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A Survey of Cognitive Digital Twin and the Potential Use of LLMs

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Abstract

Digital Twin (DT) technology is pivotal for Industry 4.0 and intelligent manufacturing, enabling real-time monitoring and high-fidelity digital representations of physical entities. However, traditional DTs face challenges in autonomous decision-making, environmental adaptability, reasoning abilities, and functionality when applied to dynamic, complex scenarios. Cognitive Digital Twin (CDT) have emerged to address these challenges, offering enhanced cognitive capabilities over conventional DT. Concurrently, advancements in Large Language Models (LLMs) present new opportunities to augment CDT through advanced semantic understanding and contextual analysis. This paper systematically reviews CDT development, elucidating their core cognitive mechanisms and assessing the impact of LLMs on their future evolution. By analyzing existing literature, we outline the developmental context, core concepts, key characteristics, and framework construction methods of CDT. We identify significant research gaps, notably the lack of systematic articulation of CDT's cognitive mechanisms and the underexplored potential of integrating LLMs to enhance their cognitive functions. Our contributions are threefold: (1) providing the research progress of CDT, (2) exploring the application potential of LLMs in enhancing CDT's cognitive capabilities, and (3) identifying key challenges in applying LLMs within manufacturing environments. Future research should focus on developing comprehensive integration frameworks for LLMs and CDT and improving the reliability and security of CDT systems. By advancing CDT technology and integrating LLM capabilities, this study hopes to support the realization of Industry 4.0.

Keywords:
Cognitive Digital Twin (CDT); Large Language Models (LLMs); Industry 4.0; Smart Manufacturing; Artificial Intelligence

1. Introduction

Digital Twin (DT) constitutes a key enabling technology for Industry 4.0 and intelligent manufacturing, thereby facilitating the digital transformation of manufacturing industries [2]. DT technology enables real-time monitoring of physical entities' states, behaviours, and performance characteristics through high-precision digital representation. According to market research, the global DT market is projected to grow from \$3.8 billion in 2021 to \$9.6 billion by 2026, demonstrating a compound annual growth rate of 20.2% [1]. While DT technology has been widely implemented across various sectors, including manufacturing, healthcare, and construction engineering, it exhibits several fundamental challenges. These constraints encompass restricted autonomous decision-making capabilities, insufficient environmental adaptability, limited reasoning abilities, and singular functionality, which collectively impede its application in complex scenarios.

In response to these challenges, CDT emerged as an advanced iteration of DT technology, first conceptualized by Adl [5] in 2016. CDT constitutes an intelligent digital mapping system of physical entities, encompassing all phases and subsystems throughout their lifecycle [10]. In comparison with traditional DT [8], CDT demonstrates significant advantages through (1) enhanced autonomous decision-making capabilities, (2) sophisticated environmental perception abilities, (3) advanced deep learning and reasoning capabilities, and (4) comprehensive multi-functional integration. These distinctive char-

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acteristics enable CDT to exhibit superior adaptability and intelligence in practical applications.

Moreover, recent advances in Large Language Models (LLMs) have yielded breakthrough progress in natural language processing [46], thereby providing novel technical support for enhancing CDT's cognitive capabilities. LLMs' sophisticated semantic understanding and contextual analysis abilities can significantly enhance CDT's performance across multiple domains, particularly in knowledge reasoning, decision support, and human-computer interaction.

Despite significant advances in both CDT and LLMs, significant research gaps remain in current studies. Primarily, the core cognitive mechanisms of CDT have not been systematically articulated [2], [8] , reflecting fundamental limitations in our understanding of developing digital systems with genuine cognitive capabilities. Furthermore, the potential of LLMs [56] in enhancing CDT's cognitive functions remains largely unexplored, representing a substantial challenge in the integration and collaborative innovation of artificial intelligence technologies. Addressing these gaps is essential not only for advancing CDT technology but also for facilitating the evolution of intelligent systems in industrial applications and smart city development.

Within this context, this study aims to investigate current research advances in CDT and evaluate the impact of LLMs on their future development. The specific objectives are twofold:

- To systematically elucidate the core cognitive mechanisms of CDT, thereby advancing the understanding of digital systems' cognitive capabilities.
- To explore the potential and methodologies of LLMs in enhancing CDT's cognitive functions, thus establishing frameworks for future development.

The significance of this research is threefold: First, it provides a comprehensive synthesis of recent CDT developments. Second, it offers the first systematic analysis of LLMs' impact on CDT evolution. Third, it establishes a theoretical framework for integrating LLMs capabilities into CDT systems. These contributions collectively advance CDT technology while providing novel perspectives and methodologies for related research and applications.

The structure of this paper is organized as follows: Section 2 presents the research methodology and analytical framework. Section 3 examines the evolution of CDT, encompassing their theoretical foundations, characteristic features, comparative advantages, and current research progress. Section 4 analyzes the impact of LLMs on CDT, discussing LLMs fundamentals, future development trajectories and research directions, followed by comprehensive conclusions in Section 5.

2. Research Method

This study adopts the Narrative Literature Review (NLR) method to systematically analyse the Cognitive Digital Twin (CDT) field. Since the concept of CDT was proposed, different researchers have provided various interpretations and designs, leading to a relatively fragmented research landscape. However, no systematic review currently integrates these studies, making it difficult for researchers to comprehensively grasp the developmental trajectory, key research themes, and future trends of CDT. To address this research gap, this study employs the NLR method to integrate diverse research findings.

We searched three major academic databases to ensure comprehensive literature retrieval: Web of Science, Scopus, and Semantic Scholar. The search keywords included "Cognitive Digital Twin," "Cognitive Digital Twins," "CDT," "CDTs," "Cognitive Twins," and "Cognitive Twin," covering paper titles, abstracts, and keywords. The initial search was completed on October 18, 2024, yielding 196 English-language publications (see Table 1 for details).

To enhance the transparency and reliability of the screening process, we established clear inclusion and exclusion criteria. The inclusion criteria consisted of peer-reviewed English-language papers that are directly related to Cognitive Digital Twins. Exclusion criteria included irrelevant publications, informal documents (such as white papers and preprints), and conference abstracts without full-text availability. Given the rapid development of CDT research, ensuring that the review is comprehensive and targeted is crucial. Therefore, we adopted a systematic three-step screening process, including cross-database deduplication, relevance screening, and supplementary retrieval through citation analysis. After the three-stage screening, we identified 77 core papers for in-depth analysis. The screening process involved cross-database deduplication, relevance assessment based on titles and abstracts, and supplementary retrieval through key paper references. The temporal distribution of the selected literature is shown in Figure. 1, while the distribution of major research areas is illustrated in Figure. 2.

Despite this study's rigorous literature retrieval strategy, certain biases may still exist. Selection bias is inherent in NLR studies, as it involves subjective selection criteria. To mitigate this risk, we conducted cross-checking among team members during the screening process to ensure consistency. Database bias may arise because this study primarily relies on Web of Science, Scopus, and Semantic Scholar, potentially leading to the omission of studies not indexed in these databases. To reduce this impact, we supplemented the review with forward and backward citation tracking and included key industry reports to cover critical research findings in the CDT field as comprehensively as possible.

Additionally, language bias may be present, as this study only includes English-language literature, potentially overlooking relevant studies in other languages. However, considering that English is the primary publication language for CDT research, the impact of this limitation is expected to be minimal. Through these measures, we strive to ensure this study's systematicity, transparency, and reproducibility, providing an accurate and in-depth review of the current state of research in the CDT field.

Table 1. Research Methodology.

Searching Index	Specific Content
Database	Web of Science, Scopus and semantic scholar
Article Types	Scientific papers published in journals and conference
Search String	”Cognitive Digital Twin”, ”Cognitive Digital Twins”, ”CDT”, ”CDTs”, ”Cognitive Twins” and ”Cognitive Twin”
Search Scope	Topic (Search title, abstract, author keywords, and keywords plus)
Language Limit	English
Search Date	2024-10-18
Number of Result	196

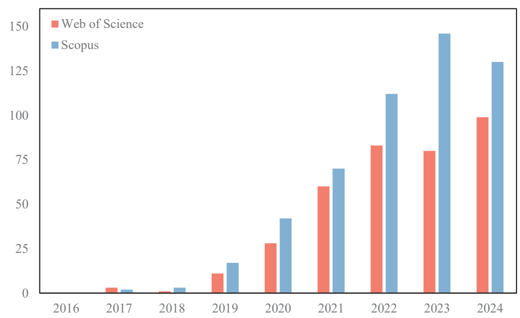

Figure 1. Number for CDT Papers Published from Scopus, and Web of Science between 2016 and 2024.

3. CDT Research Progress

3.1. Development of CDT Concept

DT is widely recognized as a key technology that is enabling intelligent manufacturing. However, traditional DT systems exhibit several challenges: they lack autonomous perception, analysis, and adaptation capabilities in dynamic and uncertain complex environments; they are unable to perform self-learning and self-design; and their functional design heavily relies on predefined engineering specifications. While some studies have attempted to construct intelligent manufacturing systems through technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and big data analytics, these systems primarily focus on building real-time data-driven automated production optimization systems, demonstrating insufficient cognitive intelligence.

To overcome these technological bottlenecks, academia has proposed various solutions to endow manufacturing processes with cognitive functions. Among these, cognitive robotic units [25] leverage deep learning and reinforcement learning to achieve intelligent decision-making for individual production units, though they struggle with system-level coordination. Cognitive operators [21] enhance human decision-making through knowledge graphs and expert systems but remain overly dependent on human intervention. Based on behavioural imitation learning, cognitive clones [35] replicate expert decision patterns but face generalization challenges in novel scenarios. Cognitive modelling [37] proposes formal frameworks for expressing cognitive processes but remains theoretical and difficult to apply in complex manufacturing contexts. In contrast, CDT, as a cognitively enhanced version of DT, systematically simulates human cognitive processes, enabling not only autonomous decision-making but also system-level human-machine collaborative interaction, offering an innovative approach to addressing these technological gaps.

The development of CDT has undergone three main stages (see Table 2): Conceptual Introduction (2016-2018), Theoretical Development (2019-2022), and Technology Integration (2023-present). In 2016, CDT was first defined as a digital representation, enhancement, and intelligent companion of physical twins [5], emphasizing its characteristics as a highly connected distributed cognitive system. This definition highlighted that CDT is not merely an extension of DT but, more importantly, possesses ”mind transfer and evolution” capabilities, meaning its knowledge and experience can persist and evolve even after the physical twin’s lifecycle ends. In 2017, IBM’s Fariz Saracevic deepened the CDT concept from the perspective of artificial intelligence and cognitive computing, proposing a cognitive reasoning framework based on sensor networks and multi-source real-time data, emphasizing the importance of adaptive capabilities in enhancing autonomous decision-making levels.

During the theoretical development period (2019-2022), researchers further enriched the connotation of CDT, defining it as a DT extension with cognitive capabilities [8,26]. This period particularly emphasized the importance of semantic capabilities. Through semantic association and cognitive level analysis, CDT can understand and interpret data changes, combining qualitative assessment with quantitative analysis to enhance understanding and control of process dynamics. Notably, CDT definitions exhibited unique characteristics across different application domains. For instance, in industrial facility maintenance, CDT was viewed as an information-driven cognitive digital replica [11], emphasizing personalized information processing and real-time monitoring and prediction capabilities. In systems engineering, CDT was defined as a conceptual framework for managing system complexity and achieving integrated simulation [22], highlighting the importance of semantic modelling and integrated simulation.

During the technology integration period (2023-present), CDT definitions have become more focused on practicality and implementability. In 2023, researchers introduced human-machine collaborative decision-making functionality, enabling CDT to assist human decision-making, particularly in rare or critical situations, ensuring system safety and effectiveness through operator collaboration.

Based on this historical analysis, this paper defines CDT as an advanced form of DT with cognitive capabilities, able to perceive environments, understand contexts, perform reasoning

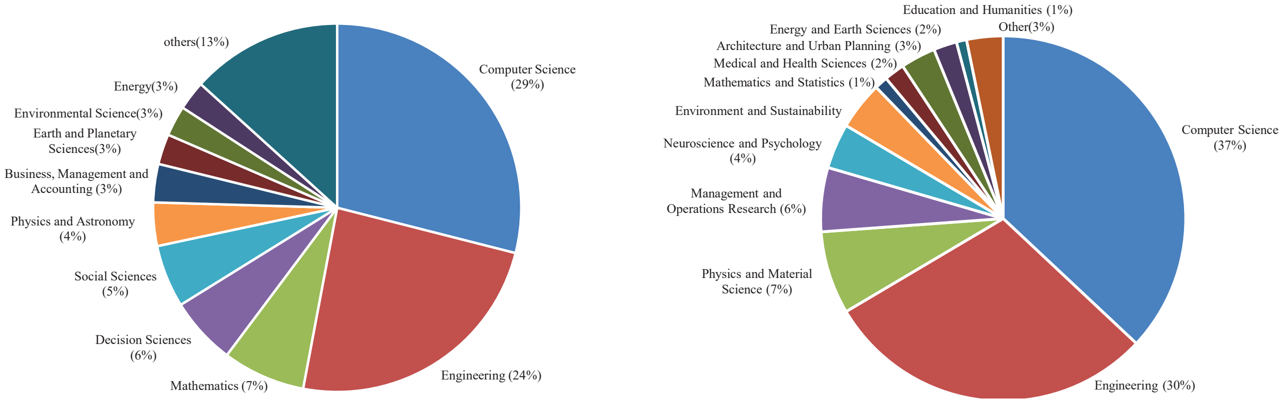

Figure 2. Number of CDT publications by field between 2016 and 2024. The first image is from Scopus and the second is from Web of Science.

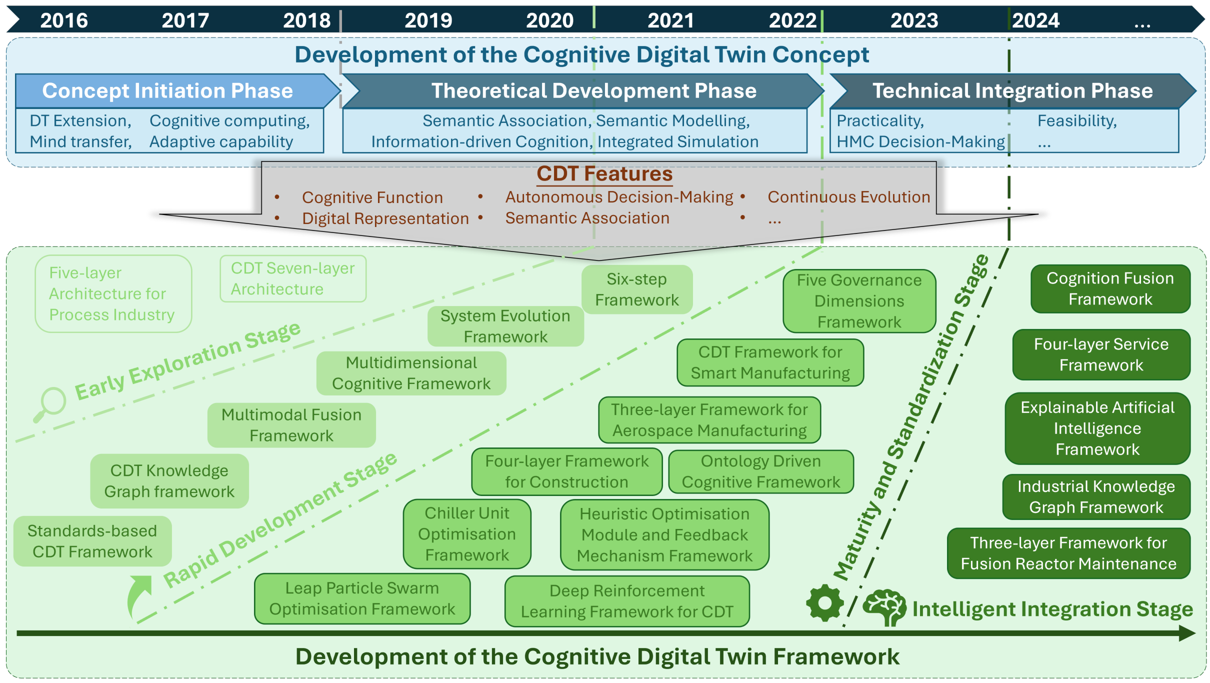

Figure 3. The development of CDT.

and decision-making, and continuously learn and optimize like humans. Compared to traditional DT, CDT's core characteristics lie in its cognitive capability implementation mechanisms, primarily including:

- Perception and Understanding Mechanism: Constructing environmental, cognitive models through continuous learning of multi-source information (sensor data, operation data, maintenance data, etc.)
- Knowledge Representation and Reasoning Mechanism: Building expert knowledge bases based on ontologies to achieve formalized knowledge expression and reasoning
- Learning and Optimization Mechanism: Achieving model self-adjustment through deep learning and generating dynamic optimization strategies through reinforcement learning
- Cognitive Closed-loop Mechanism: Continuously optimizing cognitive models through feedback iteration to enhance system comprehension and decision-making capabilities

These cognitive mechanisms enable CDT to perform autonomous analysis and decision-making in complex environments. Practice has shown that this cognitive enhancement approach has demonstrated significant value across multiple domains. Currently, CDT applications have expanded from manufacturing to architecture [24] [26], drone operations, energy [27], transportation [28], fluid dynamics [29], brain-computer interfaces [30], and healthcare [40]. In these applications, CDT

Table 2. Definition and Feature of CDT.

Paper	Time	Definition	Feature
[5]	2016	The Cognitive Digital Twin is a digital representation, augmentation and intelligent companion of its physical Twin as a whole, including its subsystems and across all of its life cycles and evolution phases	Highly interconnected distributed cognitive systems; Digital representation of PT; Achieving cross-domain collaboration between physical and virtual domains; Autonomous decision-making; Continuous learning; Continuous evolution; Adaptation and optimization; Long-term cognition; Mutual collaboration
[14]	2020	An extension of HT (Hybrid Digital Twin) incorporating cognitive features that will enable sensing complex and unpredicted behaviour and reason about dynamic strategies for process optimization, leading to a system that continuously evolves its own digital structure as well as its behaviour. A CT (Cognitive Digital Twin) is thus a hybrid, self-learning, and proactive system that will optimize its own cognitive capabilities over time based on the data it will collect and the experience it will gain. A CT will find new answers to emerging questions by combining expert knowledge with the power of HT. A CT will thus achieve synergy between the HT and the expert and problem-solving knowledge.	Digital representation; Cognitive capabilities; Autonomous decision-making; Semantic association; Continuous evolution; Human-machine collaborative decision-making;
[17]	2020	These are twins with the highest level of intelligence that can replicate human cognitive processes and execute conscious actions autonomously, with minimal or no human intervention. The following sections address the design and features of such twins.	Digital representation; Cognitive capabilities; Autonomous decision-making; Semantic association; Continuous evolution; Adaptation and optimization; Knowledge acquisition and sharing; Intelligent agents
[16]	2021	Cognitive digital twin are an extension of existing digital twin with additional capabilities of communication, analytics, and intelligence in three layers: i) access, ii) analytics, and iii) cognition.	Digital representation; cognitive capabilities; autonomous decision-making; semantic association; continuous evolution
[7]	2022	Cognitive Digital Twin (CDT) is a digital representation of a physical system that is augmented with certain cognitive capabilities and support to execute autonomous activities; comprises a set of semantically interlinked digital models related to different lifecycle phases of the physical system including its subsystems and components; and evolves continuously with the physical system across the entire lifecycle.	Digital representation; cognitive capabilities; lifecycle coverage; adaptation and optimization; continuous evolution
[22]	2022	A cognitive twin (CT) concept is proposed to encompass complexity management of SoSs (System of Systems) and their DTs, to implement integrated simulation, and to support decision-making for the SoS operations.	Digital representation; cognitive capabilities; semantic interconnection; autonomous decision-making; standardization;
[8]	2023	CDT is an extension of the existing DT by which it can perform cognitive functions.	Digital representation, cognitive capabilities
[10]	2024	A digital representation of a physical system that is augmented with certain cognitive capabilities and supports execute autonomous activities; comprises a set of semantically interlinked digital models related to different lifecycle phases of the physical system including its subsystems and components; and evolves continuously with the physical system across the entire lifecycle.	Semantic interconnection; digital representation; cognitive capabilities; adaptation and optimization; continuous evolution

effectively supports complex system management and control by implementing cognitive functions such as perception, attention, memory, reasoning, problem-solving, and learning.

Looking forward, CDT will further enhance its cognitive capabilities through deep integration with emerging technologies such as LLMs and digital relatives [45]. Particularly noteworthy is that CDT's development goal is not to replace humans but to establish new human-machine collaboration models through complementary cognitive capabilities. Under this model, CDT enables humans to focus on higher-level decision-making by providing intelligent data analysis and decision support, freeing them from repetitive tasks [21]. To deeply understand CDT's essence and lay the foundation for its integration with emerging technologies, the next section will systematically analyze and summarize the key features required for CDT, which will guide the subsequent design of CDT frameworks.

3.2. CDT Feature

Based on a systematic analysis of CDT definitions presented in Table 2, this study identifies the distinctive characteristics of CDT that differentiate it from traditional DT across four key dimensions: cognitive capabilities, system properties, standardization features, and evolutionary characteristics. This classification framework reflects both the essential attributes of CDT and its developmental trajectory.

The cognitive capability dimension represents the core features of CDT. Specifically, at the fundamental level, CDT possesses cognitive functions, including perception, attention, memory, reasoning, and learning, which simulate basic human cognitive processes. Furthermore, at an advanced level, CDT demonstrates complex cognitive abilities such as problem-solving, decision-making, and knowledge transfer, enabling it to address complex operational scenarios.

From the system properties perspective, CDT exhibits distinctive autonomy, adaptability, and semantic interconnection properties. Its autonomy is manifested in its capability to independently execute the closed-loop process of perception-analysis-decision-execution. Additionally, adaptability is reflected in its capability for dynamic adaptation to environmental changes and task requirements. Moreover, the semantic interconnection feature facilitates cross-level and cross-domain information integration and knowledge representation.

Standardization features constitute the foundation for CDT's scalable application. This encompasses three critical levels: unified data formats and interface specifications at the data level, cognitive model expression and evaluation standards at the model level, and service invocation and state synchronization specifications at the functional level. Notably, the establishment of these standards is crucial for achieving cross-platform collaboration and ecosystem development of CDT.

The evolutionary characteristics emphasize CDT's dynamic developmental nature. This evolution manifests in three aspects: progressive advancement of cognitive capabilities, dynamic updating of knowledge systems, and adaptive adjustment of system structures. Through iterative learning and experience accumulation, CDT can optimize its cognitive level, enrich its knowledge base, and refine its functional structure.

It is imperative to emphasize that these characteristics of CDT form an organic whole. Basic cognitive capabilities provide foundational support for advanced cognitive functions, while the implementation of autonomy and adaptability relies on cognitive capabilities. The evolutionary characteristics ensure continuous improvement in overall system performance. This synergistic interaction among features establishes CDT as an advanced form of traditional DT at the cognitive level.

This comprehensive analysis of these characteristics provides a theoretical foundation for understanding the essence of CDT and establishes the groundwork for subsequent discussions on implementation frameworks. The following section will detail the specific implementation approaches for these features.

3.3. Development of CDT Framework

The preceding section introduced the key characteristics of CDT: digital representation, cognitive capabilities, adaptation and optimization, autonomous decision-making, continuous evolution, and standardization. Researchers have proposed various frameworks to implement these core features of CDT. These frameworks reflect the unique cognitive requirements across different domains while demonstrating the evolutionary trends in CDT framework design. This section systematically analyzes these frameworks' design approaches, characteristics, and application scenarios.

The development of CDT frameworks has evolved from simple to complex, from singular to multidimensional approaches. Through analysis of various CDT frameworks proposed between 2016 and 2024, clear development trends and characteristics emerge.

3.3.1. Early Exploration Stage (2016-2020)

Early CDT frameworks were exemplified by Adl's seven-layer architecture [5], which pioneered the systematic integration of cognitive capabilities into the DT domain. Its core feature was a modular design encompassing components such as core, anchor, agent, robot, perspective, self-management, and defence systems, establishing the foundation for subsequent CDT framework designs. By 2020, CDT frameworks began emphasizing data processing and service management, as evidenced by the five-layer architecture proposed for process industries [14], which highlighted data-driven and service-oriented characteristics.

3.3.2. Rapid Development Stage (2021-2022)

This period's framework design exhibited several significant characteristics. First, it demonstrated a trend balancing domain specialization with generality, spanning from architecture [12] to supply chain [13]. These domain-specific frameworks maintained CDT core features while emphasizing sector-specific requirements, particularly exemplified by the six-step supply chain framework that embodied autonomy and adaptability through a complete process. Second, cognitive capability implementation became more systematic, with 2022 frameworks generally adopting layered designs. For instance, the multidimensional cognitive framework based on the OAR model [31] divided cognitive processes into unit, scenario, and system levels, each incorporating state cognition, optimization decision-making, and knowledge learning dimensions. Third, evolutionary features significantly strengthened, with framework designs increasingly emphasizing knowledge learning and capability evolution. Examples include knowledge graph integration for knowledge accumulation [18], multimodal fusion for capability enhancement [19], and closed-loop feedback for system evolution [31], reflecting CDT's transformation from static mapping to dynamic evolution. Finally, framework designs began to emphasize the construction of entire CDT ecosystems, such as frameworks based on the ISO23247 international standard [18], considering both individual CDT functionality and inter-CDT interoperability and collaboration.

3.3.3. Maturation and Integration Stage (2023)

2023 marked a breakthrough in CDT framework research, with designs becoming more systematic and standardized. Frameworks during this period exhibited four distinctive characteristics.

First, framework designs increasingly emphasized governance systems and standard specifications. The supply chain CDT framework proposed by [23] innovatively introduced five governance dimensions: sustainability, business governance, data governance, AI model governance, and regulatory standards. This framework addressed technical implementation and emphasized CDT's practicality and sustainability in actual applications. Simultaneously, the intelligent manufacturing CDT framework [8], referencing ISO23247 standards, provided a new paradigm for CDT standardization through the organic combination of requirement, service, and cognitive sub-entities.

Second, cognitive capability implementation became more systematic and hierarchical. The three-layer framework (physical, virtual, and cognitive layer) proposed for aerospace manufacturing [42] subdivided cognitive processes into object perception, situation awareness, and impact prediction sub-layers. The ontology-driven cognitive module introduced in robot disassembly [39] achieved unified knowledge representation and reasoning capabilities through storage and updating conceptual knowledge and disassembly experience.

Third, frameworks' adaptive and evolutionary features deepened. The framework proposed for production manufacturing [38] achieved dynamic feature optimization and fault prediction adjustment through heuristic optimization modules and feedback mechanisms. The DT engine and decision engine integrated into chiller optimization [44] realized system continuous optimization and evolution through multi-agent reinforcement learning (MARL).

Fourth, diverse application scenarios drove framework design innovation. The four-layer framework (observation-execution layer, data layer, reasoning layer, simulation layer) proposed in the construction field [36] emphasized the importance of semantic information reasoning and model simulation. Notably, the framework by [8] achieved organic unity of demand-driven, service-oriented, and cognitive enhancement through Cognitive Digital Twin Core Entity (CDTCE) design, providing new approaches for cross-system collaboration.

3.3.4. Intelligent Integration Stage (2024)

The year 2024 marks CDT frameworks' entry into a new stage of intelligent integration, with framework designs exhibiting three significant characteristics. Framework structures have evolved from traditional hierarchical designs toward multidimensional integration, exemplified by the cognitive fusion framework [32], innovatively proposing a three-dimensional integration architecture of the "physical world-virtual world-cognitive world," achieving intelligent interaction across space and time. The "physical-virtual-cognitive-data" four-dimensional space framework introduced in multi-robot collaboration [34] further strengthened multidimensional coordination.

Intelligence levels have significantly improved. The integration of explainable artificial intelligence (XAI) in process chain anomaly detection [43] and the application of industrial knowledge graphs for intelligent reasoning [41] mark CDT's advancement toward higher-level cognitive capabilities. The three-layer framework proposed for nuclear fusion reactor maintenance [33], through the coordination of the cognitive layer, DT integration layer, and intelligent decision layer, achieved autonomous decision-making in complex environments.

Application domains continue to expand from traditional manufacturing to emerging fields such as robot collaboration and cognitive fusion, upgrading framework functions from basic monitoring and optimization to emphasizing knowledge representation and cognitive reasoning. The five-layer service framework proposed by [10] provides standardized technical support for CDT's broad application.

3.4. Summary, Challenges and Solutions

This section has systematically reviewed the development trajectory, core characteristics, and research progress of CDT. Through comprehensive analysis, we can observe that CDT, an advanced form of DT technology, is undergoing rapid development from concept proposal to technology integration. Based on the literature analysis, several key conclusions emerge.

The conceptualization of CDT has evolved significantly from a singular to a multidimensional construct. What began as a simple definition emphasizing digital representation and intelligent companionship has developed into a comprehensive system encompassing cognitive capabilities, semantic interconnection, and continuous evolution. This enrichment in definition reflects the academic community's deepening understanding of CDT's essential characteristics.

The characteristic framework of CDT has matured into a relatively complete system. The four dimensions - cognitive capabilities, system properties, standardization features, and evolutionary characteristics - establish CDT's core advantages over traditional DT. These characteristics' implementation mechanisms and interrelationships provide theoretical guidance for CDT's practical applications. The fundamental technologies commonly employed to realize cognitive capabilities in CDT include semantic technologies, ontology modelling, and knowledge graphs. Among these, semantic technology functions as the core for data analysis, induction, and learning, as demonstrated in numerous studies [7] [15] [9]. Ontology modelling provides critical semantic infrastructure, with standardized ontology modelling ensuring semantic interoperability across different systems [8] [36]. Knowledge graphs facilitate effective semantic association and reasoning frameworks. More critically, integrating heterogeneous data has emerged as a fundamental challenge in implementing these capabilities [16].

The evolution of CDT framework research demonstrates distinct developmental stages, from the early exploration stage's basic frameworks to the rapid development stage's domain specialization, followed by the maturation stage's standardization practices, and finally reaching the current intelligent integration stage's multidimensional innovations. This progression reflects the continuous advancement and maturation of CDT technology.

However, current CDT research faces several significant challenges. First, the implementation of cognitive capabilities remains heavily dependent on traditional AI technologies (such as LSTM, generative adversarial networks [20], and graph-based methods [41]), resulting in limitations in generalization and interpretability. Moreover, traditional AI algorithms demonstrate specific limitations in processing large-scale, complex, unstructured data, often requiring substantial intervention and annotation from human experts. Third, the standardization and interoperability of CDT frameworks across different domains require strengthening. Fourth, understanding complex linguistic structures, scenarios, and contexts remains insufficient, limiting autonomous decision-making capabilities in complex scenarios.

In response to these challenges, LLMs emerged as a promising cognitive intelligence technology, offering new possibilities for CDT's further development. The robust capabilities of LLMs in natural language understanding, knowledge reasoning, and task adaptation may bring several breakthroughs for CDT. These include:

- enhanced semantic understanding and knowledge representation;
- improved processing of large-scale complex unstructured data and contextual understanding;
- advanced cross-domain knowledge transfer and scenario generalization;
- more natural human-machine collaborative decision-making;
- support for more flexible cognitive framework construction.

Therefore, the next section will systematically explore the deep integration mechanisms between LLMs and CDT, focusing on analyzing specific application methods of LLMs in enhancing CDT's core features, such as perception understanding, knowledge reasoning, and decision planning. This exploration will drive theoretical innovation in CDT and provide new approaches for its practical application across broader domains.

In the context of intelligent manufacturing and Industry 4.0, the industry is transitioning from traditional DT to CDT that provide deep perception, real-time decision-making, and adaptive optimization capabilities. CDT frameworks typically employ key technologies like multi-modal data acquisition, hierarchical semantic knowledge construction, and deep learning to tackle challenges such as heterogeneous data integration, dynamic scheduling, and high-dimensional real-time monitoring. For instance, the object network model utilizing deep convolutional neural networks [55] demonstrate distinct advantages in cognitive functions—such as perception, attention, memory, and reasoning. Additionally, frameworks focusing on lifecycle management and fault prediction integrate sensor networks, IoT, and machine learning for dynamic optimization throughout the entire lifecycle of physical assets. Strategies based on anomaly detection and bottleneck analysis [11] further illustrate the diverse approaches to achieving cognitive depth and adaptability. Overall, CDT exhibit significant potential in intelligent production, human–machine collaboration, and multi-robot coordination, providing robust support for the development of future cognitive manufacturing systems.

4. The impact of LLM and CDT

The emergence of LLMs represents a significant breakthrough in artificial intelligence technology. As deep learning models trained on massive text datasets using the Transformer architecture, LLMs have demonstrated unprecedented potential in cognitive intelligence. This section systematically analyses the six core capabilities of LLMs and their potential applications in enhancing CDT technology.

4.1. LLMs Introduction

Because LLMs are trained using the Transformer framework on large-scale data, they have six core capabilities: knowledge acquisition and representation, natural language understanding and generation, contextual learning, instruction following, step-by-step reasoning, and continuous learning. These capabilities offer new possibilities for enhancing the intelligent characteristics of CDT.

Firstly, LLMs have strong knowledge acquisition and representation abilities. Trained on multi-source heterogeneous datasets containing billions to trillions of words, LLMs have established a vast knowledge reserve. These data sources cover multiple fields, such as web texts, professional literature, news reports, and technical documents. This allows LLMs to quickly understand and process specialized knowledge from different domains, establish cross-domain knowledge associations, and provide context-based knowledge retrieval and application. This capability offers new possibilities for the knowledge representation and management of CDT.

Due to the Transformer architecture and the support of large-scale parameters, LLMs also have excellent natural language understanding and generation capabilities. This enables them to accurately understand complex linguistic structures and semantic relationships, generate fluent natural language responses that fit the context, and adapt to different language styles and professional terminologies. This capability enables more natural and efficient interactions between CDT and humans.

An important feature of LLMs is their strong contextual learning ability (In-Context Learning, ICL) [46]. This ability allows the model to quickly adapt to new tasks through a small number of examples, understand new scenarios without parameter adjustments, and infer task patterns based on examples. Additionally, through instruction fine-tuning, LLMs have obtained excellent instruction-following capabilities, can understand task instructions in natural language form, execute complex multi-step operations, and flexibly switch between different tasks. These features enhance the adaptability of CDT in different application scenarios.

Regarding complex task processing, LLMs have demonstrated strong reasoning capabilities through techniques such as Chain-of-Thought (CoT). This enables the model to decompose complex problems, show the reasoning process, and reach logical conclusions. This ability is significant for enhancing the decision-analysis capabilities of CDT. In addition, LLMs support continuous knowledge updating through techniques such as fine-tuning and Retrieval-Augmented Generation (RAG). This continuous learning ability can help CDT keep knowledge up to date and support its dynamic evolution.

However, when applying LLMs to enhance CDT, we need to address several key challenges. First is knowledge reliability, including the uncertainty of training data quality, the accuracy verification of professional domain knowledge, and the timeliness guarantee of knowledge updates. Second is the limitation of reasoning ability, which requires addressing the consistency of complex reasoning processes, the reliability of cross-domain reasoning, and the explainability of reasoning results. Finally, there are challenges in integrated applications, such as how to achieve effective integration with existing CDT architectures, meet real-time requirements, and optimize resource consumption, which require further research.

By understanding these capabilities and challenges of LLMs, we have a foundation for exploring their deep integration with CDT. The next section will analyze how to use the various capabilities of LLMs to enhance the core cognitive features of CDT, including specific application methods in perception and understanding, knowledge reasoning, and decision planning. This will promote the innovative development of CDT theory and provide new technical paths for its practical application in broader fields.

4.2. The potential application of LLM and CDT combine

Based on the above analysis of the core capabilities of LLMs and the characteristics of CDT, this section systematically explores how LLMs can enhance the cognitive abilities of CDT.

LLMs have made certain progress in DT models, LLMs have advanced DT models in several areas—geometric, mechanistic, behavioural, and rule-based. LLMs generate structured descriptions for data-centric twins in geometric models, with spatial optimization techniques enhancing layout ([52]). In mechanistic models, integrating LLMs with DT and automation deepens system understanding and supports dynamic production planning, automatic parameter configuration, and collaborative robotics ([53]), while virtual feedback and reinforcement learning balance comfort and energy use. For behavioural models, LLMs extract multimodal features and use attention mechanisms to unify semantic mapping of images, text, and video—enabling defect identification ([54]), natural language interaction, and real-time data collection, though challenges remain in handling non-text data and feedback. Lastly, in rule-based models, combining LLMs with retrieval-augmented generation and multi-agent architectures yields natural language explanations and intelligent reasoning for decision-making ([51]), improving interpretability and trust.

However, how to use LLMs to achieve and enhance cognitive abilities of CDT is still in the exploratory stage. Therefore, combining the previous introduction of CDT cognitive abilities and the features of LLMs, this subsection will introduce the potential applications of LLMs in the cognitive abilities of CDT.

Based on the previous description, the six core capabilities of LLMs—natural language understanding and generation, contextual learning, instruction following, step-by-step reasoning, and continuous learning—provide new possibilities for enhancing the cognitive modules of CDT. This enhancement may improve the interpretability and interoperability among CDT, thereby optimizing the overall performance and decision efficiency of CDT models. This section will explore the potential applications of LLMs in enhancing the basic cognitive functions of CDT (including perception, attention, memory, reasoning, and learning) as well as advanced cognitive functions (problem-solving, decision-making, and knowledge transfer).

In terms of perception capabilities, CDT need to transform multi-source heterogeneous data into structured knowledge representations. Taking industrial scenarios as an example, constructing a DT of a robotic arm requires integrating static and dynamic data from multiple sources such as operation manuals, force sensors, and control systems.

However, the structured transformation of these heterogeneous, multi-modal data still faces challenges. Compared with traditional information extraction methods that require a large amount of domain-specific labelled data, LLMs, due to their exposure to massive multi-domain data during the pre-training phase, exhibit stronger domain adaptability and knowledge transfer capabilities. Studies have shown [47] that LLMs demonstrate good potential in handling cross-domain professional text understanding and information extraction tasks.

Regarding attention mechanisms, collecting and classifying information about different entities and domain requirements. In the manufacturing field, LLMs-enhanced attention mechanisms can automatically identify and classify key information to achieve task prioritization. This mechanism not only processes structured data but also extracts key information from unstructured data (such as operation logs, maintenance records, etc.). By analyzing historical data, the system can predict potential problems and adjust resource allocation in advance.

For memory capabilities, memorizing past knowledge and events, that is, mapping structured data into knowledge. In manufacturing, knowledge graphs serve as an important means of knowledge storage, possessing reasoning and flexible semantic query capabilities. However, the construction and maintenance costs of traditional knowledge graphs are high, and real-time data processing efficiency is low. The introduction of LLMs provides new possibilities for the construction and application of knowledge graphs. Studies have shown that LLMs can significantly reduce the construction cost of knowledge graphs and improve construction efficiency and quality [48]. Additionally, LLMs can achieve dynamic updating and real-time reasoning of knowledge, overcoming the limitations of the static characteristics of traditional knowledge graphs.

Reasoning capabilities involve forming logical conclusions based on existing knowledge and experience. Through the Chain-of-Thought (CoT) method, LLMs can simulate human reasoning processes, combining stored knowledge and experience to draw logical conclusions. This capability is particularly important in complex decision-making scenarios such as production line fault diagnosis and product quality prediction. CoT-based reasoning methods, compared with traditional rule-based reasoning systems, have stronger flexibility and accuracy. Learning capabilities involve learning new knowledge and updating memory. Learning ability is one of the most critical parts of cognitive functions. The learning process of traditional CDT systems often relies on a large amount of high-quality labelled data and requires selecting specific algorithms and network structures for different tasks. The emergence of LLMs provides new possibilities for enhancing the learning capabilities of CDT:

- Few-shot learning: Since LLMs have acquired a large amount of domain knowledge during the pre-training phase, they are expected to quickly adapt to new tasks through a small number of examples. This capability may significantly reduce the adaptation cost of CDT systems in new scenarios.
- Continuous learning: LLMs are expected to enable CDT systems to continuously accumulate experience from daily operations and update the knowledge base. This dynamic learning mechanism may overcome the limitations of traditional systems that require periodic retraining.
- Cross-domain learning: The knowledge transfer capability of LLMs may help CDT systems achieve cross-domain knowledge sharing and learning, allowing experiences gained in one domain to assist in solving problems in other domains.
- Interactive learning: Through natural language interaction with operators, LLMs-enhanced CDT systems may achieve a more natural knowledge acquisition and experience accumulation process.

Problem-solving capabilities involve designing corresponding solutions based on logical conclusions given by reasoning and historical experience. LLMs-enhanced CDT exhibit strong problem-solving abilities and are capable of automatically generating solutions based on historical experience and real-time data. In manufacturing scenarios, the system can propose optimized maintenance strategies and solutions by analyzing historical fault data and current equipment status. This capability not only improves the efficiency of problem-solving but also can prevent potential problems from occurring.

Decision-making capabilities involve selecting the best solution based on past experiences and current needs. In the decision-making process, LLMs provide optimal decision recommendations for CDT by comprehensively analyzing historical data, current status, and future predictions. For example, in intelligent factory scenarios, the system can automatically formulate the optimal production plan based on production requirements, equipment status, and resource constraints. This decision support not only considers multiple decision factors but also can adapt to dynamically changing environments.

Knowledge transfer capability refers to the ability to model, predict, and optimize new physical entities or systems using existing DT models or data. LLMs significantly enhance the knowledge transfer capabilities of CDT, enabling them to apply existing experiences to new scenarios. This transfer is not limited to knowledge sharing between similar systems but can also achieve cross-domain knowledge transfer. For example, in intelligent manufacturing, the optimization experience of one production line can be quickly transferred to other similar production lines, significantly reducing the time and cost of system optimization.

In summary, LLMs provide a new technical path for enhancing CDT cognitive abilities. Based on existing research, LLMs exhibit significant potential in enhancing the basic cognitive functions (perception, attention, memory, reasoning, and learning) and advanced cognitive functions (problem-solving, decision-making, and knowledge transfer) of CDT. However, there are still several key challenges in applying LLMs to CDT systems. The primary issue is the reliability of knowledge. The ”hallucination” problem of LLMs in professional domains has not been effectively resolved. Existing methods such as fine-tuning [50] and Retrieval-Augmented Generation (RAG) [49] have their limitations: fine-tuning is prone to overfitting and consumes significant resources; although RAG supports real-time knowledge updates, it may still produce inaccurate outputs when the quality of retrieved content is suboptimal.

Secondly, there are challenges in real-time performance. CDT require real-time data processing, and the inference latency of LLMs may not meet the timeliness requirements of DT in industrial scenarios. Maintaining output quality while ensuring inference speed is an important issue. Additionally, data security and accuracy are critical issues that cannot be ignored. Industrial-grade applications have extremely high requirements for data security and computational accuracy. Although deploying LLMs locally can ensure data security, it also faces a trade-off between performance and effectiveness. Maintaining high accuracy while ensuring data security requires further research.

Finally, there are issues of interpretability and domain adaptation. The complexity of decision-making processes in industrial scenarios requires improving the interpretability and transparency of LLMs, which is crucial for enhancing human-computer collaboration efficiency and user trust. In response to these challenges, future research suggests focusing on the following directions: developing domain-specific knowledge verification mechanisms to reduce the ”hallucination” risks of LLMs in professional domains; exploring lightweight inference optimization schemes to improve the real-time performance of LLMs in industrial scenarios; researching hybrid deployment architectures that balance security and performance; enhancing research on the interpretability of decision-making processes and establishing systematic evaluation frameworks.

Breakthroughs in these research directions will help promote the practical application of LLMs in the CDT field, achieving more efficient and reliable intelligent manufacturing systems. Through continuous innovation and technological optimization, LLMs-enhanced CDT are expected to provide stronger support for the digital transformation of the manufacturing industry. Additionally, it’s worth noting that industrial scenarios often involve multimodal knowledge, including equipment images, operation videos, textual documentation, etc. Therefore, multimodal LLMs present even broader application prospects that deserve further exploration in future research.

5. Conclusion

This paper systematically reviews and summarizes the developmental history, core concepts, key characteristics, and framework construction methods of CDT. Through a comprehensive analysis of existing literature, this study reveals the critical strategic role of CDT in realizing the vision of Industry 4.0. The research indicates that although CDT has significant potential for application, existing studies are still insufficient in exploring its theoretical foundations and practical applications.

The main contributions of this paper are: (1) It systematically outlines the development context of CDT, providing a clear theoretical framework for related research; (2) It deeply explores the application potential of LLMs in enhancing the cognitive functions of CDT, offering new perspectives for CDT’s technological innovation; (3) It identifies the key challenges faced when utilizing LLMs to enhance CDT in a manufacturing environment.

Future research directions should focus on (1) Investigating comprehensive integration frameworks of LLMs and CDT, (2) Developing CDT solutions tailored to specific manufacturing scenarios, and (3) Studying methods to improve the reliability and security of CDT systems. These studies are of significant theoretical and practical importance for advancing the realization of Industry 4.0.

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