

The Synergy of Cyber-Physical Systems and Digital Twins in Enabling Industry 4.0

Arvin Shadravan

Wm Michael Barnes '64 Department of Industrial & Systems Engineering
Texas A&M University
College Station, Texas, USA
arvinshadravan@tamu.edu

Zhongyuan Li

Department of Multidisciplinary Engineering
Texas A&M University
College Station, Texas, USA
thomasli0510@tamu.edu

Hamid R. Parsaei

Wm Michael Barnes '64 Department of Industrial & Systems Engineering
Texas A&M University
College Station, Texas, USA
hamid.parsaei@tamu.edu

Abstract

Industry 4.0 is on the path to becoming the common language of global manufacturing by combining existing and upcoming technology to address modern production challenges. Its successful implementation, however, depends on developing common industry standards, which necessitates worldwide collaboration and a comprehensive approach. Standardized technical frameworks are required for integrating disparate industries and businesses into a single, flawlessly integrated network. Modern technologies such as cyber-physical systems, digital twin, internet of things, robotics, additive manufacturing and artificial intelligence have fueled smart manufacturing's rapid progress. Integrating cyber-physical systems is crucial to this transition, and manufacturers increasingly embrace it. Among the various technologies driving this integration, Cyber-physical systems and Digital Twins stand out, having sparked widespread interest across academia and industry. CPS and DTs improve industrial system intelligence, efficiency, and flexibility by utilizing feedback loops in which digital components respond to and influence physical processes. Although they share fundamental ideas, including tight cyber-physical connectivity, real-time interaction, organizational integration, and collaborative operation, CPS and DTs differ in several ways. These include their developmental paths, engineering applications, underlying technologies, mapping approaches, and critical components. This paper aims to investigate these differences and offer a more transparent, more comprehensive understanding of CPS and DT.

Keywords

Smart Manufacturing, Industry 4.0, Cyber-Physical Systems and Digital Twin.

1. Introduction

The term "Industry 4.0" or "Fourth Industrial Revolution" refers to the ongoing change of traditional manufacturing and industrial processes using digital technologies, smart devices, and advanced analytics. This paradigm change aims to create innovative factory facilities with networked systems, machines, and procedures to improve production, efficiency, and decision-making (Shadravan and Parsaei 2022). The manufacturing sector has entered the digital era due to developments in information technology, networking systems and data collecting technologies. This shift, fueled by the rapid expansion of digital technologies, poses significant worldwide challenges to the sector (Negri et al. 2017) (Shadravan and Parsaei 2023A). Despite variations among these technological solutions, their common objective is the realization of smart manufacturing, or intelligent production. Nonetheless, detailed analysis uncovers distinctions between these two concepts (Rossit et al. 2019). The term "intelligent manufacturing" originated in the 1980s, initially describing the integration of AI into manufacturing processes. In recent years, it has broadened to include technologies such as IoT, cloud computing, big data analytics, CPS, and digital twins, forming the technological foundation of contemporary smart manufacturing (Tao et al. 2017) (Shadravan and Parsaei 2023B). Figure 1 shows the phases of the Industrial Revolution:

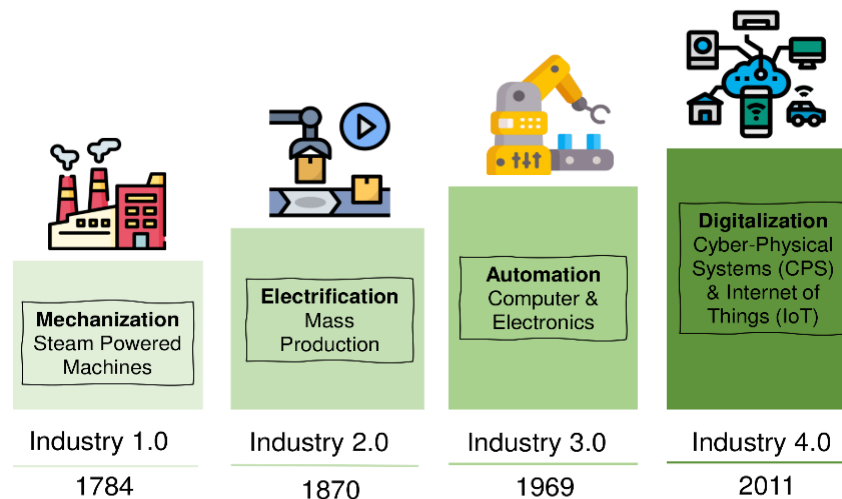


Figure 1. The four phases of the Industrial Revolution (Shadravan and Parsaei 2023C)

Intelligent manufacturing, which was previously predominantly driven by knowledge-based systems, is now migrating to a data-driven paradigm that increases knowledge via smart technologies—where "smart" refers to the ability to gather, evaluate, and utilize data effectively (Zhong et al. 2017). In this sense, smart manufacturing can be viewed as a more advanced type of intelligent manufacturing, emphasizing sophisticated data analytics and cutting-edge information and communication technologies (ICT) (Thoben et al. 2017). Looking ahead, the goal for smart manufacturing includes real-time data transfer and analysis throughout the product life cycle. Combined with model-based simulation and optimization, this will produce actionable intelligence to improve every aspect of manufacturing operations (Shadravan and Parsaei 2024A) (Liu et al. 2017A). Cyber-physical integration is at the heart of smart manufacturing, serving as a key transition enabler. Cyber-physical systems (CPS) represent advanced, multidimensional architectures that seamlessly integrate digital technologies with physical systems to enable real-time interaction and control.

Cyber-physical systems (CPS) enable real-time monitoring, responsive feedback, and intelligent control by merging the key components of control, computation, and communication, identified as the "3C" architecture. The high level of interconnectedness and continuous feedback between computer processes and physical systems allows for real-time interaction and coordination. This integrated strategy facilitates resilient, secure, and coordinated monitoring and administration of physical systems, hence increasing overall operating efficiency (Tao et al. 2018). Another important notion in cyber-physical integration is the digital twin. A digital twin is a very accurate virtual copy of a physical entity that allows for real-world simulation, continuous data interchange, and feedback creation. This technique allows for continuous, bidirectional contact among the physical and digital worlds, simplifying integration throughout the product life cycle and producing a comprehensive digital footprint of the product (Shadravan and Parsaei 2024B) (Tao

et al. 2019). Both CPS and DTs are essential strategies for establishing cyber-physical integration. However, significant concerns remain, including why these two notions coexist. Why are they used in distinct domains? How do they differ, and how do they interact? What are their key components, and which is more useful in real-world production scenarios? This study seeks to address these issues and clarify the interrelationships and distinctions between CPS and DTs by conducting a thorough examination across multiple dimensions, including their origins, techniques of layered modeling frameworks, cyber-physical integration, and fundamental structural aspects.

2. Literature Review

2.1 Evolution of Cyber-Physical Systems (CPS)

As traditional information technology (IT) progressed into next-generation IT, the emerging technologies' lower prices and greater capabilities encouraged the development and acceptance of DTs and CPS. These technologies are crucial for establishing cyber-physical integration and driving the growth of smart manufacturing, which has the potential to profoundly change traditional industrial processes and organizational structures (Shadravan and Parsaei, 2024C). The notion of cyber-physical systems (CPS) was introduced in 2006 and has evolved in tandem with the rising ubiquity of embedded technologies. Helen Gill of the National Science Foundation (NSF) created the phrase to describe the nature of complex, linked systems that went beyond the explanatory capabilities of existing IT vocabulary (Gill 2006). Since then, CPS has become a key research funding priority in the United States, and it is regarded as the main foundational element of Germany's Industry 4.0 project (Wang et al. 2016).

CPS is predicted to generate large economic benefits and drastically alter current industrial operations (Liu et al. 2017A). Despite their potential, current CPS research focuses primarily on theoretical notions, system architecture, enabling technologies, and related issues (Liu et al. 2017B), with few real-world engineering implementations. Compared to embedded systems, the Internet of Things (IoT), and sensor technologies, CPS serves as a basis. Unlike these technologies, CPS is not limited to a specific implementation or application case (Lee 2015). As a result, CPS is increasingly considered as a scientific discipline rather than a primarily engineering-focused field, a viewpoint consistent with the NSF's definition of CPS research as the development of new scientific principles and technical innovation (Monostori et al. 2018). Figure 2 depicts a conceptual map of cyber-physical systems:

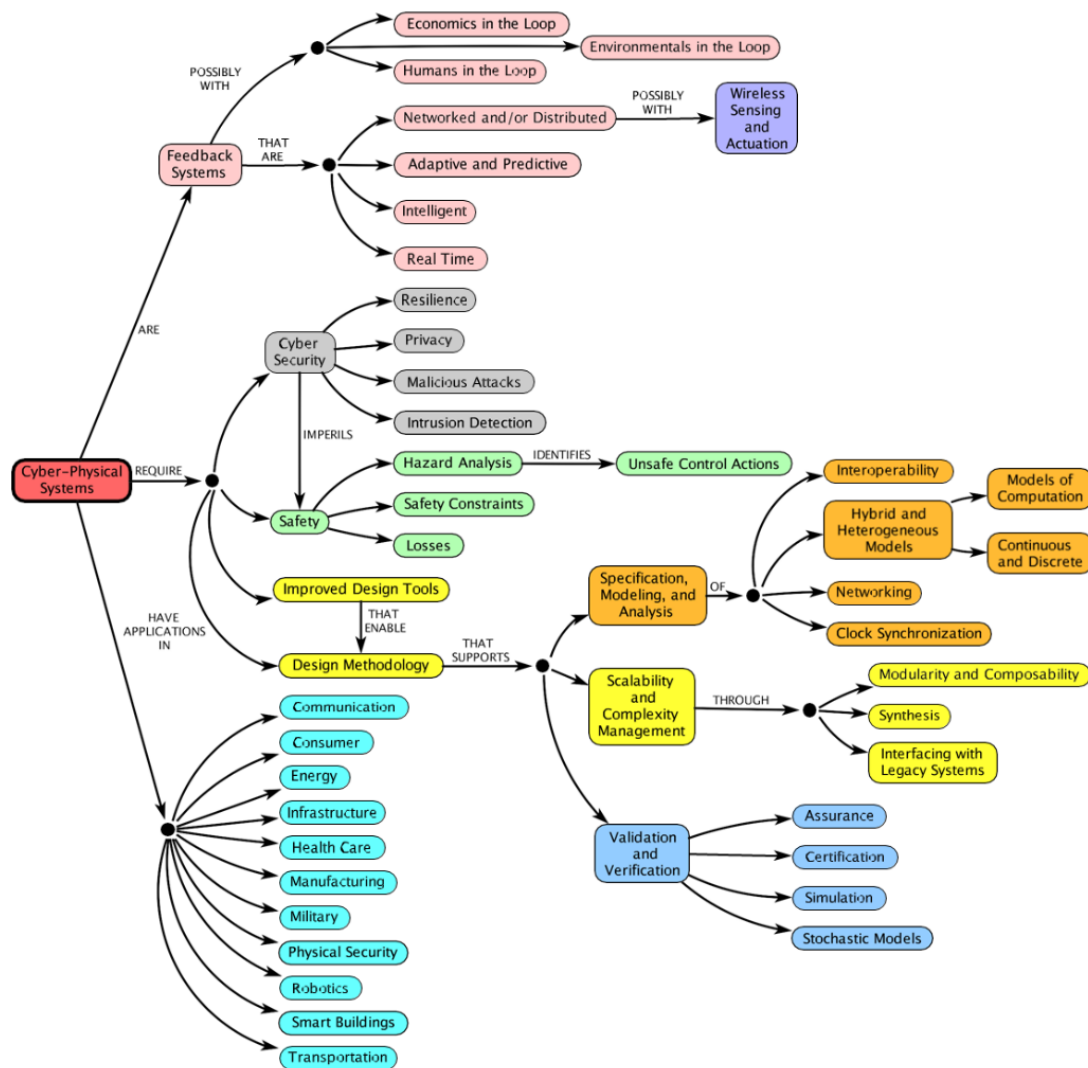


Figure 2. Concept map – Cyber-Physical Systems (Wang et al. 2015)

Advances in computing facilitated the development of numerically controlled machine tools and robotics, with microprocessors serving as the foundation of computer numerical control (CNC) systems. Computer graphics established the groundwork for computer-aided design (CAD) tools, while the rise of computer networks influenced current manufacturing processes. Database technologies were heavily used to manage data in computer-integrated manufacturing (CIM) systems. Computer vision techniques have been used in robots to recognize objects and their surroundings. The Internet revolutionized collaboration among people, systems, and human-machine hybrids, propelling advancements in concurrent engineering (CE), extended enterprises (EE), supply chains (SC), and production networks (PN) (Wiendahl et al. 2002) (Shadravan and Parsaei 2023D). Multi-agent systems have fueled the creation of holonic manufacturing systems (HMS), while wireless communication, IoT technologies, and sensor networks have allowed for fine-grained manufacturing environments with increased process traceability (Schuh et al. 2007).

Embedded technology has made smart automation and the installation of product-service systems possible. Simultaneously, semantic web technologies improved interoperability across manufacturing platforms, while cloud computing enabled service-based models via ontology-driven cloud manufacturing. Grid computing has also aided the development of grid manufacturing concepts. Overall, computer science and information and communication technologies (ICT) have significantly impacted the evolution of modern industrial systems. However, this growth has not been unidirectional; the complexity and changing demands of manufacturing have also fueled innovation in the

computing and communication industries. The parallel and synergistic nature of these processes emphasizes the accelerating fusion between the physical and digital systems (Fig. 3) (Monostori et al. 2016).

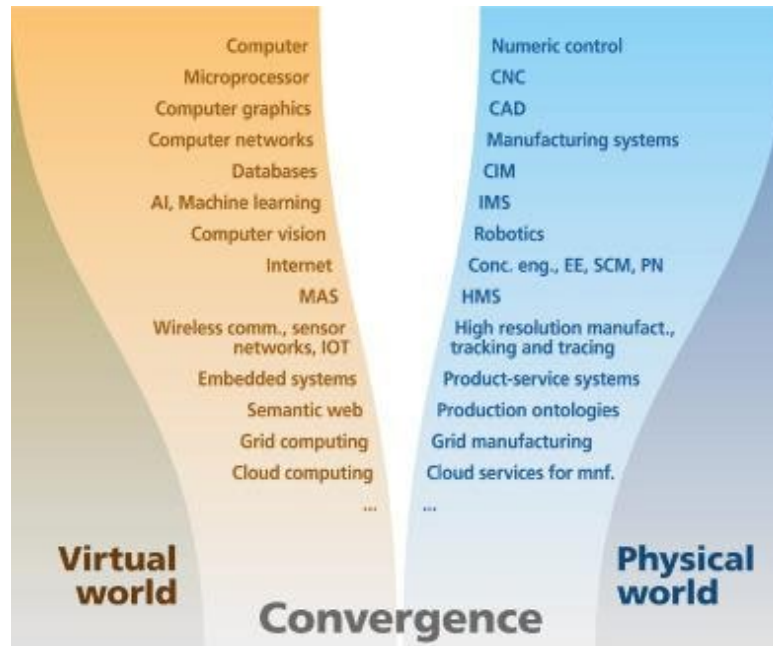


Figure 3. Cyber-Physical Systems and Digital Twin's Interplay (Monostori et al. 2016)

2.2 Evolution of Digital Twin (DT)

Michael Grieves initially mentioned Digital Twin (DT) during a 2003 talk on product lifecycle management (PLM) at the University of Michigan. The concept was primarily theoretical at the time because the requisite enabling technologies had not yet matured (Grieves 2014). To solve increasingly complex technical difficulties, organizations like NASA and the United States Air Force began using DTs for health monitoring and predicting the remaining useful life of aerospace vehicles (Negri et al. 2017). Today, the rapid expansion of information technology has accelerated the development and implementation of DTs. DTs have swiftly gained popularity as a study topic due to their new approach to aligning physical processes with their virtual equivalents. The use of Digital Twins (DTs) has expanded across numerous industrial domains, including product design, production planning, digital shop floor management, process optimization, and predictive maintenance and health monitoring (Tao et al. 2019) (Zhang et al. 2017) (Uhlemann et al. 2017). Major industry leaders such as General Electric, Siemens, PTC, Dassault Systèmes, and Tesla have adopted DTs to enhance product performance, increase manufacturing flexibility, and strengthen competitiveness. In this context, DTs have gained broad acceptance in engineering applications, positioning them as a more practice-oriented concept compared to cyber-physical systems (CPS), which remain predominantly theoretical and foundational in nature (Perno et al., 2022) (Schleich et al. 2017).

3. Research Methodology

In terms of origins and evolution, CPS and DTs emerged concurrently, owing to advances in next-generation information technology. Both have sparked great interest among academic researchers and industry personnel as fundamental ways to achieve cyber-physical convergence. Despite sharing a common goal, CPS are typically seen as part of scientific research, whereas DTs are more directly related to engineering applications. In practical industrial settings, DT technologies improve the precision and efficiency of engineering systems.

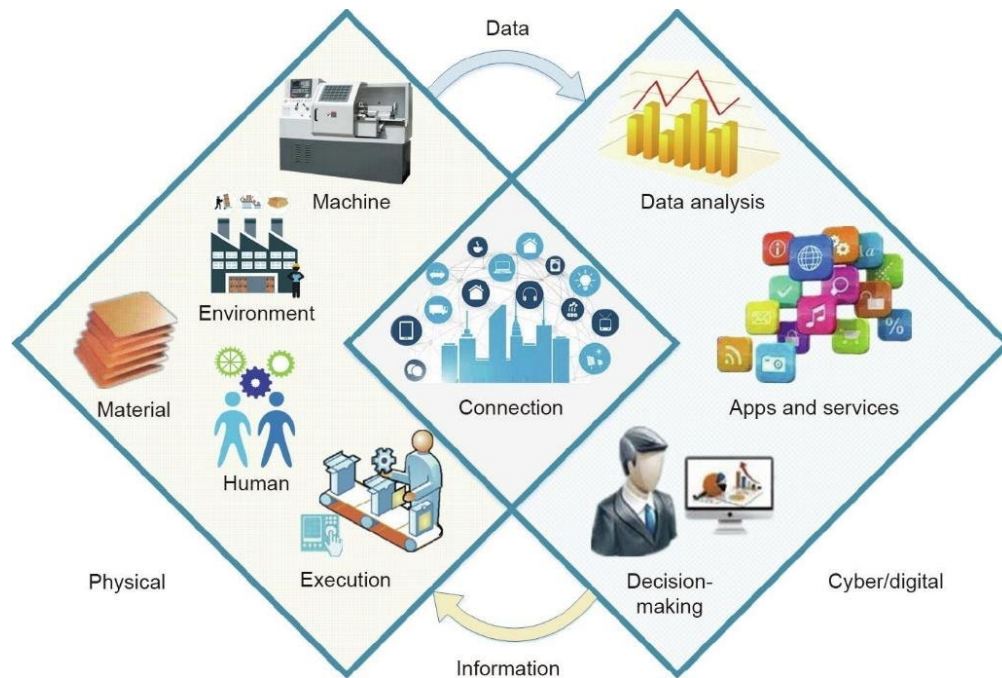


Figure 4. Physical vs. Digital worlds (Tao et al. 2019)

Cyber-physical systems (CPS) combine computational elements with physical processes, whereas a Digital Twin (DT) generates a digital replica of a physical system for real-time monitoring and optimization. Cyber-physical systems (CPS) integrate computational components with physical processes, while Digital Twins (DTs) create real-time digital replicas of physical systems for monitoring and optimization purposes. In the context of manufacturing, both CPS and DTs share a fundamental architecture composed of two key layers: the physical layer and the cyber-digital layer. As illustrated in Fig. 4, the physical layer encompasses core production elements, commonly described as "human, machine, material, and environment", which are directly involved in the execution of manufacturing tasks.

The cyber-digital layer, enhanced by ubiquitous technologies and intelligent services, includes capabilities such as data acquisition, advanced analytics, and computational intelligence. These features introduce new functionalities that enhance the efficiency and responsiveness of industrial operations. Within this integrated framework, the physical layer is responsible for sensing and collecting operational data, as well as executing actions based on instructions from the cyber-digital layer. In turn, the cyber-digital layer processes incoming data, generates intelligent insights, and issues control commands to the physical environment. This continuous and dynamic interaction forms a closed feedback loop, wherein the cyber-digital domain actively shapes physical operations, and real-time data from the physical layer continuously informs and refines cyber-digital decision-making. Such interconnectivity is fundamental to the advancement of intelligent and responsive manufacturing systems (Söderberg et al. 2017) (Tao et al. 2019).

3.1 Cyber-physical correspondence within CPS

At its core, CPS improves the systems by incorporating computing and communication technologies that interact with the physical world. Cyber-physical systems (CPS) are characterized by the close integration of computation, communication, and control—commonly referred to as the "3C" model—which enables real-time sensing, adaptive control, and the provision of information services in complex and dynamic environments. In contrast to Digital Twins (DTs), CPS places greater emphasis on the computational and communicative functions of the cyber domain, utilizing these capabilities to enhance the accuracy and efficiency of physical operations. The academic literature presents various CPS architectural models, including three-tier, five-tier, and service-oriented frameworks, which are primarily designed to support system control rather than create a mirrored digital representation (as seen in DTs). Resembling DTs, CPS also employs feedback loops to maintain continuous synchronization and interaction between the cyber and physical layers. This interaction facilitates real-time responsiveness, mutual mapping, and collaborative functionality between the two domains. However, a key distinction lies in their structural design: while DTs typically operate on a one-to-one mapping between a physical asset and its digital counterpart, CPS often adopts a one-to-many

configuration, where a single cyber system monitors and controls multiple physical components. Consequently, the cyber-physical relationship in CPS is generally defined by a one-to-many connection (Wang et al. 2015) (Somers et al. 2023).

3.2 Mapping between digital models and physical systems in DTs

Digital Twins (DTs) are intended to give a detailed functional and physical model of a system, product, or component (Söderberg et al., 2017). A key first stage in this approach is to establish high-fidelity simulated models that closely duplicate the shape, material qualities, operational behavior, and underlying principles of their real-world counterparts. These digital models reflect the form and geometry of real entities and their changing states, functions, and behavior throughout time (Schleich et al. 2017). The virtual model serves as a "twin" precisely replicating its real counterpart. Beyond duplication, DTs optimize operations and impact physical processes via digital feedback mechanisms (Vachálek et al. 2017). Control is essential in both cyber-physical systems (CPS) and digital twins. Its primary goal is to ensure that a system operates within acceptable boundaries despite disturbances. In CPS, the interaction of cyber-physical components is very important, whereas in DTs, virtual models change alongside their physical counterparts throughout the product or system lifespan. Control in both CPS and DTs is bidirectional, moving from the physical world to the cyber-digital domain and vice versa. In the first direction, the dynamic nature of the physical world needs real-time data collecting, as a system's properties can alter over time. Sensors collect this data and send it to the digital model to ensure proper synchronization.

This is especially important for DTs, because constant real-time input powers virtual simulations of processes and their evolution. Conversely, the cyber-digital domain converts the gathered data into control signals, which are subsequently delivered to physical actuators for implementation. DTs and CPS use mathematical modeling and modern computer technologies to forecast future conditions and detect flaws. This predictive capability allows for proactive maintenance and control techniques, decreasing the impact of unforeseen events or hostile disruptions via real-time cyber-physical interactive control (Pivoto et al. 2021).

3.3 Digital Model, Digital Shadow, and Digital Twin

3.3.1 Digital Model

A digital model is a virtual depiction of an existing or proposed physical entity; nevertheless, it does not automatically exchange data between the physical and digital equivalents. This model may provide a detailed or simplified depiction of the object. Common examples include simulation models of future factories, mathematical models of product designs, and other representations that do not require real-time or automated data integration. While existing digital data from physical systems can be used to create these models, all data transfer is done manually. As a result, modifications to the physical object have no direct effect on the digital model.

3.3.2 Digital Shadow

Building on the idea of a Digital Model, a Digital Shadow is a configuration in which data flows automatically and one-way from a physical object to its digital counterpart. In this configuration, all changes to the real object's status are automatically mirrored in the digital version. On the other hand, the physical thing is unaffected by changes to the digital model.

3.3.3 Digital Twin

Enabling seamless, bidirectional data flow between a physical asset and its digital counterpart, a Digital Twin facilitates real-time monitoring and interaction. Within this framework, digital representation not only mirrors the current state of the physical system but can also exert influence or control over its operations. Changes caused by other physical or digital components can also impact the digital twin. This bidirectional relationship means that every change in the physical object is immediately mirrored in the digital version, and modifications to the digital model can directly impact the physical counterpart (Kritzinger et al. 2018).

Production planning and control include employing statistical models for order planning, increasing decision-making with in-depth diagnostics, and allowing production units to plan and execute orders autonomously (Rosen et al. 2015).

Maintenance: A Digital Twin allows for examining how state changes affect upstream and downstream processes. It facilitates the formulation and evaluation of predictive maintenance programs and condition monitoring using descriptive analytics and machine learning approaches. Furthermore, it simplifies the monitoring and analysis of

machinery or process data throughout the machine's lifecycle, increasing transparency into the machine's health state (Lee et al. 2013) (D'Addona et al. 2017) (Susto et al. 2015).

Layout planning: It allows for continuous evaluation and planning of production system layouts, as well as automatic, application-independent data collecting and variation, hence increasing layout design flexibility and adaptability (Uhlemann et al. 2017).

4. Discussion

DTs and CPS have many commonalities, including integrating the physical and digital domains. Despite this shared ground, they are distinct concepts with separate origins, focuses, and applications. This section compares CPS and DTs, looking at their differences, similarities, and interconnections from several perspectives. CPS gained significant popularity after Helen Gill coined the phrase, drawing attention from academics and government, particularly as CPS became a basic component of Germany's Industry 4.0 strategy. Over time, DTs have risen in popularity and are now frequently employed in a variety of technical fields. CPS is generally considered a scientific field, whereas DTs are more directly associated with practical engineering applications. Both DTs and CPS are structured around two fundamental layers: the cyber and physical layer. They improve precision, efficiency, and operational control in the physical domain by utilizing real-time data interaction and control methods. However, their focus inside the cyber layer varies. DTs concentrate on developing high-fidelity virtual models that have a one-to-one correlation with their physical counterparts.

In contrast, CPS emphasizes the integration of control, communication, and computing (the "3C"), which frequently involves one-to-many interactions in which a single cyber system governs several physical components. Both systems rely on actuators and sensors to transmit data along with enabling real-time control in both the digital and physical domains. Digital models are critical in DTs for analyzing physical behavior and performing predictive analysis using incoming data. While sensors and actuators are essential components of CPS, the core of DTs is data processing and model correctness. CPS and DTs can also be organized hierarchically into unit, system, and system-of-systems (SoS) levels, however, the criterion for each level varies due to their varied emphasis. Finally, by integrating with sophisticated information technologies, both CPS and DTs make major contributions to the evolution of smart manufacturing, providing more intelligent, adaptive, and optimal industrial solutions.

5. Conclusion

Smart manufacturing is quickly becoming an essential path for the industry, with cyber-physical interaction and integration serving as key pillars for its implementation. DTs and CPS are two of the primary technologies driving this convergence. Both serve important roles, but they are not entirely interchangeable. This study investigated the association between CPS and DTs using comprehensive comparative analysis from many angles. It examines their contrasts, interconnections, and complementary functions in facilitating cyber-physical integration. This paper examined CPS and DTs across multiple dimensions, highlighting their commonalities and differences and providing a better understanding of how each contributes to the smart manufacturing landscape. As CPS and DTs emerge as essential enablers of intelligent production systems, further research is needed to realize their potential fully and overcome the remaining implementation hurdles.

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Biographies

Arvin Shadravan is a PhD student in the Wm Michael Barnes '64 Department of Industrial & Systems Engineering at Texas A&M University, College Station, TX, USA. He received his M.S. from Texas A&M University in May 2024. His research focuses on Industry 4.0 and Smart Manufacturing.

Zhongyuan Li is a Ph.D. student in the Department of Multidisciplinary Engineering at Texas A&M University, College Station, USA. His research focuses on Industry 4.0, particularly digital transformation in the service sector, data-driven applications, and big data analytics. With over 12 years of experience in data analytics across various industries, he is a certified professional data engineer with expertise in intelligent systems and data-driven decision-making. He has authored more than 20 peer-reviewed publications, including journal articles, conference papers, and book chapters, contributing to the field of advanced data analytics and industrial digitalization.

Hamid R. Parsaei, Ph.D., P.E., is a professor at the Wm Michael Barnes '64 Department of Industrial & Systems Engineering at Texas A&M University, College Station, TX, USA. His recent book, *Reconfigurable Manufacturing Enterprises for Industry 4.0* (co-authored by Dr. Ibrahim Garbie), received the 2022 IISE Joint Publishers Book-of-the-Year award. Dr. Parsaei is a registered professional engineer in Texas. He serves on the IEOM Global Council and was president of the IEOM from 2021 to 2023.