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ANALYSIS DIMENSIONS FOR UNDERSTANDING DIGITAL TWINS: A DISCUSSION IN THE BRAZILIAN SCENARIO

DIMENSÕES DE ANÁLISE PARA O ENTENDIMENTO DE GÊMEOS DIGITAIS: UMA DISCUSSÃO NO CENÁRIO BRASILEIRO

DIMENSIONES DEL ANÁLISIS PARA LA COMPRENSIÓN DE LOS GEMELOS DIGITALES: UNA DISCUSIÓN EN EL ESCENARIO BRASILEÑO

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ABSTRACT
Objective: To identify important aspects for the analysis of digital twins and discuss digital twins created for the Brazilian industry based on characteristics of this technology.
Methodology: A literature review of digital twins definitions and analysis of digital twins created for the Brazilian industry considering five analysis dimensions.
Originality/relevance: Proposition and use of a set of dimensions to analyze digital twins, which can be used by researchers and practitioners for better understanding and characterizing digital twins proposals.
Results: Considering the digital twins created for the Brazilian industry, we found these proposals distinguish in some aspects, mainly the data flow between physical and digital objects, system level, and cognitive capabilities, but aspects such as interoperability, cognitive processes, and life cycle are uncovered in these digital twins. These aspects, however, are responsible for the innovation and disruption digital twins can provide to the Industry.
Contribution: Definition of dimensions to analyze digital twins and evidence of the presence and absence of some characteristics in digital twins created for the Brazilian industry.

Keywords: Digital Twin; Brazilian Industry; Industry 5.0.

RESUMO
Objetivo: Identificar aspectos importantes para a análise dos gêmeos digitais e discutir os gêmeos digitais criados para a indústria brasileira com base nas características desta tecnologia.
Metodologia: Uma revisão de literatura das definições de gêmeos digitais e análise de gêmeos digitais criados para a indústria brasileira considerando estas cinco dimensões de análise.
Originalidade/relevância: Proposição e uso de um conjunto de dimensões para analisar gêmeos digitais, que pode ser usado por pesquisadores e profissionais para melhor entendimento e caracterização das propostas de gêmeos digitais.
Resultados: Considerando os gêmeos digitais criados para a indústria brasileira, descobriu-se que essas propostas se distinguem em alguns aspectos, principalmente no fluxo de dados entre objetos físicos e digitais, nível do sistema e capacidades cognitivas; mas aspectos como interoperabilidade, processos cognitivos e ciclo de vida não estão profundamente contemplados nesses gêmeos digitais. Tais aspectos, no entanto, são responsáveis pela inovação e disrupção que os gêmeos digitais podem proporcionar à indústria.
Contribuição: Definição de dimensões para análise de gêmeos digitais e comprovação da presença e ausência de características em gêmeos digitais criados para indústria brasileira.

Palavras-chave: Gêmeo Digital; Indústria Brasileira; Indústria 5.0.

RESUMEN
Objetivo: Identificar aspectos importantes para el análisis de los gemelos digitales y discutir los gemelos digitales creados para la industria brasileña a partir de las características de esta tecnología.
Metodología: revisión de la literatura sobre definiciones de gemelos digitales y análisis de gemelos digitales creados para la industria brasileña considerando cinco dimensiones de análisis.

Originalidad/relevancia: Proposición y uso de un conjunto de dimensiones para analizar gemelos digitales, que pueden ser utilizados por investigadores y profesionales para comprender y caracterizar mejor las propuestas de gemelos digitales.
Resultados: Considerando los gemelos digitales creados para la industria brasileña, encontramos que estas propuestas distinguen en algunos aspectos, principalmente el flujo de datos entre objetos físicos y digitales, nivel de sistema y capacidades cognitivas, pero aspectos como la interoperabilidad, los procesos cognitivos y el ciclo de vida. no se contemplan profundamente en estos gemelos digitales. Estos aspectos, sin embargo, son responsables de la innovación y la disrupción que los gemelos digitales pueden brindar a la industria.
Contribución: Definición de dimensiones para analizar gemelos digitales y evidencia de la presencia y ausencia de algunas características en gemelos digitales creados para la industria brasileña.

Palabras clave: Gemelo Digital; Industria Brasileña; Industria 5.0

1. INTRODUCTION

In the recent approach of smart industry, new social development concepts, such as sustainability, human-centricity, and carbon emissions, began to gain more attention to attend to the demands of a modern and innovative society, frequently called Society 5.0. Instead of purely technocentric or even business-centric approaches that have characterized most past developments, we need a balanced approach between automation and human/society involvement contributing to well-being. This is one of the objectives of Industry 5.0, which is regarded as the next industrial revolution. Its objective is to leverage the creativity of human experts in collaboration with efficient, intelligent, and accurate machines, in order to obtain resource-efficient and user-preferred manufacturing solutions compared to Industry 4.0 (Maddikunta et al., 2022). Compared to past industrial revolutions that emphasized more on the economic aspect of sustainability, the Industry 5.0 vision leans toward human centricity and societal needs (Leng et al., 2022).

The enabling technologies of Industry 5.0 are a set of complex systems that combine technological trends such as edge computing, digital twins (DT), internet of things (IoT), big data analytics, collaborative robots (cobots), 6G network and blockchain, which are integrated with cognitive skills and innovation that can help industries increase production and deliver customized products more quickly technologies (Maddikunta et al., 2022). In this paper, the focus is to explore the topic of digital twins in the current scenario of the Brazilian Industry.

Digital twins are an emerging concept in which a digital replica of any physical object is built in order to make simulations, monitoring, visualizations, tests, and configurations of the replicated object. DTs represent very realistic models of industrial products and processes, their behaviors and interactions with the real world, being used not only for representation purposes but also for predictions (Durão et al., 2018).

Digital Twin is recognized as a key enabling technology of Industry 4.0 (Hyre et al., 2022; Zheng et al., 2022) and Industry 5.0 (Leng et al., 2022; Maddikunta et al., 2022; Müller, 2020; Xu et al., 2021). Accenture's latest executive report highlighted that 87% of the executives acknowledge DT technology as an increasingly fundamental tool to enable a strategic collaboration with business partners (D'Amico et al., 2022). In the Brazilian scenario, there is a recognition of the current importance of digital twins to digital transformation in enterprises according to Durão et al. (2018) but, although industry representatives are familiar with the Digital Twin concept and claim to use it in processes, most of the cases it is used only a simulation model. The main obstacles to the implementation of DT are a robust integration of data to allow a representation with high fidelity and real-time control of the line.

The use of digital twin is in its infancy in the Brazilian industry, but it is possible to identify some DT proposals in the context of the Brazilian Industry, such as in the area of electric engineering (Araujo Jr et al., 2021; Fernandes et al., 2022; João et al., 2020), civil engineering (Lima et al., 2022), and agriculture (Alves et al., 2023). In this work, we discuss concepts, definitions, and applications of digital twins in the scope of Brazilian companies to help researchers and practitioners identify opportunities and resolve misconceptions. We identify and detail some important aspects of analysis of digital twins and discuss reported digital twins created for Brazilian companies based on these aspects.

The remainder of this paper is organized as follows: Section 2 presents the theoretical background of the research, highlighting opportunities of DTs in Industry, essential characteristics of DTs, and references architectures that support the use of DTs; Section 3 presents the method used to identify and define the aspects to analyze digital twins; Section 4 presents the results of the analysis of DT approaches for the Brazilian industry. Finally, Section 5 presents the concluding remarks and limitations of this work.

2. BACKGROUND

This section presents the theoretical background of this study, highlighting opportunities and uses of DTs in Industry 4.0 and 5.0 (subsection 2.1); essential characteristics of DTs in the current industrial scenario (subsection 2.2) and references architectures that support the use of DTs for Industry (subsection 2.3).

2.1 Digital Twins in Industry

First introduced more than 20 years ago as part of a university course on Product Lifecycle Management (PLM) (Grieves, 2014), the concept of DT has recently emerged as our society becomes more interconnected (Batty, 2018). In recent years, the Digital Twin concept has been incorporated into industrial activities and is among the key factors for the design of the industry of the future (Wright and Davidson, 2020).

Shafto et al. (2012) was one of the first authors to refer to virtual copies of physical systems belonging to the North American aerospace context through NASA as a Digital Twin. According to its first definition, Digital Twin is a multi-physical, multi-scale, and probabilistic system simulation tool that uses automatically collected real data to mirror physical behavior through a virtual model, aiming to evaluate and recommend changes to optimize the real systems. More recently, Tao et al. (2018) defined digital twin as a set formed by three main components: i) physical systems, which we want to mirror; ii) virtual systems, which represent the physical in a detailed and sufficient manner; and iii) communication and synchronism between both systems. Lu et al. (2019) corroborates this definition to affirm digital twin has proved to be a practical method to integrate the physical and virtual world of manufacturing operations and to support manufacturing strategies in terms of more efficient and intelligent decision-making.

Regarding the use and applications of DTs in Industry, there are many examples of opportunities and advantages. In general, DT provides opportunities for improved product lifecycle management in manufacturing and also represents a significant change from the actual methods, processes, and tools used by the enterprises in processes of digital transformation (Holler et al., 2016; Kritzinger et al., 2018). DTs are capable of capturing data and providing features such as the recommendation of design specifications, the identification of design contradictions, and the verification of conformity between design specifications and project requirements. DT is compelling as a potential means to reduce the time and cost to develop new products, support fielded products, and enable rapid innovation to respond to new market opportunities (Rebentisch et al., 2021). DTs can enable Industry 5.0 to overcome technical issues by identifying them at a faster speed, identifying items that can be reconfigured or renewed on the basis of their productivity, making predictions at a higher accuracy rate, predicting future errors, avoiding huge financial losses (Maddikunta et al., 2022).

Finally, it is important to highlight that some essential characteristics are required for the DTs to perform complex tasks in the scope of Industry 4.0 and 5.0. In this sense, the next subsections explain such characteristics, highlighting the semantic and cognition capabilities of DTs.

2.2 Characteristics of Digital Twins

Cognition capabilities are an important topic related to modern DT proposals and therefore an aspect of interest to analyze DT implementations. It is well accepted that the main capabilities related to cognition for DTs are perception, attention, memory, reasoning, problem-solving, and learning (Al Faruque et al., 2021).

Perception is the process of forming useful representations of data related to the physical twin and its physical environment for further processing. Examples: real-time monitoring or data analytics on various data streams spanning from sensory data (Eirinakis et al., 2022). **Attention** is the process of focusing selectively on a task or a goal or certain sensory information either by intent or driven by environmental signals and circumstances (Al Faruque et al., 2021), for example using anomaly detection tools (statistical process control, complex event processing, ML-based tools) (Eirinakis et al., 2022). **Memory** corresponds to a single process that includes: working, episodic and semantic memory; encoding and storing information; and information retrieval (McDermott and Roediger, 2018). Key technologies for the memory of DTs are the use of databases, metadata, ontologies, and knowledge graphs. **Reasoning** can be defined as drawing conclusions consistent with a starting point – a perception of the physical twin and its environment, a set of assertions, a memory, or some mixture of them (Johnson-Laird, 2010). Examples of reasoning capabilities are root-cause analysis tools, simulations of the impact of the detected disruptions, evaluations of the impact of machines malfunction, and crane bottleneck (Eirinakis et al., 2022). **Problem-Solving** can be defined as the process of finding a solution for a given problem or achieving a given goal from a starting point (Al Faruque et al., 2021). It is achieved using optimization and simulation (Eirinakis et al., 2022), for instance. Finally, **learning** is the process of transforming the experience of the physical twin into reusable knowledge for a new experience (Al Faruque et al., 2021), predicting unwanted events in the operation before they happen and offering the best possible solutions (Abburu et al., 2020). Key technologies for learning in DTs are ML techniques, neural networks, knowledge graphs, DT models, etc, integrated with persistence technologies.

Another important characteristic of DTs is its **semantic capacity** to help solve problems related to interoperability. Interoperability problems are an issue while integrating systems and equipment in the manufacturing industry, often related to different models and systems of the lifecycle of a product. It is expected that the DT supports the integration of systems and models across different lifecycle phases and collaborates with the level of interoperability. In general, DT proposals use some semantic technologies (e.g. semantic modeling, ontologies, knowledge graphs) to reach the semantic interoperability of data, digital models, and information.

2.3 Reference Architectures

The need for a bidirectional lifecycle-extended integration between the physical world and its DT mandates a relevant supporting reference architecture (Koulamas and Kalogeras, 2018). Furthermore, reference architectures are necessary to treat aspects of interoperability among DTs and also trust and security measures. In this subsection, we mentioned common reference architectures of Industry 4.0 and 5.0, specifically RAMI 4.0 (Aheleroff et al., 2021; Schweichhart, 2019), IIRA (Schweichhart, 2019), and AAS (Belyaev, 2021). The idea behind these architectures is to provide a common view of the Industry and guide efforts on the implementation of a unified strategy.

RAMI 4.0 is a reference architecture model for Industry 4.0, presented at the Hannover Messe 2015, with the authorship of the industrial associations BITCOM, VDMA, and ZVEI (Zezulka et al., 2016). RAMI 4.0 is a service-oriented architecture that combines the fundamental elements and IT of Industry 4.0 in a structured three-dimension layer model (Aheleroff et al., 2021; Schweichhart, 2019). Conceptualized on a 3D model and developed in a service-oriented architecture (SOA), its focus is on manufacturing, process automation, digitization, and communication technologies.

IIRA (Industrial Internet Reference Architecture) is an open, standards based architecture for IIoT systems that was developed by the IIC (Industrial Internet Consortium), which is an organization formed by 5 companies: AT-T, Cisco, General Electric, Intel, and IBM with the objective of facilitating the implementation of IIoT (Industrial Internet of Things) in companies (Buchheit et al., 2017).

The AAS aims to "enable partners in value creation networks to exchange meaningful information by conforming to a specified set of standardized elements" (Belyaev, 2021). AAS will be the identification card of an asset in Industry 4.0. Furthermore, it will be responsible to provide controlled access to said information and provide a representation of the entire lifecycle of the asset (Moreno et al., 2023).

3 METHODOLOGY

The vision of digital twins has been detailed and improved over the years. In this section, we discuss our method of analysis of digital twins approaches. This method is based on the different DT definitions and considers distinct aspects of these models.

First, we searched for definitions of digital twins in literature and compared these definitions (Section 3.1). Next, we defined a set of criteria to analyze digital twins (Section 3.2). Finally, DT proposals reported by Brazilian companies were analyzed based on these criteria (Section 4).

3.1 Analyzing Digital Twins Definitions

One of the first discussions on a distinction among DT types considers data flow automation (Kritzinger et al., 2018). According to these authors, **Digital Model** is the case where the digital object (a representation of an existing or planned physical object) does not use any form of automated data exchange between it and the physical object. **Digital Shadow** includes the existence of automated one-way flow between the state of the physical object and the digital object. **Digital Twin** is used only for the case where the "data flow between physical object and data object are fully integrated into both directions". Although this typology is still well accepted and referred to in the literature, it contains a certain level of ambiguity as demonstrated by Falekas and Karlis (2021).

Abburu et al. (2020) propose a typology of DTs based on the data flow but also consider cognitive capacities. These authors show a three-layer approach to the different twins: so-called Digital Twins and Cognitive Twins. **Digital Twin** is considered a digital replica of a physical system that captures the attributes and behaviors of that system. In their point of view, a DT is typically materialized as a set of multiple isolated models that are either empirical or first-principles based. **Hybrid Twin (HT)** is an extension of DT in which the isolated DT models are intertwined to recognize, forecast and communicate less optimal (but predictable) behavior of the physical counterpart just before such behavior occurs. An HT integrates data from various sources (sensors, databases, etc.) with the DT models and has predictive capabilities. **Cognitive Digital Twin (CDT)** is an extension of HT incorporating cognitive features that enable sensing complex and unpredicted behavior. According to the authors, CDT is thus a hybrid, self-learning, and proactive system that will optimize its own cognitive capabilities over time based on the data it collects and the experience it gains.

From the first reference to the term **Cognitive Digital Twin** at an industrial workshop in 2016 (Adl, 2016), other authors (Abburu et al., 2020; Al Faruque et al., 2021; Ali et al., 2021; Lu et al., 2020) presented complementary and similar definitions for this kind of DT. The recent definition of (Zheng et al., 2022) encompasses the majority of these definitions from a literature review. According to these authors, Cognitive Twin is a “digital representation of a physical system that is augmented with certain cognitive capabilities and support to execute autonomous activities; comprises a set of semantically interlinked digital models related to different lifecycle phases of the physical system including its subsystems and components; and evolves continuously with the physical system across the entire lifecycle”. This definition includes beyond cognitive capacity, the characteristics related to multiple system levels and multiple lifecycle phases. While DT corresponds to a single system (or product, subsystem, component, etc.), and focuses on a single lifecycle phase, a CDT consists of multiple digital models corresponding to different subsystems and components of a complex system, focusing on multiple lifecycle phases of the asset(Zheng et al., 2022).

Cognitive capabilities (e.g., perception, attention, memory, reasoning, etc.) are required to perform complex tasks and a Cognitive DT is not required to have all these capabilities. On the other side, it is not clear what is the threshold for a DT not to be considered cognitive, and the term has been used widely in the recent literature. The implementation and realization of these cognitive capabilities in DTs are far from a simple task. In this sense, (Al Faruque et al., 2021) arguments in favor of three critical operations in the design stage which cognition enables and enhances: **(i) search; (ii) share; and (iii) scale**. For example, perception and attention allow the search operation to selectively focus on a set of appropriate models. Problem-solving can further improve the search operation by enabling it to identify the most suitable digital twin model. Learning support for the share operation, because it enables transforming the experience into knowledge reusable by a new DT.

The **semantics** also is considered a fundamental characteristic of DTs and appears in some definitions of DT, such as **Cognitive DTs** and **Semantic DTs**. Some authors propose the term **Semantic Digital Twin**. According to (Ku¨mpel et al., 2021), Semantic DT is a semantically enhanced virtual representation of a retail store environment, connecting an ontology-based symbolic knowledge base with a scene graph. The scene graph provides a realistic 3D model of the store, which is enhanced with semantic information about the store, its shelf layout, and contained products. (Boje et al., 2021) highlighted that a Semantic Digital Twin should enable proactive modeling, connecting among various planning systems (i.e. heterogeneous datasets), tracking, and optimization of construction processes and their associated off- and on-site resources. (Douglas et al., 2021) assert that a fully Semantic Digital Twin is capable of leveraging acquired knowledge with the use of AI-enabled agents, agent-driven socio-technical platforms, and a variety of digital technologies and techniques (i.e. machine learning, deep learning, data mining, and data analysis) employed to create a self-reliant, self-updatable and self-learning DT.

In some definitions of **Cognitive DTs** it is possible to identify references to semantic capabilities as necessary requirements for this DT type. (Boschert et al., 2018) defines a next-generation digital twin as a description of a component, product, system, or process by a set of well-aligned, descriptive, and executable models which is the semantically linked collection of the relevant digital artifacts including design and engineering data, operational data and behavioral descriptions. In its turn, (Lu et al., 2020) defines cognitive twin as a DT with augmented semantic capabilities for identifying the dynamics of virtual model evolution, promoting the understanding of interrelationships between virtual models, and enhancing the decision-making based on DT. In the definition of (Zheng et al., 2022), Cognitive DT "comprises a set of semantically interlinked digital models related to different lifecycle phases of the physical system including its subsystems and components". In many cases, a Cognitive DT can be constructed by integrating multiple related DTs using ontologies, semantic modeling, knowledge graphs, and lifecycle management technologies.

Considering the literature revised and the different concepts used to define Cognitive and Semantic Twins, it is important to highlight that in our opinion **cognition** and **semantics** are complementary and essential characteristics to make smart, autonomous, predictive, and self-learning Digital Twins, and necessary to the current context of the application of DTs in Industry 5.0.

Finally, other authors present different DT types, such as Enhanced Cognitive Twin (Eirinakis et al., 2020), Semantic Digital Twin (Beetz, 2021; Di´ez and De Lara, 2021), next-generation Digital Twin (Falekas and Karlis, 2021), and the six-type typology (Imaginary, Monitoring, Predictive, Prescriptive, Autonomous, and Recollection) (Ariesen-Verschuur et al., 2022; Verdouw et al., 2021). These typologies overlap with DT types mentioned previously in this section.

3.2 How digital twins can be analyzed

According to the DT definitions discussed in the last section, it is possible to compare digital twins in five aspects: i) data flow, ii) interoperability level, iii) system level, iv) the cognitive process it performs, and iv) how the DT supports the product lifecycle. In this section, we present our analysis method (Figure 1).

Digital twins can be compared regarding their **data flow** (Kritzinger et al., 2018). Considering the model-asset communication, the data can flow automatically in both directions *(bi-directional communication)*, from the asset to the model *(uni-directional communication)*, or with no automatic data flow between the asset and the model - *no data flow*. Prototypes are usually the first model used to simulate a machine's behavior and act as proof of concept of the digital twin. These prototypes (or data models) are generally considered DTs with no automatic communication. Finally, when the data flows are realized among a DT and other DTs, this DT is considered *interconnected*.

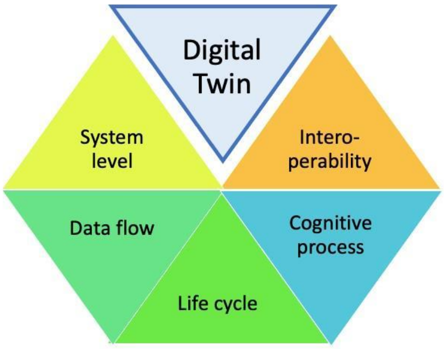


Figure 1: Five dimensions to analyze digital twins

The **interoperability** dimension describes how the DT can interpret the data. The Levels of Conceptual Interoperability Model (LCIM) (Turnitsa, 2005) is a useful model to understand heterogeneous system communication. LCIM has been applied to different domains (Wang et al., 2009; Wassermann and Fay, 2017) and it is useful to understand the capabilities of the digital twin regarding data manipulation. The *syntactical* level refers to structured data, while the *semantic* level corresponds to the description (meaning) of the data. Asset Administration Shell addresses these two interoperability levels. *Pragmatic* interoperability demands a common understanding of context. Pragmatics in computation addresses the problem of finding the appropriate communication partner, establishing and maintaining exchange with him (Wassermann and Fay, 2017), which is primarily performed by orchestration methods. Orchestrating digital twins is, however, an open problem. Besides a protocol for negotiating a task, it is necessary a public catalog of digital twins with a description of the contract and policies. Next, the *dynamic* interoperability level relates to the understanding of the effect of the exchanged data on the sender and receiver. To this, it is necessary to have a shared state model where the digital twin is capable of understanding its inner state and the state model of its communication partner.

DTs can be seen as digital models of a simple asset or a complex machine. Cognitive DTs represent such complex digital models able to communicate with other (generally simpler) DTs to, for instance, identify anomalies in the product line, search for optimized solutions, and negotiate a solution. The **system level** dimension considers the granularity of the DT regarding the ecosystem to which it belongs: part, component, subsystem, system, or system-of-systems (Zheng et al., 2022).

The capacity of digital twins to handle complex tasks is related to their cognitive capabilities. The implementation and realization of these capabilities is a complex task and frequently it is difficult to identify them in the proposals of DT. Some technologies used in the **cognitive process** of DTs can encompass two or more capabilities at the same time (i.e., machine learning techniques and knowledge graphs can be used for the memory of DTs and also for reasoning). In this sense, a strategy of identification of the cognition for DTs is to associate operations with the capabilities that make possible the cognitive process.

Digital twins are strongly related to data processing, and the Information Processing Theory (Kmetz, 2018) was used to define the four stages[1] of processing information in digital twin ecosystem: *collect*, *search*, *share*, and *scale*. **Collect** is the process of retrieving and gathering the appropriate data from assets to perform an operation; **Search** is the process of identifying the appropriate digital twin models of a manufacturing system by searching over the Internet across search mechanisms; **Share** is the process of sharing relevant information gained during the life cycle of the digital twin of a manufacturing system to a new digital twin in its early design, development stage, and usage; and **Scale** is the process of sharing knowledge across non-overlapping domains of a manufacturing system.

Finally, digital twins can be analyzed according to **life cycle** management. In the manufacturing industry, it is common that there exist multiple related digital models to the different phases (production design, simulation, planning, production, maintenance, recycling, etc.) of the lifecycle of a product. Unfortunately, these different models and systems manifest a low degree of interoperability, and this creates problems, for instance when different enterprises or branches of an enterprise interact. In this sense, it is expected that proposals of DTs more semantic and cognitive support the integration of models across different lifecycle phases (Zheng et al., 2022). Therefore, it is not a trivial task and still a challenge for DTs to evolve digital models to cover the entire life cycle of the asset. In this dimension, we classify

[1] These stages are strongly motivated by the three processes described in (Al Faruque et al., 2021).

the proposals of DTs according to the covering of the lifecycle in *full, partial,* or *single* part of the product or asset lifecycle. It is expected DTs implement technologies capable of covering the different phases of the lifecycle of a product and maintain a good level of interoperability.

4 DISCUSSION

This section presents four reports of digital twins in the Brazilian context (Alves et al., 2023; Araujo Jr et al., 2021; Fernandes et al., 2022; Lima et al., 2022) chosen for their relevance and diversity. For analysis of these works and better comparability, it was decided to map the five dimensions of analysis on a 5-point scale according to the mapping shown in Table 1. The result of the analysis of each work was projected as a spider chart (Figure 2).

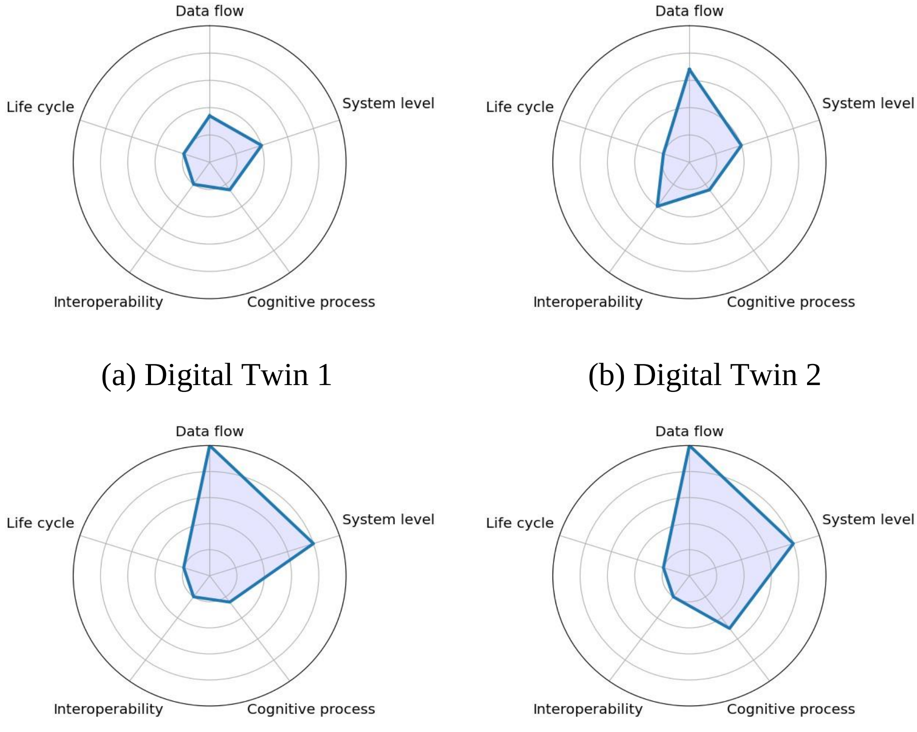
Table 1

Mapping of the dimension values to a scale

Dimension	Value	Mapping
Data flow	no data flow	0
	unidirectional communication	1.7
	bidirectional communication	3.4
	interconnected	5
System level	part	1
	component	2
	subsystem	3
	system	4
	system of systems	5
Cognitive process	collect	1.25
	search	2.5
	share	3.75
	scale	5
Interoperability	systematic	1
	semantic	2
	pragmatic	3
	dynamic	4
	conceptual	5
Life cycle	single	1.7
	partial	3.4
	full	5

a) Digital Twin 1: the work by Lima et al. (2022) (Figure 2a) presents the concept of a digital twin to help engineering teams manage bridges and viaducts. For this, the authors present a case study of the creation of a digital twin for bridges and viaducts in the city of SÃo Paulo. The geometry of these buildings was surveyed using a terrestrial *laser scanner* using the point cloud technique and later the 3D parametric modeling of the bridges and viaducts was created.

Through sensors applied along the structure and manual recording carried out by the point teams, it is possible to identify and record anomalies in the structure in a mobile application that allows directly mapping the impacted structural elements. Based on this information, a treatment and maintenance management system was built for the identified anomaly, which contains the pre-registration of treatments, budgets and their respective schedules. The purpose of these digital twins, therefore, is to monitor a physical structure and it has a unidirectional data flow between the sensors and the digital model. As the digital twin acts in isolation, there is no need to achieve higher levels of interoperability and, consequently, high cognitive level tasks are not performed by this model. Although the model can capture data throughout the life of the building, there are no automatic and synchronous changes of the model in relation to the state of the physical entity and, thus, the level of lifecycle treatment is considered low.



(a) Digital Twin 1 (b) Digital Twin 2

(c) Digital Twin 3 (d) Digital Twin 4

Figure 2: Proposals of digital twins in Brazilian enterprises.

b) Digital Twin 2: in the area of agriculture, the work of Alves et al. (2023) (Figure 2b) stands out, which presents a digital twin to compose an irrigation management system for more economical and, therefore, smarter use from water. The system is composed of sensors and actuators, that is, it has a bidirectional data flow between the physical and virtual object and allows irrigation plan prescriptions to be planned by the digital twin and applied in the irrigated area. For this, sensors collect atmospheric, soil and plant information, allowing the monitoring of the farm's environment. As the authors describe the proposed irrigation system as being under development, the case study was carried out using a simulation environment in the Plant Simulation tool. Indeed, the use of simulation tools is usually a first step in the development of digital twins. For communication with the sensors, the authors use the OPC UA (Open Platform Communications Unified Architecture) and store the data in an RDF database, which already allows some level of interoperability between digital twins (although this is not the objective of the authors). Although the digital twin does indeed allow a change of the physical object, low-level cognitive tasks of the digital twin are still performed. Interaction with the farm's lifecycle is low and the models are not automatically synchronized with a more abrupt physical change in the farm environment, such as changing planting areas.

Electrical engineering is currently one of the areas that most apply the concept of digital twins (Wang et al., 2022; Yu et al., 2022), and we highlight this paper the work of Araujo Jr et al. (2021) and Fernandes et al. (2022).

c) Digital Twin 3: in Araujo Jr et al. (2021) (Figure 2c), a digital twin for a water cooling system in a power plant is presented. The authors developed digital twins of a water cooling system of five internal combustion engines in a thermoelectric plant, based on fuzzy inference systems, to incorporate improvements in the energy efficiency of the cooling system. Their computational model can process a large amount of data, relating internal and external parameters of the system for the automatic generation of rules from a set of numerical data. To validate their methodology, data from a thermoelectric plant located in the city of Jo˜ao Pessoa, Brazil, are used. The data correspond to a day of operation of the plant, where measurements of the power of the fans, controlled temperature, room temperature, and number of fans were recorded. Their digital twins have problem-solving and reasoning cognitive capabilities due to the ability to automate learning from new measurements, incorporating knowledge into the system through the automatic generation of new rules. It is noteworthy that, according to the dimension of the cognitive process, the presence of these capabilities is not enough for the DT to perform high-level cognitive processes. This digital twin receives from the sensors and sends messages to the actuators in a bidirectional communication.

d) Digital Twin 4: in (Fernandes et al., 2022; João et al., 2020) (Figure 2d), the authors discuss the best practices for the development of a digital twin for the electrical power sector found during the development of a project carried out by Enel Distribuição São Paulo. The authors discuss how their digital twin influences the workforce activities of human interface operation. Like Lima et al. (2022), 3D models of the power plant were created using external equipment (in their case, drones). Although some technical aspects are not clear in the text, it is possible to identify concepts of interconnectivity among digital twins and the use of DT in different system levels.

Complex tasks demand a certain level of interoperability and cognition. The dimensions of interoperability, cognitive processes and life cycle received a low value in all these proposals. Lifecycle management is an important characteristic of cognitive digital twins, as stated by Zheng et al. (2022), but is not trivial to produce models that cover multiple lifecycle phases and it is reflected in Figure 2. On the other hand, we argue that there is room for innovative proposals in the Brazilian industry when using the DT concept to carry out high-level cognitive processes.

5 CONCLUDING REMARKS

In this paper, we discussed definitions of digital twins and some use cases of the Brazilian industry. As a contribution, we identify and detail an analysis model composed of five aspects: data flow, interoperability level, system level, cognitive process, and system lifecycle. Digital twins created for the Brazilian industry were compared using this analysis model.

The use of digital twins in the Brazilian industry is in its infancy and there is not a representative number of DT proposals for this domain. On the other side, there is a large room for opportunities and innovative solutions, considering also regional and economic aspects of the Brazilian industry.

Our analysis method can help researchers and practitioners to better understand the characteristics, capabilities, and applications of DTs, encouraging new works and DT proposals.

As limitations of the current stage of the research, we argue it is important to realize further analyses considering other DTs of the Brazilian Industry and the international community. However, one of the difficulties of this kind of study is finding well-detailed relevant DT proposals. It is worth mentioning our analysis was based on the DT description of each work but it may be error-prone since some authors are not clear about some aspects we have analyzed.

In future work, we suggest evolving the analysis proposed to an analytical framework. In this sense, other researchers can extend the analytical framework by including new dimensions, according to the need of the application domain or new capabilities demanded by Industry 5.0.

REFERENCES

Abburu, S., Berre, A.J., Jacoby, M., Roman, D., Stojanovic, L., Stojanovic, N. (2020) Cognitwin - hybrid and cognitive digital twins for the process industry. In: *Proceedings of the 2020 IEEE International Conference on Engineering, Technology and Innovation*, ICE/ITMC 2020.

Adl, A.E. (2016). The cognitive digital twins: Vision, architecture framework and categories.

Aheleroff, S., Xu, X., Zhong, R.Y., Lu, Y. (2021). Digital twin as a service (dtaas) in industry 4.0: an architecture reference model. *Advanced Engineering Informatics 47*, 101225.

Al Faruque, M.A., Muthirayan, D., Yu, S.Y., Khargonekar, P.P. (2021). Cognitive digital twin for manufacturing systems. In: *Proceedings of the Design, Automation and Test in Europe, DATE*, vol. 2021-February, p. 440 – 445.

Ali, M.I., Patel, P., Breslin, J.G., Harik, R., Sheth, A. (2021). Cognitive digital twins for smart manufacturing. *IEEE Intelligent Systems 36(2)*, 96–100.

Alves, R.G., Maia, R.F., Lima, F. (2023). Development of a digital twin for smart farming: Irrigation management system for water saving. *Journal of Cleaner Production* p. 135920.

Araujo Jr, C.A.A.d., Villanueva, J.M.M., Almeida, R.J.S.d., de Medeiros, I.E.A. (2021). Digital twins of the water cooling system in a power plant based on fuzzy logic. *Sensors 21(20)*, 6737.

Ariesen-Verschuur, N., Verdouw, C., Tekinerdogan, B. (2022). Digital twins in greenhouse horticulture: A review. *Computers and Electronics in Agriculture*.

Batty, M. (2018). Digital twins. *Environment and Planning B: Urban Analytics and City Science*, *45*(5), 817-820.

Beetz, J. (2021). Semantic digital twins for the built environment-a key facilitator for the European green deal? In: *CEUR Workshop Proceedings*, vol. 2887.

Belyaev, A. (2021). Modelling the semantics of data of an asset administration shell with elements of eclass. Joint white paper from Plattform Industrie 4.0 and ECLASS.

Boje, C., Kubicki, S., Guerriero, A. (2021). A 4d bim system architecture for the semantic web. *Lecture Notes in Civil Engineering 98*, 561 – 573.

Boschert, S., Heinrich, C., Rosen, R. (2018). Next generation digital twin. In: *Proc. tmce*, vol. 2018, pp. 7–11, Las Palmas de Gran Canaria, Spain.

Buchheit, M., Karmarkar, A., Schrecker, S., LeBlanc, J. (2017). The industrial internet of things volume g1: Reference architecture. IIC: PUB G 1.

D'Amico, R.D., Erkoyuncu, J.A., Addepalli, S., Penver, S. (2022). Cognitive digital twin: An approach to improve maintenance management. *CIRP Journal of Manufacturing Science and Technology 38*, 613 – 630.

Diéz, A., De Lara, J. (2021). Semantic digital twins for organizational development. In: *CEUR Workshop Proceedings*, vol. 2887.

Douglas, D., Kelly, G., Kassem, M. (2021). Bim, digital twin and cyber-physical systems: crossing and blurring boundaries. arXiv preprint arXiv:2106.11030.

Durão, L.F.C.S., Haag, S., Anderl, R., Schützer, K., Zancul, E. (2018). Digital twin requirements in the context of industry 4.0. In: Chiabert, P., Bouras, A., Noël, F., Ríos, J. (eds.) *Product Lifecycle Management to Support Industry 4.0*, pp.204–214, Springer International Publishing, Cham, ISBN 978-3-03001614-2

Eirinakis, P., Kalaboukas, K., Lounis, S., Mourtos, I., Rozanec, J.M., Stojanovic, N., Zois, G. (2020). Enhancing cognition for digital twins. In: *Proceedings - 2020 IEEE International Conference on Engineering, Technology and Innovation*.

Eirinakis, P., Lounis, S., Plitsos, S., Arampatzis, G., Kalaboukas, K., Kenda, K., Lu, J., Rozanec, J.M., Stojanovic, N. (2022). Cognitive digital twins for resilience in production: A conceptual framework. *Information (Switzerland) 13(1)*.

Falekas, G., Karlis, A. (2021). Digital twin in electrical machine control and predictive maintenance: state-of-the-art and future prospects. *Energies 14(18)*.

Fernandes, S.V., João, D.V., Cardoso, B.B., Martins, M.A., Carvalho, E.G. (2022). Digital twin concept developing on an electrical distribution system—an application case. *Energies 15(8)*, 2836.

Grieves, M.: Digital twin: manufacturing excellence through virtual factory replication (2014). White paper 1(2014), 1–7.

Holler, M., Uebernickel, F., Brenner, W. (2016). Digital twin concepts in manufacturing industries-a literature review and avenues for further research. In: *Proceedings of the 18th International Conference on Industrial Engineering (IJIE)*, Seoul, Korea, pp. 10–12.

Hyre, A., Harris, G., Osho, J., Pantelidakis, M., Mykoniatis, K., Liu, J. (2022). Digital twins: Representation, replication, reality, and relational (4rs). *Manufacturing Letters 31*, 20–23 (2022), ISSN 2213-8463.

João, D.V., Lodetti, P.Z., Martins, M.A.I., Almeida, J.F. (2020). Virtual and augmented reality applied in power electric utilities for human interface improvement– a study case for best practices. In: *2020 IEEE Technology & Engineering Management Conference (TEMSCON)*, pp. 1–4, IEEE.

Johnson-Laird, P.N.: Mental models and human reasoning (2010). *Proceedings of the National Academy of Sciences* 107(43), 18243–18250.

Kmetz, J. L. (2018). The Information Processing Theory of Organization: Managing technology accession in complex systems. Routledge.

Koulamas, C., Kalogeras, A. (2018). Cyber-physical systems and digital twins in the industrial internet of things [cyber-physical systems]. *Computer 51(11)*, 95–98 (2018), https://doi.org/10.1109/MC.2018.2876181

Kritzinger, W., Karner, M., Traar, G., Henjes, J., Sihn, W. (2018). Digital twin in manufacturing: A categorical literature review and classification. *Ifac-PapersOnline 51(11)*, 1016–1022.

Kümpel, M., Mueller, C.A., Beetz, M. (2021). Semantic digital twins for retail logistics. In: *Dynamics in Logistics*: Twenty-Five Years of Interdisciplinary Logistics Research in Bremen, Germany, pp. 129–153, Springer International Publishing Cham.

Leng, J., Sha, W., Wang, B., Zheng, P., Zhuang, C., Liu, Q., Wuest, T., Mourtzis, D., Wang, L. (2022). Industry 5.0: Prospect and retrospect. *Journal of Manufacturing Systems 65*, 279–295, ISSN 0278-6125.

Lima, G., Factori, L., Junqueira, M., dos Santos, R., Borba, L., Gonçalves, O. (2022). Aplicação de conceitos de gêmeo digital e bim: Estudo de caso na gestão de pontes e viadutos. In: *4º Congresso Português de Building Information Modelling*, vol. 1.

Lu, J., Zheng, X., Gharaei, A., Kalaboukas, K., Kiritsis, D. (2020). Cognitive twins for supporting decision-makings of internet of things systems. In: *Proceedings of 5th International Conference on the Industry 4.0 Model for Advanced Manufacturing: AMP 2020*, pp. 105–115, Springer.

Lu, Y., Min, Q., Liu, Z., Wang, Y. (2019). An iot-enabled simulation approach for process planning and analysis: a case from the engine re-manufacturing industry. *International Journal of Computer Integrated Manufacturing 32*(4-5), 413– 429.

Maddikunta, P.K.R., Pham, Q.V., Prabadevi, B., Deepa, N., Dev, K., Gadekallu, T.R., Ruby, R., Liyanage, M. (2022). Industry 5.0: A survey on enabling technologies and potential applications. *Journal of Industrial Information Integration 26*, 100257.

McDermott, K.B., Roediger, H.L. (2018). Memory (encoding, storage, retrieval). *General Psychology FA2018*. Noba Project: Milwaukie, OR pp. 117–153.

Moreno, T., Almeida, A., Toscano, C., Ferreira, F., Azevedo, A. (2023). Scalable digital twins for industry 4.0 digital services: a dataspaces approach. *Production & Manufacturing Research 11(1)*, 2173680 (2023), https://doi.org/10.1080/21693277.2023.2173680, URL https://doi.org/10.1080/21693277.2023.2173680

Müller, J.: Enabling technologies for industry 5.0 (2020). *European Commission* pp. 8–10.

Rebentisch, E., Rhodes, D.H., Soares, A.L., Zimmerman, R., Tavares, S. (2021). The digital twin as an enabler of digital transformation: a sociotechnical perspective. In: *International Conference on Industrial Informatics (INDIN)*, pp. 1–6.

Schweichhart, K. (2019). Rami 4.0 reference architectural model for industrie 4.0. *In-Tech 66(2)*, 15.

Shafto, M., Conroy, M., Doyle, R., Glaessgen, E., Kemp, C., LeMoigne, J., Wang, L. (2012). Modeling, simulation, information technology & processing roadmap. *National Aeronautics and Space Administration 32*(2012), 1–38.

Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H., Sui, F. (2018). Digital twin-driven product design, manufacturing and service with big data. *The International Journal of Advanced Manufacturing Technology 94*, 3563–3576.

Turnitsa, C. (2005). Extending the levels of conceptual interoperability models. In: *Proceedings IEEE summer computer simulation conference*, IEEE CS Press.

Verdouw, C., Tekinerdogan, B., Beulens, A., Wolfert, S. (2021). Digital twins in farming systems. *Agric. Syst 189*, 103046.

Wang, W., Tolk, A., Wang, W. (2009). The levels of conceptual interoperability model: applying systems engineering principles to m&s. In: *Proceedings of the 2009 Spring Simulation Multiconference*, pp. 1–9.

Wang, Y., Kang, X., Chen, Z. (2022). A survey of digital twin techniques in smart manufacturing and management of energy applications. *Green Energy and Intelligent Transportation*, p. 100014.

Wassermann, E., Fay, A. (2017). Interoperability rules for heterogeneous multi-agent systems: Levels of conceptual interoperability model applied for multi-agent systems. In: *2017 IEEE 15th International Conference on Industrial Informatics (INDIN)*, pp. 89–95, IEEE.

Wright, L., Davidson, S. (2020). How to tell the difference between a model and a digital twin. *Advanced Modeling and Simulation in Engineering Sciences* 7(1), 1–13.

Xu, X., Lu, Y., Vogel-Heuser, B., Wang, L. (2021). Industry 4.0 and industry 5.0 - inception, conception and perception. *Journal of Manufacturing Systems* 61, 530–535.

Yu, W., Patros, P., Young, B., Klinac, E., Walmsley, T.G. (2022). Energy digital twin technology for industrial energy management: Classification, challenges and future. *Renewable and Sustainable Energy Reviews* 161, 112407.

Zezulka, F., Marcon, P., Vesely, I., Sajdl, O. (2016). Industry 4.0 - an introduction to the phenomenon. *IFAC-PapersOnLine* 49(25), 8–12.

Zheng, X., Lu, J., Kiritsis, D. (2022). The emergence of cognitive digital twin: vision, challenges and opportunities. *International Journal of Production Research* 60(24), 7610 – 7632.