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Conceptualizing Cognitive and Agentic Digital Twins

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Abstract. Digital Twins (DTs) have extended beyond the original concept of a static digital model, to a dynamic, data-driven, and increasingly intelligent cyber-physical structure, which underlies modern Industry 4.0 systems. The paper gives a comprehensive and integrative conceptualization of DTs, Cognitive Digital Twins (CDTs), and agentic AI-enhanced DTs through an organized narrative literature review which synthesizes the foundational definitions, the theoretical differences between DTs and Cyber-Physical Systems (CPS), and the evolution of Digital Models and Digital Shadows to fully synchronous, two-way DTs. The research synthesizes the major architectural models, such as layered, multi-dimensional, cognitive and agentic models, and discusses the facilitating technologies that enable real-time synchronization, semantic reasoning, and autonomous decision-making. The state-of-the-art analysis indicates that the key research trends include ecosystem-based DTs, AI-driven analytics, semantic enrichment, and the development of LLM-enabled agentic DTs that are able to plan and coordinate actions in a goal-oriented manner. The paper also compares industrial and open-source DT platforms, outlines the present-day limitations in semantic interoperability, cognitive integration, and autonomy and demonstrates real-world applications in manufacturing, healthcare, smart cities, and energy systems. The discussion proposes future research directions such as standardized cognitive layers, safe LLM grounding, multi-DT coordination, and governance frameworks of autonomous DT ecosystems. Overall, the paper contributes a unified conceptual model and a holistic synthesis that connects theory, architecture, technology, and application, providing a foundation for advancing the next generation of intelligent Digital Twin systems.

Keywords: Digital Twin, Cognitive Digital Twin, Agentic AI, Large Language Models, Cyber-Physical Systems, Semantic Interoperability, Multi-Agent Systems

1. Introduction

The accelerated evolution of digital technologies has reshaped how physical systems are conceived, operated, and optimized across industrial and societal domains. Within this broader transformation, the Digital Twin (DT) has emerged as a foundational paradigm of Industry 4.0, enabling the creation of dynamic, data-driven virtual counterparts of physical assets, processes, and systems. A DT is commonly defined as a continuously updated digital representation that maintains real-time synchronization with its physical entity through bidirectional data exchange (Tao et al., 2018). This capability distinguishes DTs from traditional simulation models, which operate in static or isolated environments without real-time feedback.

The conceptual origins of DTs can be traced to Michael Grieves' early work in product lifecycle management, where he introduced the idea of a virtual counterpart to a physical system (Grieves, 2002; Grieves, 2014). In parallel, the concept of Cyber-Physical Systems (CPS) emerged from the National Science Foundation, where Helen Gill coined the term to describe systems integrating computation, communication, and control with physical processes (Gill, 2008). Although both DTs and CPS aim to achieve cyber-physical integration, they differ fundamentally: CPS represent a scientific category emphasizing the 3C model—computation, communication, and control—while DTs represent an engineering category focused on high-fidelity modeling, lifecycle integration, and predominantly one-to-one digital–physical mapping (Tao et al., 2019).

Recent advances in IoT, cloud and edge computing, artificial intelligence (AI), and big data analytics have accelerated the evolution of DTs toward more autonomous and intelligent forms (Fuller et al., 2020). However, traditional DTs still face limitations in autonomous decision-making, environmental adaptability, reasoning, and cognitive understanding**,** particularly in dynamic and uncertain environments (Liu, Ji, Guo, Xu & Polzer, 2025). These limitations have motivated the emergence of the Cognitive Digital Twin (CDT)**,** first conceptualized by Adl (2016), which extends DTs with cognitive capabilities such as perception, semantic understanding, reasoning, learning, and adaptive decision-making. CDTs simulate human-like cognitive processes and support system-level human–machine collaboration, enabling more robust operation in complex scenarios (Liu et al., 2025).

In parallel, the rise of agentic AI—AI systems capable of autonomous goal-directed reasoning, planning, action, and self-improvement—has opened new opportunities for enhancing DT intelligence. Agentic AI architectures, particularly those leveraging Large Language Models (LLMs)**,** provide advanced semantic interpretation, contextual reasoning, and multi-agent coordination capabilities (Hasan & Nguyen, 2026). Integrating agentic AI with DTs transforms them from passive mirrors into active cognitive ecosystems**,** where LLM-based agents interpret DT states, simulate actions, evaluate strategies, and execute decisions in closed-loop fashion (Hasan & Nguyen, 2026). This convergence enables DTs to support adaptive, explainable, and resilient decision-making across cyber-physical environments.

Today, DTs and CDTs are deployed across manufacturing, healthcare, smart cities, and energy systems. In manufacturing, DTs support predictive maintenance, production optimization, and lifecycle management (Tao & Zhang, 2017). In healthcare, patient-specific DTs enable personalized diagnostics and treatment planning (Barricelli et al., 2019). Smart cities leverage DTs for integrated urban planning and infrastructure management (Batty, 2018), while the energy sector uses DTs and agentic AI-enhanced DTs for grid balancing, distributed energy coordination, and resilience under uncertainty (Hasan & Nguyen, 2026). Industrial leaders such as General Electric, Siemens, PTC, Dassault Systèmes, and Tesla have deployed DTs to enhance product performance, manufacturing flexibility, and operational intelligence (Tao et al., 2019).

Despite these advances, the DT landscape remains fragmented, with inconsistent definitions, heterogeneous architectures, and varying implementation approaches across disciplines. As highlighted in recent literature, the reliance on continuous data exchange raises significant concerns regarding cybersecurity and data privacy, while large-scale DT deployments introduce challenges related to interoperability, scalability, data governance, and ethical considerations. These issues become more pronounced as DTs evolve toward autonomous, AI-driven, and cognitive paradigms, where decision-making may occur with limited human oversight (Rasheed et al., 2020; Liu et al., 2025).

Given these challenges, there is a clear need for a comprehensive and multidisciplinary framework that integrates the theoretical foundations, enabling technologies, architectures, and application domains of Digital Twins, Cognitive Digital Twins, and agentic AI-enhanced DT systems. Addressing this gap is essential for advancing both academic understanding and practical implementation.

To respond to this need, this paper provides a structured and integrative conceptualization of Digital Twins. The specific objectives are:

1. To analyze the theoretical foundations and definitions of DTs and CDTs
2. To examine the current state of the art and emerging research trends
3. To identify key enabling technologies and architectural models
4. To evaluate existing platforms and application domains
5. To discuss challenges, limitations, and future research directions

By achieving these objectives, the paper contributes a unified perspective that bridges the gap between theory and practice, offering a coherent foundation for future research and development in Digital Twin systems.

2. Methodology

This study adopts a narrative literature review (NLR) methodology to synthesize the conceptual evolution, technological foundations, and emerging research directions of Digital Twins (DTs), Cognitive Digital Twins (CDTs), and agentic AI–enhanced DT systems. The NLR approach is appropriate for multidisciplinary and rapidly evolving domains where definitions, architectures, and applications vary significantly across fields such as manufacturing, cyber-physical systems, artificial intelligence, and systems engineering. Given the fragmented nature of DT and CDT research, this method enables a structured yet flexible integration of diverse perspectives, allowing for a comprehensive understanding of the state of the art. The methodology used is shows in Figure 1.

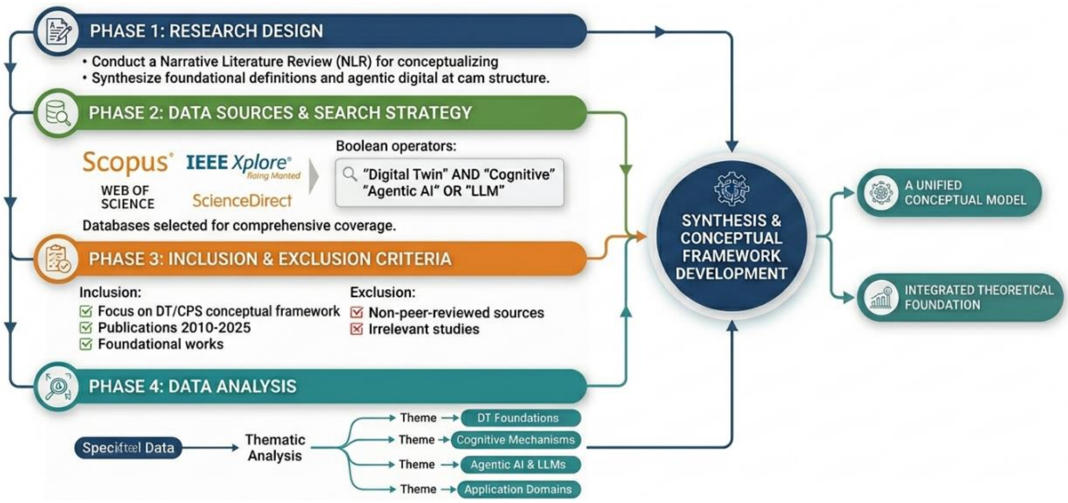

Figure 1. Methodology used in this study.

2.1. Research Design

The research design follows a structured narrative approach aimed at identifying, analyzing, and synthesizing foundational and contemporary literature. This includes classical DT and CPS sources (Grieves, 2002; Gill, 2008; Tao et al., 2019), recent advancements in CDT (Liu et al., 2025), and emerging work on agentic AI–DT integration (Hasan & Nguyen, 2026). The objective is to trace the conceptual progression from traditional DTs to cognitive and autonomous DT systems, highlighting the technological enablers, architectural models, and research gaps that shape this evolution.

2.2. Data Sources and Search Strategy

A comprehensive literature search was conducted across major academic databases, including:

- IEEE Xplore
- Scopus
- Web of Science
- ScienceDirect
- Semantic Scholar

The search process employed a combination of keywords and Boolean operators to ensure broad coverage. The primary keywords included:

- "Digital Twin"
- "Cognitive Digital Twin"
- "Cognitive Twins"
- "Agentic AI"

- “LLM Digital Twin”
- “Cyber Physical Systems”
- “Smart Manufacturing”
- “Virtual Twin”

Search queries were refined iteratively to balance relevance and coverage. For example, combinations such as “Digital Twin AND architecture” and “Digital Twin AND applications” were used to target specific dimensions of the concept. This expanded keyword set reflects the evolution of DT research toward cognitive and agentic paradigms, as highlighted in recent CDT and agentic AI literature (Liu et al., 2025; Hasan & Nguyen, 2026).

2.3. Inclusion and Exclusion Criteria

To ensure relevance and academic rigor, the following inclusion criteria were applied:

- Peer reviewed journal articles and conference papers
- Publications from 2010 to 2025
- Foundational DT/CPS works
- CDT conceptual and architectural studies
- Agentic AI–DT integration research
- Papers addressing enabling technologies, architectures, or applications

Exclusion criteria included:

- Non peer reviewed sources (white papers, preprints without full text)
- Publications lacking conceptual or technical relevance
- Redundant or derivative studies

These criteria align with the methodological rigor applied in recent CDT reviews (Liu et al., 2025).

2.4. Data Analysis

Thematic analysis was used to examine the selected literature and identify emergent trends, recurrent patterns, and conceptual structures (Braun & Clarke, 2006). The analysis focused on the following key themes:

1. Definitions and theoretical foundations of DTs, CDTs, and CPS
2. Cognitive mechanisms and semantic reasoning capabilities
3. Agentic AI and LLM based decision making
4. Architectural models for DT, CDT, and AI DT integration
5. Application domains across manufacturing, energy, healthcare, and infrastructure
6. Challenges, limitations, and research gaps

The analytical frameworks employed in CDT and agentic AI surveys are reflected in this topic structure (Liu et al., 2025; Hasan & Nguyen, 2026).

2.5. Methodological Limitations

The narrative review style offers depth and flexibility, but it also has some drawbacks. Because study inclusion is interpretive, selection bias may occur. In accordance with best practices in CDT literature reviews, cross-database searches, citation chaining, and team cross-checking were used to lessen this (Liu et al., 2025). Furthermore, some cutting-edge advancements—especially in LLM-driven reasoning, multi-agent coordination, and autonomous DT architectures—may not yet be completely represented in the scholarly literature due to the quick development of CDT and agentic AI research. Notwithstanding these drawbacks, the approach offers a thorough and logical synthesis that aids in the creation of an integrated conceptual framework.

3. Theoretical Framework and Conceptualization

Digital Twins (DTs) have evolved from relatively static digital models into dynamic, data-driven, and increasingly cognitive cyber–physical constructs. This section consolidates core definitions, architectural perspectives, and classification schemes from the DT and CPS literature, and then extends the evolution toward Cognitive Digital Twins (CDTs) and agentic AI–enhanced DTs.

3.1. Core definitions and historical evolution of Digital Twins

The DT concept emerged in the early 2000s in the context of Product Lifecycle Management (PLM), when Grieves described a *"digital informational construct about a physical system, created as an entity on its own and linked with the physical system in question"* that should ideally contain all information obtainable from its physical counterpart (Grieves, 2002; Grieves, 2014). Later, NASA formalized DTs as *"an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin"* (Glaessgen & Stargel, 2012).

Over time, DTs expanded beyond aerospace and PLM into manufacturing systems, production lines, and factories. Tao et al. position DTs as an engineering-oriented counterpart to the more science-oriented notion of Cyber-Physical Systems (CPS): *"compared with CPS, DT is akin to an engineering category"* (Tao et al., 2019), with pervasive industrial applications in product design, production line design, DT shop floors, and prognosis and health management. Lu et al. further generalize DTs as *"a virtual representation of manufacturing elements such as personnel, products, assets and process definitions, a living model that continuously updates and changes as the physical counterpart changes"* (Lu et al., 2020).

In manufacturing, this evolution can be summarized as:

- Static digital models (CAD, simulation) used offline for design and planning.
- Connected, data-driven DTs that synchronize with physical assets in (near) real time.

- Lifecycle-spanning DTs that integrate design, production, logistics, and service.
- Cognitive and agentic DTs that embed AI, learning, and autonomous decision-making (Liu et al., 2025; Hasan & Nguyen, 2026).

This progression provides the foundation for understanding how DT architectures relate to and interact with CPS structures.

3.2. Cyber–physical integration and DT architectures

CPS and DTs are specifically compared by Tao et al. as complimentary but different approaches to cyber-physical integration. According to Tao et al. (2019), CPS is described as "the integration of computational and physical processes" with tight coupling of computing, communication, and control (3C), where architectures "focus on control rather than on mirrored models" and the mapping from cyber to physical is usually one to many. DTs, on the other hand, place a strong emphasis on one-to-one mapping and high fidelity virtual models: "the mapping relationship between the physical and digital worlds of a DT provides a one to one correspondence... the virtual models and physical entities have a similar appearance, like twins, and the same behaviors, like a mirror image" (Tao et al., 2019).

From an architectural perspective, a number of complementary viewpoints become apparent:

- Hierarchical CPS/DT levels (unit, system, system of systems): Tao et al. demonstrate the composition of unit level DTs (e.g., a machine tool), system level DTs (production lines, factories), and SoS level DTs (cross enterprise, lifetime spanning) (Tao et al., 2019).
- 5 Dimensional DT architecture: Bazaz et al. contend that "the 5 dimensional structure of the Digital Twin... covers all requirements to represent the physical space in the virtual space" (Bazaz et al., 2019) and suggest a five-layer DT structure consisting of cyber physical data store, primary processing, models and algorithms, analysis, and user interface.
- Digital Twin reference model: Lu et al. reduce DTs to three fundamental technical elements: data processing, a communication method, and an information model (Lu et al., 2020).

When taken as a whole, these perspectives support a similar pattern: DTs are situated at the nexus of industrial communication protocols, analytics/AI pipelines, and standardized information models (such as STEP, MTConnect, and OPC UA) that sustain a real-time, bidirectional connection between the physical and digital worlds.

3.3. Classification of Digital Models, Digital Shadows, and Digital Twins

By differentiating three levels of integration—Digital Model (DM), Digital Shadow (DS), and Digital Twin (DT)—Kritzinger et al. refine the conceptual development of DTs. The direction and automation of data flow between physical and digital entities determine their classification:

- Digital Model (DM): a digital representation without automated data exchange—*"a Digital Model is a digital representation… that does not use any form of automated data exchange between the physical object and the digital object"* (Kritzinger et al., 2018).
- Digital Shadow (DS): one-way automatic data flow from physical to digital—*"a change in state of the physical object leads to a change of state in the digital object, but not vice versa"* (Kritzinger et al., 2018).
- Digital Twin (DT): fully integrated, bidirectional data flow—*"a change in state of the physical object directly leads to a change in state of the digital object and vice versa"* (Kritzinger et al., 2018).

According to their literature review, "only 18 percent of them are really describing a Digital Twin with a bidirectional data transfer, even though the majority of papers used the term Digital Twin" (Kritzinger et al., 2018). This suggests that many implementations classified as DTs are actually Digital Shadows or even static models.

For organizing the development of DT implementations in manufacturing, this three-level classification is quite helpful:

1. From DM to DS: adding automated sensing and one-way data integration.
2. From DS to DT: closing the loop with control, actuation, and decision feedback.
3. Beyond DT: enriching DTs with cognition, learning, and autonomous behavior (Liu et al., 2025).

3.4. Cognitive Digital Twins (CDTs)

By including learning, reasoning, and adaptability into the digital representation, cognitive digital twins expand on conventional DTs. Although monitoring, prediction, and optimization are already supported by classical DTs, they usually rely on pre-established models and regulations. In contrast, CDTs incorporate AI and machine learning to continually improve their internal models and decision policies using contextual information, historical traces, and streaming data (Liu et al., 2025).

According to Bazaz et al., "all the parts of the system are expressed with relations, actions, and communication between them; therefore, by changing one part or parameter, other related objects are changed automatically by artificial intelligent methods" (Bazaz et al., 2019). In a similar vein, Lu et al. contend that "pervasive use of advanced sensor based data analytics, modeling, and simulation" is necessary for smart manufacturing and that DTs enable "data driven operation monitoring and optimization" when paired with Big Data and AI (Lu et al., 2020).

In a CDT, cognition manifests along several dimensions:

- Perception
- Understanding

- Learning
- Reasoning and planning
- Self-adaptation

CDTs thus move DTs from being primarily descriptive and predictive to becoming prescriptive and self-improving, capable of adapting their behavior over time. Building on these cognitive capabilities, the next step in this evolution is the integration of agentic AI—particularly LLM-enabled agents—into DT ecosystems, which introduces goal-directed behavior, autonomous planning, and coordinated action across multiple twins.

3.5. Agentic AI and LLM-enhanced Digital Twins

The next step in the evolution is the integration of agentic AI—software agents capable of goal-directed behavior—and large language models (LLMs) into DT ecosystems. While the reviewed DT literature predates LLMs, it already points toward middleware and service layers where such capabilities can be embedded.

Bazaz et al. describe a C2PS architecture in which *"the fourth layer of C2PS is an intelligent service layer comprising a number of services… [that] permits analysis, simulation, optimization and prediction"*, acting as middleware between cyber objects and system usage (Bazaz et al., 2019). Lu et al. conceptualize DTs as *"middleware architecture that abstracts its physical counterpart for high-level engineering management systems to make near real-time decisions"* (Lu et al., 2020). These service and middleware layers are natural insertion points for agentic AI and LLM-based components.

In an agentic, LLM-enhanced DT environment:

- Autonomous agents can orchestrate simulations, optimization runs, and control actions based on high-level goals (e.g., minimizing energy, maximizing OEE, balancing throughput and robustness) (Hasan & Nguyen, 2026).
- LLMs can:
    - Interpret unstructured inputs (maintenance logs, operator notes, standards) (Liu et al., 2025).
    - Explain DT behavior and recommendations in natural language to human stakeholders (Liu et al., 2025).
    - Generate candidate configurations, test plans, or what-if scenarios by leveraging both DT data and domain knowledge (Liu et al., 2025).
- Multi-agent coordination can span multiple DTs (machines, lines, factories), enabling negotiation and distributed decision-making across a production network (Hasan & Nguyen, 2026).

This agentic layer effectively turns DTs into active participants in the manufacturing system, not just passive mirrors.

3.6. Integrating DT, CDT, and agentic AI: A unified conceptual model

Bringing these strands together, the evolution of DTs in manufacturing can be conceptualized as a layered, capability-building progression:

1. Foundational DT (DM/DS/DT):
   - Information models (STEP, MTConnect, OPC UA, ISO 13399, etc.) define the digital representation (Lu et al., 2020).
   - Industrial communication protocols and IoT infrastructure provide sensing and actuation (Tao et al., 2019).
   - Data processing pipelines maintain one-way (DS) or bidirectional (DT) synchronization (Kritzinger et al., 2018).
2. Cognitive DT (CDT):
   - Analytics, machine learning, and knowledge bases (as in Bazaz's analysis and knowledge layers) support prediction, diagnosis, and optimization (Bazaz et al., 2019; Liu et al., 2025).
   - Models co-evolve with physical processes, as Tao et al. describe: *"using bidirectional dynamic mapping, the physical entities and virtual models co-evolve"* (Tao et al., 2019).
3. Agentic, LLM-enhanced DT:
   - Autonomous agents operate on top of CDTs, using their state and predictive models to plan and execute actions (Hasan & Nguyen, 2026).
   - LLMs provide flexible reasoning over heterogeneous information and natural-language interaction with humans, while remaining grounded in DT data and constraints (Liu et al., 2025).
   - Multi-DT coordination enables system-of-systems optimization across factories and supply networks, aligning with Lu's vision of *"virtually connected production networks"* built from interconnected DTs (Lu et al., 2020).

Conceptually, this unified model preserves the one-to-one mapping and high-fidelity modeling emphasized by Tao et al. (2019), the layered architecture and data-centric view of Bazaz et al. (2019), and the reference-model clarity of Lu et al. (2020), while extending them with cognition and agency. However, even with this unified progression, several conceptual and practical gaps remain.

3.7. Conceptual gaps and research opportunities

Despite rapid progress, several conceptual and practical gaps remain—many already identified in the reviewed literature:

- True DT vs. DS/DM: Kritzinger et al. show that most "DT" implementations are actually Digital Shadows or Models. There is a need for clearer criteria, benchmarks, and reference implementations that demonstrate genuine bidirectional, closed-loop DTs in industrial settings (Kritzinger et al., 2018).
- Standardized cognitive layers: While Bazaz et al. and Lu et al. outline analysis and intelligent service layers, there is no widely accepted reference model for

CDTs that specifies how learning, reasoning, and knowledge management should be integrated with DT cores (Bazaz et al., 2019; Lu et al., 2020).

- Integration of LLMs with DTs: Existing DT architectures were not designed with LLMs in mind. Research is needed on:
    - Safe grounding of LLM outputs in DT state and constraints (Liu et al., 2025).
    - Architectures for combining symbolic/standardized models (STEP, OPC UA) with probabilistic, language-based reasoning (Liu et al., 2025).
    - Human-in-the-loop patterns where LLMs mediate between DTs and operators without bypassing safety and control logic (Hasan & Nguyen, 2026).
- Multi-DT and SoS-level intelligence: Tao et al. and Lu et al. both highlight system-of-systems and production-network perspectives, but most implementations remain at unit or system level. There is a gap in methods for coordinating multiple DTs/CDTs via agentic AI to achieve global objectives (e.g., energy, resilience, sustainability) across networks (Tao et al., 2019; Lu et al., 2020).
- Data ownership, governance, and trust: Bazaz et al. explicitly flag data ownership and privacy as major obstacles—*"data ownership is a complicated issue… the degree of ownership needs to be determined to ascertain the value gained from usage of the data for each creator"* (Bazaz et al., 2019). As DTs become more cognitive and agentic, questions of governance, accountability, and explainability become even more critical.

4. State of the Art

4.1. Overview of current research trends

The state of the art in Digital Twin (DT) research shows how quickly isolated, asset-centric models have given way to linked, intelligent, and more autonomous cyber-physical ecosystems. Recent research highlights ecosystem-based DTs, where numerous twins interact across production lines, factories, and distributed infrastructures, whereas early DT implementations concentrated on monitoring and simulation (Tao et al., 2019; Fuller et al., 2020).

The incorporation of AI-driven analytics is a significant trend that allows DTs to shift from descriptive and predictive roles to prescriptive and independent decision making (Rasheed et al., 2020). This covers real-time optimization, surrogate modeling, and reinforcement learning.

The advent of Cognitive Digital Twins (CDTs) builds on these advancements by introducing capabilities such as perception, learning, reasoning, and semantic understanding (Liu et al., 2025). More recently, agentic AI and LLM-enhanced DTs have enabled goal-directed planning, multi-agent coordination, and natural-language interaction, transforming DTs into active participants in cyber-physical systems (Hasan & Nguyen, 2026). These advances are enabled by foundational technologies that provide sensing, computation, analytics, and semantic capabilities.

4.2. Enabling technologies

A number of fundamental technologies support the development of DTs:

- The Internet of Things (IoT): Enables constant sensing and communication between digital and physical objects (Atzori et al., 2010).
- Cloud computing: Provides DT models and analytics with scalable processing and storage (Armbrust et al., 2010).
- Edge computing: Facilitates real-time, low-latency processing for time-sensitive applications (Shi et al., 2016).
- Machine learning and artificial intelligence: Improve DT's prediction, anomaly detection, optimization, and cognitive reasoning skills (Goodfellow et al., 2016; Liu et al., 2025).
- Big data analytics: Facilitates the integration, storage, and extraction of insights from enormous amounts of data (Chen et al., 2014; Rasheed et al., 2020).
- Semantic technologies: In CDTs, reasoning, interoperability, and lifecycle knowledge integration are made possible by ontologies and knowledge graphs (Liu et al., 2025).

4.3. Key research contributions

The DT landscape has been shaped by a number of foundational works:

- Tao et al. (2018, 2019) developed lifecycle integrated DT designs and defined DTs as an engineering category separate from CPS.
- Kritzinger et al. (2018): Clarified DT maturity levels by establishing the DM/DS/DT classification.
- Lu et al. (2020): Developed a DT reference model with a focus on data processing, communication mechanisms, and information models.
- Bazaz et al. (2019): Described intelligent service layers and presented the five-dimensional DT architecture.
- Fuller et al. (2020): Ecosystem level architectures and synthesized DT applications.
- Rasheed et al. (2020) noted issues with model integrity and scalability in industrial DT deployment.
- Liu et al. (2025) defined the CDT concept and associated cognitive underpinnings.
- Hasan & Nguyen (2026): demonstrated multi-agent collaboration and autonomous reasoning in agentic AI-enhanced DTs.

4.4. Application domains

DTs are currently used in a variety of industries:

- Manufacturing: adaptive scheduling, process optimization, and predictive maintenance (Tao & Zhang, 2017; Fuller et al., 2020).

- Healthcare: Individualized treatment planning and physiological modeling tailored to each patient (Barricelli et al., 2019).
- Smart cities: Infrastructure management, transportation optimization, and integrated urban planning (Batty, 2018).
- Energy systems: distributed energy coordination, renewable energy forecasting, and grid monitoring (Rasheed et al., 2020; Hasan & Nguyen, 2026).
- Aerospace: assessing structure health and simulating missions (Glaessgen & Stargel, 2012).

4.5. Challenges identified in the literature

Despite advancements, a number of issues still exist:

- Interoperability: Cross-platform integration is hampered by the absence of common models and protocols (Tao et al., 2018; Kritzinger et al., 2018).
- Scalability: Data, model, and computational complexity are challenges for large-scale DT ecosystems (Rasheed et al., 2020).
- Cybersecurity: Constant data sharing makes systems more susceptible to intrusions (Fuller et al., 2020).
- Data governance: Unresolved problems with data ownership, origin, and quality (Bazaz et al., 2019; Liu et al., 2025).
- Model fidelity: It is theoretically challenging to maintain precise, real-time synchronization across dispersed DTs (Rasheed et al., 2020).
- Cognitive and agentic integration: Safe LLM grounding, semantic alignment, and human-in-the-loop governance are necessary for CDTs and agentic DTs (Liu et al., 2025; Hasan & Nguyen, 2026).
- System of systems coordination: It is still difficult to coordinate several DTs across cities, factories, or energy networks (Tao et al., 2019; Lu et al., 2020).

In Section 6, platform capabilities and limits are further examined, offering a more thorough look at how existing DT platforms handle—or fail to address—these issues.

5. Architectures of Digital Twins

5.1. Overview of architectural models

Architectural models specify how intelligence is integrated throughout the system, how data moves between digital and physical things, and how Digital Twins (DTs) are organized. The research shows a transition from straightforward, layered systems to multidimensional, cognitive, and agentic frameworks that facilitate autonomous decision making, semantic reasoning, and real-time synchronization (Tao et al., 2019; Lu et al., 2020; Liu et al., 2025).

5.2. Three-layer architecture

The three-layer model is one of the earliest and most basic DT designs. It consists of:

1. Physical Layer: Actuators, sensors, and the actual system
2. Digital Layer: Models, simulations, and virtual representations

3. Application Layer: Decision support, analytics, and visualization interfaces

Though it lacks the granularity needed for contemporary DT ecosystems, especially those involving remote assets, real-time analytics, or multi-agent coordination, this model offers a conceptual basis.

5.3. Five-layer architecture

The five-layer architecture is a more comprehensive and popular approach that consists of:

1. The Physical Entity Layer
2. Layer of Data Acquisition
3. Layer of Communication
4. Layer of Data Processing
5. The Application Layer

This architecture captures the core data flow and processing mechanisms of DT systems and is frequently referenced in manufacturing and industrial applications (Tao et al., 2018). However, it still focuses primarily on data movement and computation rather than cognition, semantics, or autonomy.

5.4. Multi-dimensional and advanced DT architectures

Researchers have suggested multidimensional structures that include extra layers as DT systems have become more complicated, including:

- Orchestration and service layers (Bazaz et al., 2019)
- Layers of lifecycle management (Lu et al., 2020)
- Layers of knowledge and semantics (Liu et al., 2025)
- Layers of governance and security
- Layers of user interaction and cooperation

A five-dimensional DT architecture that incorporates data, models, analytics, knowledge, and user interaction was presented by Bazaz et al. (2019). Lu et al. (2020) put forth a reference model that focused on data processing pipelines, communication mechanisms, and information models.

The necessity for DTs to allow cross-domain integration, interoperability, and lifecycle continuity is reflected in these sophisticated models.

5.5. Architectures for Cognitive Digital Twins (CDTs)

By including cognitive processes as perception, semantic comprehension, reasoning, and learning, cognitive digital twins expand conventional architectures (Liu et al., 2025). Typical CDT architectures consist of:

- Layers of semantics and ontology for representing knowledge
- Layers of cognitive processing for learning and reasoning
- Layers of context awareness for dynamic adaption

- Layers of human-machine collaboration

These layers allow CDTs to autonomously improve their internal models, comprehend system context, and analyze diverse data.

5.6. Architectures for agentic AI–enhanced DTs

Additional architectural requirements brought about by agentic AI include:

- Layers of agent orchestration for multi-agent collaboration, tool usage, and planning
- LLM-based reasoning layers for explaining and interpreting natural language
- Autonomy layers for closed-loop decision-making and goal-directed behavior
- Grounding and safety layers to guarantee that LLM outputs stay in line with DT limitations (Hasan & Nguyen, 2026).

By using these architectures, DTs are transformed from passive digital mirrors into autonomous, active cyber-physical agents that can communicate with other distributed systems. Follow, the next session shows the comparative analysis of architectures (see table 1).

5.7. Comparative analysis of architectures

Table 1. Comparative analysis of architectures

Architecture	Strengths	Limitations	Best Use Cases
3 layer	Simple, intuitive	Lacks detail; no cognition	Small systems, education
5 layer	Balanced, widely used	Limited semantic/cognitive support	Industrial DTs, manufacturing
Multi dimensional	Rich, lifecycle oriented	Complex to implement	Enterprise DT ecosystems
CDT architectures	Cognitive reasoning, learning	Requires semantic models	Adaptive, intelligent systems
Agentic DT architectures	Autonomy, multi-agent coordination	Requires governance and safety	Distributed, dynamic environments

Note. *This table is the authors' own synthesis and comparative analysis.*

5.8. Interoperability and standardization

One of the most important issues in DT architecture is still interoperability. Cross-platform integration is hampered by the absence of common information models, communication protocols, and semantic frameworks (Tao et al., 2018; Kritzinger et al., 2018). New initiatives concentrate on:

- Standardized ontologies (e.g., OPC UA, ISO 10303/STEP)
- Semantic interoperability frameworks for CDTs (Liu et al., 2025)
- Governance and data ownership models (Bazaz et al., 2019)

- Cross-domain DT ecosystems for smart cities and energy networks (Lu et al., 2020)

In order to enable system of systems DT architectures, in which several DTs work together across domains, interoperability must be achieved.

6. Digital Twin Platforms

Technology platforms that offer the framework for data integration, modeling, simulation, analytics, and increasingly cognitive and agentic capabilities are essential to the deployment of Digital Twins (DTs). The scalability, interoperability, semantic richness, and domain specialization of these platforms vary. Platform needs go beyond conventional data pipelines to support reasoning, autonomy, and multi-agent coordination as DTs develop into Cognitive Digital Twins (CDTs) and agentic AI-enhanced DTs (Liu et al., 2025; Hasan & Nguyen, 2026).

6.1. Industrial Platforms

Industrial DT platforms prioritize dependability, security, and integration with corporate systems and are made for large-scale, production-grade deployments.
Microsoft Azure Digital Twins: Using the Digital Twin Definition Language (DTDL), Azure Digital Twins offers a graph-based modeling environment. Scalable analytics, real-time data ingestion via Azure IoT Hub, and interaction with AI and simulation services are all supported. It may be used to represent diverse, interconnected systems like energy networks, factories, and smart buildings because of its graph-based methodology.

By combining data from IoT sensors, enterprise systems, and 3D visualization engines, AWS IoT TwinMaker AWS makes it possible to build DT applications. It is ideal for operational intelligence and industrial monitoring because it has a strong emphasis on scalability, multi-source data fusion, and smooth connection with AWS analytics and machine learning services.

An industrial IoT platform designed specifically for manufacturing settings is Siemens MindSphere MindSphere. It offers data collection, analytics, visualization, and Siemens automation system integration solutions. In line with the DT architectures outlined by Tao et al. (2019) and Lu et al. (2020), MindSphere is widely utilized for shop floor analytics, production optimization, and predictive maintenance.

The 3DEXPERIENCE Platform from Dassault Systems PLM, manufacturing (DELMIA), simulation (SIMULIA), and systems engineering (CATIA/MBSE) are all integrated into a single virtual twin environment by the 3DEXPERIENCE platform. It reflects the lifecycle-oriented DT approach proposed by Grieves (2002, 2014) and is widely utilized in the automotive, aerospace, and industrial equipment sectors. It supports lifecycle-spanning DTs.

6.2. Open-Source and Research Platforms

Open source platforms are essential for experimentation, prototyping, and scholarly study. They provide extensibility, flexibility, and transparency—essential elements for CDT and agentic AI research.

Eclipse Ditto is a framework for managing digital representations of Internet of Things devices, including state management, real-time synchronization, and communication over REST/MQTT. Semantic DT modeling and interoperability studies make extensive use of it.

FIWARE provides a modular architecture for creating intelligent applications, such as data processing components, IoT agents, and context brokers. Because of its excellent interoperability and open standards, it is frequently utilized in infrastructure and smart city DT research.

Simulation-focused systems (OpenModelica, Gazebo, OpenDT) are widely utilized for virtual commissioning, co-simulation, and physics-based modeling. These platforms are crucial for CDT research since transparent and adaptable architectures are needed for model coevolution, semantic reasoning, and AI-driven adaptation (Liu et al., 2025).

6.3. Platform Capabilities

DT platforms generally offer the following fundamental functions across industrial and research ecosystems:

- Real-time data integration: Sensor and corporate data streams are continuously ingested.
- Modeling and simulation: Data-driven, physics-based, or hybrid models to depict system behavior.
- Analytics and visualization: 3D/VR interfaces, anomaly detection, dashboards, and predictive analytics.
- Interoperability: Using APIs, ontologies, and standardized protocols (such OPC UA, MQTT, and DTDL) to integrate with external systems.
- Cloud integration and scalability: Elastic compute and storage for extensive DT installations.
- Emerging semantic and cognitive layers: context-aware decision making, knowledge graphs, and reasoning based on ontologies (Liu et al., 2025).
- Agentic orchestration (emerging): autonomous planning, LLM-based reasoning, and multi-agent coordination (Hasan & Nguyen, 2026).

The architectural layers outlined in Section 5 are immediately implemented and operationalized by these platform capabilities, especially the transition from fundamental DT architectures to cognitive and agentic DT frameworks (Tao et al., 2019; Lu et al., 2020; Liu et al., 2025).

6.4. Limitations of Current Platforms

Current DT platforms have a number of drawbacks despite tremendous advancements:

- Limited semantic interoperability: The majority of platforms lack ontology-driven reasoning and rely on static schemas.
- Inadequate cognitive abilities: Not many platforms facilitate learning, perception, or semantic comprehension.
- Early-stage agentic AI integration: New safety and governance layers are needed for LLM-based reasoning and autonomous planning (Hasan & Nguyen, 2026).
- Difficulties in coordinating systems: There is still little multi-DT orchestration across cities, factories, or energy networks (Tao et al., 2019; Lu et al., 2020).
- Data governance and ownership issues: Data provenance, access control, and ownership are still unclear, as noted by Bazaz et al. (2019).

These drawbacks emphasize the necessity of next-generation DT platforms that can support multi-agent, autonomous, and cognitive DT ecosystems.

7. Case Studies

Several industries have implemented digital twin (DT) technologies, showcasing their adaptability and influence in practical settings. The following case studies show how DTs—and increasingly Cognitive Digital Twins (CDTs) and agentic AI-enhanced DTs—are used in energy systems, smart cities, manufacturing, and healthcare. These illustrations support the technological and architectural concepts covered in Sections 3-6.

7.1. Manufacturing: Predictive maintenance and operational intelligence

DTs are extensively utilized in the industrial industry for lifecycle management, process optimization, and predictive maintenance. General Electric's Digital Twin program for jet engines, which continuously streams sensor data from turbines into high fidelity virtual models to track performance, identify anomalies, and forecast component degradation, is a well-known example (Fuller et al., 2020; Rasheed et al., 2020).

These DTs make use of:

- Telemetry in real time
- Hybrid models based on physics and data
- Anomaly detection and predictive analytics
- Algorithms for maintenance optimization

This strategy has increased asset reliability and decreased unscheduled downtime. The application of CDTs to integrate context-aware reasoning, adaptive learning, and multi-agent coordination for scheduling and resource allocation is growing as manufacturing systems become more sophisticated (Liu et al., 2025; Hasan & Nguyen, 2026).

7.2. Healthcare: Personalized and simulation-based medicine

DTs facilitate patient-specific modeling in the medical field to aid in clinical decision making, diagnosis, and treatment planning. For instance, scientists have created digital twins of the human heart that mimic hemodynamics and cardiac electrophysiology in various physiological settings (Barricelli et al., 2019).

These DTs allow clinicians to:

- Test treatment strategies virtually
- Predict patient-specific responses
- Optimize surgical planning
- Reduce risk in complex interventions

As CDTs emerge, healthcare DTs increasingly incorporate semantic reasoning, contextual interpretation of medical data, and adaptive learning, enabling more robust and personalized clinical support (Liu et al., 2025).

7.3. Smart cities: Urban planning and infrastructure optimization

Smart cities use DTs to model and optimize complex urban environments. Cities such as Singapore have implemented large-scale urban Digital Twins to optimize planning, mobility, and resource management, leveraging integrated data from transportation, energy, and environmental systems (Batty, 2018; Fuller et al., 2020).
Urban DTs support:

- Traffic flow optimization
- Energy demand forecasting
- Environmental monitoring
- Infrastructure resilience analysis
- Emergency response planning

As cities evolve into interconnected cyber-physical ecosystems, CDTs and agentic DTs enable multi-system coordination, autonomous scenario evaluation, and cross-domain optimization, aligning with the system-of-systems perspective described by Tao et al. (2019) and Lu et al. (2020).

7.4. Energy systems: Grid intelligence and renewable integration

Power grids, distributed energy resources, and renewable energy systems are all monitored and optimized by DTs in the energy sector. DTs assist:

- Grid monitoring in real time
- Forecasting loads
- Identification of faults
- Integration of renewable energy
- Coordination of distributed energy

According to Rasheed et al. (2020), DTs enhance grid stability and operational effectiveness by fusing real-time data with physics-based models. Autonomous grid balancing, multiagent negotiation, and resilience optimization are made possible by emerging agentic AI-enhanced DTs, especially in decentralized energy networks (Hasan & Nguyen, 2026).

7.5. Cross-case synthesis

Several recurring trends appear in every domain:

- The synchronization of digital and physical systems in real time
- Data-driven and physics-based hybrid modeling
- AI-enhanced analytics for optimization and forecasting
- CDTs are being used more frequently for reasoning and adaption
- The development of agentic DTs for independent decision-making
- The increasing demand for semantic integration and interoperability

The unified DT–CDT–agentic AI model presented in Section 3 is validated by these case studies, which show how foundational, cognitive, and agentic capabilities appear in real-world cyber–physical settings.

8. Discussion

This paper's analysis shows how Digital Twins (DTs), Cognitive Digital Twins (CDTs), and agentic AI-enhanced DTs can revolutionize manufacturing, healthcare, smart cities, and energy systems. To fully fulfill the concept of intelligent, autonomous, and interoperable cyber-physical ecosystems, however, a number of crucial issues must be resolved.

8.1. Interoperability and integration challenges

The integration of disparate systems is a recurring obstacle to the widespread implementation of DT. Different formats, semantics, and communication protocols are used by DTs to obtain data from a variety of sources, including sensors, enterprise systems, simulation models, and external services. The scale and dependability of DT ecosystems are constrained by the lack of common information models and bidirectional synchronization methods, as noted by Tao et al. (2019) and Kritzinger et al. (2018).

These difficulties are exacerbated by CDTs, which make semantic interoperability, ontology alignment, and knowledge representation crucial for facilitating learning, reasoning, and context-aware adaptation (Liu et al., 2025). CDT cognition is still fragmented and domain-specific in the absence of uniform semantic frameworks.

8.2. Privacy, security, and ethical considerations

There are serious privacy and security hazards associated with using real-time, high-resolution data. Sensitive patient data privacy is crucial in fields like healthcare

(Barricelli et al., 2019). Because constant data transmission increases vulnerability to cyberattacks, industrial and urban DTs have similar concerns (Fuller et al., 2020).

As DTs progress toward autonomy, ethical issues become more crucial:

- Decision accountability: When an autonomous DT makes a bad or damaging choice, who is at fault?
- Explainability and transparency: To preserve confidence, CDTs and agentic DTs must offer understandable justification.
- Fairness and bias: AI-driven DTs may inherit biases from training data, which could have an impact on the quality of their decisions.
- Human oversight: To guarantee safe human in the loop or human on the loop control, agentic DTs need governance frameworks (Hasan & Nguyen, 2026).

These problems highlight the necessity of strong ethical standards, legal frameworks, and governance.

8.3 Technological limitations

There are still a number of technological constraints despite developments in IoT, cloud computing, and AI:

- Data latency and bandwidth limitations: In large-scale or safety-critical environments, real-time synchronization across distributed systems is still difficult (Shi et al., 2016).
- Computational complexity: Cognitive reasoning, multiagent coordination, and high fidelity simulations all demand substantial computational resources (Rasheed et al., 2020).
- Model fidelity and coevolution: When physical systems change more quickly than their digital counterparts, it becomes challenging to maintain accurate, continually updated models (Lu et al., 2020).
- Platform limitations: According to Liu et al. (2025) and Hasan & Nguyen (2026), current DT platforms do not have native support for semantic reasoning, cognitive layering, or agentic orchestration.

These drawbacks emphasize the necessity of next-generation DT platforms that can facilitate autonomy, cognition, and system-of-system coordination.

8.4. Future research directions

Several research directions emerge, building on the restrictions mentioned above and the gaps noted in Section 3.7:

1. Standardization of DT frameworks: To enable interoperability across domains, standardized ontologies, communication protocols, and reference architectures are essential (Tao et al., 2019; Bazaz et al., 2019).
2. Integration with upcoming technologies: In DT ecosystems, technologies like edge AI, blockchain, and federated learning can improve data integrity, privacy, and distributed intelligence (Rasheed et al., 2020).

3. Development of autonomous and agentic DT systems: As autonomous planning, multi-agent coordination, and LLM-based reasoning become more prevalent in DTs, new designs and safety measures will be needed (Hasan & Nguyen, 2026).
4. Ethical, societal, and governance frameworks: Research must address transparency, accountability, justice, and human oversight since DTs have an impact on decisions in energy, healthcare, and transportation.
5. Cognitive and semantic enrichment of DTs: CDTs' ability to reason, learn, and adapt depends on developments in knowledge graphs, semantic modeling, and cognitive architectures (Liu et al., 2025).

8.5. Synthesis

Overall, the conversation shows that although DTs have reached a considerable level of maturity, advances in interoperability, semantics, governance, and platform design are necessary to move toward cognitive, autonomous, and agentic DT ecosystems. Realizing the full potential of DTs in complex, dynamic, and networked contexts will require addressing these issues.

9. Conclusions

From static digital models, digital twins (DTs) have developed into dynamic, data-driven, and increasingly sophisticated cyber-physical entities. The development of Cognitive Digital Twins (CDTs) and agentic AI-enhanced DTs has been documented in this study across foundational definitions, architectural models, enabling technologies, platforms, and real-world applications.

According to the report, DTs are increasingly essential for real-time monitoring, predictive analytics, and lifecycle optimization in manufacturing, healthcare, smart cities, and energy systems. While agentic AI adds autonomous planning, multi-agent coordination, and natural language interaction, CDTs expand these capabilities by adding perception, semantic comprehension, reasoning, and learning. When taken as a whole, these advancements indicate that DTs will become active, adaptable, and independent actors in intricate cyber-physical ecosystems rather than merely passive digital mirrors.

But in order to fully achieve this goal, the study also identifies enduring issues that need to be resolved. Cross-platform integration is hampered by diverse data formats, communication protocols, and semantic models, making interoperability a significant obstacle. As DTs handle sensitive data and make decisions that have practical ramifications, privacy, security, and ethical considerations become more crucial. Large-scale deployments are still hampered by technological constraints like latency, processing complexity, and model accuracy. Despite their strength, current DT platforms do not have native support for agentic orchestration, semantic interoperability, or cognitive reasoning.

Coordinated developments in distributed intelligence, standardization, semantic modeling, and governance frameworks are needed to address these issues. Future studies should concentrate on creating unified DT architectures, including cutting-edge technologies like edge AI and blockchain, and creating moral standards for autonomous DT systems. The shift to CDTs and agentic DTs also necessitates new approaches for system of systems coordination, human in the loop supervision, and safe LLM grounding.

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