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Review article

Digital twins in manufacturing: A unified conceptual framework

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ABSTRACT

Digital Twins (DTs) have the potential to transform how manufacturers conceive, design, manage, and optimize products, manufacturing systems, and services. However, their rapid evolution has led to a fragmented landscape in terms of conceptualization, applications, maturity levels, and enabling technological capabilities, creating a misalignment between academic research and industrial implementation. This paper addresses these challenges by proposing a unified conceptual framework for DTs in manufacturing, which integrates DT applications and maturity levels across product, production, and service domains and derives a theory-driven DT definition. To this end, two complementary frameworks are developed: the Digital Twin Application-based Framework and the Digital Twin Technological Capabilities Framework, which together classify DT applications, maturity levels, and technological capabilities within the three manufacturing domains. To establish conceptual clarity and account for the evolving, adaptive, and granular nature of DTs, the framework introduces a definition grounded in Complex Adaptive Systems (CAS) Theory, framing DTs as dynamic, interconnected systems that evolve in complexity and functionality based on domain-specific needs. Overall, this research contributes to promote an alignment between academia and industry by providing a structured analysis and comprehensive conceptualization of DTs in manufacturing.

1. Introduction

Within modern manufacturing, the introduction of new digital technologies and the evolution of Cyber-Physical Systems (CPS) have become crucial factors in reshaping the industry (You & Feng, 2020). Within this transformative context, Digital Twins (DTs) stand out as complex systems, offering decision support by leveraging models and data collected from both physical and virtual sources (Kritzinger et al., 2018). This concept has gained considerable attention in both academic and industrial realms, demonstrating significant potential to conceive, design, manage and optimize manufacturing systems, enhance product development, and improve decision-making across various domains (Barricelli et al., 2019; Böttjer et al., 2023; Cimino et al., 2019). However, despite their promise, there remains a notable gap between the theoretical advancements in academia and the practical implementation of DTs in industry (Sharma et al., 2022; Tao et al., 2024). This gap is accentuated by a lack of practical guidelines, tools, and standardized frameworks that facilitate the successful adoption of DTs in real-world industrial settings (Shao & Helu, 2020; Sharma et al., 2022). Furthermore, the democratization of DT development has been hindered by the insufficient technological capabilities and resources, limiting DT's accessibility to a broader range of manufacturers, particularly small and medium-sized enterprises (SMEs) (Marra et al., 2024; Yasin et al., 2021).

Before addressing these implementation challenges, it is essential to first establish a clear and unified conceptualization of what constitutes a DT. The current understanding of DTs seems to be affected by poor consistency and heterogeneity (Tao, Sui, et al., 2019), with varying definitions and interpretations across academia and industry. Some definitions, as presented in the analysis by (Barricelli et al., 2019; Boyes & Watson, 2022; Negri et al., 2017), emphasize DTs as merely high-fidelity digital replicas, while others extend the concept to encompass real-time data integration, predictive analytics, and closed-loop control. This conceptual discrepancy results in fragmented research efforts, where current studies usually build upon differing assumptions, of what a DT entails, limiting the final capability, or service, the DT system can provide (Boyes & Watson, 2022). As a result, different types of DTs have emerged (Barricelli et al., 2019; Botín-Sanabria et al., 2022; Ruzsa, 2021), each shaped by these varying interpretations.

For instance, current DT definitions tend to follow either an application-driven (Madni et al., 2019; Zhuang et al., 2018) or a technology-driven (Al-Ali et al., 2018; Glaessgen & Stargel, 2012; Javaid et al., 2023; Negri et al., 2017) approach, as suggested by Emmert-Streib

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(2023). This has led to a fragmentation in terms of its applications –resulting in various use cases across the manufacturing field (Atalay et al., 2022; Cimino et al., 2019; Errandonea et al., 2020; Hu et al., 2021; Kritzinger et al., 2018; Liu et al., 2021; Negri et al., 2017; Villegas et al., 2024a)– and its level of integration, further contributing to the rise of different types of DTs, i.e. maturity levels, with specific capabilities given to the implemented technologies.

As DT research progresses, new applications of DTs in manufacturing rise, highlighting their adaptive nature as they evolve to meet specific requirements within different application domains. This, in turn, leads to the development of new application-driven DT definitions, for example, Madni et al. (2019) define a DT as a "virtual instance of a physical system (twin) that is continually updated with the latter's performance, maintenance, and health status data throughout the physical system's life cycle". This definition might be applicable to DT applications in the product/production domain but not necessarily to the service domain in manufacturing. Moreover, by primarily focusing on real-time updates and status monitoring, this definition limits the DT's role to a monitoring tool, overlooking its potential to enable predictive, prescriptive, or autonomous capabilities.

Something similar happens with the emergence of new technologies, where the exploration of these gives rise to new types and, therefore, definitions of DTs, reinforcing their evolving nature. In this sense, DTs are evolving systems shaped by continuous advancements in technology and domain-specific requirements. For example, Javaid et al. (2023) define a DT as a " software model of a physical thing" that could be represented as "a simple algorithm that forecasts how a product or process will perform based on real-world data". While this definition acknowledges the capability provided by advanced data analytics, with the incorporation of Internet of Things (IoT) and Artificial Intelligence (AI) to improve output results, it seems to oversimplify the complexity of DTs by reducing them to a forecasting algorithm, without considering other characteristics such as real-time synchronization and bidirectional interaction. This finally leads to different capabilities provided by the DT system, either in a narrow or in a broad scope depending on the level of integration of the technologies at their background.

As seen in the previous examples, regardless of whether DT definitions follow an application-driven or technology-driven approach, they tend to focus on specific application domains and levels of maturity, often leaving out other essential capabilities. This reflects the granular nature of DTs, where each instance must be tailored to meet specific technological and domain requirements. This ongoing conceptual fragmentation has led to a widespread yet disjointed body of knowledge, which has further hindered the possibility of establishing a standardized, universally accepted DT definition in manufacturing (Villegas et al., 2024a).

This lack of consensus, in terms of definition and cohesion of body of knowledge, has not only complicated the on-going research efforts but also hindered the alignment needed for practical implementation (Boyes & Watson, 2022; Sharma et al., 2022). In this sense, the poor inconsistency and heterogeneity has led industry adopters to misaligned expectations or misguided directions, making it difficult for organizations to rely on well-established and commonly accepted standardized methodologies and best practices guidelines for the DT implementation (Evangeline & Anandhakumar, 2020; Kamath et al., 2020; Newrzella et al., 2021; Tao, Sui, et al., 2019). Although first, without a shared understanding of DTs, it becomes difficult to develop the necessary tools, frameworks, or guidelines needed to bridge the gap between theory and practice.

1.1. *Research Objective, Research Questions and Contributions*

Considering the gap between extant theory and practice of DTs, the objective of this paper is to propose a unified conceptual framework for understanding DTs in manufacturing. This is realized through the introduction of: 1) two complementary frameworks –classifying DT applications and technological capabilities– and 2) a comprehensive, theory-driven definition that captures the DT emerging characteristics. To achieve this, the study first seeks to systematically synthesize and integrate insights from existing DT scientific literature, establishing a comprehensive understanding of DTs that accounts for their evolving, adaptive, and granular nature –building upon the viewpoints of both applications and technologies. This then provides the knowledge background to establish a comprehensive DT definition grounded in Complex Adaptive Systems (CAS) Theory.

To support this objective, the study is guided by the following primary research question (**RQ1**): *What constitutes a Digital Twin in the context of manufacturing, in terms of its definition, application domains, technological capabilities, and maturity levels?* And further explored through the sub-questions:

- **RQ1.1**: Which applications and enabling technological capabilities define the current landscape of Digital Twins across the product, production, and service domains in manufacturing?
- **RQ1.2**: How can Digital Twins be defined to reflect their inherent characteristics, as shaped by their current applications and technological capabilities in manufacturing?

By addressing these questions, this paper contributes in two key ways:

1) it establishes a structured taxonomy that classifies DT applications, maturity levels, and technological capabilities, which finally leads to a comprehensive landscape of DTs built on two foundational frameworks –the **Digital Twin Application-based Framework** and the **Digital Twin Technological Capabilities Framework**; and
2) it proposes a general definition of DTs that addresses their evolving, adaptive, and granular nature by drawing on CAS theory.

These contributions form the basis of the proposed unified conceptual framework, which aims to offer a clearer and more structured understanding of DTs in manufacturing. Ultimately, it seeks to promote alignment between academic research and industrial practices while laying the foundation for future DT development.

The remainder of this paper is structured as follows: Section 2 describes the research methodology employed in this study, including the systematic literature review. Section 3 presents an in-depth review of existing DT literature within the manufacturing context, focusing first on delineating the manufacturing domains to then identify the main DT applications and their corresponding maturity levels. Section 4 then introduces the development of the **Digital Twin Application-based Framework** and the **Digital Twin Technological Capabilities Framework** based on the insights of the reviewed literature. Section 5 proposes a comprehensive DT definition for manufacturing grounded in CAS theory. Section 6 discusses the findings and identifies areas for future research, and Section 7 concludes with key implications for both academia and industry.

2. Research Methodology

This section outlines the methodology employed to address the primary research question, **RQ1** *What constitutes a Digital Twin in the context of manufacturing, in terms of its definition, application domains, technological capabilities, and maturity levels?*, and its related sub-questions (**RQ1.1, RQ1.2**) for this research. The research methodology, first presented, combines both non-systematic and systematic literature review approaches to comprehensively explore existing scientific knowledge and address the fragmentation identified in current DT research. Then, the application and results of these reviews are reported in terms of queries, eligibility criteria and eligible papers. The presented steps were designed to provide the foundational insights necessary for constructing the **Digital Twin Application-based Framework** alongside the **Digital Twin Technological Capabilities Framework**, as an integrative review process, to then derive a general DT definition grounded in CAS theory. The main outputs of the research are explained in the remainder of the paper, from Section 3 onward.

2.1. Research Design

To develop a unified landscape on DTs in manufacturing, the methodology was structured into three main phases:

1. *Exploration Phase* – Research Framing
   - Preliminary Exploration: To establish a general understanding of the topic and contextualize the scope of the study, a non-systematic snowball methodology was initially employed. This step aimed to gain a broad overview of the current research around DTs, allowing for the identification of major thematic areas, highlighting inconsistencies in existing definitions, and uncovering initial research gaps. The insights gathered during this stage were then used to frame the research problem and formulate the research questions.
   - Primary Exploration: A Systematic Literature Review (SLR) was conducted to analyze existing DT definitions, implementation use cases, proposed architectural framework or diagrams and general reviews of DTs in manufacturing. This method was chosen to ensure a structured, unbiased and comprehensive review that allows to map the DT landscape (in terms of manufacturing domain, application and maturity level DT implementation might lay on), to then set the basis of a general DT definition.
2. *Analysis Phase* – Frameworks Development
   - An integrative review process was then conducted to synthesize the insights from the SLR into the **Digital Twin Application-based Framework**, classifying DT applications by manufacturing domain and maturity level. Using this classification as a foundation, the **Digital Twin Technological Capabilities Framework** was then developed to identify the essential technological capabilities required for deploying DTs at each maturity level.
3. *Synthesis Phase* – Theoretical Abstraction through CAS Lens
   - Acknowledging the evolving, adaptive, and granular nature of DTs in manufacturing, derived from the insights of the two frameworks, a CAS perspective was applied to contextualize DTs as dynamic systems with emergent properties. This approach aimed to provide a theory-driven perspective to represent, in a synthetic way, the characteristics brought by the DT's landscape, while avoiding any application or technology bias to define DTs.

2.1.1. Exploratory Phase – Research Framing

The exploratory phase began with a non-systematic snowball review, initiated from (Negri et al., 2017) as key seed article. This was selected due to its relevance to the field, providing a comprehensive analysis and discussion of the definitions of DTs up to 2017, making it an ideal reference to begin the exploration. This Preliminary Exploratory review led to the review of 32 relevant articles, with research scopes providing reviews of the concept, existing challenges, and reference architectures or frameworks for their implementation in manufacturing, leaving aside, for this first exploration phase, concrete implementation use cases. This initial set of papers revealed three major research problems (RPs) hindering the development of a comprehensive understanding of DTs in manufacturing:

- **RP1**: Lack of a consistent and universally accepted DT definition. (Boyes & Watson, 2022; Hyre et al., 2022; Negri et al., 2017; Pronost et al., 2021; Sharma et al., 2022)
- **RP2**: Different degrees of DT implementation across manufacturing. (Barricelli et al., 2019; Botín-Sanabria et al., 2022; Grieves & Vickers, 2017; Kritzinger et al., 2018; Ruzsa, 2021; Singh et al., 2021)
- **RP3**: Misalignment between academia and industry in DT understanding. (Evangeline & Anandhakumar, 2020; Kamath et al., 2020; Tao, Sui, et al., 2019)

These RPs directly informed the formulation of the study's main research question: *What is a Digital Twin in the context of manufacturing?* This question aims to address the inconsistency and heterogeneity in DT understanding. However, to address each RP correspondingly, subsequent RQ were formulated.

For instance, to tackle the underlying aspects of **RP1** and **RP2**, the study further refines **RQ1** into sub-questions. **RQ1.1** (*Which applications and enabling technological capabilities define the current landscape of Digital Twins across the product, production, and service domains in manufacturing?*) investigates the primary applications and technological capabilities of DTs in product, production, and service domains in manufacturing. This sub-question aims to provide an overview and understand the diverse ways in which DTs are applied in manufacturing. Building on this, a reflection on the emerging applications, maturity levels, and technological capabilities of DTs, is made possible; this corresponds to an examination of how DTs can be classified to reflect their varying maturity levels, technologies, and capabilities across the manufacturing domains. Meanwhile, **RQ1.2** (*How can Digital Twins be defined to reflect their inherent characteristics, as shaped by their current applications and technological capabilities in manufacturing?*) directly addresses **RP1** by exploring a more comprehensive and systematic definition of DTs that aligns with their dynamic characteristics as new applications and technologies are considered within their deployment. By doing so, both **RQ1.1** and **RQ1.2** contribute to address **RP3**, as a clear classification and definition of DTs can help to pave the way to bridge the gap between academic research and practical industrial applications in manufacturing.

With these refined research questions in place, the Primary Exploration sought to systematically analyze existing literature. A systematic literature search was conducted across Scopus, IEEE Xplore, and Web of Science to extract DT definitions, implementation use cases, proposed architectural frameworks or diagrams and general reviews of DTs in manufacturing to answer **RQ1** and its subsequent RQs. Additionally, the search considered DTs' role in sustainability, recognizing its significance in shaping the future of smart and sustainable manufacturing. Taking into consideration this objective the general structure of the query used on the databases was as follows (general search within title, abstract, and keywords):

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Digital Twin AND manufactur* AND
[product OR production OR process*
OR (service* OR serviti?ation)
OR sustainab*] AND (LIMIT-TO(DOCTYPE,”re”))
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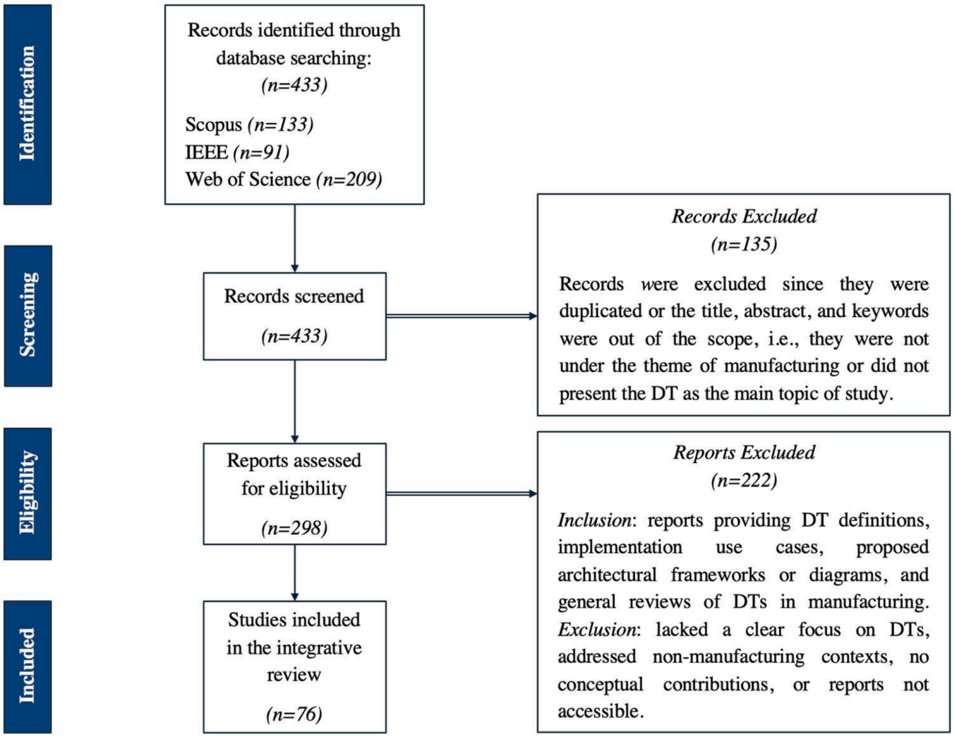
The first keyword, *Digital Twin*, represents the core term, while *manufactur** operator serves to capture variations such as "manufacturing" and "manufacture" and limit the scope to manufacturing. To address DT applications along the manufacturing domains, derived based on insights from Kalpakjian (2001), the query includes the keywords *product, production*, and *process**, ensuring coverage of DT applications in product lifecycle management, production systems, and manufacturing processes. Besides, to account for those DT applications in manufacturing-related services and servitization trends, the query includes *service* and *serviti?ation**. The inclusion of *sustainab** aims to introduce a specific focus to reflect the growing role of DTs in sustainable manufacturing. Finally, the *(LIMIT-TO(DOCTYPE, 're'))* operator refines the search to review articles, ensuring a focus on synthesized knowledge and established research trends.

This research string was used as input for the Identification phase on the PRISMA Flow Diagram (Moher et al., 2010) (see Fig. 1). This protocol was adopted to ensure transparency, rigor, and reproducibility in the review process. This resulted in the extraction of 433 articles, encompassing diverse perspectives on DT definitions, applications, and technological capabilities across manufacturing.



Records were excluded since they were duplicated or the title, abstract, and keywords were out of the scope, i.e., they were not under the theme of manufacturing or did not present the DT as the main topic of study.

Inclusion: reports providing DT definitions, implementation use cases, proposed architectural frameworks or diagrams, and general reviews of DTs in manufacturing. *Exclusion*: lacked a clear focus on DTs, addressed non-manufacturing contexts, no conceptual contributions, or reports not accessible.

Fig. 1. PRISMA Flow Diagram: Digital Twins in Manufacturing.

The next phase, Screening, focused on refining the initial pool of articles to ensure relevance and alignment with the objective of the research. Titles, abstracts, and keywords were carefully reviewed to exclude duplicates and studies unrelated to the research scope. This step reduced the pool to 298 articles, narrowing the focus to studies directly relevant to the objectives of this research.

In the Eligibility phase, a detailed review of the full text of these 298 articles was conducted. This step involved the analysis of their alignment with the study's primary and secondary research questions, as well as their potential contribution to addressing the identified research problems. The main inclusion criteria focused on studies that provided DT definitions, punctual implementation use cases, proposed architectural frameworks or diagrams, and general reviews of DTs in manufacturing. Conversely, studies were excluded if they lacked a clear focus on DTs, (i.e., if the term was only mentioned but without being central to the study), addressed non-manufacturing contexts (e.g., use of DT in architecture, medicine, agriculture, mining, and smart cities domains), provided shallow discussions without conceptual contributions (e.g., studies with vague or high-level mentions of DTs, lacking detailed theoretical grounding or technical implementation descriptions), or were papers not accessible. At this stage, the recurring presence of **RP1** (Lack of consistent and universally accepted DT definition) and **RP2** (Different degrees of DT implementation across manufacturing) highlighted the fragmented landscape of DTs in manufacturing that has further contributed to **RP3** (Misalignment between academia and industry in DT understanding). The persistence of these research problems, even under a systematic review approach, validated the earlier exploratory insights and confirmed the need for a comprehensive and unified framework for understanding and classifying DTs in manufacturing. To this end, at the Inclusion phase, a refined set of articles was selected according to their insights provided into specific DT applications, degrees of implementation (which in this study are denoted as maturity levels), technological capabilities, and conceptual frameworks.

2.1.2. *Analysis Phase – Frameworks Development*

Building upon the refined set of selected studies, this phase focused on developing two interrelated frameworks that provide a structured understanding of DTs in manufacturing. The **Digital Twin Application-based Framework** was designed to classify DT applications according to their manufacturing domain (product, production, or service) and their maturity level, ranging from model-driven to fully autonomous DTs (detailed dimensions presented in Section 3). This classification synthesized insights from the literature to create a structured mapping of DT applications across varying levels of sophistication. Once established, the **Digital Twin Technological Capabilities Framework** was derived to identify the essential technological capabilities required for DT deployment at each maturity level per manufacturing domain. This framework served as a bridge between DT functionalities and the enabling technologies, ensuring that the classification of DTs was grounded in both practical and theoretical considerations. Both frameworks are further presented in Section 4.

2.1.3. *Synthesis Phase – Theoretical Abstraction through CAS Lens*

Recognizing the evolving, adaptive, and granular nature of DTs in manufacturing, and motivated by **RQ1.2**, the study leveraged CAS theory to conceptualize DTs beyond specific –either application or technology-dependent– classifications. The insights derived from the two frameworks highlighted the inherent characteristics of DTs –how they dynamically evolve, interact with their environment, and respond to external requirements. Applying a CAS perspective allowed for a holistic theoretical abstraction that captured the characteristics and behavior brought by the DT's landscape, ensuring that the proposed definition was application- and technology-agnostic and applicable across diverse manufacturing domain contexts. This approach provided a theory-driven foundation to unify DT conceptualizations and address the inconsistency and heterogeneity in existing research.

3. A Multi-dimensional Structured Taxonomy for Digital Twins in Manufacturing

From the review of the selected articles, it was identified that DTs, in the context of manufacturing, can be categorized into three key dimensions: manufacturing domains, applications, and maturity levels. These dimensions emerged as fundamental features in order to address the fragmented landscape of DTs in manufacturing. In particular, each dimension serves a distinct purpose: i) manufacturing domains provide the contextual foundation for DT deployment, ii) applications highlight the functional roles that DTs can fulfill, and iii) maturity levels reflect the technological progression and sophistication considered in the DT implementation. The following subsections will cover these three dimensions, presenting the findings in detail.

3.1. Manufacturing Domains

The literature confirmed the initial expectations established during the setup of the SLR: manufacturing, in the context of DT implementation, constitutes a complex ecosystem structured around three domains: product, production, and service (the preliminary findings published in (Villegas et al., 2024b) are initially proving this evidence) (see Fig. 2). These domains represent distinct but interconnected areas of focus within the product and manufacturing lifecycle. They encapsulate, on the one hand, the lifecycle stages a product (or eventually an asset) undergoes –from initial conception to its ongoing support after sale– and, on the other, the processes and activities that ensure efficient and effective manufacturing operations. In their entirety, they allow to define the first dimension for structuring the taxonomy of DTs in manufacturing.

The three domains are discussed hereinafter based on related references.

- **Product Domain**: This domain spans the entire lifecycle of a product, beginning with its initial design and development (Cimino et al., 2019; Grieves & Vickers, 2017; Gunal, 2019; Negri et al., 2017; Rosen et al., 2015; Tao, Cheng, et al., 2018; Tao, Zhang, Liu, et al., 2019; X. Zhang & Zhu, 2019), moving through its use and maintenance (Aivaliotis et al., 2019; Corallo et al., 2021; D'Amico et al., 2022; Errandonea et al., 2020; Qi & Tao, 2018; Rojek et al., 2020; Wang et al., 2021), considering its eventual role as an operational asset, and finally getting to its improvement based on its performance throughout its middle-of-life (Boschert & Rosen, 2016; Corallo et al., 2021; Glaessgen & Stargel, 2012; Kritzinger et al., 2018; Schleich et al., 2017; Tao, Zhang, Liu, et al., 2019; Zheng et al., 2018). The domain addresses the integration of digital tools to model, monitor, and manage product-related aspects throughout its lifecycle, ensuring that the product evolves to meet performance and operational requirements.
- **Production Domain**: This domain is concerned with the execution of manufacturing processes, focusing on the systems and resources involved in producing goods. It highlights activities related to optimizing production efficiency (Cimino et al., 2019; Corallo et al., 2021; Grieves & Vickers, 2017; Gunal, 2019; Lu et al., 2020; Pires et al., 2019; Stark et al., 2017; Tao, Zhang, Liu, et al., 2019; Touckia, 2023; Uhlemann et al., 2017; Villalonga et al., 2021; X. Zhang & Zhu, 2019; Zhao et al., 2019), ensuring product quality (Gunal, 2019; Hao et al., 2020; Knapp et al., 2017; Lattanzi et al., 2021; Tao, Sui, et al., 2019; Tao, Zhang, Liu, et al., 2019; X. Zhang & Zhu, 2019), and managing the logistic flows across the supply chain, as required to support manufacturing operations (An et al., 2023; Ivanov, 2020; Ivanov, Dolgui, & Sokolov, 2019; Ivanov, Dolgui, Das, et al., 2019; Ivanov & Das, 2020; Ivanov & Dolgui, 2021; Nguyen et al., 2022; Qi, Zhao, et al., 2018). As such, the domain plays a central role in translating design concepts into tangible outcomes while balancing cost, quality, time and sustainable considerations when required.
- **Service Domain**: Encompassing a broad scope of topics inclusive of service delivery, operational risks, and learning, this domain emphasizes the importance of maintaining operational continuity and supporting end-user needs. To this end, the domain includes processes that ensure reliable service system performance (Bolton et al., 2018; Kunath & Winkler, 2018; Orozco-Romero et al., 2020; Stark et al., 2019; L. Zhang et al., 2022), minimize operational risks (Bevilacqua et al., 2020; Cimino et al., 2019; Ivanov & Dolgui, 2021), and provide means for continuous learning and improvement within manufacturing environments (Cimino et al., 2019; Gunal, 2019; Havard et al., 2019; Madni et al., 2019; Pires et al., 2019; Qi, Tao, et al., 2018).

3.2. Digital Twin Applications

Based on the identified manufacturing domains, this subsection deeps down into the specific applications of DT within each manufacturing domain. At their core, these complex systems enable functionalities such as real-time monitoring, simulation, or data-driven decision-making (Ding et al., 2019; Friederich et al., 2022; Negri et al., 2021; Soori et al., 2023). Building on these functionalities, researchers have developed specific DT solutions, mainly referred to as DT services (Aheleroff et al., 2021; Steindl & Kastner, 2021; Tao et al., 2022; Tao, Zhang, & Nee, 2019), aligning with the role of DTs as Product-Service Systems (PSS) (see Fig. 3).

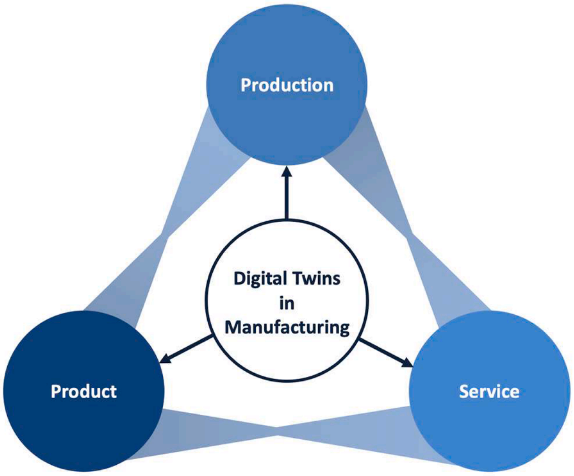


Fig. 2. Digital Twins in Manufacturing – Manufacturing Domains.

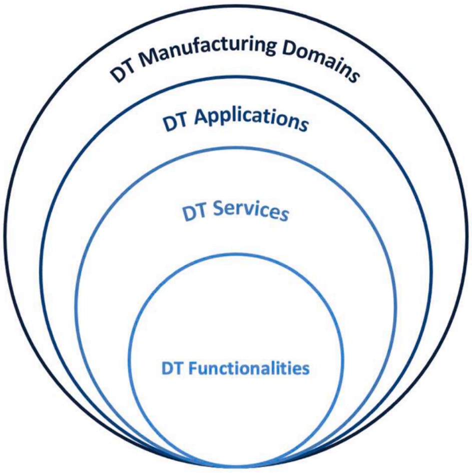


Fig. 3. Hierarchical Structure of Digital Twin Components in Manufacturing.

The classification presented at this work organizes them into broader categories, i.e. applications, to reflect their practical implementation under specific areas relevant to each manufacturing domain. In this sense, the presented DT applications might integrate multiple DT services to address complex manufacturing challenges under the given manufacturing domain. For example, a DT application for *Production Optimization* might include DT services such as production scheduling, downtime reduction, and shop floor management, among others. By categorizing applications in this manner, a comprehensive overview is provided of how DTs can contribute to optimize processes and outcomes across the product, production, and service domains.

To identify and categorize such DT applications, a structured coding approach was employed. Initially, generalized statements (1st order codes) were established, extracting and synthesizing the fundamental function of each DT implementation case. These statements were then grouped into higher-level categories (2nd order categories) that represent the primary DT applications identified in manufacturing. Finally, these categories were aggregated according to their respective manufacturing dimensions (product, production, and service) as illustrated in Table 1.

The DT applications relevant to each manufacturing domain are hereinafter illustrated, detailing what is outlined in the broad spectrum of Fig. 4. Such applications determine the second dimension for structuring the taxonomy of DTs in manufacturing.

- **Product Design Optimization**: this application highlights the role of the DTs in refining the product design phase. Through the use of advanced simulation models and virtual prototypes, manufacturers can iteratively test and optimize product designs before physical prototypes are created. This enhances functionality, performance, and cost-effectiveness while reducing development cycles and time-to-market. (Cimino et al., 2019; Grieves & Vickers, 2017; Gunal, 2019; Negri et al., 2017; Rosen et al., 2015; Tao, Cheng, et al., 2018; Tao, Zhang, Liu, et al., 2019; Zhang & Zhu, 2019)
- **Product Maintenance**: DTs contribute to predictive and proactive maintenance by monitoring product condition throughout its lifecycle. This capability extends the lifespan of products, prevents unexpected downtimes, and reduces maintenance costs, particularly for assets critical to manufacturing operations. (Aivaliotis et al., 2019; Corallo et al., 2021; D'Amico et al., 2022; Errandonea et al., 2020; Qi & Tao, 2018; Rojek et al., 2020; Wang et al., 2021)
- **Product Performance**: By simulating product behavior under various operating conditions, DTs allow manufacturers to analyze performance and identify areas for improvement. These insights support more accurate designs and reduce testing on physical systems, ultimately enhancing product reliability and quality. (Boschert & Rosen, 2016; Corallo et al., 2021; Glaessgen & Stargel, 2012; Kritzinger et al., 2018; Schleich et al., 2017; Tao, Zhang, Liu, et al., 2019; Zheng et al., 2018)
- **Production Optimization**: DTs enable the simulation and analysis of production processes to identify inefficiencies and optimize resource utilization. This leads to streamlined operations, increased productivity, and enhanced shop-floor management flexibility. (Cimino et al., 2019; Corallo et al., 2021; Grieves & Vickers, 2017; Gunal, 2019; Lu et al., 2020; Pires et al., 2019; Stark et al., 2017; Tao, Zhang, Liu, et al., 2019; Touckia, 2023; Uhlemann et al., 2017; Villalonga et al., 2021; X. Zhang & Zhu, 2019; Zhao et al., 2019)
- **Quality Control Optimization**: Leveraging DTs for quality assurance involves real-time monitoring and analysis of production data to detect defects and maintain quality standards. This reduces waste, minimizes rework, and ensures consistent product quality. (Gunal, 2019; Hao et al., 2020; Knapp et al., 2017; Lattanzi et al., 2021; Tao, Sui, et al., 2019; Tao, Zhang, Liu, et al., 2019; X. Zhang & Zhu, 2019)
- **Supply Chain Management**: DTs can play a crucial role in optimizing supply chain operations. By creating digital representations of the supply chain network, manufacturers can enhance visibility,

Table 1
Coding Procedure for Identification of DT Applications.

1st Order Codes (Generalized statements)	2nd Order Categories (DT Applications)	Aggregated Dimension (Manufacturing Domains)
Test and validate product prototypes virtually	Product Design Optimization	Product
Improve product designs before physical development		
Perform virtual simulations of product characteristics		
Analyze virtual product prototypes		
Monitor product conditions in real-time	Product Maintenance	
Predict failures or degradation in product components		
Support proactive maintenance strategies		
Optimize maintenance schedules based on actual product usage		
Track and monitor real-time product performance	Product Performance	
Analyze product behavior under varying operational conditions		
Identify opportunities for product improvement		
Simulate product usage scenarios		
Model and test production processes	Production Optimization	Production
Detect constraints in production workflows		
Examine and improve production sequences		
Plan and optimize production timelines		
Examine and improve asset availability		
Track and control product quality in real-time	Quality Control Optimization	
Identify and reduce production defects		
Monitor compliance to quality standards		
Enhance inspection and validation processes		
Optimize logistics and supply chain processes	Supply Chain Management	
Enhance traceability across the supply chain		
Forecast and manage supply chain disruptions		
Optimize inventory and resource allocation		
Enhance responsiveness of logistics activities		
Improve efficiency and responsiveness in service operations	Service Delivery Optimization	Service
Enhance customer experience through optimized services		
Enable product-service integration and servitization strategies		
Facilitate customized service offerings		
Identify and mitigate operational risks	Risk Management	
Predict and manage risks across manufacturing services		
Support proactive decision-making for operational safety		
Monitor and optimize safety protocols		
Simulate training scenarios in virtual environments	Training and Education	
Enhance workforce skills through virtual training		

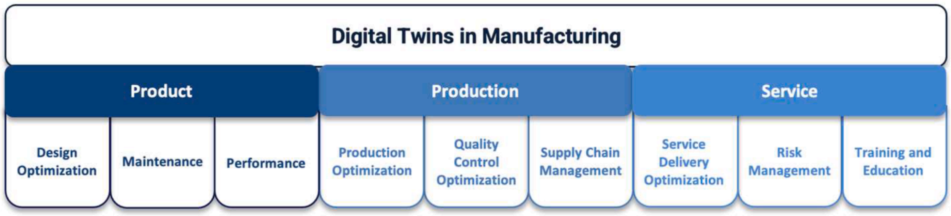


Fig. 4. Digital Twins in Manufacturing – Digital Twin Applications.

traceability, and coordination across the entire supply chain. This application assists in optimizing inventory levels and improving overall supply chain efficiency and resilience. (An et al., 2023; Ivanov, 2020; Ivanov, Dolgui, & Sokolov, 2019; Ivanov, Dolgui, Das, et al., 2019; Ivanov & Das, 2020; Ivanov & Dolgui, 2021; Nguyen et al., 2022; Qi, Zhao, et al., 2018)

- **Service Delivery Optimization**: In the service domain, DTs can contribute to optimizing the delivery of services related to manufactured products. By monitoring and analyzing service processes, manufacturers can enhance service efficiency, reduce response times, and improve customer satisfaction. This application is particularly valuable in industries where pre-sales and post-sale services are integral to the overall customer experience, to enable product personalization and servitization, gain competitive advantage, and optimize after-sale services. (Bolton et al., 2018; Kunath & Winkler, 2018; Orozco-Romero et al., 2020; Stark et al., 2019; Zhang et al., 2022)
- **Risk Management**: In this application, DTs can help in identifying and mitigating risks associated with operations and service delivery. By continuously monitoring operational parameters and performance metrics, manufacturers can proactively identify potential issues, assess their impact, and implement preventive measures to manage and mitigate risks effectively. (Bevilacqua et al., 2020; Cimino et al., 2019; Ivanov & Dolgui, 2021)
- **Training and Education**: DTs can be leveraged as a virtual system for training and education purposes. Manufacturers can use digital replicas of products and production processes to train personnel, simulate operational scenarios, and enhance the skills of the workforce. This application contributes to workforce readiness, training costs reduction, and ensures a knowledgeable and skilled workforce to reduce operational risks. (Cimino et al., 2019; Gunal, 2019; Havard et al., 2019; Madni et al., 2019; Pires et al., 2019; Qi, Tao, et al., 2018)

3.3. *Digital Twin Maturity Levels*

The DT maturity levels presented in this section align with, and break down, the evolving conceptualization first introduced by Grieves & Vickers (2017), which distinguishes between DT Prototype, DT Instance, and DT (later also referred to as Intelligent DT (Grieves, 2022)). Furthermore, the maturity levels mirror the commonly used DT categories proposed by Kritzinger et al. (2018): Digital Model, Digital Shadow, and Digital Twin. The proposed alignment presents a broader classification that ranges from Conventional DTs (Model DT and Connected DT) to Intelligent DTs (Predictive DT, Prescriptive DT, and Autonomous DT), as initially outlined in the preliminary findings reported in (Villegas et al., 2024b) (see Fig. 5). This detailed breakdown into five maturity levels is driven by the need to better capture the evolving nature of DTs and the different levels of sophistication in their implementation.

To ensure analytical transparency and reproducibility in the classification of DT implementations by maturity level, a structured coding approach was applied (see Table 2). Generalized statements describing functional characteristics of DTs (1st order codes) were retrieved from the literature and then grouped under five categories that reflect the DT maturity levels used in this study (2nd order categories): *Model DT, Connected DT, Predictive DT, Prescriptive DT*, and *Autonomous DT*. These statements capture the core functionalities and enabling mechanisms

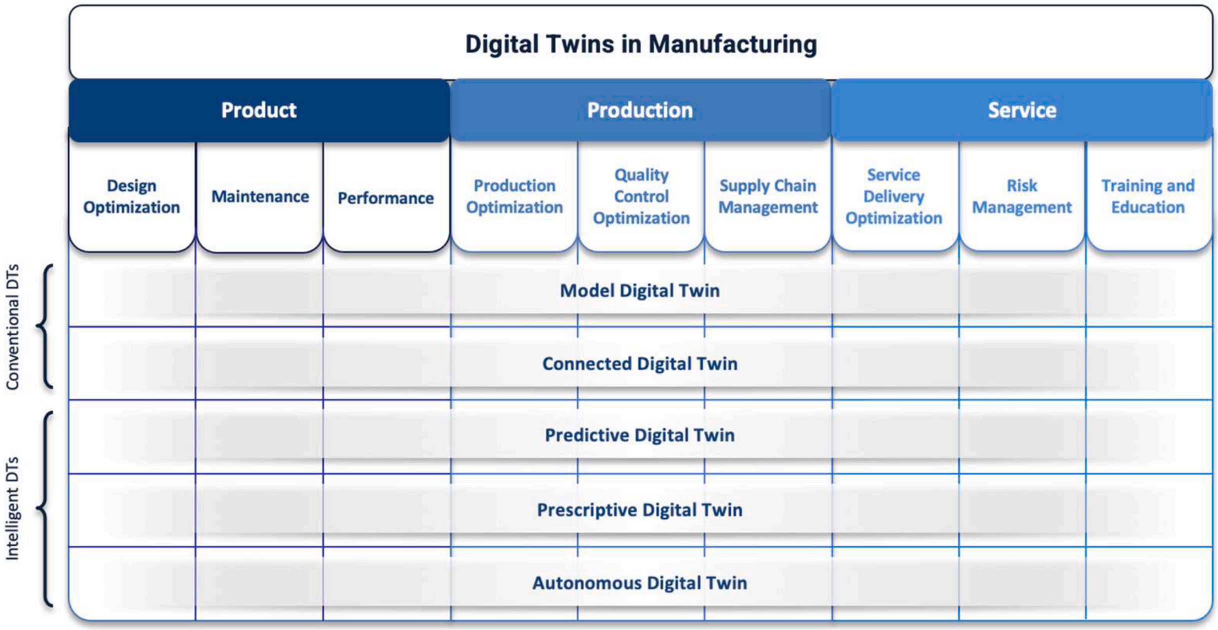


Fig. 5. Digital Twins in Manufacturing – Maturity Levels.

Table 2
Coding Procedure for Identification of DT Maturity Levels.

1st Order Codes (Generalized statements)	2nd Order Categories (DT Maturity Levels)
Create a static digital model of a physical system	Model DT
Use offline simulations and manual data entry	
Parameterize the digital model manually	
Connect physical system to digital model for real-time data flow	Connected DT
Collect data automatically from sensors and devices	
Display current state of the system to the user	
Integrate historical and real-time data for predictions	Predictive DT
Apply predictive models	
Provide the user with predictive insights or forecasts	
Apply prescriptive models	Prescriptive DT
Recommend optimal actions to users based on analysis	
Deliver actionable recommendations for decision-making	
Enable the system to make and execute decisions autonomously	Autonomous DT
Implement self-x capabilities	
Adapt and optimize operations in real time without human intervention	

found in the reviewed use cases while reflecting the evolving nature of DTs.

Existing classifications of DTs seem to be rigid, failing to account for their evolving nature by establishing one fixed “Digital Twin” category that does not accurately reflect the progressive development of DT capabilities, thereby creating ambiguity in defining and distinguishing different DT implementations. This rigidity has further motivated the debate over what qualifies as a DT, broadening the gap between academia and industry.

The proposed maturity levels aim to establish a common taxonomy for the levels of sophistication of DTs in manufacturing, preserving the term "Digital Twin" across the spectrum of the maturity levels to acknowledge ongoing implementation efforts, even when full DT capabilities have not yet been realized. Rather than disqualifying partial implementations, this approach promotes transparency in five maturity levels of DT applications, ensuring clarity and consistency in terminology. By doing so, it helps prevent premature claims of full DT capabilities –an issue highlighted in (Villegas et al., 2024a) and (Negri et al., 2020)– while recognizing the gradual improvements made in DT implementations. This transparency is deemed essential for bridging the gap between academia and industry, as it promotes a shared understanding of DTs in terms of their maturity and the capabilities that can be achieved for DT applications at given levels, further appealing to the granular nature of the DTs. To address the need for a standardized naming convention while accounting for different maturity levels, a spectrum has been identified as represented in Fig. 6 to Fig. 9, while each maturity level is hereinafter defined aligning to selected references from literature.

- **Model Digital Twin**: (DT Prototype (Grieves & Vickers, 2017) or Digital Model (Kritzinger et al., 2018)) at this maturity level the DT is primarily based on a static model of the Physical System (which, for instance, might or might not exist). It represents the system’s structure, components, and their relationships. The *Model DT* provides a basic understanding of the system but lacks real-time data connection and dynamic capabilities (Barricelli et al., 2019; Botín-Sanabria et al., 2022; Ruzsa, 2021; Singh et al., 2021). For instance, data flows manually (i.e., with user intervention to manually parametrize the static model) from the Physical System into the Digital System and vice versa (see Fig. 6), creating a linkage between them but not as a device-to-device connection (i.e., disconnected, with no real-time data connection). Something important to highlight at this point is that a *Model DT*, at the Digital System, can be represented from a simple black box model up to a high-fidelity hyper-realistic one.
- **Connected Digital Twin**: (DT Instance (Grieves & Vickers, 2017) or Digital Shadow (Kritzinger et al., 2018)) the Digital System is now connected in real-time with the Physical System. In this sense, data is automatically collected from the physical asset/process, from defined data sources, and consumed as an input for the virtual replica of the system, enabling a unidirectional, open-loop synchronization of data (see Fig. 7). This enables the DT to execute simulations or analyses based on real data gathered from sensors, devices, and other sources embedded within the physical system. By integrating real-time data, the *Connected DT* provides a representative replica of the system’s current state and behavior that provides basic insights to the user to support the decision-making process (actions to be executed manually, by the user, into the Physical System). (Botín-Sanabria et al., 2022; Ruzsa, 2021)
- **Predictive Digital Twin**: (DT (Grieves & Vickers, 2017; Kritzinger et al., 2018) or Intelligent DT (Grieves & Vickers, 2017)) as the DT becomes more sophisticated, it can leverage historical and real-time data to automatically provide information in terms of predictive insights (see Fig. 8). By applying advanced analytics techniques such as machine learning and statistical modeling, the *Predictive DT* can passively, upon predetermined variables, anticipate future behavior, performance, and potential issues. This enables the automatic delivery of information, in terms of predictions, which is then interpreted by the user to support enhanced decision-making and implement appropriate changes in the physical system. (Barricelli et al., 2019)
- **Prescriptive Digital Twin**: (DT (Grieves & Vickers, 2017; Kritzinger et al., 2018) or Intelligent DT (Grieves & Vickers, 2017)) having the basis on predictive capabilities, the *Prescriptive DT* goes a step further, entering into the early stages of active roles, by improving user’s decision support through the delivery of actionable recommendations from which the user can select and implement the most appropriate course of action (see Fig. 8). It can simulate different scenarios, evaluate trade-offs, and propose optimal courses of action.

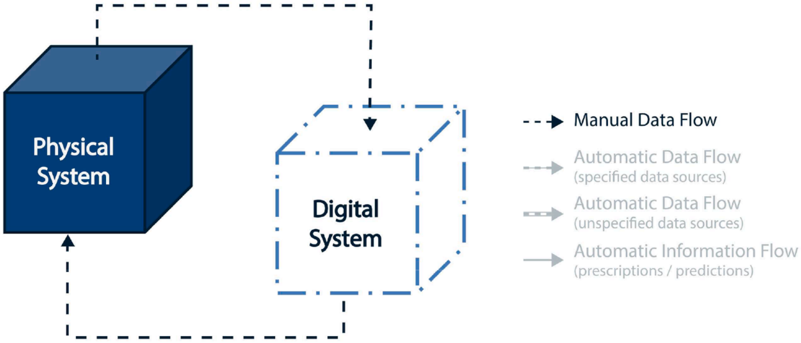


Fig. 6. Model Digital Twin (adapted from (Kritzinger et al., 2018)).

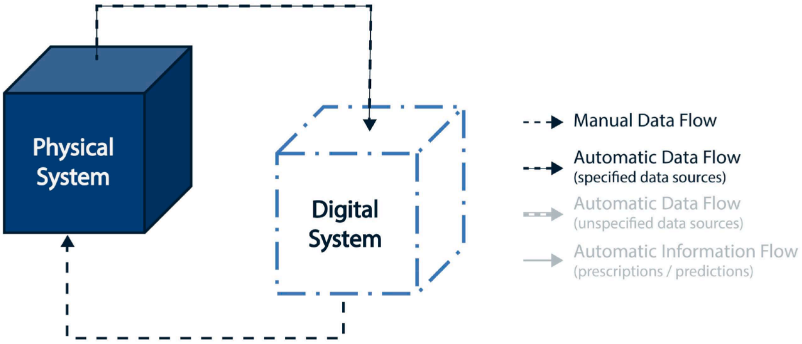


Fig. 7. Connected Digital Twin (adapted from (Kritzinger et al., 2018)).

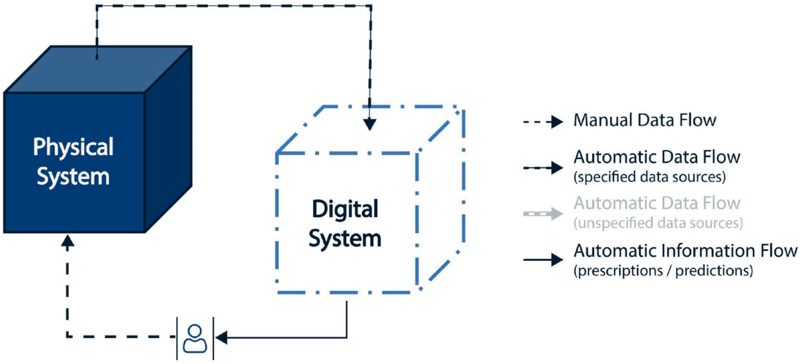


Fig. 8. Predictive and Prescriptive Digital Twin (adapted from (Kritzinger et al., 2018)).

The *Prescriptive DT* might help organizations optimize their operations and products, reduce costs, and improve overall performance.

- **Autonomous Digital Twin**: (DT (Grieves & Vickers, 2017; Kritzinger et al., 2018) or Intelligent DT (Grieves & Vickers, 2017)) the highest maturity level for a DT is the autonomous stage. At this level, the DT leverages self-x capabilities (i.e. self-learning, self-optimization, and self-adaptation) providing it with cognitive abilities that fully unlock its active role. This enables the DT to autonomously elaborate on data from unspecified sources. On one side, at this maturity level, authors claim the DT to have the ability to operate and make decisions independently (closing the loop). In this end, it is capable of establishing bidirectional data synchronization between the physical and digital systems, enabling it to act upon the physical environment based on its understanding of system behavior and the predictions/prescriptions according to the objectives it is deployed for (context awareness capabilities) (see Fig. 9 **a)**). It can learn from its interactions, adapt to changing conditions, and optimize its own performance (Maschler et al., 2021; Singh et al., 2021; Tao, Sui, et al., 2019; Zhao et al., 2019). On the other side, it is claimed that it has the ability to leverage self-x capabilities and context awareness, but with the main aim to augment human decision-making process (Al Faruque et al., 2021; Ashtari Talkhestani et al., 2019; Grieves, 2022; Ramasubramanian et al., 2022) (see Fig. 9 **b)**).

3.4. From the Fragmentation in Digital Twin's Knowledge to a Unified Framework

From the previous analysis, it becomes evident that the widespread adoption of DTs across manufacturing has led to a broad yet fragmented body of knowledge regarding their applications and maturity levels in different manufacturing domains.

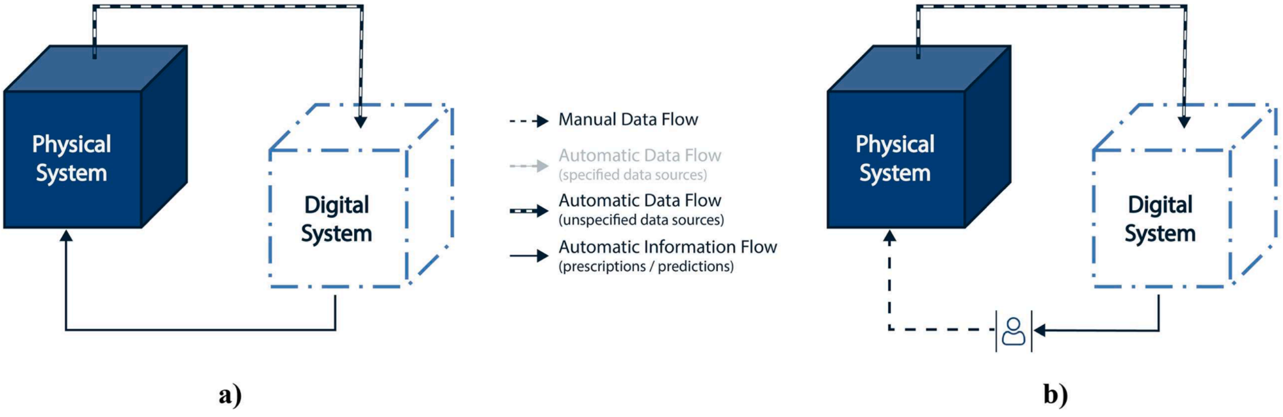


Fig. 9. Autonomous Digital Twin (adapted from (Kritzinger et al., 2018)).

While the proposed multi-dimensional taxonomy –built on manufacturing domains, applications and maturity levels– aims to promote an initial alignment and transparency in DT implementation, the combined application-maturity dimensions remain largely disjointed. As discussed before, DTs exhibit an adaptive nature, as they can be deployed across multiple domains in manufacturing, such as product, production, and service, each with its unique set of applications, thus with a unique set of requirements. Similarly, the evolving nature of DTs is reflected in their maturity levels, which vary from basic digital models to fully autonomous systems, with each level implying different functionalities and technological capabilities. But the disconnection in this fragmented DT landscape is evident when considering that a DT developed for a specific application at one maturity level may require a substantial redefinition of its requirements and capabilities if either dimension changes. In other words, any shift in the target application or maturity level can directly affect the DT's performance, integration strategies, and/or overall value proposition. This reflects the inherently granular nature of DTs, where different applications, driven by their business value, may evolve under the different levels of sophistication due to the technological capabilities.

Thus, as evidenced from the literature findings, there is a clear need for a comprehensive framework that integrates these dimensions –applications and maturity levels– to effectively address the granular nature of DTs. Such a framework would not only standardize terminology and classification criteria but also offer practical guidance for adapting DT implementations as technological capabilities evolve and applications extend or change in requirements. Ultimately, it would lead to a unified classification of DT applications that could be adopted across different manufacturing domains.

4. Framework Development

To address the identified fragmentation and establish a holistic synthesis of existing literature, while promoting a unified understanding of the DT landscape, an integrative review approach was adopted. This method allows the synthesis of insights from representative literature (Fan et al., 2022), in this case, the selected articles identified at the Included phase of the SLR. The result of such analysis led to the development of two core frameworks designed to provide both clarity and structure to the fragmented landscape of DT research in manufacturing. These frameworks were envisioned to address the challenges identified at **RP1, RP2**, and **RP3**, ensuring that both application- and technology-driven perspectives are adequately integrated.

4.1. Development of the Digital Twin Application-based Framework

The development of the **Digital Twin Application-based Framework** (see Fig. 10) began with a systematic classification of the selected DT publications. The goal was to categorize these publications based on the type of DT solution and level of integration they reported (i.e., following the coding in Table 1 and Table 2, correspondingly). This classification process involved extracting specific attributes from each article, including the application type and its associated maturity level, to provide general expectations for the functionalities that a DT might exhibit at different levels of sophistication of the DT implementation. Additionally, the framework provides a business-oriented perspective by associating applications with specific potential business values that they might bring to companies. These were directly retrieved from the reviewed papers by analyzing either the objective for which the DT was implemented or the final benefits observed after the implementation. For example, in the *Production* domain, the application of DT for *Production Optimization* is linked to business values such as downtime reduction, improved production workload, optimized resource utilization, and enabled flexibility, all contributing to the increase of operational efficiency and cost reduction. These business values were derived from the reviewed literature by analyzing either the objectives behind the DT implementations or the outcomes reported. For instance, statements such as "minimizing idle time" were interpreted as optimized resource utilization; "improving production throughput" as improved production workload; "improving asset availability" as downtime reduction; and "enhancing flexibility in resource allocation" as enabled flexibility. Similarly, "optimizing shopfloor workflows" was mapped to optimized production shifts and shopfloor management.

The horizontal axis of the framework is composed by the applications, outlined in Section 3.2, mapped into one of three manufacturing domains (product, production, or service) described in Section 3.1. The vertical axis represents the five maturity levels of DTs, ranging from model to autonomous DTs, as described in Section 3.3. This dual-axis approach ensured that each DT application was not only contextualized by its domain but also assessed by its progression in sophistication. At each application-maturity level quadrant, a general expectation of the DT is defined, derived from the articles represented at that point (see Appendix A). For cases where no explicit references to maturity or application were found, informed assumptions (with respect to its general expectation) were made based on the general definition of the maturity level, ensuring that the framework remained comprehensive. These specific cases are marked with a light gray fill at the framework.

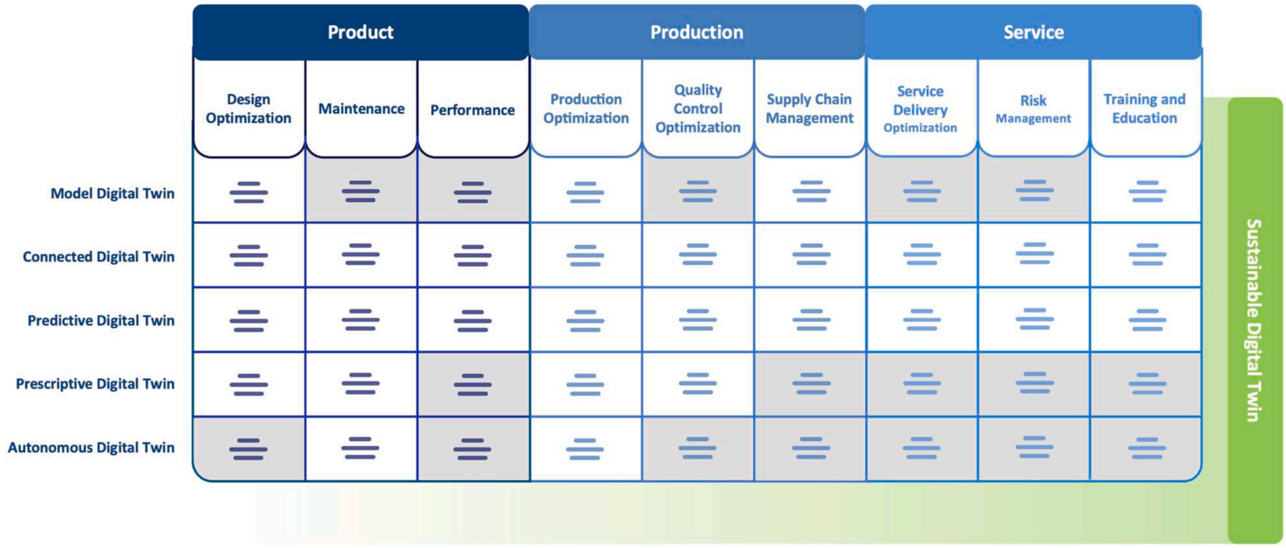


Fig. 10. Digital Twin Application-based Framework – Overview (see Appendix A for a detailed view).

Having a look through sustainability lenses, by acknowledging its importance for the future of smart and sustainable manufacturing, the review of the literature reveals that sustainability plays a significant role in various applications of DTs, or in a general sense, across the domains of manufacturing (product, production, and service). This is materialized through the classification of the selected articles at a bottom layer of the framework, defined with the end purpose to distinguish the contributions to the sustainability dimensions within each manufacturing dimension. The literature in fact provides examples of how DTs can be effectively employed for monitoring and optimizing energy consumption in a plant or process, reducing emissions (Abdoune et al., 2023; Constantinescu et al., 2020; May & Psarommatis, 2023; Min et al., 2019), minimizing waste generation (through optimized raw material utilization) within the production of a product (Azamfirei et al., 2023; Bazaz et al., 2019; Kim, 2019; Min et al., 2019), and decreasing the carbon footprint of products (He & Bai, 2021). This collective evidence underscores a central focus on resource efficiency, highlighting its direct connection with the environmental pillar of sustainability. Simultaneously, this focus aligns with the economic pillar of sustainability by promoting cost savings through the implementation of efficient production processes and optimized resource utilization. Regarding its connection to the social pillar of sustainability, literature also provides examples of DT applications in enhancing workplace safety (Bevilacqua et al., 2020; Cimino et al., 2019) and optimizing job allocation and scheduling (Sit & Lee, 2023). Thus, it can be said that, overall, a DT solution should be designed for a specific application, with a defined maturity level, and could further be aligned with sustainable application requirements, giving rise to the development of a Sustainable Digital Twin (SDT).

Building on this general structure, the rest of the selected articles were then populated across the framework. To illustrate this process, two exemplar cases are illustrated hereinafter.

Zhao et al. (2019) implemented a DT to autonomously control a micro-dots punching machine. The authors presented a model that utilizes a high-precision online detection and control system to create a digital representation of the physical system. This DT allowed for real-time monitoring and analysis of the punching process. Additionally, a novel staggered punching approach was proposed, and a joint optimization model was developed to coordinate the micro-punching system and the staggered process. The DT was enabled with context-awareness capabilities, allowing for an autonomous adjustment of the system. This was done by analyzing errors and compensating them during the punching process. Reflecting on the characteristics of the deployed DT at the presented use case, and addressing it at a specific quadrant of the proposed **Digital Twin Application-based Framework**, it was mapped into the DT for *Production Optimization* application as it was used to analyze and compensate the punching process. Due to its capabilities, it was mapped into the *Autonomous DT* maturity level, as it had the ability to do autonomous adjustment based on its context.

In contrast, Tao et al. (2019) illustrated the creation of a DT as the virtual representation of a bicycle, connected to its real counterpart in the physical space. Through the use of IoT and mobile Internet technologies, the virtual space gathered data from the real bicycle, including speed, acceleration, wheel pressure, and user comments. This data was then utilized to establish a virtual model that accurately reflected the real bicycle status. Throughout the lifecycle of the bicycle, the virtual space and physical space co-evolved, with the virtual space continuously collecting, analyzing, and accumulating data from the physical space. The authors stated that this data could be leveraged for the design or redesign of future generations of bicycles, enabling continuous improvement and optimization. In this case, the application of the DT was addressed as a DT for *Product Design Optimization* and for *Product Performance*. Given its capabilities it was framed under the *Connected DT* maturity level, as the model only used the data to perform simulations of future designs while monitoring its current performance status. Authors also proposed a further improvement of the DT with simulation model to predict the performance and within their general process of building a functional DT, although not included in the bicycle use case, they acknowledge the relevance of the use of machine learning models to perform predictive designs based on the analysis of the simulated designs, and advanced AI techniques to enhance the DT with cognitive abilities to provide simple design recommendations. In this matter, this publication was also mapped under the *Predictive DT* maturity level for *Product Design Optimization* and *Product Performance,* and at the *Prescriptive DT* maturity level for *Product Design Optimization*.

4.2. Development of the Digital Twin Technological Capabilities Framework

Building upon the structure of the **Digital Twin Application-based Framework**, the **Digital Twin Technological Capabilities Framework** (see Fig. 11) was developed to identify and categorize the technological requirements for DTs across domains and maturity levels. This framework aims to bridge the gap between the theoretical applications of DTs and the technological capabilities needed for their practical implementation.

The process began by revisiting the selected articles to extract technological attributes linked to the DT use cases already classified within the **Digital Twin Application-based Framework**. Each use case, within each domain-maturity level quadrant, was examined through: 1) the system level, referring to the architectural logic of data synchronization (i.e., whether the DT operated in a disconnected, open-loop or closed-loop configuration), and 2) the technology level, considering technologies that: (i) enable interaction between the physical and digital systems (e.g., sensors, communication protocols, integration of external data), (ii) support the level of sophistication of the DT, thereby underpinning its maturity level (e.g., simulation, predictive/prescriptive analytics, AI/ML models), and (iii) facilitate the interaction between the DT and the human user or other systems (e.g., visualization tools, AR/VR, DT platform). These attributes were then categorized into two groups: essential capabilities, frequently cited in the revised literature, and "nice-to-have" capabilities (placed below the dotted lines, within Appendix B, for domain-maturity level quadrant), less commonly referenced but still valuable depending on specific requirements addressed by the DT applications. It is important to note that lower maturity-level capabilities might eventually serve as foundational elements for higher-level DT implementations.

To illustrate this process, a couple of exemplar cases are discussed. In particular, as shown by Villegas et al. (2024b), the study by Flores-García et al. (2020) investigated the use of DTs for quality control and production optimization of a manufacturing system using Discrete Event Simulation (DES). To this end, the article was first classified as a contribution in the *Production* domain. Then, by its close examination, the essential capability of leveraging a simulation model was identified as an enabler of the *Model DT* maturity level, as observed in other use cases (Cimino et al., 2019; Stark et al., 2017; Tao & Zhang, 2017; Zhuang et al., 2021). Furthermore, capabilities such as data storage, predictive analytics, and closed-loop feedback were classified within the *Predictive DT* maturity level. Similarly, optimization and prescriptive analytics were highlighted for their role in *Prescriptive DTs*, while self-adjustment capabilities pointed towards the requirements for *Autonomous DTs*. Another example, bringing back (Zhao et al., 2019), with their demonstration of the deployment of a DT for micro-punching system control, that leveraged the use of advanced AI and machine learning algorithms to enable autonomous decision-making, allowed the classification of these technological capabilities into the *Autonomous DT* maturity level within the *Production* domain.

Overall, an important aspect of this framework's development was the recognition of existing gaps in the adoption of technological capabilities at certain manufacturing domains and maturity levels. As suggested in (Villegas et al., 2024b), a logical response to bridge these gaps is the extension of the framework by adopting a knowledge transfer

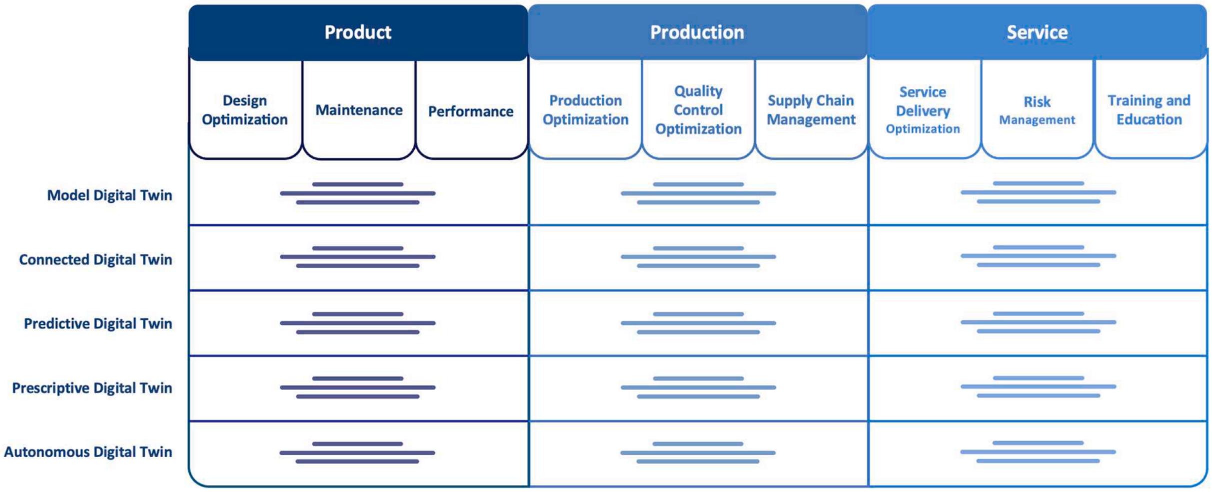


Fig. 11. Digital Twin Technological Capabilities Framework – Overview (see Appendix B for a detailed view).

approach. This refers to the transfer of technologies and related capabilities from one manufacturing domain to another given a certain maturity level (shown in blue text within Appendix B). Such transfers were driven by the recognition of commonalities in requirements across domains and the novelty of the technological capability implemented. For example, advanced analytics and simulation techniques, common in *Product* and *Production* domains at a *Prescriptive* maturity level, were identified as transferable capabilities to *Service* domain, further considering these as part of the core enablers of the maturity level itself. Another example, to illustrate the knowledge transfer process, given the novelty of technology, comes when looking into the implementation of DT platforms for the development of DTs. Such technological capability appears in the *Product* domain at the *Autonomous* maturity level. This technology, even though its use has not yet been reported in the *Production* and *Service* domains, as it starts gaining momentum and relevance in manufacturing, holds the potential to enhance DT applications in these domains. This cross-domain knowledge transfer highlights the interconnection of DT technological capabilities and their potential to expand the type of DT application at different manufacturing domains.

4.3. Interrelation of the Frameworks

The combination of the **Digital Twin Application-based Framework** and the **Digital Twin Technological Capabilities Framework** forms a comprehensive and structured basis for analyzing DTs in manufacturing. Together, these frameworks provide complementary perspectives, addressing both the functional roles of DTs and the technological requirements that enable these functions across varying maturity levels and manufacturing domains. This leads to a structured and unified solution to capture the evolving, adaptive, and granular nature of DTs.

The interrelation between these frameworks promotes a deeper understanding of the DT implementation, which might help academic researchers and industrial practitioners to systemically implement DTs. While the **Digital Twin Application-based Framework** categorizes DTs by their practical applications, the **Digital Twin Technological Capabilities Framework** ensures a linkage to the technological requirements to realize these. This dual structure allows multiple stakeholders to identify gaps, prioritize investments, and strategize their DT development efforts effectively.

To illustrate this interrelation, the case of the bicycle DT presented by Tao et al. (2019) is revisited as a hypothetical worked example, reinterpreted to demonstrate how the two frameworks could be jointly applied in a systematic manner to a practical context. The authors initially aimed to create a virtual representation of a bicycle to monitor its real-time performance and use that data to improve future designs. Based on this objective, the first step for a practitioner using the proposed frameworks –with the aim to plan for the development of a DT– would be to systematically map these requirements within the **Digital Twin Application-based Framework** (see Fig. 12). This begins with identification of the manufacturing domain to which the intended application belongs. In this case, since the physical system is a single bicycle within a 'bicycle-sharing' fleet, the application falls within the *Product domain*. Once the domain is identified, the second step is to determine the intended application. For this use case two relevant applications are *Product Performance*, for real-time performance monitoring, and *Product Design Optimization*, for improving future designs. Following the Product Lifecycle Management logic, and given the current state of the use case, the application objective that can be prioritized is *Product Performance* through real-time monitoring. The third step requires the practitioner to go through the maturity levels. This includes analyzing the statements that describe what is expected from a DT for the identified application at each maturity level and matching them with the objective of the intended use. In the bicycle use case, with the aim to monitor its real-time performance, its objective aligns with the expectation of a *Connected DT* (for *Product Performance*): "The DT is able to collect real-time data, from sensors and other sources, of the physical product, to simulate and present the current performance state of the product".

Once the domain, application, and maturity level are defined, the fourth and final step is to identify the necessary essential and/or "nice-to-have" capabilities within the **Digital Twin Technological Capabilities Framework** (see Fig. 12). To function as a *Connected DT* for *Product Performance*, the framework presents a set of technological capabilities, in addition to the ones available at the lower-level *Model DT*, including IoT sensors for real-time data acquisition, cloud computing, and data-driven simulation. In Tao et al. (2019) use case, the authors used IoT and mobile Internet technologies to gather and store data on speed, acceleration, wheel pressure, and comments from the user, which was then used to create a virtual model. Since not all essential and/or "nice-to-have" technological capabilities from the framework were implemented in this use case, the analysis highlights the framework's role in providing practitioners with a comprehensive set of options from which to select, according to the specific requirements of their application.

As the use case evolved, the authors' objective shifted toward *Product Design Optimization*, with their intention to leverage historical data and simulation to redesign the bicycle. This new objective requires the DT to advance to a higher maturity level – specifically, the **Predictive DT** level. The framework defines this level as: "The DT is used for predictive

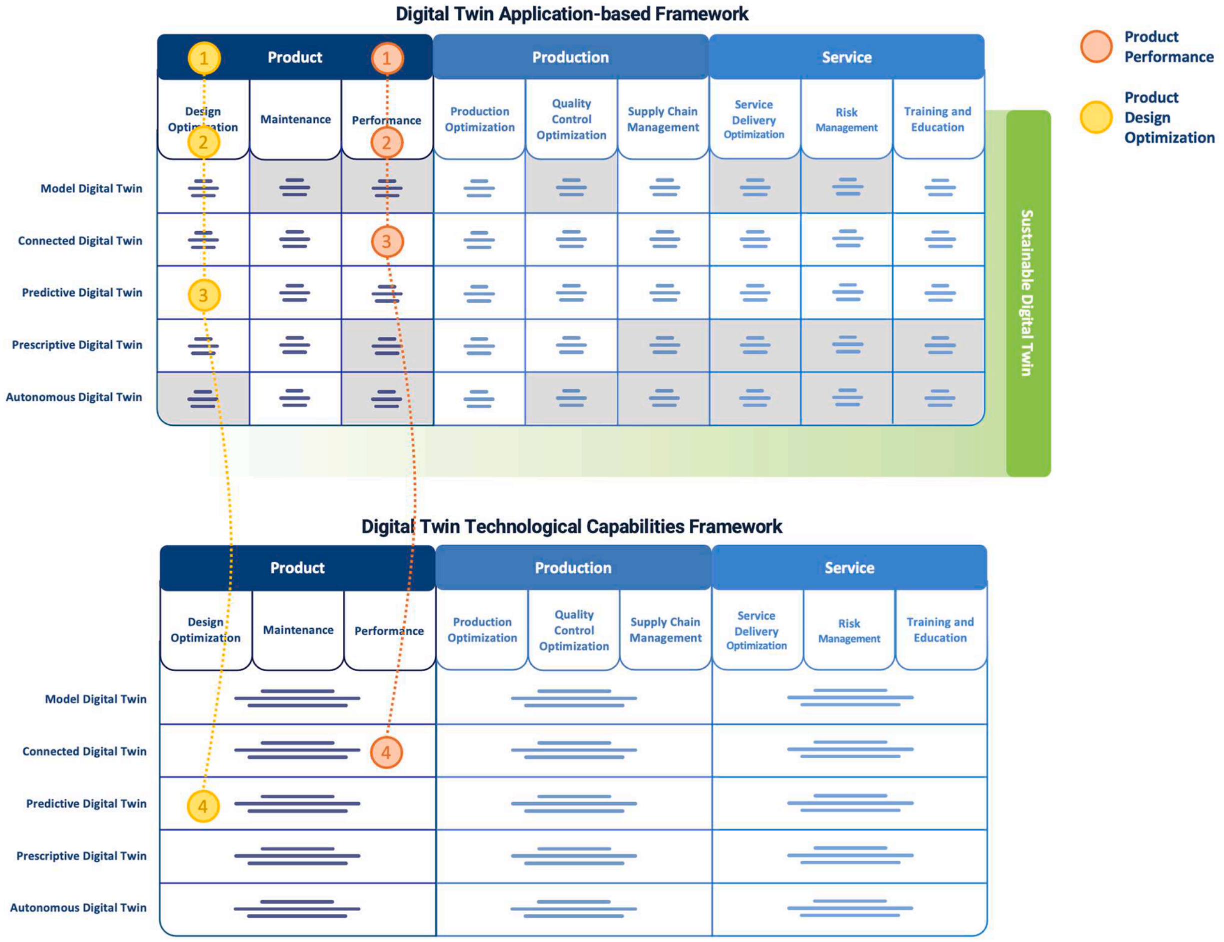


Fig. 12. Interrelation of the Frameworks: step-by-step guidance through Tao et al. (2019) use case.

analysis, allowing engineers to simulate and estimate different scenarios to optimize product design before physical testing". This aligns with the second objective of the use case, which aimed to update the bicycle's design scheme. While the initial *Connected DT* relied primarily on IoT and mobile Internet, achieving the *Predictive DT* requires additional technological capabilities such as advanced simulation models for predictive analytics, as outlined in the **Digital Twin Technological Capabilities Framework**. For instance, within this perspective, the authors proposed testing variables such as brake distance, tire wear, speed, and backseat durability under various conditions through simulation to iteratively improve the design. This example, once again, illustrates how practitioners can use the framework to identify and prioritize technological capabilities based on evolving application needs.

This example demonstrates the strength of the two frameworks in supporting a systematic and adaptable approach to design DT applications over time. Their interrelation allows practitioners to move from identifying business objectives to selecting the technological capabilities that support specific DT applications upon specific maturity levels. However, while the frameworks provide a structured lens for understanding DT applications and maturity levels with their corresponding general expectation of the DT and technological capabilities, these frameworks do not provide a comprehensive definition that reflects their complexity. Addressing the evolving, adaptive, and granular nature of DTs requires a further step towards a unified definition that accounts for their dynamism in terms of applications and evolving maturity levels. Establishing such a definition would strengthen the conceptual foundation of DT research, ensuring consistency and alignment between academia and industry while guiding future advancements in DT implementation.

5. Proposed Definition of Digital Twins in Manufacturing

From the literature findings and the developed frameworks, it is evident that DTs in manufacturing hold the potential to drive innovation across product, production, and service domains by integrating physical and digital systems. However, as their applications and enabling technologies advance, these systems continuously evolve, potentially giving rise to new definitions and increasing ambiguity around the concept of a DT among academic researchers and industrial practitioners. In fact, despite their growing significance, a unified definition is still lacking.

To address this gap, this article proposes a definition grounded in *Complex Adaptive Systems Theory*, offering a lens to understand DTs as complex systems whose degree of complexity and functionality aligns with the requirements of their specific applications. The intended use of this unified definition of DTs is to capture their evolving nature –i.e., DTs advance through maturity levels as new technological capabilities are adopted and new functionalities are then provided through DT services– adaptive nature –i.e., DTs are applicable across diverse manufacturing domains and applications– and granular nature –i.e., each DT, tailored to a specific application, may evolve under different maturity levels.

The proposed definition derives from the analysis done by Emmert-Streib (2023), which identifies common approaches to define DTs –namely, the application-driven and technology-driven approaches– and explains why these have failed to provide solid, commonly accepted definitions while proposing one taking a fresh theory-driven approach. Emmert-Streib (2023) emphasizes, on the one hand, that the application-driven approach, often seen in the literature, provides valuable domain-specific insights but limits its applicability (or representativeness) to other domains or fields, not addressing the interdisciplinary potential of DTs. On the other hand, the technology-driven approach, while offering practical implementation details, can become complex and overloaded with non-essential details, limiting (by its definition) the capabilities of the DTs and making it difficult to grasp the core concepts.

Therefore, Emmert-Streib (2023) adopts a theory-driven perspective, aiming for an abstract and generalized definition to avoid domain-specific constraints and implementation biases. This scholar defines a DT as *"a mathematical model with an updating mechanism that generates data which are indistinguishable from its physical counterpart"*, and remarks that for the *"complexity science community a mathematical model with an updating mechanism is called a complex adaptive system"*. Furthermore, Emmert-Streib defines a DT system to show the role of the DT: *"A digital twin system (DTS) is a structured system that processes data from an experiment (EX) and a digital twin (DT) via analysis methods (M) and decision-making (DM). Hence, on the highest abstraction level a digital twin system (DTS) is a decision-making system."*

While this theory-driven perspective offers valuable abstraction and holds potential for broader generalization, it also reveals certain biases and limitations. The proposed definition by Emmert-Streib (2023) leans towards a data science perspective, which may limit other critical aspects of DTs, such as their maturity and integration levels. Moreover, this definition of a DT aligns more closely with what is traditionally referred to as a Digital Model (or *Model DT*), reducing it to a *mathematical model*. For what concerns the definition of the role of the DT, this better reflects what a DT should encompass; at an architectural level, setting the bidirectional synchronization between the physical and the digital system, and at a functional level, capturing elements like data analytics and decision-making. However, even this broader view overlooks the inherent inter-domain complexity and the dynamic evolution of DTs across varying applications and maturity levels.

To address these gaps, the proposed definition in this article adopts CAS theory, as derived from Emmert-Streib (2023) but with a broader scope to capture the evolving, adaptive, and granular nature of DTs, emphasizing their role as adaptive and complex systems shaped by their application requirements and the technological advancements supporting them.

5.1. Definition of Digital Twins in Manufacturing: Theoretical Abstraction through CAS Lens

Complex Adaptive Systems Theory provides a framework for understanding systems composed of multiple interacting components that present a collective behavior, adaptation, and self-organization in response to changes in their environment (Dooley, 1997). Originating from fields such as biology, economics, and social sciences, CAS theory has been increasingly applied to engineering and manufacturing to analyze systems characterized by complexity and dynamism (Emmert-Streib, 2023; Grieves, 2022; Ivanov et al., 2021; Jones et al., 2021).

At its core, CAS theory identifies a system as "adaptive" if it can adjust its structure, behavior, or interactions to meet new challenges or changes in its environment. This adaptability builds upon the fundamental concepts of Dooley (1997):

1. Agents and Interactions: a CAS consists of independent agents –entities with specific roles or functions– that interact with one another. These interactions drive the system's overall behavior, often producing emergent properties.
2. Emergence: refers to the system-level properties or behaviors that arise from the collective interactions of agents. These emergent properties cannot be fully understood by examining the individual components in isolation.
3. Feedback Loops: CASs are characterized by continuous feedback between agents and the overall system. Feedback loops, both positive and negative, allow the system to refine its behavior and adapt to changing conditions.
4. Self-organization: CASs exhibit a high degree of self-organization, wherein the system forms structures or patterns without external control. This property enables adaptability and resilience.
5. Non-linearity: The relationships between agents in a CAS are often non-linear, meaning small changes in one part of the system can lead to significant, unpredictable impacts elsewhere.
6. Co-evolution: The system evolves alongside its environment, with agents adapting not only to external changes but also to each other. This dynamic interplay shapes the system's development over time.

Drawing on CAS theory, DTs can be seen as systems composed by interconnected agents, digital and physical entities or systems, capable of interacting and adapting in response to changes in their environment. This adaptability reflects their granular nature, whereby each DT, tailored to a specific application, may evolve along a distinct maturity path depending on the requirements and dynamics of its operational environment/manufacturing domain in which it is deployed (adaptive nature). In this context, the maturity level of a DT (evolving nature) mirrors its ability to handle complexity, which is intrinsically related to the requirements of its intended application and enabled by a set of technological capabilities.

This given, the conceptualization of DTs in manufacturing promoted in this research moves away from making applications and technologies a vital and central part of the definition. This stands in contrast to those definitions that prioritize these elements so as to favor generalizability, acknowledging that it is the environment's requirements, that sets the need for specific applications alongside with the enabling technologies, that completely defines the DT itself.

Building on these principles, DTs can be conceptualized as complex systems capable of adjusting their complexity and functionality to meet the dynamic demands of their applications. This dynamic adaptability enables to consider DTs to co-evolve with the physical systems they represent, reflecting changes in manufacturing environments and business objectives.

The following comprehensive formal definition of DTs in manufacturing is then proposed:

> *"A Digital Twin in manufacturing is a Complex Adaptive System where the dependency of the digital system (data, models, and services) and the physical system (products, assets, production lines, supply chains, etc.) enables its dynamic adaptation in complexity and functionality to meet the evolving requirements of its application environment (product, production, and service domains)"*

This definition aligns with CAS theory, which suggests that a system's adaptive behavior emerges from the interconnections and co-evolutionary relationships between its constituent agents. In the context of a DT, the digital and physical systems are these agents where their mutual dependency is what states the necessary interconnection for the system to function as a cohesive whole. This relationship is crucial for understanding how DTs interact with other systems, whether physical or digital, to form a networked ecosystem, and where the interactions drive emergent properties, such as monitoring, predictive, prescriptive insights, and autonomous operations, which reflect DTs' maturity and integration levels.

Under this conceptualization, the characterization of a DT is no longer static in its nature; instead, it co-evolves with the specific requirements of given manufacturing domains and applications. For example, a DT initially implemented for basic product performance monitoring (product domain) might start as a *Connected DT*, focusing on data acquisition and visualization. As requirements evolve, this same DT can dynamically adapt its complexity and functionality to incorporate advanced analytics for failure forecasting (*Predictive DT*), or even integrate AI for autonomous design recommendations (*Prescriptive DT*), thereby showcasing its dynamic capability to evolve in complexity and functionality as requirements evolve over its application environment. Similarly, a DT for a production line (production domain), starting as a *Connected DT* for throughput tracking, could evolve to integrate energy optimization models or real-time scheduling algorithms, becoming a *Predictive* or *Prescriptive DT* for process efficiency. This illustrates how the proposed definition encompasses the DT's evolution across both application domains and evolving requirements, allowing for a flexible and comprehensive understanding of the DT concept regardless of its specific application or stage of development in a maturity path.

This CAS-based perspective highlights the inter-domain complexity and dynamic evolution of DTs across different applications and maturity levels, effectively addressing their granular nature. The previously introduced frameworks –which categorize DT applications, maturity levels, and enabling technologies– reinforce the view of DTs as systems that evolve over time and adapt to the specific manufacturing domain in which they are deployed. Recognizing the connection between a theory-driven general definition and its instantiation into application-specific needs and technological maturity levels is therefore essential. The CAS theory-driven definition of DTs, combined with the application- and capability-based frameworks, provides a unified conceptual foundation for understanding DTs in manufacturing. This is a pragmatic choice of this research, aimed to address the limitations of current common definitions by reflecting the complex role DTs might play in manufacturing ecosystems.

5.2. Proposed Digital Twin Theory-driven Definition Against Common Definitions

As previously mentioned, current DT definitions tend to follow either an application-driven (Madni et al., 2019; Zhuang et al., 2018) or a technology-driven (Al-Ali et al., 2018; Glaessgen & Stargel, 2012; Javaid et al., 2023; Negri et al., 2017) approach, as suggested by Emmert-Streib (2023), leading to inherent limitations in their domain applicability and adaptability to varying levels of complexity.

For instance, Glaessgen & Stargel (2012) defines a DT as "an integrated multi-physics, multi-scale, probabilistic simulation of a complex product and uses the best available physical models, sensor updates, etc., to mirror the life of its corresponding twin." This definition is distinctly technology-driven, emphasizing advanced simulation capabilities tailored primarily for complex product performance prediction. However, its strong focus on simulation and the product domain limits its evolution, thus fixing its functionality to predictive analysis, and applicability to complex product engineering scenarios. Similarly, Javaid et al. (2023) offer a technology-driven perspective, defining a DT as "a software model of a physical thing" that could be represented as "a simple algorithm that forecasts how a product or process will perform based on real-world data". Although this definition takes a step further and includes the production domain by considering the "process", it still frames the DT primarily as a predictive analytical tool. This narrow interpretation does not account for the dynamic adaptation to evolving requirements of its application environment. As such, the definition limits the DT's role to performance forecasting rather than encompassing broader functionalities such as prescriptive control, optimization, or autonomous decision-making, which might vary depending on the application requirements.

Negri et al. (2017) also provides a definition with a strong technological influence, stating that a DT "is meant as the virtual and computerized counterpart of a physical system that can be used to simulate it for various purposes, exploiting a real-time synchronization of the sensed data coming from the field". While acknowledging the importance of real-time synchronization and the use of sensed data, a key element to keep the interaction between the physical and the digital systems, this definition's primary emphasis remains on the DT's role as a simulation model. This technological focus, as in (Glaessgen & Stargel, 2012), can constrain the perceived scope of the DT. This limits its conceptualization to a tool predominantly used for simulation for "various purposes", rather than allowing for its evolution towards more proactive and autonomous roles, where the DT might need to perform functions beyond mere simulation.

On the application-driven side, Madni et al. (2019) define a DT as "a virtual instance of a physical system (twin) that is continually updated with the latter's performance, maintenance, and health status data throughout the physical system's life cycle". This definition is clearly tailored to specific applications within asset and maintenance management, and specifically condition monitoring. While highly effective for its intended purpose, its explicit focus on "performance, maintenance, and health status data" and application "throughout the physical system's life cycle" significantly narrows its domain applicability. Therefore, it does not easily extend to broader manufacturing domains and related applications, nor account for the potential of DTs to evolve in functionality beyond the specific monitoring task.

Finally, the ISO23247 (2021) standard defines a DT as "a fit for purpose digital representation of an observable manufacturing element with a means to enable convergence between the element and its digital representation at an appropriate rate of synchronisation". This definition, crucial for standardization within the manufacturing domain, inherently follows an application-driven approach. Its "fit for purpose" and "observable manufacturing element" statements, pragmatic for industrial implementation, imply a large scope of manufacturing domains in which DT application might be deployed, thus referring to the DTs' adaptive nature. Besides this robust foundation in applicability, its flexibility in functionality is yet limited. This limits its dynamic characteristic to evolve in accordance with the application and environment requirements, where the DT might go beyond maintaining "convergence" and "synchronisation" with the physical element it represents.

In contrast to these common definitions, the proposed definition, grounded in CAS theory, aims to frame the DTs as dynamic, interconnected systems that evolve in complexity and functionality based on domain-specific needs. The proposed definition has two major distinctive features.

- First, the nature of a complex adaptive system allows to move beyond current definitions that reduce DTs to "static" models, i.e., models linked to a fixed level of complexity and functionality. Unlike Glaessgen & Stargel (2012)'s and Negri et al. (2017)'s focus on simulation models, or Javaid et al. (2023)'s simple predictive algorithm, the CAS-based definition inherently implies that DTs "dynamically" respond and evolve in alignment with the changing needs of their application environment. As a result, emergent properties, implicit in the definition, can range from monitoring to predictive and prescriptive insights, and even to autonomous operations –functionalities that may be distributed across different manufacturing domains and applications.
- Second, the proposed definition highlights DTs as interconnected digital (data, models, and services) and physical (products, assets, production lines, supply chains, etc.) systems. This broader phrasing extends beyond definitions such as Madni et al. (2019)'s "virtual instance of a physical system" or Javaid et al. (2023)'s "software model of a physical thing" by emphasizing systemic connection. On the digital side, it encompasses not only simulations or algorithms but also a wider range of entities, such as the data, models, and services required for the function of the DT. On the physical side, it expands the scope beyond individual products to include assets, production lines, supply chains, etc., acknowledging applicability across the full spectrum of manufacturing domains (product, production, and service).

Further reflections help to clarify the implications of this theory-driven definition:

- First, it is worth explaining how DT “dynamically” adapts in complexity and functionality to meet the evolving requirements of its application environment. Three key concepts embedded in the definition are relevant to this end. The phrase "enables its dynamic adaptation in complexity" acknowledges that a DT’s internal structure and level of detail are not fixed but can change in response to needs, ultimately leading to multiple levels of sophistication represented through the maturity levels. Similarly, the “adapts in functionality" statement suggests a broader, evolving set of capabilities from monitoring to prediction, prescription, and autonomous operations, adapted in different application scopes. Last but not least, the explicit mention of "evolving requirements" and "application environment (product, production, and service domains)" addresses the adaptive nature across domains and applications, ensuring that the DT’s form and function are driven by the specific, changing needs of its context.
- Second, a particular aspect of the proposed definition, and one that differentiates it from interpretations that strictly separate the virtual and physical realms, is the explicit consideration of the high level of dependency between the digital and physical system in realizing DT as a CAS. This leads to considering the physical system within the DT’s conceptual boundary as key prerequire to enable dynamic adaptation within the application environment. The proposed definition is not that far from well-known definitions. It aligns with Grieves (2005)’s initial conception of the Digital Twin Model, which comprises three core elements: the physical space, the digital space, and the data and information interactions between them (Grieves & Vickers, 2017), Tao, Zhang, et al. (2018)’s five-dimension DT model for complex equipment, which builds on Grieves (2005)’s initial model and adds DT data and services, and Kritzinger et al. (2018)’s which recognizes that the physical system is intrinsically linked to the DT’s functional existence through continuous interaction between the physical and digital systems.

  In addition, three key considerations reinforce the dependency between digital and physical systems in realizing DT as a CAS.

  - First, DTs build upon the architecture of CPS, which are, by definition, formed by the tight coupling and coordination of digital and physical components (Ashtari Talkhestani et al., 2019; Ding et al., 2019; Flores-García et al., 2020; Qi, Zhao, et al., 2018). By building on this architecture, the DT concept inherits this foundational characteristic.
  - Second, the interaction between digital and physical components in a DT is a constitutive property, which determines a relationship of mutual dependency. Correspondingly, the digital representation’s identity and functional purpose are inherently defined by its connection to a specific physical instance, and vice-versa.
  - Third, the mutual dependency intensifies as the DT matures. The evolution from a static Model DT, where the physical system might or might not exist, to a Connected, Predictive, and ultimately Prescriptive or Autonomous DT, is not merely an internal digital upgrade; it represents a deepening dependency on the physical system and its co-evolution (e.g. by upgrading its sensing capabilities). While enabling technological capabilities are essential, it is in fact the continuous data stream from the physical system that provides the context, allows to trigger a context-aware dynamism, ultimately enabling the adaptive behaviors that define the most advanced DT services.

Finally, from a CAS theory perspective, a system’s boundary must encompass all elements that significantly influence its behavior; in other words, ignoring the physical system’s strong influence on the digital counterpart appears to lead to an incomplete or inaccurate system definition. This ultimately leads to an integrated viewpoint on the digital system and the physical system. On the one hand, and as aforementioned, the digital system, in its essence, is a dynamic representation that relies on continuous inputs from its physical counterpart to function, adapt, and provide value. On the other hand, the physical system is not merely an external entity but an integral part of the broader concept of a DT system that triggers the dynamic adaptation. In the end, including the physical system within the definition’s scope reflects the mutual dependency and allows for a more holistic understanding of the DT as a comprehensive engineered system, in particular a CAS, ultimately enabling capabilities such as dynamic interaction, feedback loops, and emergent behaviors that are crucial for its evolving nature. At the same time, and in coherence with CAS theory, digital and physical systems are two independent agents – entities with specific roles or functions – whose interaction and mutual dependency drive the system’s overall behavior.

6. Discussion

This study addresses the question of what constitutes a DT in the manufacturing context while exploring its primary applications, technological capabilities, and classification across maturity levels. Besides, by grounding the definition of DTs in CAS theory, the proposed conceptualization offers a comprehensive perspective that captures the evolving, adaptive, and granular nature of DTs. The following discussion analyzes how these findings contribute to a general understanding of DTs in manufacturing and their classification, finally highlighting some possible implications for future research and industrial implementation.

To contribute to answering the primary research question (**RQ1:** *What constitutes a Digital Twin in the context of manufacturing,* ***in terms of its definition****, application domains, technological capabilities, and maturity levels?*), **RQ1.2** aimed to define DTs within the manufacturing context, considering their inherent characteristics. As a result, this study proposes a theory-driven definition, outlining DTs as Complex Adaptive Systems composed of digital and physical entities that dynamically adjust their complexity and functionality to meet application-specific requirements according to the environment in which they are deployed. By doing so, this definition acknowledges the evolutionary nature of DTs, recognizing their ability to evolve alongside technological advancements and operational needs. In addition, the incorporation of CAS theory allows for a more general understanding of DTs as systems featuring emergent properties, non-linearity, feedback loops, and a potential for self-organization. Unlike previous definitions that lead to a rigid concept (i.e., “static” models, see Section 5.2), this conceptualization therefore fully reflects the “dynamic” interaction between the physical and digital systems and stands at the background of applicability across diverse manufacturing domains and maturity levels; this allows to comprehensively address the evolving, adaptive, and granular nature of DTs.

To finally give an answer to **RQ1** (*What constitutes a Digital Twin in the context of manufacturing, in terms of its definition,* ***application domains, technological capabilities****, and* ***maturity levels****?*), **RQ1.1** sought to identify the primary applications and technological capabilities associated with DTs in manufacturing. From the application perspective, the findings confirm that DTs can serve as pivotal enablers of innovation across product, production, and service domains. In the product domain, DTs facilitate the product lifecycle management, optimizing product design, maintenance and performance. In the production domain, DTs can support the optimization of manufacturing processes, quality control and improve operational efficiency across the supply chain. In the service domain, DTs enable the delivery of personalized services, management of risks, and training and education platforms. From the technological perspective, DTs rely on a combination of multiple technologies enabling data management, modeling, connectivity, and analytics capabilities that change depending on the maturity of the DT system that is deployed. Indeed, as DTs evolve through different maturity levels, the needed technological capabilities evolve from basic model-based representations to a sophisticated interconnected set of technologies that allow the deployment of autonomous systems capable of augmenting human decision-making and supporting even self-optimization. In the end, building on the findings achieved from **RQ1.1**, a classification is set-up for DTs in manufacturing, reflecting their emerging applications and maturity levels. This study then leads to align the identified DT applications with the proposed DT maturity levels, offering a common taxonomic viewpoint that creates an alignment and transparency in DT implementation by means of multiple dimensions: the manufacturing domains, applications, and maturity levels realizable through the technological capabilities. In particular, at the foundational level, Model DTs function as digital representations with minimal synchronization with their physical counterparts. As DTs advance in maturity, they integrate real-time data, predictive analytics, and prescriptive optimization, ultimately reaching the level of Autonomous DTs.

Considering the proposed DT-theory driven definition, it should be remarked that the progression in complexity and functionality is not merely due to a technological upgrade but rather a response to the manufacturing requirements. Coherently with this mindset, the adaptability of DTs ensures that their evolution is guided by application-driven needs, rather than an arbitrary technological roadmap. In any case, both the **Digital Twin Application-based Framework** and the **Digital Twin Technological Capabilities Framework** provide a structured yet flexible approach to concretely understand and classify DTs, allowing stakeholders to assess the current state of their DT implementation and systematically strategize future developments accordingly (as analyzed in Section 4.3).

From a Systems Engineering (SE) perspective, the proposed frameworks may be further expanded to support an end-to-end methodology for DT system design. In traditional SE approaches, the development of complex systems begins with the capture of stakeholder requirements, proceeds through functional decomposition, and ends in the definition of physical and digital components and their enabling technologies. In this sense, the **Digital Twin Application-based Framework** can be used as a tool to represent and identify high-level goals or stakeholder needs, while the **Digital Twin Technological Capabilities Framework** can guide the selection of appropriate technologies for implementation. However, a key intermediate layer is still missing: one that enables the functional decomposition of those high-level requirements into specific DT services. Given their tailored nature in addressing specific solutions, these services would define the system's functional architecture, i.e., functional blocks framed under the technological capabilities required to realize the intended solution (as done in the Digital Twins Capabilities Periodic Table (van Schalkwyk, 2022)), and would allow for the definition of specific Key Performance Indicators (KPIs) relevant to each implementation use case. In this sense, one can also imagine that the hierarchical structure of DT components in manufacturing, which links domains to applications and then to services and functionalities (see Fig. 3 above), becomes a good practice for moving from an application-based perspective to identifying and exploiting the technological capabilities for DTs across manufacturing domains, applications, and maturity levels.

As an overall conclusion, built on the evidence gathered from the state of the art, it can be stated that the presented frameworks spot some future areas of research on DTs in manufacturing. First, within the **Digital Twin Application-based Framework**, some missing applications were identified (marked in light gray within Appendix A), indicating opportunities for further development. Further on, DT applications should progressively increase in maturity, as most existing implementations –particularly in the product and production domains– have been deployed at mid-maturity levels (Connected DT and Predictive DT). Advancing toward higher maturity levels, such as Prescriptive DTs and Autonomous DTs, requires addressing gaps in application scope and ensuring that DTs can support increasingly complex decision-making and self-adaptive capabilities. From the **Digital Twin Technological Capabilities Framework**, it was identified that there is a need for a further exploration on the application of the transferred technologies across different manufacturing domains (e.g. from product to production domain, or from product to service domain) and assess how they can help in the deployment of higher maturity DT applications.

Last but not least, the conceptualization should lead to a mindset open to dynamic changes in the industrial implementation. Particularly, the proposed definition emphasizes the need for DTs to be designed with adaptability in mind. Therefore, given the dynamic nature of manufacturing environments, rigid DT architectures may become obsolete as new technologies emerge. Instead, by adopting the principles of CAS theory, DTs should be conceived and developed as adaptive systems, capable of evolving with industry application needs and technological innovations. All in all in this direction, DTs are required to evolve from "static" implementations –fit for specific purposes– toward a more agile and flexible approach, aimed at ensuring effectiveness to meet any change in the current and future industrial requirements.

7. Conclusion

This study has provided a comprehensive analysis of DTs in manufacturing, addressing their definitions, applications, technological capabilities, and maturity levels. Moreover, by grounding the conceptualization of DTs in two fundamental core frameworks and CAS theory, this research has proposed a unified conceptual framework that captures the evolving, adaptive, and granular nature of DTs, moving beyond static representations to highlight its dynamic characteristics. The findings emphasize that DTs should not be viewed as isolated digital replicas but as integrated digital-physical systems that evolve with technological advancements and operational demands.

One of the key contributions of this study is the structured classification of DTs, proposing a common taxonomy and demonstrating how DTs progress from basic digital models to fully autonomous systems along their applications in manufacturing. This classification stresses the fact that DT development is not merely a matter of increasing technological sophistication but rather a response to the growing requirements of manufacturing environments. The study also reinforces the importance of aligning DT technological capabilities with specific manufacturing applications, ensuring that technological advancements are driven by the practical industry needs rather than theoretical frameworks or technological roadmap alone.

On the one hand, for researchers, this study provides a foundation for further exploration into the maturity and evolution of DTs. The proposed frameworks offer a structured approach to assessing DT applications and technological capabilities, which can be used to guide future research on DT implementation in manufacturing. This framework aims to be flexible enough to cope with future DT implementations, being able to grow either horizontally –integrating new applications into the manufacturing domains–, vertically –integrating new maturity levels–, or even taking a step further into a detailed analysis for the classification of DT services within the available DT applications. Moreover, with the adoption of the proposed common taxonomy, DT research could benefit from transparency, labelling DT implementations according to the achieved capabilities, and recognizing the ongoing efforts towards achieving highly mature DT applications while providing a real overview of the maturity of DT's landscape. Additionally, grounding DTs in CAS theory, besides enabling the capacity to provide a general theory-driven DT definition that reflects the evolving, adaptive, and granular nature of DTs, it opens new research streams. For instance, it might motivate the investigation of how self-adaptive and resilient digital systems can be developed in dynamic industrial contexts. Researchers can also explore methods to sustain such self-adaptiveness by means of, e.g., an enhancement of DT scalability, an enrichment through the integration of emerging AI-driven decision-making tools (such as Gen AI), and, more in general, an examination of the role of knowledge management in facilitating dynamic DT implementation.

On the other hand, for industrial practitioners, the unified conceptual framework offers a practical guide for DT implementation, enabling an understanding of DT potential and aligning expectations with the achievable outcomes. In particular, the framework supports strategic decision-making by providing a structured overview of DT applications, maturity levels, and technological capabilities across product, production, and service domains. This helps practitioners to identify suitable DT solutions tailored to their specific needs, facilitating effective resource allocation and investment planning in DT technologies. Furthermore, the common taxonomy promotes better communication and collaboration within the industry, fostering the development of standardized methodologies and best practices for DT implementation.

Last but not least, the research calls for stronger collaboration between academia and industry to bridge the gap between theoretical advancements and practical applications, ensuring that DTs continue to evolve as enablers of smart, resilient, and sustainable manufacturing. The unified conceptual framework – jointly adopting the theory-driven definition and two concrete frameworks for understanding DTs in manufacturing – is also proposed as a means to provide an initial alignment in the meaning of DTs in manufacturing between the academic and industrial perspectives. Once such initial alignment in the conceptualization of DTs has been established, future research could then focus on developing a methodology for their systematic implementation, potentially grounded in Systems Engineering principles, and aligned with the CAS perspective, with the end purpose to convert stakeholders' requirements into tailored, easy-to-implement DT solutions.

Declaration of competing interest

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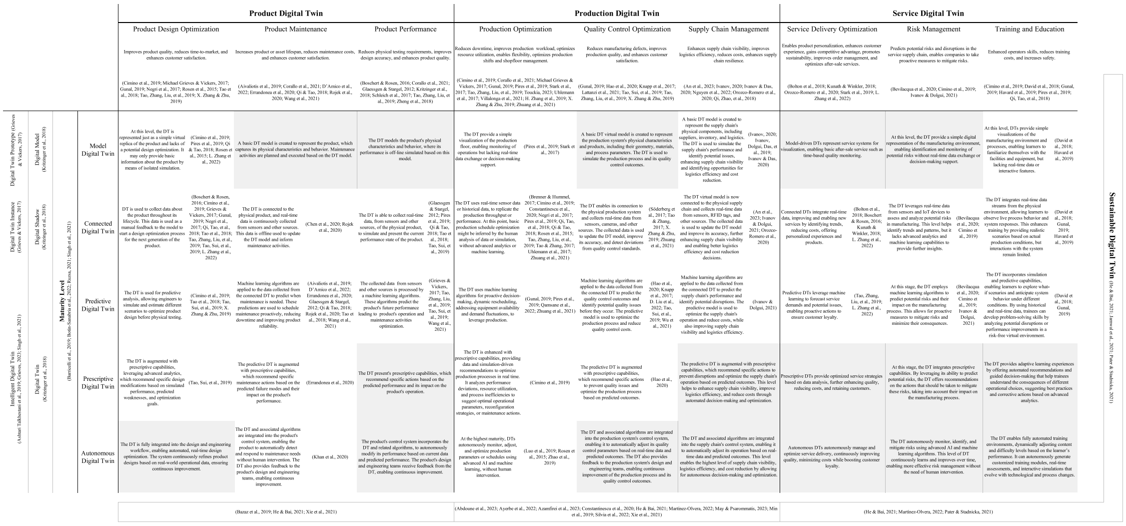
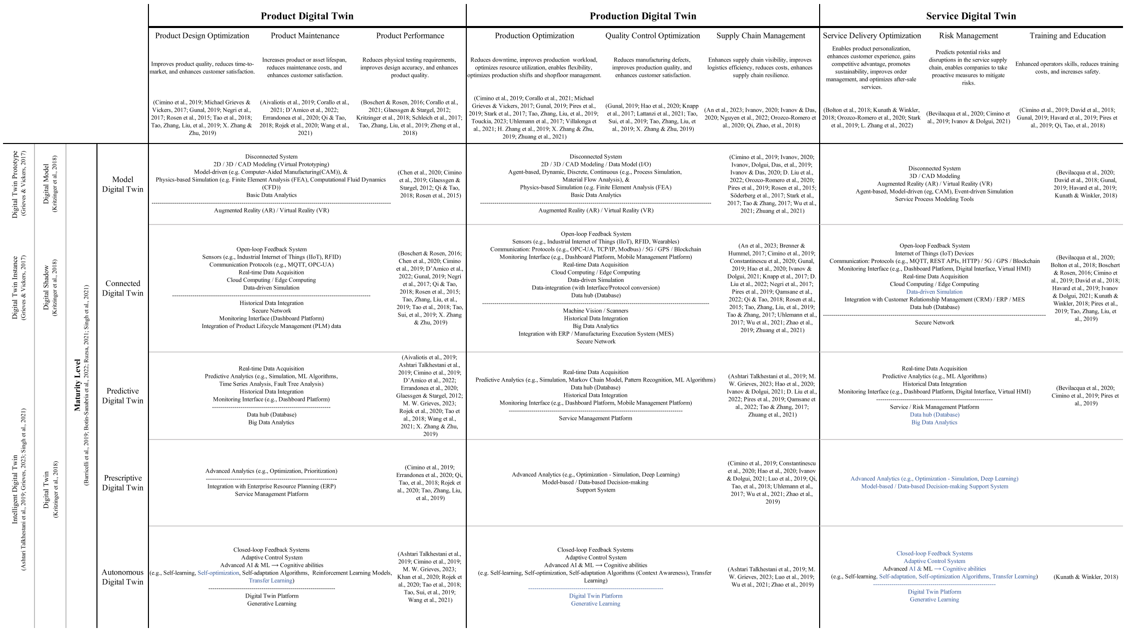
Appendix A



			Product Digital Twin			Production Digital Twin			Service Digital Twin		
			Product Design Optimization	Product Maintenance	Product Performance	Production Optimization	Quality Control Optimization	Supply Chain Management	Service Delivery Optimization	Risk Management	Training and Education
			Improves product quality, reduces time-to-market, and enhances customer satisfaction.	Increases product or asset lifespan, reduces maintenance costs, and enhances customer satisfaction.	Reduces physical testing requirements, improves design accuracy, and enhances product quality.	Reduces downtime, improves production workload, optimizes resource utilization, enables flexibility, optimizes production shifts and shopfloor management.	Reduces manufacturing defects, improves production quality, and enhances customer satisfaction.	Enhances supply chain visibility, improves logistics efficiency, reduces costs, enhances supply chain resilience.	Enables product personalization, enhances customer experience, gains competitive advantage, promotes sustainability, improves order management, and optimizes after-sale services.	Predicts potential risks and disruptions in the service supply chain, enables companies to take proactive measures to mitigate risks.	Enhanced operators skills, reduces training costs, and increases safety.
		Maturity Level (Barricelli et al., 2019; Botín-Sanabria et al., 2022; Ruzsa, 2021; Singh et al., 2021)	(Cimino et al., 2019; Michael Grieves & Vickers, 2017; Gunal, 2019; Negri et al., 2017; Rosen et al., 2015; Tao et al., 2018; Tao, Zhang, Liu, et al., 2019; X. Zhang & Zhu, 2019)	(Aivaliotis et al., 2019; Corallo et al., 2021; D'Amico et al., 2022; Errandonea et al., 2020; Qi & Tao, 2018; Rojek et al., 2020; Wang et al., 2021)	(Boschert & Rosen, 2016; Corallo et al., 2021; Glaessgen & Stargel, 2012; Kritzinger et al., 2018; Schleich et al., 2017; Tao, Zhang, Liu, et al., 2019; Zheng et al., 2018)	(Cimino et al., 2019; Corallo et al., 2021; Michael Grieves & Vickers, 2017; Gunal, 2019; Pires et al., 2019; Stark et al., 2017; Tao, Zhang, Liu, et al., 2019; Touckia, 2023; Uhlemann et al., 2017; Villalonga et al., 2021; H. Zhang et al., 2019; X. Zhang & Zhu, 2019; Zhuang et al., 2021)	(Gunal, 2019; Hao et al., 2020; Knapp et al., 2017; Lattanzi et al., 2021; Tao, Sui, et al., 2019; Tao, Zhang, Liu, et al., 2019; X. Zhang & Zhu, 2019)	(An et al., 2023; Ivanov, 2020; Ivanov & Das, 2020; Nguyen et al., 2022; Orozco-Romero et al., 2020; Qi, Zhao, et al., 2018)	(Bolton et al., 2018; Kunath & Winkler, 2018; Orozco-Romero et al., 2020; Stark et al., 2019; L. Zhang et al., 2022)	(Bevilacqua et al., 2020; Cimino et al., 2019; Ivanov & Dolgui, 2021)	(Cimino et al., 2019; David et al., 2018; Gunal, 2019; Havard et al., 2019; Pires et al., 2019; Qi, Tao, et al., 2018)
Digital Twin Prototype (Grieves & Vickers, 2017)	Digital Model (Kritzinger et al., 2018)	Model Digital Twin	At this level, the DT is represented just as a simple virtual replica of the product and lacks of a potential design optimization. It may only provide basic information about the product by means of isolated simulation. (Cimino et al., 2019; Pires et al., 2019; Qi & Tao, 2018; Rosen et al., 2015; L. Zhang et al., 2022)	A basic DT model is created to represent the product, which captures its physical characteristics and behavior. Maintenance activities are planned and executed based on the DT model.	The DT models the product's physical characteristics and behavior, where its performance is off-line simulated based on this model.	The DT provide a simple visualization of the production floor, enabling monitoring of operations but lacking real-time data exchange or decision-making support. (Pires et al., 2019; Stark et al., 2017)	A basic DT virtual model is created to represent the production system's physical characteristics and products, including their geometry, materials, and process parameters. The DT is used to simulate the production process and its quality control outcomes.	A basic DT model is created to represent the supply chain's physical components, including suppliers, inventory, and logistics. The DT is used to simulate the supply chain's performance and identify potential issues, enhancing supply chain visibility and identifying opportunities for logistics efficiency and cost reduction. (Ivanov, 2020; Ivanov, Dolgui, Das, et al., 2019; Ivanov & Das, 2020)	Model-driven DTs represent service systems for visualization, enabling basic after-sale service such as time-based quality monitoring.	At this level, the DT provide a simple digital representation of the manufacturing environment, enabling identification and monitoring of potential risks without real-time data exchange or decision-making support.	At this level, DTs provide simple visualizations of the manufacturing environment and processes, enabling learners to familiarize themselves with the facilities and equipment, but lacking real-time data or interactive features. (David et al., 2018; Havard et al., 2019)
Digital Twin Instance (Grieves & Vickers, 2017)	Digital Shadow (Kritzinger et al., 2018)	Connected Digital Twin	DT is used to collect data about the product throughout its lifecycle. This data is used as a manual feedback to the model to start a design optimization process for the next generation of the product. (Boschert & Rosen, 2016; Cimino et al., 2019; Grieves & Vickers, 2017; Gunal, 2019; Negri et al., 2017; Qi, Tao, et al., 2018; Tao et al., 2018; Tao, Zhang, Liu, et al., 2019; Tao, Sui, et al., 2019; L. Zhang et al., 2022)	The DT is connected to the physical product, and real-time data is continuously collected from sensors and other sources. This data is offline used to update the DT model and inform maintenance activities. (Chen et al., 2020; Rojek et al., 2020)	The DT is able to collect real-time data, from sensors and other sources, of the physical product, to simulate and present the current performance state of the product. (Glaessgen & Stargel, 2012; Pires et al., 2019; Qi & Tao, 2018; Tao et al., 2018; Tao, Sui, et al., 2019)	The DT uses real-time sensor data or historical data, to replicate the production throughput or performance. At this point, basic production schedule optimization might be inferred by the human analysis of data or simulation, without advanced analytics or machine learning. (Brenner & Hummel, 2017; Cimino et al., 2019; Constantinescu et al., 2020; Negri et al., 2017; Pires et al., 2019; Qi, Tao, et al., 2018; Qi & Tao, 2018; Rosen et al., 2015; Tao, Zhang, Liu, et al., 2019; Tao & Zhang, 2017; Uhlemann et al., 2017; Zhuang et al., 2021)	The DT enables its connection to the physical production system and collects real-time data from sensors, cameras, and other sources. The collected data is used to update the DT model, improve its accuracy, and detect deviations from quality control standards. (Söderberg et al., 2017; Tao & Zhang, 2017; X. Zhang & Zhu, 2019; Zhuang et al., 2021)	The DT virtual model is now connected to the physical supply chain and collects real-time data from sensors, RFID tags, and other sources. The collected data is used to update the DT model and improve its accuracy, further enhancing supply chain visibility and enabling better logistics efficiency and cost reduction decisions. (An et al., 2023; Ivanov & Dolgui, 2021; Orozco-Romero et al., 2020)	Connected DTs integrate real-time data, improving and enabling new services by identifying trends, reducing costs, offering personalized experiences and products. (Bolton et al., 2018; Boschert & Rosen, 2016; Kunath & Winkler, 2018; L. Zhang et al., 2022)	The DT leverages real-time data from sensors and IoT devices to assess and analyze potential risks in manufacturing. This level helps identify trends and patterns, but it lacks advanced analytics and machine learning capabilities to provide further insights. (Bevilacqua et al., 2020; Cimino et al., 2019)	The DT integrates real-time data streams from the physical environment, allowing learners to observe live process behavior and system responses. This enhances training by providing realistic scenarios based on actual production conditions, but interactions with the system remain limited. (David et al., 2018; Gunal, 2019; Havard et al., 2019)
Intelligent Digital Twin (Ashtari Talkhestani et al., 2019; Grieves, 2023; Singh et al., 2021)	Digital Twin (Kritzinger et al., 2018)	Predictive Digital Twin	The DT is used for predictive analysis, allowing engineers to simulate and estimate different scenarios to optimize product design before physical testing. (Cimino et al., 2019; Tao et al., 2018; Tao, Sui, et al., 2019; X. Zhang & Zhu, 2019)	Machine learning algorithms are applied to the data collected from the connected DT to predict when maintenance is needed. These predictions are used to schedule maintenance proactively, reducing downtime and improving product reliability. (Aivaliotis et al., 2019; D'Amico et al., 2022; Errandonea et al., 2020; Glaessgen & Stargel, 2012; Qi & Tao, 2018; Rojek et al., 2020; Tao et al., 2018; Wang et al., 2021)	The collected data from sensors and other sources is processed by a machine learning algorithms. These algorithms predict the product's future performance leading to product's operation and maintenance activities optimization. (Grieves & Vickers, 2017; Tao, Zhang, Liu, et al., 2019; Tao, Sui, et al., 2019; Wang et al., 2021)	The DT uses machine learning algorithms for proactive decision-making, dynamic rescheduling, addressing equipment availability and demand fluctuations, to leverage production. (Gunal, 2019; Pires et al., 2019; Qamsane et al., 2022; Zhuang et al., 2021)	Machine learning algorithms are applied to the data collected from the connected DT to predict the quality control outcomes and identify potential quality issues before they occur. The predictive model is used to optimize the production process and reduce quality control costs. (Hao et al., 2020; Knapp et al., 2017; D. Liu et al., 2022; Tao, Sui, et al., 2019; Wu et al., 2021)	Machine learning algorithms are applied to the data collected from the connected DT to predict the supply chain's performance and identify potential disruptions. The predictive model is used to optimize the supply chain's operation and reduce costs, while also improving supply chain visibility and logistics efficiency. (Ivanov & Dolgui, 2021)	Predictive DTs leverage machine learning to forecast service demands and potential issues, enabling proactive actions to ensure customer loyalty. (Tao, Zhang, Liu, et al., 2019; L. Zhang et al., 2022)	At this stage, the DT employs machine learning algorithms to predict potential risks and their impact on the manufacturing process. This allows for proactive measures to mitigate risks and minimize their consequences. (Bevilacqua et al., 2020; Cimino et al., 2019; Ivanov & Dolgui, 2021)	The DT incorporates simulation and predictive capabilities, enabling learners to explore what-if scenarios and anticipate system behavior under different conditions. By using historical and real-time data, trainees can develop problem-solving skills by analyzing potential disruptions or performance improvements in a risk-free virtual environment. (David et al., 2018; Gunal, 2019)
		Prescriptive Digital Twin	The DT is augmented with prescriptive capabilities, leveraging advanced analytics, which recommend specific design modifications based on simulated performance, predicted weaknesses, and optimization goals. (Tao, Sui, et al., 2019)	The predictive DT is augmented with prescriptive capabilities, which recommend specific maintenance actions based on the predicted failure modes and their impact on the product's performance. (Errandonea et al., 2020)	The DT present's prescriptive capabilities, which recommend specific actions based on the predicted performance and its impact on the product's operation.	The DT is enhanced with prescriptive capabilities, providing data and simulation-driven recommendations to optimize production processes in real time. It analyzes performance deviations, resource utilization, and process inefficiencies to suggest optimal operational parameters, reconfiguration strategies, or maintenance actions. (Cimino et al., 2019)	The predictive DT is augmented with prescriptive capabilities, which recommend specific actions to prevent quality issues and optimize the production process based on predicted outcomes. (Hao et al., 2020)	The predictive DT is augmented with prescriptive capabilities, which recommend specific actions to prevent disruptions and optimize the supply chain's operation based on predicted outcomes. This level helps to enhance supply chain visibility, improve logistics efficiency, and reduce costs through automated decision-making and optimization.	Prescriptive DTs provide optimized service strategies based on data analysis, further enhancing quality, reducing costs, and retaining customers.	At this stage, the DT integrates prescriptive capabilities. By leveraging its ability to predict potential risks, the DT offers recommendations on the actions that should be taken to mitigate these risks, taking into account their impact on the manufacturing process.	The DT provides adaptive learning experiences by offering automated recommendations and guided decision-making that help trainees understand the consequences of different operational choices, suggesting best practices and corrective actions based on advanced analytics.
		Autonomous Digital Twin	The DT is fully integrated into the design and engineering workflow, enabling automated, real-time design optimization. The system continuously refines product designs based on real-world operational data, ensuring continuous improvement.	The DT and associated algorithms are integrated into the product's control system, enabling the product to automatically detect and respond to maintenance needs without human intervention. The DT also provides feedback to the product's design and engineering teams, enabling continuous improvement. (Khan et al., 2020)	The product's control system incorporates the DT and related algorithms, to autonomously modify its performance based on current data and predicted performance. The product's design and engineering teams receive feedback from the DT, enabling continuous improvement.	At the highest maturity, DTs autonomously monitor, adjust, and optimize production parameters or schedules using advanced AI and machine learning, without human intervention. (Luo et al., 2019; Rosen et al., 2015; Zhao et al., 2019)	The DT and associated algorithms are integrated into the production system's control system, enabling it to automatically adjust its quality control parameters based on real-time data and predicted outcomes. The DT also provides feedback to the production system's design and engineering teams, enabling continuous improvement of the production process and its quality control outcomes.	The DT and associated algorithms are integrated into the supply chain's control system, enabling it to automatically adjust its operation based on real-time data and predicted outcomes. This level enables the highest level of supply chain visibility, logistics efficiency, and cost reduction by allowing for autonomous decision-making and optimization.	Autonomous DTs autonomously manage and optimize service delivery, continuously improving quality, minimizing costs while boosting customer loyalty.	The DT autonomously monitor, identify, and mitigate risks using advanced AI and machine learning algorithms. This level of DT continuously learns and improves over time, enabling more effective risk management without the need of human intervention.	The DT enables fully automated training environments, dynamically adjusting content and difficulty levels based on the learner's performance. It can autonomously generate customized training modules, real-time assessments, and interactive simulations that evolve with technological and process changes.
		Sustainable Digital Twin (He & Bai, 2021; Jamwal et al., 2021; Pater & Stadnicka, 2021)	(Bazaz et al., 2019; He & Bai, 2021; Xie et al., 2021)			(Abdoune et al., 2023; Ayerbe et al., 2022; Azamfirei et al., 2023; Constantinescu et al., 2020; He & Bai, 2021; Martinez-Olvera, 2022; May & Psarommatis, 2023; Min et al., 2019; Silvia et al., 2022; Xie et al., 2021)			(He & Bai, 2021; Martinez-Olvera, 2022; Pater & Stadnicka, 2021)		

Fig. A.1. Digital Twin Application-based Framework.

Appendix B



				Product Digital Twin			Production Digital Twin			Service Digital Twin		
				Product Design Optimization	Product Maintenance	Product Performance	Production Optimization	Quality Control Optimization	Supply Chain Management	Service Delivery Optimization	Risk Management	Training and Education
				Improves product quality, reduces time-to-market, and enhances customer satisfaction.	Increases product or asset lifespan, reduces maintenance costs, and enhances customer satisfaction.	Reduces physical testing requirements, improves design accuracy, and enhances product quality.	Reduces downtime, improves production workload, optimizes resource utilization, enables flexibility, optimizes production shifts and shopfloor management.	Reduces manufacturing defects, improves production quality, and enhances customer satisfaction.	Enhances supply chain visibility, improves logistics efficiency, reduces costs, enhances supply chain resilience.	Enables product personalization, enhances customer experience, gains competitive advantage, promotes sustainability, improves order management, and optimizes after-sale services.	Predicts potential risks and disruptions in the service supply chain, enables companies to take proactive measures to mitigate risks.	Enhanced operators skills, reduces training costs, and increases safety.
				(Cimino et al., 2019; Michael Grieves & Vickers, 2017; Gunal, 2019; Negri et al., 2017; Rosen et al., 2015; Tao et al., 2018; Tao, Zhang, Liu, et al., 2019; X. Zhang & Zhu, 2019)	(Aivaliotis et al., 2019; Corallo et al., 2021; D'Amico et al., 2022; Errandonea et al., 2020; Qi & Tao, 2018; Rojek et al., 2020; Wang et al., 2021)	(Boschert & Rosen, 2016; Corallo et al., 2021; Glaessgen & Stargel, 2012; Kritzinger et al., 2018; Schleich et al., 2017; Tao, Zhang, Liu, et al., 2019; Zheng et al., 2018)	(Cimino et al., 2019; Corallo et al., 2021; Michael Grieves & Vickers, 2017; Gunal, 2019; Pires et al., 2019; Stark et al., 2017; Tao, Zhang, Liu, et al., 2019; Touckia, 2023; Uhlemann et al., 2017; Villalonga et al., 2021; H. Zhang et al., 2019; X. Zhang & Zhu, 2019; Zhuang et al., 2021)	(Gunal, 2019; Hao et al., 2020; Knapp et al., 2017; Lattanzi et al., 2021; Tao, Sui, et al., 2019; Tao, Zhang, Liu, et al., 2019; X. Zhang & Zhu, 2019)	(An et al., 2023; Ivanov, 2020; Ivanov & Das, 2020; Nguyen et al., 2022; Orozco-Romero et al., 2020; Qi, Zhao, et al., 2018)	(Bolton et al., 2018; Kunath & Winkler, 2018; Orozco-Romero et al., 2020; Stark et al., 2019; L. Zhang et al., 2022)	(Bevilacqua et al., 2020; Cimino et al., 2019; Ivanov & Dolgui, 2021)	(Cimino et al., 2019; David et al., 2018; Gunal, 2019; Havard et al., 2019; Pires et al., 2019; Qi, Tao, et al., 2018)
Digital Twin Prototype (Grieves & Vickers, 2017)	Digital Model (Kritzinger et al., 2018)	**Maturity Level** (Barricelli et al., 2019; Botín-Sanabria et al., 2022; Ruzsa, 2021; Singh et al., 2021)	Model Digital Twin	Disconnected System 2D / 3D / CAD Modeling (Virtual Prototyping) Model-driven (e.g. Computer-Aided Manufacturing(CAM)), & Physics-based Simulation (e.g. Finite Element Analysis (FEA), Computational Fluid Dynamics (CFD)) Basic Data Analytics ---------- Augmented Reality (AR) / Virtual Reality (VR)		(Chen et al., 2020; Cimino et al., 2019; Glaessgen & Stargel, 2012; Qi & Tao, 2018; Rosen et al., 2015)	Disconnected System 2D / 3D / CAD Modeling / Data Model (I/O) Agent-based, Dynamic, Discrete, Continuous (e.g., Process Simulation, Material Flow Analysis), & Physics-based Simulation (e.g. Finite Element Analysis (FEA) Basic Data Analytics ---------- Augmented Reality (AR) / Virtual Reality (VR)		(Cimino et al., 2019; Ivanov, 2020; Ivanov, Dolgui, Das, et al., 2019; Ivanov & Das, 2020; D. Liu et al., 2022; Orozco-Romero et al., 2020; Pires et al., 2019; Rosen et al., 2015; Söderberg et al., 2017; Stark et al., 2017; Tao & Zhang, 2017; Wu et al., 2021; Zhuang et al., 2021)	Disconnected System 3D / CAD Modeling Augmented Reality (AR) / Virtual Reality (VR) Agent-based, Model-driven (eg, CAM), Event-driven Simulation Service Process Modeling Tools		(Bevilacqua et al., 2020; David et al., 2018; Gunal, 2019; Havard et al., 2019; Kunath & Winkler, 2018)
Digital Twin Instance (Grieves & Vickers, 2017)	Digital Shadow (Kritzinger et al., 2018)		Connected Digital Twin	Open-loop Feedback System Sensors (e.g., Industrial Internet of Things (IIoT), RFID) Communication Protocols (e.g., MQTT, OPC-UA) Real-time Data Acquisition Cloud Computing / Edge Computing Data-driven Simulation ---------- Historical Data Integration Secure Network Monitoring Interface (Dashboard Platform) Integration of Product Lifecycle Management (PLM) data		(Boschert & Rosen, 2016; Chen et al., 2020; Cimino et al., 2019; D'Amico et al., 2022; Gunal, 2019; Negri et al., 2017; Qi & Tao, 2018; Rosen et al., 2015; Tao, Zhang, Liu, et al., 2019; Tao et al., 2018; Tao, Sui, et al., 2019; X. Zhang & Zhu, 2019)	Open-loop Feedback System Sensors (e.g., Industrial Internet of Things (IIoT), RFID, Wearables) Communication: Protocols (e.g., OPC-UA, TCP/IP, Modbus) / 5G / GPS / Blockchain Monitoring Interface (e.g., Dashboard Platform, Mobile Management Platform) Real-time Data Acquisition Cloud Computing / Edge Computing Data-driven Simulation Data-integration (with Interface/Protocol conversion) Data hub (Database) ---------- Machine Vision / Scanners Historical Data Integration Big Data Analytics Integration with ERP / Manufacturing Execution System (MES) Secure Network		(An et al., 2023; Brenner & Hummel, 2017; Cimino et al., 2019; Constantinescu et al., 2020; Gunal, 2019; Hao et al., 2020; Ivanov & Dolgui, 2021; Knapp et al., 2017; D. Liu et al., 2022; Negri et al., 2017; Pires et al., 2019; Qamsane et al., 2022; Qi & Tao, 2018; Rosen et al., 2015; Tao, Zhang, Liu, et al., 2019; Tao & Zhang, 2017; Uhlemann et al., 2017; Wu et al., 2021; Zhao et al., 2019; Zhuang et al., 2021)	Open-loop Feedback System Internet of Things (IoT) Devices Communication: Protocols (e.g., MQTT, REST APIs, HTTP) / 5G / GPS / Blockchain Monitoring Interface (e.g., Dashboard Platform, Digital Interface, Virtual HMI) Real-time Data Acquisition Cloud Computing / Edge Computing Data-driven Simulation Integration with Customer Relationship Management (CRM) / ERP / MES Data hub (Database) ---------- Secure Network		(Bevilacqua et al., 2020; Bolton et al., 2018; Boschert & Rosen, 2016; Cimino et al., 2019; David et al., 2018; Havard et al., 2019; Ivanov & Dolgui, 2021; Kunath & Winkler, 2018; Pires et al., 2019; Tao, Zhang, Liu, et al., 2019)
Intelligent Digital Twin (Ashtari Talkhestani et al., 2019; Grieves, 2023; Singh et al., 2021)	Digital Twin (Kritzinger et al., 2018)		Predictive Digital Twin	Real-time Data Acquisition Predictive Analytics (e.g., Simulation, ML Algorithms, Time Series Analysis, Fault Tree Analysis) Historical Data Integration Monitoring Interface (e.g., Dashboard Platform) ---------- Data hub (Database) Big Data Analytics		(Aivaliotis et al., 2019; Ashtari Talkhestani et al., 2019; Cimino et al., 2019; D'Amico et al., 2022; Errandonea et al., 2020; Glaessgen & Stargel, 2012; M. W. Grieves, 2023; Rojek et al., 2020; Tao et al., 2018; Wang et al., 2021; X. Zhang & Zhu, 2019)	Real-time Data Acquisition Predictive Analytics (e.g., Simulation, Markov Chain Model, Pattern Recognition, ML Algorithms) Data hub (Database) Historical Data Integration Monitoring Interface (e.g., Dashboard Platform, Mobile Management Platform) ---------- Service Management Platform		(Ashtari Talkhestani et al., 2019; M. W. Grieves, 2023; Hao et al., 2020; Ivanov & Dolgui, 2021; D. Liu et al., 2022; Pires et al., 2019; Qamsane et al., 2022; Tao & Zhang, 2017; Zhuang et al., 2021)	Real-time Data Acquisition Predictive Analytics (e.g., ML Algorithms) Historical Data Integration Monitoring Interface (e.g., Dashboard Platform, Digital Interface, Virtual HMI) ---------- Service / Risk Management Platform Data hub (Database) Big Data Analytics		(Bevilacqua et al., 2020; Cimino et al., 2019; Pires et al., 2019)
			Prescriptive Digital Twin	Advanced Analytics (e.g., Optimization, Prioritization) ---------- Integration with Enterprise Resource Planning (ERP) Service Management Platform		(Cimino et al., 2019; Errandonea et al., 2020; Qi, Tao, et al., 2018; Rojek et al., 2020; Tao, Zhang, Liu, et al., 2019)	Advanced Analytics (e.g., Optimization - Simulation, Deep Learning) Model-based / Data-based Decision-making Support System		(Cimino et al., 2019; Constantinescu et al., 2020; Hao et al., 2020; Ivanov & Dolgui, 2021; Luo et al., 2019; Qi, Tao, et al., 2018; Uhlemann et al., 2017; Wu et al., 2021; Zhao et al., 2019)	Advanced Analytics (e.g., Optimization - Simulation, Deep Learning) Model-based / Data-based Decision-making Support System		
			Autonomous Digital Twin	Closed-loop Feedback Systems Adaptive Control System Advanced AI & ML ⟶ Cognitive abilities (e.g., Self-learning, Self-optimization, Self-adaptation Algorithms, Reinforcement Learning Models, Transfer Learning) ---------- Digital Twin Platform Generative Learning		(Ashtari Talkhestani et al., 2019; Cimino et al., 2019; M. W. Grieves, 2023; Khan et al., 2020; Rojek et al., 2020; Tao et al., 2018; Tao, Sui, et al., 2019; Wang et al., 2021)	Closed-loop Feedback Systems Adaptive Control System Advanced AI & ML ⟶ Cognitive abilities (e.g. Self-learning, Self-optimization, Self-adaptation Algorithms (Context Awareness), Transfer Learning) ---------- Digital Twin Platform Generative Learning		(Ashtari Talkhestani et al., 2019; M. W. Grieves, 2023; Luo et al., 2019; Wu et al., 2021; Zhao et al., 2019)	Closed-loop Feedback Systems Adaptive Control System Advanced AI & ML ⟶ Cognitive abilities (e.g., Self-learning, Self-adaptation, Self-optimization Algorithms, Transfer Learning) ---------- Digital Twin Platform Generative Learning		(Kunath & Winkler, 2018)

Fig. B.1. Digital Twin Technological Capabilities Framework.

Data Availability

Data will be made available on request.

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