness while others focus on technical capability [7, 30, 31]. Rather than adopting any single schema as universal, this paper synthesizes a five-level progression that is especially useful for engineering informatics.

At **L1**, the DT is essentially representational. It may be geometrically rich, but it remains largely static and disconnected from operational feedback. At **L2**, automated data synchronization appears; the system can monitor asset state but mainly supports descriptive visibility. At **L3**, predictive analytics become central: the DT can estimate future states, identify anomalies, and support diagnosis. At **L4**, the system becomes prescriptive and often federated, meaning that multiple subsystems or lifecycle information sources are coordinated to recommend actions. At **L5**, the DT acquires adaptive, cognitive, or semi-autonomous properties, potentially including language-based interaction, learning-based policy adjustment, and constrained closed-loop control [15, 16, 30, 31].

Two observations follow. First, maturity is multidimensional. A system may be highly advanced in synchronization but weak in semantics, validation, or governance. Second, most real deployments remain well below full autonomy. Review evidence in manufacturing and construction repeatedly shows that the majority of reported DTs still cluster around connected monitoring and predictive support rather than true autonomous operation [9, 13]. This makes maturity analysis useful not as a marketing taxonomy, but as a way to expose where capability gaps actually lie.

5. AI-Enhanced Digital Twins

5.1. Machine learning for prediction and optimisation

Machine learning is already deeply embedded in DT research. In manufacturing, AI-supported DTs are used for quality monitoring, fault diagnosis, predictive maintenance, and process optimization [22, 27]. Broader DT surveys likewise show strong emphasis on forecasting, anomaly detection, and surrogate modelling, especially where high-fidelity simulation is too slow for operational use [4, 5]. This is one of the clearest sources of DT value: the DT can continuously compare observed and expected behaviour and use that comparison to support timely intervention.

However, purely data-driven models are not sufficient for many engineering applications. Engineering decisions must often respect conservation laws, safety envelopes, physical constraints, and causal structure. The stronger trend is therefore not "AI replacing engineering models," but AI augmenting them. Hybrid DT analytics use data-driven components to improve adaptability and efficiency while preserving the interpretive and constraint-aware benefits of domain models.

5.2. LLMs and natural-language operationalisation

A more recent shift is the introduction of LLMs into the DT stack. Here the main contribution is not high-frequency numeric prediction, but semantic mediation. LLMs can support natural-language querying, document-grounded decision support, and orchestration across fragmented operational information sources [29]. They also make DTs more accessible to non-specialist users by lowering the interface barrier between humans and complex model ecosystems.

Beyond interface design, more ambitious work now treats DT updating itself as a language-model problem. The CALM-DT framework is a notable example: it uses in-context learning to adapt DT behaviour at inference time when variables, actions, or relevant knowledge change, thereby reducing dependence on full retraining [17]. This is especially relevant for engineering environments where equipment configurations, sensor availability, or process states change frequently.

Table 1
Reference architecture synthesis for digital twin systems, based on [8, 19, 23–25, 27, 29].

Layer	Typical technologies	Primary role	Engineering-informatics concern
Sensing and connectivity	IoT/IIoT sensors, PLCs, SCADA/BMS interfaces, machine vision, edge gateways	Capture and synchronize physical-state data	Latency, coverage, data quality, update frequency
Semantic integration	Ontologies, knowledge graphs, BIM/IFC mappings, RDF/OWL-style schemas	Align heterogeneous data and relations	Interoperability, contextual meaning, traceability
Analytics and simulation	Physics-based models, ML/DL, surrogate models, optimization, anomaly detection	Predict, diagnose, simulate, and optimise	Validity, robustness, explainability, computational cost
Interaction and decision support	Dashboards, XR, cockpit interfaces, conversational LLM interfaces	Deliver insights and enable action	Usability, trust, human oversight, accountability

Table 2
A practical five-level digital twin maturity synthesis adapted from [15, 30, 31].

Level	Capability profile	Typical outcome
L1 Representational	Static or manually updated digital representation	Visualization, documentation, offline analysis
L2 Connected monitoring	Automated data ingestion and state tracking	Live monitoring and descriptive analytics
L3 Predictive	Coupled historical and runtime analytics support forecasting and diagnosis	Condition assessment, anomaly detection, scenario anticipation
L4 Prescriptive / federated	Multi-model or multi-system reasoning supports recommendations and coordinated optimization	Decision support across assets, processes, or subsystems
L5 Autonomous-cognitive	Adaptive reasoning and closed-loop action under human-governed constraints	Partial or conditional autonomy, self-adjustment, agentic support

5.3. Toward cognitive twins and world-model-driven autonomy

The frontier of DT research increasingly overlaps with foundation models, cognitive architectures, and world-model ideas. Recent syntheses describe a shift from passive DTs toward AI-augmented twins that can support autonomous management, richer reasoning, and scenario imagination [16]. Related work on cognitive DT generations frames this trajectory as an evolution from monitoring instruments toward meta-cognitive ecosystems capable of reflective and adaptive behaviour [15].

World-model-oriented DT research pushes this even further by focusing on latent dynamics, planning, and agentic decision making under uncertainty [18]. For engineering informatics, this is a provocative direction because it suggests that DTs may eventually become not only representations of physical systems but also operational internal models used by intelligent agents for planning and action. Yet this remains an emerging research frontier. Industrial evidence is still limited, and questions of trustworthiness, constraint handling, and verification remain open [16, 18].

6. Lifecycle Applications

One of the strongest arguments for DTs is their ability to connect information across the lifecycle. Yet review evidence consistently shows that DT adoption is highly uneven across phases.

6.1. Design

In design, DTs support virtual prototyping, parameter studies, and scenario testing before costly physical commitments are made. In manufacturing-oriented lifecycle reviews, design use remains important but less prevalent than production and operation [9]. The engineering-informatics value at this stage lies in creating structured digital continuity: early design models can later be linked to operational and maintenance evidence rather than abandoned after handover.

6.2. Construction and manufacturing

In construction, DTs are used for progress tracking, quality monitoring, logistics coordination, and the integration of BIM with operational data. Reviews in the built environment show strong interest but also considerable fragmentation in implementation practices and lifecycle coverage [10, 11, 13, 14]. In manufacturing, DTs are more mature in process optimization, equipment monitoring, and near-real-time production support [22, 27]. Across both sectors, the common pattern is clear: DTs are most effective when the information loop between planned and actual states is explicit and continuously updated.

6.3. Operation and maintenance

Operation and maintenance remain the dominant DT application zone. Manufacturing reviews, construction reviews, and infrastructure reviews all report concentration in predictive maintenance, condition monitoring, diagnostics, and operational optimization [9, 12, 13]. This dominance is unsurprising. Runtime data are abundant, maintenance costs are high, and the economic value of avoiding downtime is readily measurable. For engineering informatics, O&M also provides the richest opportunity for closing the digital thread because operational evidence can be fed back into future design and planning decisions.

6.4. End-of-life and circularity

End-of-life applications remain relatively underdeveloped, but the literature increasingly points toward DT value in disassembly planning, remanufacturing, asset history tracing, and circular-economy decision support [9, 21]. This is an important research gap. A lifecycle-spanning DT should not stop at operation; it should preserve the informational lineage needed for reuse, refurbishment, and responsible retirement.

7. Challenges and Limitations

7.1. Interoperability and semantic fragmentation

Interoperability remains one of the most persistent DT barriers. Standards such as ISO 23247 provide useful structure in manufacturing, but they do not by themselves solve cross-domain semantic alignment [8, 19]. In construction and building DTs, reviewers repeatedly highlight fragmentation among BIM, sensor platforms, enterprise systems, and operational databases [13, 14, 24]. Without a semantic integration layer, DTs risk becoming data-rich but operationally incoherent.

7.2. Validation, verification, and model drift

DT value depends on whether the digital side remains valid enough for the engineering decision being made. Yet physical assets age, degrade, are repaired, and change context over time. This creates model drift and the possibility of silent divergence between digital assumptions and physical reality [4, 26]. The problem becomes even harder when AI components are embedded in the DT. High predictive performance is not sufficient if the model is brittle, poorly calibrated, or difficult to audit [16]. Verification and validation must therefore be treated as ongoing lifecycle obligations rather than one-time acceptance tasks.

7.3. Scalability and real-time constraints

Many attractive DT visions assume high-frequency synchronization, multi-model analytics, and low-latency response. In practice, this places strong pressure on communication infrastructure, storage, and computation. Edge-based DT frameworks offer one response by localising processing and reducing cloud burden [23], but scaling from a single asset to system-of-systems DTs remains difficult. The challenge is especially acute where DTs are expected to support operational optimisation rather than after-the-fact reporting [22].

7.4. Governance, organization, and trust

DT challenges are not only technical. Cross-lifecycle DT deployment requires data ownership agreements, organizational coordination, skills, and governance structures that many sectors still lack [13, 21]. Human trust is equally important. Interactive DT environments and LLM-supported interfaces may make systems easier to query, but they also raise questions about accountability, hallucination risk, and appropriate levels of human oversight [28, 29]. In engineering contexts, good interfaces are not enough; auditable reasoning and clear responsibility boundaries are essential.

8. Future Research Directions

Several research directions appear especially important for engineering informatics.

First, DT research should move toward *semantically interoperable twin ecosystems*. The real promise of DTs lies not only in better single-asset models, but in the coordinated operation of multiple twins across systems and lifecycle phases. Achieving this requires stronger semantic alignment, shared interfaces, and more reusable information models [8, 19, 24].

Second, DT intelligence should become *more hybrid and more trustworthy*. Rather than framing the future as a contest between physics and AI, engineering informatics should prioritize architectures in which learning-based components operate with explicit constraints, audit trails, and verification mechanisms [4, 16]. The question is not whether AI can be inserted into DTs, but under what conditions AI improves engineering reliability.

Third, DT research should remain *human-centered even as autonomy increases*. LLM-based operational interfaces and cockpit-style interaction environments are promising because they can democratize access to DT functionality [28, 29]. But autonomy should be layered, inspectable, and governed. In many engineering domains, the realistic target is not fully human-out-of-the-loop control, but well-designed human-on-the-loop collaboration.

Fourth, lifecycle research should better address *handover, retrofit, and end-of-life closure*. Current DT practice is still heavily concentrated in operation and maintenance [9, 13]. Engineering informatics can make a distinctive contribution by designing information structures that preserve continuity from design through decommissioning and circular reuse.

Table 3
Typical digital twin applications across the lifecycle, synthesized from [9–14, 21].

Lifecycle phase	Typical DT functions	Observed maturity pattern
Design	Virtual prototyping, parameter studies, simulation-based what-if analysis	Moderate conceptual interest; lower deployment than O&M
Construction / manufacturing	Progress monitoring, quality control, process optimization, synchronization of planned vs. actual state	Growing deployment; manufacturing generally more mature than construction
Operation / maintenance	Predictive maintenance, diagnostics, energy optimization, condition-based management	Dominant application area across sectors
End-of-life	Disassembly support, remanufacturing, traceability, circularity planning	Comparatively underdeveloped but strategically important

Finally, the emergence of *cognitive twins and world-model-oriented DTs* deserves close but critical attention. These approaches may enable richer scenario imagination and adaptive reasoning, but they remain early-stage and require far stronger evidence in safety-critical settings [15, 18]. The future of DTs will depend not only on how intelligent they become, but on how well that intelligence can be validated, explained, and governed.

9. Conclusion

Digital twins have matured from an appealing metaphor into a major systems concept in engineering informatics. Yet their practical meaning still varies widely. This review has argued for a stricter interpretation in which DTs are lifecycle information systems characterised by synchronized representation, semantic integration, analytics, and decision support. On this basis, it synthesized a transferable architecture, a practical five-level maturity model, and a forward-looking account of AI-enhanced DTs.

The analysis shows that most deployed DTs remain concentrated in connected monitoring and predictive support, especially in operation and maintenance. Semantic interoperability, validation, scalability, and governance continue to limit broader lifecycle deployment. At the same time, the AI frontier is shifting rapidly. LLMs are already changing how humans interact with DTs, while world-model-oriented research points toward more adaptive and agentic futures.

For engineering informatics, the central challenge is therefore not simply to build more DTs, but to build better ones: semantically interoperable, lifecycle-spanning, computationally viable, and trustworthy enough to support real engineering decisions. The most meaningful future progress will come from integrating physical fidelity with auditable intelligence and from treating DTs as enduring information infrastructures rather than isolated digital artefacts.

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No new data were generated or analysed in this study.

Conflict of 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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