Journal of Industrial Information Integration 48 (2025) 100974

Contents lists available at ScienceDirect

Journal of Industrial Information Integration

journal homepage: www.sciencedirect.com/journal/journal-of-industrial-information-integration

Full Length Article

Cognitive Digital Twin for industrial maintenance: operational framework for fault detection and diagnosis

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A R T I C L E I N F O

Keywords:
Cognitive Digital Twin
Digital Twin
Maintenance
Fault detection
Fault diagnosis
Ontology
Manufacturing

A B S T R A C T

Digital Twin is a cutting-edge technology designed to address disruptions in manufacturing operations by supporting humans in complex maintenance decisions via advanced data analytics and real-time synchronization. However, as the complexity of decisions increases, enhanced capabilities are required, such as reasoning and context awareness, leading to the Cognitive Digital Twin (CDT) concept. In this context, this work offers two contributions. First, it presents a state-of-the-art review on CDT for maintenance in manufacturing, identifying Fault Detection and Diagnosis (FDD) as a relevant investigation area. Second, it proposes a novel CDT framework specifically tailored to support FDD in industrial maintenance. The contributions are twofold: (i) an ontology that formalises maintenance expert knowledge and supports diagnostic reasoning; and (ii) data-driven algorithms that elaborate data from the physical system, and instantiate or update the proposed ontology. The structured integration of ontology and data analytics into an operational CDT framework enables and properly places all six cognitive capabilities - perception, attention, memory, reasoning, problem-solving, and learning - within a domain-specific framework tailored to maintenance, and especially to support FDD decisions. The CDT output is the augmented information flowing to the maintenance decision-making process, which is held by the maintenance staff, who, after the completion of the FDD activity, can act back on the physical asset with the required maintenance interventions. The CDT framework is finally tested in a laboratory setting, demonstrating its functional effectiveness in supporting maintainers in the FDD decision-making process by formalizing knowledge and guiding reasoning.

1. Introduction

The current industrial context is characterised by high demand volatility and unpredictable events leading to supply chain and operations management disruptions [1]. Manufacturing companies are thus requested to cope with such a situation by developing both long-term strategies for risk mitigation as well as field-level solutions for decision augmentation [2]. Amongst shopfloor-related key enablers, Digital Twins (DTs) are one of the most promising for the enhancement of the understanding, monitoring and controlling of the system supporting decision-making [3–5]. Introduced in 2002 by Micheal Grieves at the University of Michigan, the DT is defined as the virtual mirroring representation of a physical entity (e.g., system, device, machine, production process, or a living organism), containing all its information and, thus, able to digitally reproduce its operation and behavior in real-time [6–8]. At field-level, DTs may be employed for different contexts and decisions such as real-time state monitoring, energy consumption analysis and prediction, intelligent optimization and update, behaviour analysis, and product maintenance strategy, as listed by Tao et al. [9]. Over the years, the concept of DT itself has evolved to accommodate new technologies as well as to cope with complex decision-making environments. Indeed, the automatic feedback loop from the virtual counterpart to the physical one has been proven to be not always effective and required for all applications; as a matter of fact, human-based knowledge and actions are still usually necessary. This is especially true for maintenance, for which DT has been mainly employed given the need to preserve production assets and to guarantee satisfactory performance levels and optimized resource and cost management [10,11], especially looking at machine and system health state evaluation [12]. Maintenance-focused DT has always considered humans therein as

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https://doi.org/10.1016/j.jii.2025.100974

Available online 12 October 2025

human expertise as a core and vital ingredient [13]; in fact, maintenance is one of the domains in which tacit knowledge and operator experience are of utmost importance for successful practice, especially in problem-solving [14,15]. Also, from the managerial perspective, maintenance has always been a main lever for companies as it accounts for about 15 % to 70 % of the cost of ownership in many sectors [16], for 65 % of the total energy used by industries in economically advanced countries [17], and expenses 60 % – 70 % of the total costs of production lifecycle [18]. This has contributed to the technological and paradigmatic evolution of DTs, as they are starting to evolve and assume an intelligent and cognitive characterization, leading towards the concept of Cognitive Digital Twin (CDT), where human knowledge is leveraged and integrated [19]. The CDT can be intended as an augmented DT with human-like cognitive capabilities (attention, perception, memory, reasoning, learning, and problem-solving), promoting its self-adaptiveness, awareness, collaboration, and enhanced decision-making abilities [20]. These capabilities allow CDT to continuously evolve with the real system throughout its lifecycle, adapting to dynamic changes and unpredictable disruptions [21].

Despite recent efforts in DTs and CDTs for maintenance, only a few works have presented CDT solutions, and mostly conceptual ones, with little focus on formalizing human knowledge through semantic technologies (i.e., ontologies) as a constituting element enabling the cognitive capabilities of the DT. Moreover, regardless of the human-intensive nature of some maintenance activities, such as FDD, no CDT framework appears to offer explicit support for FDD.

1.1. Research objective, questions and contributions

Given the above premises, this research work explores CDT for maintenance leveraging semantic technologies as a key enabler to formalize tacit and unstructured expert knowledge inside the end solution for maintenance application.

To pursue this objective, two research questions (RQ) are meant to be addressed:

- RQ1: What is the state-of-the-art of Cognitive Digital Twin for maintenance in manufacturing?

RQ 1.1: What are the cognitive capabilities enabled by the current Digital Twin solutions for maintenance in manufacturing?

RQ 1.2: What are the gaps related to the Cognitive Digital Twin for maintenance in manufacturing?

- RQ2: How to develop a CDT framework to support fault detection and diagnosis for maintenance in manufacturing?

In response to the RQs, the present research proposes the following two contributions:

1. The research literature is reviewed and interpreted to provide a comprehensive overview of the state-of-the-art of DTs and CDTs in maintenance. This contribution addresses RQ1 and is presented in Section 2.2. Furthermore, a mapping of the cognitive capabilities in DTs and CDTs, along with the identification of their main enabling technologies, is provided in Section 2.2.1, in response to RQ1.1. Finally, the main research gaps from the literature are outlined and discussed in Section 2.3 (RQ1.2).
2. Regarding RQ2, a novel CDT framework for industrial maintenance is designed and developed by better scoping the problem to FDD as one of the most human content-demanding activities [20]. While ontology and data analytics are well-established technological elements, the novelty of this contribution lies in their integrated use within a unified, operational CDT framework tailored specifically to support cognitive capabilities in FDD tasks. This contribution is presented in Section 3 and has required (i) a new elaboration of the definition of the cognitive capabilities and their enabling technologies tailored to FDD (Section 3.2.1), which was not present in the literature and (ii) the identification of the main constituting elements of the CDT framework (Section 3.2.2): in particular, (ii.i) a new ontology that formalises maintenance expert knowledge and support maintenance staff in FDD decisions thanks to its reasoning capabilities was developed (Section 3.2.2.1) and (ii.ii) data-driven algorithms that elaborate real-time or historical data, and instantiate or update the proposed ontology was described (Section 3.2.2.2). The CDT output is the augmented information flowing to the maintenance decision-making process, which is held by the maintenance staff, who, after the completion of the FDD activity, can act back on the physical asset with the required maintenance interventions. The CDT framework is finally tested in a laboratory setting, demonstrating its functional effectiveness in supporting FDD (Section 4). Therefore, the goal is to improve the FDD engineering process, not through performance benchmarking, but by enabling structured, interpretable, and reusable knowledge to support human-in-the-loop decisions.

The paper is structured as follows: Section 2 presents the scientific literature review methodology and results framing CDT state-of-the-art in maintenance; Section 3 proposes a framework for CDT development; Section 4 deals with ontology verification and CDT framework assessment for FDD via a laboratory case. Section 5 presents a broader discussion and managerial implications, including key findings, lessons learned for implementation replicability, and insights on generalizability and scalability. Finally, Section 6 draws conclusions and outlines future research directions.

2. Literature review on CDT for maintenance applications in manufacturing

To define the state-of-the-art and interpret the adoption of CDT for maintenance in manufacturing, a Systematic Literature Review (SLR) is executed. The SLR is conducted following the three main steps of the standard proposed by Tranfield et al. [22], which are planning the review, conducting the review, and reporting and dissemination. This allows the reproducibility and transparency of the review, minimizing its subjectivity.

The remainder of the section is organised so that, firstly details on the adopted methodology are described (2.1), then results are presented (2.2) heading towards the identification of the scientific gaps and concluding remarks (2.3).

2.1. Systematic literature search methodology

For the execution of the systematic search, coherently with the research objective and questions addressed in this study, two sets of keywords are defined. The first group includes ‘Digital Twin’, while the second includes ‘asset management’ and ‘maintenance’. The choice of selecting the more generic keyword ‘Digital Twin’ instead of its specification ‘Cognitive Digital Twin’ is given by the need to broaden the search boundaries to guarantee higher reliability of the review. Whereas, for what concerns the second group of keywords, ‘asset management’ (AM) is added in addition to ‘maintenance’ as a matter of results completeness as AM is often interpreted as maintenance depending on the field and context of the application [23]. Hence, expanding the domain of the SLR to both asset management and maintenance would enrich the analysis by providing a broader, more integrated perspective on how DT and CDT are explored for maintenance in manufacturing.

In the end, the search string results to be *(Digital Twin) AND (maintenance OR asset management)*, combined by linking keywords inside of the same group with the Boolean operator OR, and the two groups with the operator AND. Afterwards, appropriate eligibility criteria are set, limiting the number of possible studies and preventing them from being out of the scope of the review:

- English-written documents.
- Peer-reviewed journal and conference papers.
- Documents published from 2002, which corresponds to the year when the term Digital Twin was firstly introduced [24].
- Queries limited to the fields of engineering, computer science, energy, material science, and social sciences, given the multidisciplinary of the topic.

The search was conducted in the databases of Scopus, Web of Science, and IEEE Explore using the research query and the eligibility criteria previously reported and led to obtaining a total amount of 1335 papers.

After the removal of duplicates, the remaining papers underwent a three-phase screening procedure meant to filter the documents not aligned with the scope of the research based on four main Exclusion Criteria (EC):

- EC1: The full text of the document is not available.
- EC2: The document is out of topic (the paper is not aligned with the defined topic of research and RQs).
- EC3: The document is out of the manufacturing field of application.
- EC4: The document doesn't present any link between the concepts of DT and maintenance or asset management.

The first screening phase is performed by inspecting the documents' titles and abstracts and concludes with the selection of 69 papers. The second screening phase is performed on the chosen articles from the precedent phase by analyzing their content and ends with the selection of 57 documents and the removal of 13. Last, a snowball analysis performed on the references of the selected papers leads to the inclusion of 6 additional documents, which are considered for content purposes. In the end, 57 studies are identified as relevant and utilized for the succeeding analysis to contextualize and build knowledge on the state-of-the-art DT applications in the field of maintenance.

The literature review methodology and its application summary are presented in Fig. 1.

In the next session, the main literature review results are presented. For the sake of clarity, despite the enlargement of the domain of the search, hereinafter reference will be explicitly made to maintenance only, while AM will be implicitly considered in reference to the entire lifecycle dimension of assets.

2.2. Literature review results

With the increasing seek for efficiency and optimization of the maintenance activity, DT technology has progressively started to be adopted in this application field [12] by both researchers and practitioners.

Given its fundamental role in pursuing the continuous growth of competitive markets, allowing for the optimization of the productivity and quality of production systems [25], maintenance is experiencing significant growth.

From a lifecycle perspective, the focus so far has primarily been on managing the Middle of Life (MoL) phase of assets, using various preventive maintenance strategies. Driven by advancements in Industry 4.0 technologies, these strategies have gradually evolved into more advanced predictive approaches, aiming to anticipate faults before they occur. As shown in Fig. 2, often at the expense of other practices such as corrective and condition-based maintenance, the majority of DT studies focus on predictive maintenance (PdM) (approximately 45 % of the papers) and health state assessment (HAS) (around 17 % of the papers). These areas contribute to optimizing manufacturing process stability, product quality, and maintenance efficiency.

In detail DTs, by leveraging technologies like Machine Learning (ML) algorithms and simulation tools, support PdM by forecasting the future moment in which the equipment should fail, to keep a high level of reliability and availability [11]. In this direction, most PdM studies provide methodologies aimed at improving the understanding of the degradation status of assets and components and so optimizing the computation of their Remaining Useful Life (RUL). The resulting

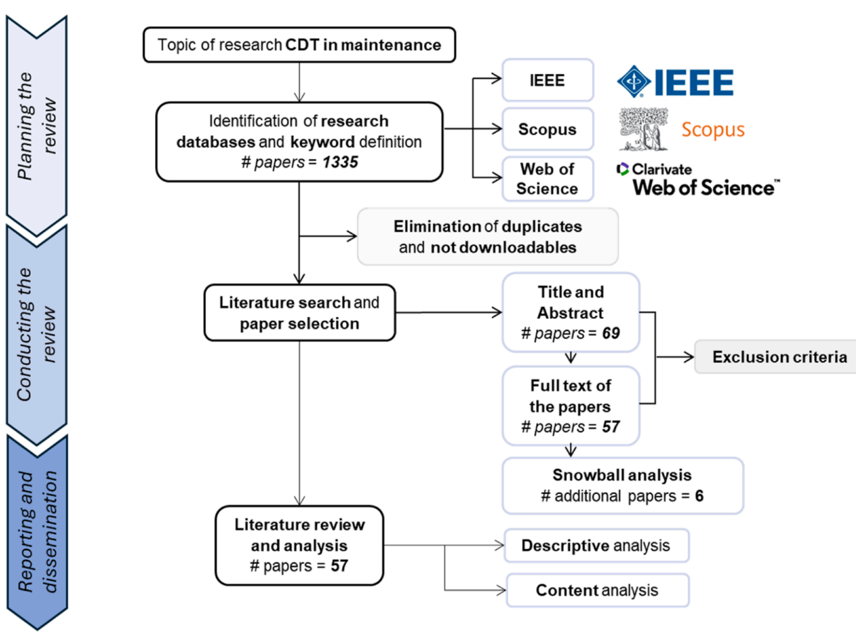

Fig. 1. Literature Review methodology (left-hand side, based on Tranfield et al. [22]) and its application (right-hand side).

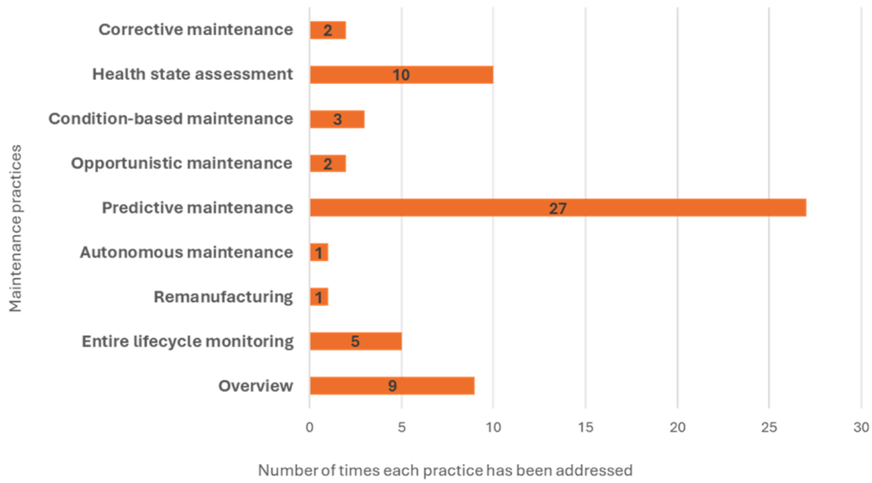

Fig. 2. Maintenance practices identified in the literature (for the sake of clarity, entire lifecycle monitoring mainly refers to AM).

information can be exploited to guarantee the stability of the manufacturing process and the required production quality [26], to understand the components' degradation status in complex engineering assets [27], to identify the optimal maintenance action time [28], or to avoid unplanned downtimes and consequently optimally handle anomalies alleviating their consequences and supporting resilience in production [1].

Moving to HSA, which the analysis highlights as the second most addressed maintenance practice, DTs are mainly employed in verifying the ability of the equipment and its components to perform their designed functions [29]. For this purpose, some studies propose a methodology for assessing and estimating the health state of production systems aimed at timely detecting discrepancies between the actual behavior of the asset and the designed one (fault or degradation detection), and so allowing triggering an early maintenance intervention [30, 31]. Others also stress the importance of the detection and diagnosis activity in enhancing decision-making support and guidance, and how it contributes to increasing productivity [32] and improving the active support of corrective actions on equipment [29,33]. In HSA applications, data analytics, ML algorithms, and simulation tools are the most leveraged technologies in DTs.

Another enabling technology that, starting from 2019, has been identified in the analysed literature as relevant for DT applications in PdM and HSA is ontology, which makes use of expressiveness and reasoning capabilities, inference potentialities, and allows interoperability [25,34,35] for increasing context-awareness, interpretability of the information, and data integration. Hence, the ability of DTs to track the through-life degradation of assets [10] and evaluate the failures' criticalities and diagnosis [25] is enhanced. However, implementations of ontology-based DTs in maintenance, and specifically in FDD, are not widely spread.

Next Section 2.2.1 drills down the analysis to CDT for maintenance, narrowing the scope of the analysis to discuss such advancements.

2.2.1. *Cognitive Digital Twin in maintenance*

The first appearance of the term Cognitive Digital Twin in the industry sector is attributed to Ahmed El Adl, who introduced it in 2016 as 'a digital representation, augmentation and intelligent companion of its physical twin as a whole, including its subsystems across all its life cycles and evolution phases' [36]. Indeed, technologies, when synergically exploited and integrated with expert human knowledge, can enable human-like cognitive capabilities in DTs [1,20], which allow them to augment their abilities in representing and enhancing the physical system, leading towards the CDT.

Building on this foundation, several studies have extended the CDT concept to different domains. Focusing on the domain of analysis of this paper, some authors have begun to explore the potential of the CDT in addressing maintenance challenges. D'Amico et al. (2022) propose an ontological approach to DTs for maintenance management, describing the evolution toward cognitive DTs through ontology and degradation models, though without a full implementation. Eirinakis et al. (2022) present a CDT framework for enhancing production resilience, identifying tools such as data analytics, databases, domain knowledge systems, and simulations to materialize cognition. Castanier et al. (2021) discuss the evolution from DTs to CDTs by integrating predictive capabilities using ML and simulation tools. Last, Abburu et al. (2020) introduce a hybrid CDT architecture for fault prediction in process industries via ML and mathematical modeling. From these contributions, therefore, the CDT emerges as a DT enhanced with cognitive capabilities tailored to specific applications, made possible by the synergistic combination of enabling technologies.

To further characterize the CDT landscape, this study maps the

Table 1
Mapping of the papers with respect to the cognitive capabilities defined by Zheng et al. (2022).

Cognitive capabilities	Definition of the cognitive capabilities by Zheng et al. (2022)	Papers	Enabling technologies
Perception	Capability of forming useful representations of data related to the physical twin and its physical environment	57 papers	Data analytics, semantic technologies, simulation tools, ML models
Attention	Capability of focusing selectively on a task or a goal or certain sensory information either by intent or driven by environmental signals and circumstances	57 papers	Data analytics, ML models, IoT
Memory	Capability of encoding information, storing and maintaining information, and retrieving information	57 papers	Database, semantic technologies, cloud
Reasoning	Capability of drawing conclusions consistent with a starting point	36 / 57 papers	Semantic technologies, ML models, data analytics
Problem-solving	Capability of finding a solution for a given problem or achieving a given goal	9 / 57 papers	Data analytics, ML models
Learning	Capability of transforming the experience of the physical twin into reusable knowledge for a new experience	23 / 57 papers	Data analytics, ML models

presence of cognitive capabilities, based on the definitions by Zheng et al. 2022, within the DT solutions identified in the literature, together with their enabling technologies. As shown in Table 1 (the full table with references is provided in Annex 1), all DTs exhibit perception, attention, and memory, which appear fundamental across applications. For example, perception allows structuring incoming data into the DT [37]. Attention filters and monitors relevant variables, enabling the detection of faults [38], while memory allows the retention of historical and temporary data [1]. By contrast, reasoning, problem-solving, and learning are more selective and are primarily observed in works explicitly focused on CDTs.

Some technologies, or more appropriately, combinations of technologies, are identified in the SLR as enabling DTs to be enhanced with human-like capabilities. For instance, perception and attention can be triggered using data analytics [37,38]. Memory can be obtained using persistent technologies like databases or semantic technologies, like ontologies [1]. Reasoning capability can be enabled by employing ML models [39] as well as ontologies [35], while learning can be activated by ML algorithms [40]. Instead, in the case of problem-solving, none of the papers provides an implementation case, highlighting the difficulty in automating this capability, which, in most cases, is still left to humans. Therefore, for the sake of the classification, the studies in which the developed approaches are able to suggest solutions and not only provide pieces of information, like in Dhada et al. (2021), are classified as compliant with this capability.

2.3. Research gaps and concluding remarks

Based on the review and interpretation of the current state of the art about CDT and reinterpreted DT with cognitive capabilities for maintenance, it is possible to define some research gaps currently present in the scientific literature:

To date, only a limited number of works have developed and implemented CDT frameworks and solutions in the manufacturing domain, with few points of contact with maintenance. For instance, Eirinakis et al. (2022) introduce a conceptual CDT framework aimed at production resilience, but without operational deployment. Notably, no operational CDT framework grounded in semantic technologies has been implemented specifically for maintenance, particularly one that formalizes expert knowledge through ontologies to enable cognitive capabilities in support of FDD decision-making. Certain maintenance activities, such as FDD, are inherently human-intensive, relying heavily on the tacit knowledge and decision-making abilities of experts, especially during diagnosis. However, compared to strategies like PdM and HAS, despite FDD being a foundational step, it remains underrepresented [42]. While PdM is frequently praised for its ability to predict failures, RUL estimation, and optimize maintenance schedules, the crucial role of FDD in identifying and diagnosing faults before the prediction is performed has been underexplored. Also, despite the importance of FDD in ensuring operational reliability, no comprehensive CDT frameworks have been proposed to effectively capture and utilize human knowledge to support or enhance these processes.

Building on the gaps, some concluding remarks can be drawn to address several aspects of CDT for maintenance in the manufacturing industry:

1. The elaboration of the definition of the cognitive capabilities in CDT, and the analysis of its key enablers of technology and asserted knowledge in the domain of maintenance, specifically in FDD, will allow for the enabling and implementation of the CDT.
2. The integration and formalization of human tacit knowledge as part of the development of maintenance ontologies, starting from FDD, where actions are still based on human-machine interactions, will support human decision-making process and enable further capabilities of CDT.

Given the above premises, this research addresses the identified gaps by proposing a CDT framework for FDD in maintenance. Hence, Section 3 describes the proposed CDT framework, and Section 4 shows how it has been tested and assessed in a laboratory setting.

3. CDT framework for fault detection and diagnosis decision-making support in maintenance

Stemming from the literature review results shown in Section 2, this Section 3 aims at describing the proposed CDT framework in light of FDD, as one of the processes requiring significant human content, both in terms of knowledge, decisions and action, for the optimal execution of related activities. Firstly, the role of expert knowledge within FDD is clarified in Section 3.1 as a propaedeutic digression to streamline the CDT framework description. Then, Section 3.2 goes through the characteristics of the proposed framework, which is built on the concurrent use of semantic technologies, namely ontologies, and data analytics.

3.1. The role of expert knowledge in fault detection and diagnosis

The current scientific research has demonstrated an increasing commitment toward the full exploitation of DTs' technological capabilities [43]. However, if digitalization revolutionized the manufacturing sector by integrating technologies and interconnecting machines prioritizing process automation, it didn't consider how the cooperation between machines and humans (with their expert knowledge, adaptivity, and decision-making capabilities) could lead to process empowerment [40,43]. This gap is especially evident in maintenance, where human expert knowledge and decision-making capabilities remain central [44]. Considering the processes of fault detection, diagnosis, and repair, the human role is fundamental [45], as these tasks rely heavily on expertise and are typically not standardized. Moreover, to limit intervention time, they must be performed in short time spans, and human error must be reduced to the minimum [46]. For this reason, fault diagnosis requires both technical proficiency and a deep understanding of the machine's structure and operation to generate and test diagnosis hypotheses [47].

With the advancement of digital technologies, the production environment is growing in complexity. This leads to increasing both [46] the required level of expertise, involving multidisciplinary knowledge, and the amount of machine state information to manage, along with the probability of errors during maintenance activities [46]. Systems need to be carefully monitored and maintained to avoid unexpected events [28], reducing the impact of failure and performance loss on productivity, costs, environment, and workers. Nevertheless, complexity increases system vulnerability, and regardless of the adopted maintenance strategy, failures still occur. To muffle their effect, efficient FDD techniques are increasingly demanded to be aware of the health status of each machine and its parts [28,47].

In this setting, the adoption of DTs offers support to operators in understanding processes and equipment by enabling anomaly detection, efficient data analysis for diagnosis, which helps narrowing possible fault causes, repairing action recommendations, and displaying relevant metrics [40]. Still, human knowledge is needed in the decision-making process for the interpretation of the results of the analyses and the actuation of the optimal decision [48]. Given the need for intelligent reasoning in fault identification and isolation, especially in unforeseen scenarios, humans ultimately bear responsibility for interpreting data and ensuring effective maintenance outcomes.

3.2. CDT framework in maintenance: a proposal for fault detection and diagnosis

To comprehensively present the CDT framework, it is first required to i) define cognitive capabilities for FDD (Section 3.2.1), and ii) describe the framework with a focus on enabling technologies (Section 3.2.2) already framed according to results presented in Table 1.

3.2.1. Definitions of the cognitive capabilities in fault detection and diagnosis

Before detailing the CDT framework and mapping cognitive capabilities to its constituting elements, it is necessary to outline the definitions of these capabilities as applied to the specific domain of FDD. The FDD-specific definitions are proposed in Table 2, also highlighting their main enablers. These definitions were elaborated by combining the ones proposed by Zheng et al. (2022) and Eirinakis et al. (2022): the first provided a general definition of the cognitive capabilities of CDT, while the second reported more domain-specific definitions for Prognostics and Health Management. For comparison, the original reference definitions, along with their tailored elaboration for FDD, are provided in Annex 2.

In the following Section 3.2.2, the CDT framework for FDD will be presented in detail.

Table 2
Proposed FDD-specific definitions of the cognitive capabilities for FDD in maintenance and enabling technologies.

Cognitive capability	Proposed FDD-specific definition	Enabling Technology
Perception	Capability of forming structured human and machine-readable representations of data related to the physical twin and its physical environment, to allow the identification and prediction of anomalies and events in the system.	It can be enabled by data analytics, ML models, semantic technologies, and simulation tools.
Attention	Capability of focusing selectively on a task or information either by intent or driven by environmental signals. It allows a prompt and proper reaction to the identification of an anomaly, triggering diagnosis activity involving the appropriate tools.	It can be enabled by data analytics, ML models, and IoT.
Memory	Capability of encoding information, storing and maintaining information, and retrieving information. It allows the storage of relevant fault diagnosis information for the correct functioning and modelling of the technologies employed in support of the activity and for the performance of offline analysis of the fault.	It can be enabled by persistent technologies, such as databases and semantic technologies (ontology), and the cloud.
Reasoning	Capability of deriving knowledge and conclusions (fault diagnosis) about the state of the system and the fault, and its causes.	It can be enabled by semantic technologies like ontologies and knowledge graphs, simulation tools, data analytics, and ML models.
Learning	The ability to convert established and new derived knowledge gained by experience and the CDT during the FDD process into reusable insights for future applications.	It can be enabled by ML models and data analytics. Technologies like ontology, knowledge graph, and simulation tools can be exploited in support of the human learning process. The human is then able to provide asserted knowledge and feedback aimed at improving the technology and the physical system.
Problem-solving	Capability of finding a solution for a given problem or achieving a given goal and acting back on the real system.	As the most difficult capability to automate, technologies like ontology, ML models, data analytics tools, and simulation tools can be employed in support of the human decision-making process by suggesting possible solutions to be implemented by the human on the physical system.

3.2.2. CDT framework in maintenance: a proposal for fault detection and diagnosis

Based on the delineated cognitive capabilities, the proposed CDT framework for FDD in maintenance (Fig. 3) starts from the physical layer, where sensor data from the physical asset is retrieved. This data is successively collected into the server, which bridges the physical and virtual layers, and fed to the CDT in the virtual layer (arrow 1). The CDT includes multiple interacting technologies (arrow 2), which are classified with reference to Cho et al. (2019) into two categories:

1. Analytics & Synchronization technologies: these encompass data-driven algorithms used to process real-time and historical data, perform analyses, and populate or update the ontology.
2. Knowledge Management technologies: these include databases for integrating and managing large volumes of historical and current data, and ontologies for knowledge modelling, formalization, and reasoning.

Afterward, the elaborated information output from the CDT serves as input to the maintenance decision-making process (arrow 3) in the physical layer, which is held by the maintenance staff, who, following the FDD activity, can intervene on the physical asset (arrow 4). This interaction is not unidirectional: operators critically evaluate the output from the CDT, validating its inferences, refining the fault hypotheses if needed, and using this insight to guide both the physical action and potential knowledge updates in the system. This human decision-making process is not limited to interpreting outputs but also contributes to the evolution of the CDT by validating or refining diagnostic conclusions. In this sense, human plays a central role in adapting and improving the system over time.

As highlighted in the SLR, depending on the application case, full automation in DTs, as well as in CDTs, is rarely reached. Therefore, enabling cognition within DTs, so realize the concept of CDT, requires an effective combination of technology and human capabilities. In the specific case of FDD proposed in this paper, the technologies of data analytics, ontology, and database are rationally integrated and combined in support of maintenance staff to enable all six cognitive capabilities. Hereafter, the core CDT elements are described, highlighting the enabled cognitive capabilities:

1. Ontology: belonging to the branch of symbolic AI, ontologies provide an opportunity to resolve problems of both syntactic and semantic interoperability by using logic-based theories that frame ontological entities in an unambiguous, human- and machine-readable manner [49]. This knowledge-modelling semantic technology also offers a rich understanding of the context, i.e., what is happening inside the system under analysis, thereby enhancing both interpretation and reasoning capabilities. Hence, ontology can be used as a support to maintenance staff in the execution of tasks where a deep level of context awareness is required, as in the FDD activity.

   After the modelling of the assertive knowledge about the system and the process, related data can be fed into the ontology in a timely manner, for the identification of the root causes of the anomaly and the failure modes thanks to its *reasoning* cognitive capability and

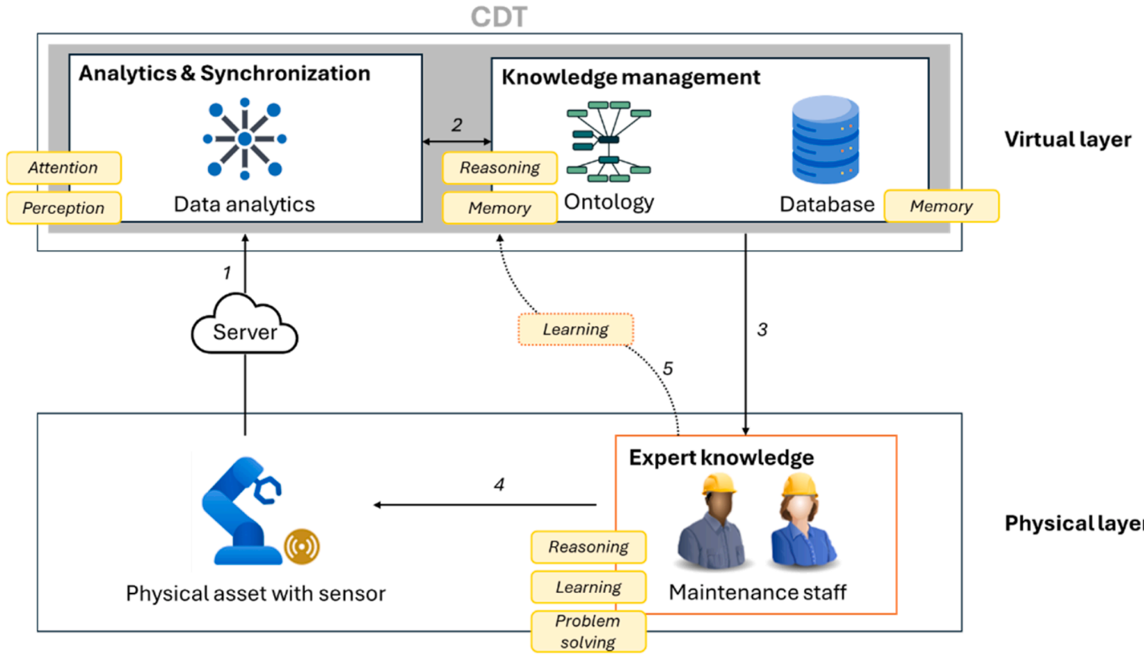

Fig. 3. Cognitive Digital Twin framework for FDD decision-making support in maintenance.

context awareness. Moreover, the formalization of the knowledge performed by this technology is, with databases, a form of encoding, storing, and keeping the relevant information typical of the *memory* capability.

It is important to note that the ontology does not evolve automatically based on accumulating data; rather, it is enriched through expert input. Maintenance staff, upon completing diagnosis and intervention, may revise or refine the knowledge structure, thereby supporting the CDT's *learning* capability through human involvement (arrow 5 in Fig. 3). Additionally, the ontology enables a cascade reasoning process, whereby the identification of one anomaly may lead to inferred conclusions regarding other related components or failure modes, further supporting systemic diagnosis and contextual awareness.

2. Data analytics: thanks to their accuracy and fast response time, data analytics are suitable, based on the data retrieved from the physical layer and stored in the database, to detect the probable occurrence of a fault in a physical asset and to assess its degradation condition. These algorithms are not designed for optimizing detection performance, but to activate and sustain the ontology's reasoning capability as part of the broader engineering of the FDD process. To do so, according to the condition-based maintenance strategy, once the monitored data reaches an unwarranted threshold computed on the basis of past operational data, a warning is triggered to alert maintenance staff of the possible unhealthy status of the equipment. Thus, data analytics allow the enabling of the *perception* and *attention* cognitive capabilities for the structuring of the collected physical twin data and the detection of anomalies. Importantly, maintenance staff may use their diagnostic experience to suggest refinements to the configuration of these algorithms, improving their contextual relevance.

3. Database: in nowadays production environments, vast amounts of data are generated from various sources like the shop floor, production management systems, and maintenance management systems. This data, if managed effectively, can provide valuable insights for optimizing processes and improving decision-making [50]. Recent advancements in database technologies, such as NoSQL databases, allow for more flexible and efficient storage and retrieval of this data, especially for unstructured or semi-structured information [51]. Thus, these systems can integrate and store a high volume and variety of historical and real-time operational data, and so enabling the *memory* cognitive capability.

4. Expert knowledge: expert knowledge (e.g., designers, maintenance, and production personnel) about the system and the related FDD process is a fundamental input to the virtual layer of the CDT. Thanks to the formalization of this knowledge, data analytics and ontology technologies are able to provide a meaningful output. This can then be elaborated by the maintenance staff who, by exploiting their *learning, reasoning*, and *problem-solving* capabilities, can inspect the real system for the identification of the actual cause of failure, and act back on the physical equipment. Hence, data analytics' information can be used for the timely detection of the fault and activate the fast response of the operators; instead, ontologies, based on the detection-related information provided by data analytics, can then be exploited for the generation of the diagnosis-related hypothesis. After the repair task is completed, the newly acquired experience can be used to refine the diagnostic models and update the formal knowledge within the CDT. This human feedback mechanism is key to enabling the *learning* capability of the system, ensuring that the CDT framework remains adaptive and relevant over time (arrow 5 in Fig. 3).

The interaction process between the maintenance staff (specified as maintenance domain experts and maintenance technicians) and the main system components with which it interacts, namely the ontology (transformed into a knowledge graph when instantiated) and data analytics, is summarized in the flowchart in Fig. 4.

Given the central role of semantic technologies, particularly ontologies, and data analytics in supporting FDD within the proposed CDT framework, these are the areas in which this paper contributes most

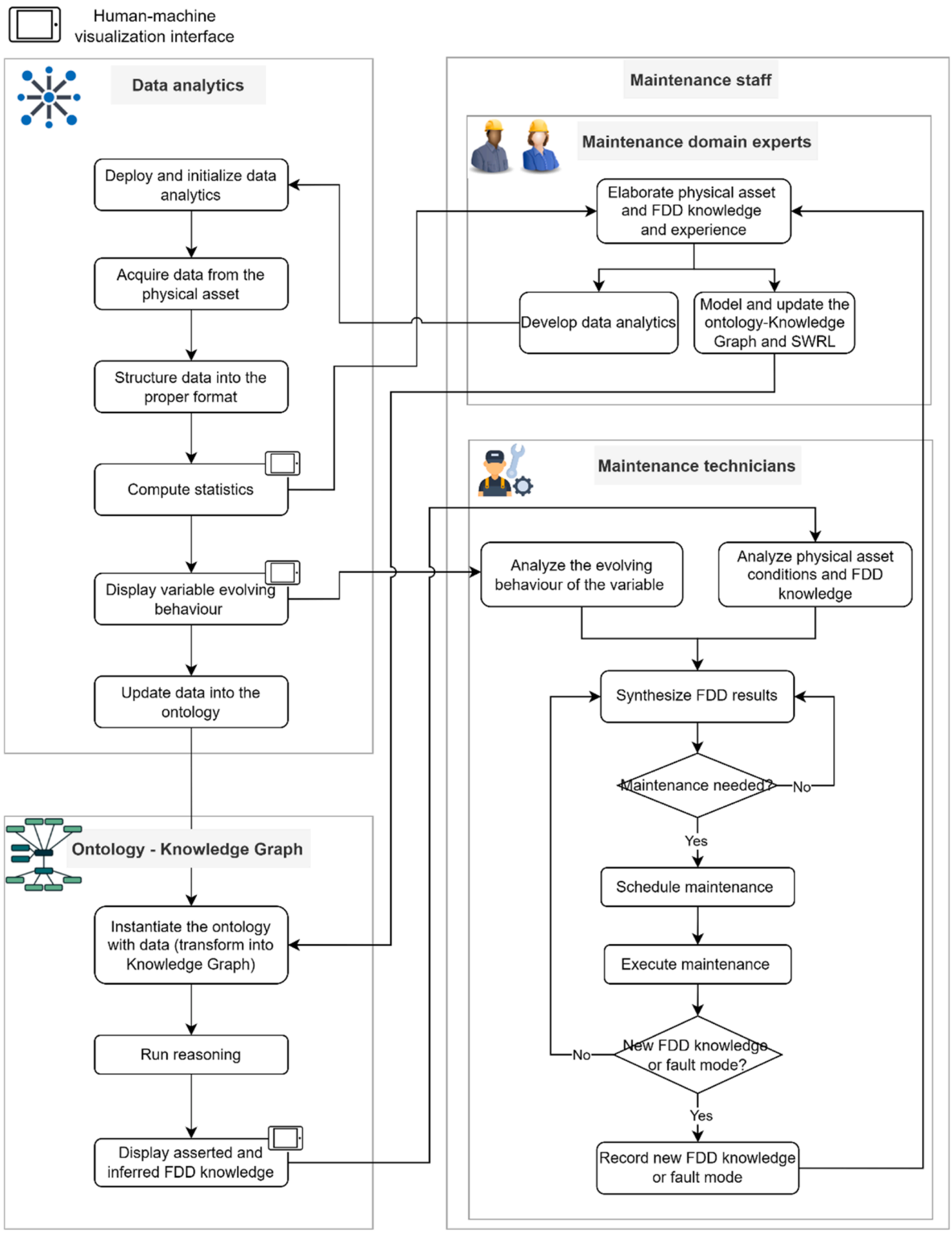

Fig. 4. Flowchart illustrating the interaction between data analytics, ontology-knowledge graph, and maintenance staff in the proposed CDT framework for fault detection and diagnosis.

significantly. Accordingly, Section 3.2.2.1 presents a novel ontology for FDD (FDDO – fault detection and diagnosis ontology), while Section 3.2.2.2 provides an overview of the data-driven algorithms developed in support of the functioning and instantiation of the FDDO. While other enabling technologies are also important, they are not the primary focus of this work and are therefore not explored in depth. Interested readers can refer to the following works for more information [52–54].

3.2.2.1. Ontology for fault detection and diagnosis (FDDO). As the field of ontology in FDD remains underdeveloped [55], it was deemed necessary to extend available ontologies to a more comprehensive one to enhance system interoperability, scalability, and semantic consistency in the domain. Ontologies provide a formal, shared, and machine-interpretable representation of knowledge, enabling interoperability among heterogeneous systems, facilitating knowledge reuse, and supporting automated reasoning for decision-making [49]. In industrial contexts, they play a key role in ensuring agility and resilience by providing a common semantic foundation across systems and stakeholders [49], which in the maintenance and FDD domain translates into more accurate fault diagnosis, improved decision support, and enhanced coordination among maintenance staff.

Hence, the starting point for this work was the contribution by Franciosi et al. 2022 [56], which compares multiple maintenance-related ontologies and non-ontological resources such as international norms to define a taxonomy. The taxonomy was based on the integration of such resources, considering also best practices from established associations, like IOF (Industrial Ontologies Foundry) (see afterwards more details on knowledge reuse practice for the present research work). Therefore, stemming from this contribution, this paper elaborates and extends an ontology, named FDDO, that embeds specific FDD-domain concepts.

Methodologically speaking, AMODO (asset management ontology development methodology) [57] has been followed, which consists of the following macro-phases:

1. Specification: the first macro-phase is meant to define and clarify (i) the domain addressed by the ontology, (ii) the selected reference foundational ontology that allows for the standardization and reuse of the concepts modeled through the ontology, which guarantees that the ontology has a predefined ontological commitment, (iii) the competency questions (CQs) that the ontology must answer to ensure its validity to meet the needs of the final stakeholders of the ontology, and (iv) the proper implementation language and annotation properties, balancing formality of the ontology and its description and executability.
2. Knowledge elicitation: the second macro-phase is meant to retrieve useful domain-related knowledge to be included into the ontology, which may derive from both ontological and non-ontological resources, therefore bringing out knowledge reuse as pivotal.
3. Conceptualization: the third macro-phase has the objective of formally representing the ontology concepts' definitions and axioms.
4. Formalization and implementation: the fourth macro-phase, which will be addressed in Section 4 (application case), has the objective to formalize and implement the ontology in the selected language. In this phase, the instantiation of the ontology at the application level and its validation are performed.

Table 3
Competency questions of the ontology for fault detection and diagnosis.

Competency question	Knowledge type
CQ1. What are the machine units of the machine?	Asserted
CQ2. What are the components of the machine unit?	Asserted
CQ3. What is the flow associated with the component x?	Asserted
CQ4. What is the primary failure cause that is associated with the failure mode?	Asserted
CQ5. What are the failure modes of the fault x?	Asserted
CQ6. What is the state of component x?	Inferred
CQ7. Is the machine doing the set up?	Inferred
CQ8. Is the component x of the system operating with its nominal function?	Inferred
CQ9. Are there negative and positive deviations affecting the process?	Inferred
CQ10. Is the component x in a total state of failure?	Inferred

1-Specification. The FDDO aims to provide a formalized base averting the complete utilization of knowledge for FDD applications in industrial maintenance. Therefore, in order to meet the needs of the final stakeholders, which is depicted in the CDT framework as the maintenance staff, the FDDO should be able to answer 10 CQs, listed in Table 3, with both asserted (explicitly modeled) and inferred (derived through reasoning) knowledge related to the FDD process and the machine to be monitored and inspected.

The FDDO has been modelled according to OWL language with the support of the ontology editor Protégé. To define inference rules among classes and instances, they have been implemented using SWRL, while the activation of the reasoning has been made possible through the adoption of Pellet reasoner.

The selected reference foundational ontology (or top-level) is the Basic Formal Ontology (BFO), compliant with the ISO 21838 standard [58] and with established guidelines by IOF, which represents the highest level of generalization of the knowledge independent from any domain. As emphasized by both Ameri et al. (2022) [49], Savic et al. (2023) [59], and Franciosi et al. (2025) [60] aligning domain ontologies with upper ontologies such as BFO and established standards like IOF not only ensures semantic consistency and interoperability, but also enhances the scalability, adaptability, and long-term sustainability of complex industrial systems through the seamless integration of heterogeneous data sources.

2-Knowledge elicitation. Going through the hierarchical structure of the ontology, Common Core Ontologies (CCO) (i.e., the two sub-ontologies Information Entity Ontology (IEO) and Artifact Ontology (AO) have been reused), and Information Artifact Ontology (IAO) (i.e., the father class of Information content entity and its child class Identifier have been reused) have been selected as reference domain-independent ontologies. These allow the introduction of more targeted concepts that can be reused in the developed ontology, continuing to ensure alignment with reference ontologies and reusability of their concepts as they are all grounded on BFO. This approach follows best practices highlighted in the literature, where reusing well-established ontological resources ensures semantic consistency, supports system interoperability, and reduces development effort [49]. To further lower down the level of detail of the ontology to the maintenance domain, related concepts have been introduced and positioned in the ontology by confronting both non-ontological resources like IEC 60812:2018 [61], ISO 14226:2006 [62], IEC 60300-3-11:2009 [63], and domain-specific ontologies like Karray et al. [64], Montero et al. [65], Polenghi et al. [57], and IOF [66, 56]. All of these resources have been compared and analysed considering the goal of FDD; given some inconsistencies and that none of them was specifically though for FDD (also, some of them are at the moment not finalized or released, like IOF Maintenance Ontology), afterwards in the Conceptualization macro-phase of AMODO, more details will be provided on the defined taxonomy. To summarize, on the basis of this retrieved taxonomy/ontologies, related concepts have been modeled and positioned in the FDDO as presented in Fig. 5, alongside related resources.

3-Conceptualization. For the modelling of the FDD domain, related concepts from the non-ontological sources of the FMEA (Failure Mode and Effect Analysis) and HAZOP (Hazard and Operability Study) have

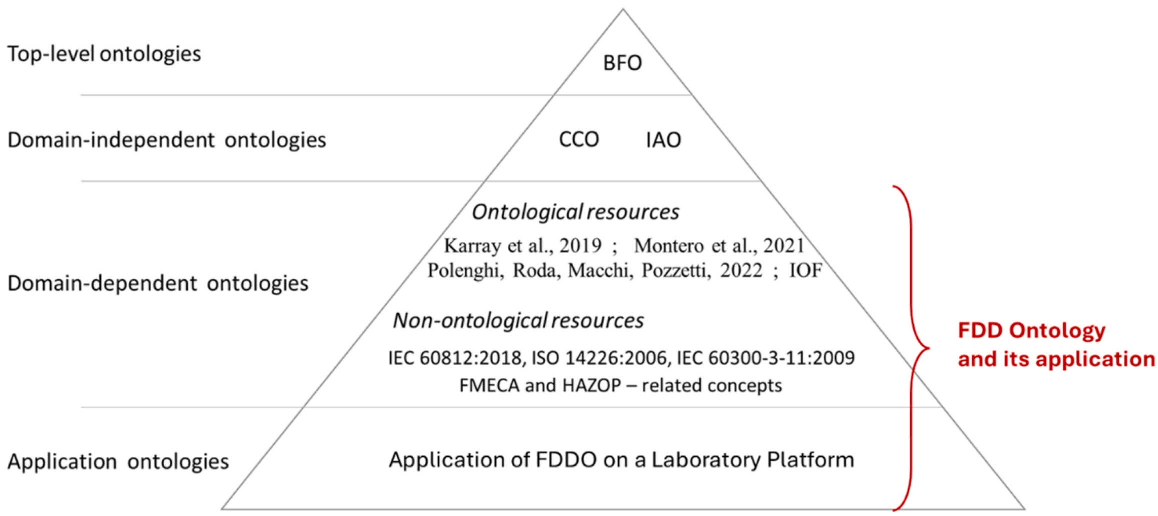

Fig. 5. Layers of the ontology for FDD (FDDO).

Table 4
System characterization and FMEA classes of the ontology for fault detection and diagnosis (FDDO).

Class	Sub-class	Source	Natural language definition
Material artifact		CCO	A Material Entity that was designed by some Agent to realize a certain Function.
	Component	FDDO	A CCO:MaterialArtifact that has role a FDDO:ComponentRole
	Machine	FDDO	A CCO:MaterialArtifact that has role a FDDO:MachineRole
	Machine unit	FDDO	A CCO:MaterialArtifact that has role a FDDO:MachineUnitRole
	Product	FDDO	A CCO:MaterialArtifact that has role a FDDO:ProductRole
	Sensor	FDDO	A CCO:MaterialArtifact that has role a FDDO:SensorRole
	Tool	FDDO	A CCO:MaterialArtifact that has role a FDDO:ToolRole
Object aggregate		BFO	An object aggregate is a material entity consisting exactly of a plurality (≥1) of objects as member parts which together form a unit
	System	FDDO	A BFO:ObjectAggregate that has member a CCO:MaterialArtifact
Failure mode		IOF (definition by FDDO)	A BFO:Disposition of a CCO: MaterialArtifact to exhibit the consequence of a Failure mechanism through which a failure occurs
	Electromechanical Failure Mode	FDDO	A IOF:FailureMode whose characteristic is Electromechinal
	Hydraulic Failure Mode	FDDO	A IOF:FailureMode whose characteristic is Idraulic
	Mechanical Failure Mode	FDDO	A IOF:FailureMode whose characteristic is Mechanical
	Pneumatic Failure Mode	FDDO	A IOF:FailureMode whose characteristic is Pneumatic
Failure cause		IOF (definition by ISO 14224: 2016)	Circumstances associated with design, manufacture, installation, use and maintenance that have led to a failure
Identifier		FDDO	A CCO:DesignativeInformationContentEntity that is used to uniquely identify an entity within a particular context
	ComponentID	FDDO	A FDDO:Identifier that relates to a FDDO:Component
	FailureCauseID	FDDO	A FDDO:Identifier that relates to a IOF:FailureCause
	FailureModeID	FDDO	A FDDO:Identifier that relates to a IOF:FailureMode
	MachineID	FDDO	A FDDO:Identifier that relates to a FDDO:Machine
	MachineUnitID	FDDO	A FDDO:Identifier that relates to a FDDO:MachineUnit
	SensorID	FDDO	A FDDO:Identifier that relates to a FDDO:Sensor
Role		BFO	A role b is a realizable entity such that b exists because there is some single bearer that is in some special physical, social, or institutional set of circumstances in which this bearer does not have to be & b is not such that, if it ceases to exist, then the physical make-up of the bearer is thereby changed
	ComponentRole	FDDO	A BFO:Role borne by a FDDO:Component when it is involved in carrying out some part of a BFO:Process
	MachineRole	FDDO	A BFO:Role borne by a FDDO:Machine when it is involved in carrying out some part of a BFO:Process
	MachineUnitRole	FDDO	A BFO:Role borne by a FDDO:MachineUnit when it is involved in carrying out some part of a BFO:Process
	ProductRole	FDDO	A BFO:Role borne by a FDDO:Product when it is trasformed in some part of a BFO:Process
	SensorRole	FDDO	A BFO:Role borne by a FDDO:Sensor when it provides a BFO:Function that is of type "monitoring" of another CCO:MaterialArtifact
	ToolRole	FDDO	A BFO:Role borne by a FDDO:Tool when it is involved in carrying out some part of a BFO:Process

been employed and semantically revised to create a common source of reusable knowledge for FDD applications. The FMEA and HAZOP are used, after a preliminary functional analysis about the normal functioning of a system, for the study of abnormal situations affecting it and the identification of the causes and consequences of the occurring degradation [47]:

Table 5
HAZOP classes of the ontology for fault detection and diagnosis (FDDO).

Class	Sub-class	Source	Natural language definition
Variable		FDDO	A BFO:DescriptiveInformationContentEntity that is measured by a FDDO:Sensor
Deviation		FDDO	A BFO:RealizableEntity that is measured by a FDDO:Sensor and can lead to some FDDO:StateOfFailure
	Negative	FDDO	A FDDO:Deviation that occurs when a FDDO:Variable falls below its normal or expected value
	Positive	FDDO	A FDDO:Deviation that occurs when a FDDO:Variable falls above its normal or expected value
State of failure		FDDO	A IOF:State that occurs when a CCO:MaterialArtifact or FDDO:System no longer performs its intended BFO:Function or fails to meet specified performance criteria
Flow		FDDO	A BFO:RealizableEntity involving a CCO:MaterialArtifact and FDDO:Variable that, when a IOF:FailureMode occurs, undergoes a FDDO:Deviation

- The system characterization and FMEA classes, which are listed and defined in Table 4, allow for the identification of known and potential failure causes, failure modes (with their nature), their major effects on the different parts of the system, and thus suggest the possible area of intervention.

- The HAZOP classes, which are listed and defined in Table 5, allow identify anomalies by focusing on the operability of the system through logical sequences of cause-deviation-consequence of process parameters [67].

The FMEA and HAZOP classes of the ontology for FDD and their object properties (asserted properties in continuant lines and inferred properties in dashed lines) are shown in Fig. 6.

The complete hierarchy of FDDO, from top-level ontology BFO to leaf classes, is shown in Fig. 7.

The disclosed classes were therefore linked through properties and rules such that the FDDO is able to assess the health state of the monitored components and to recognize, once a component degradation/failure has been identified, the primary cause of failure, the mode of failure, and the resulting sequence of detectable deviations on the process. Hence, the FDDO has been modelled to furnish adequate support to maintainers' decision-making process when performing the FDD task by providing both asserted and inferred knowledge about specific characteristics of the modelled equipment and its process, as well as knowledge directly related to the FDD activity.

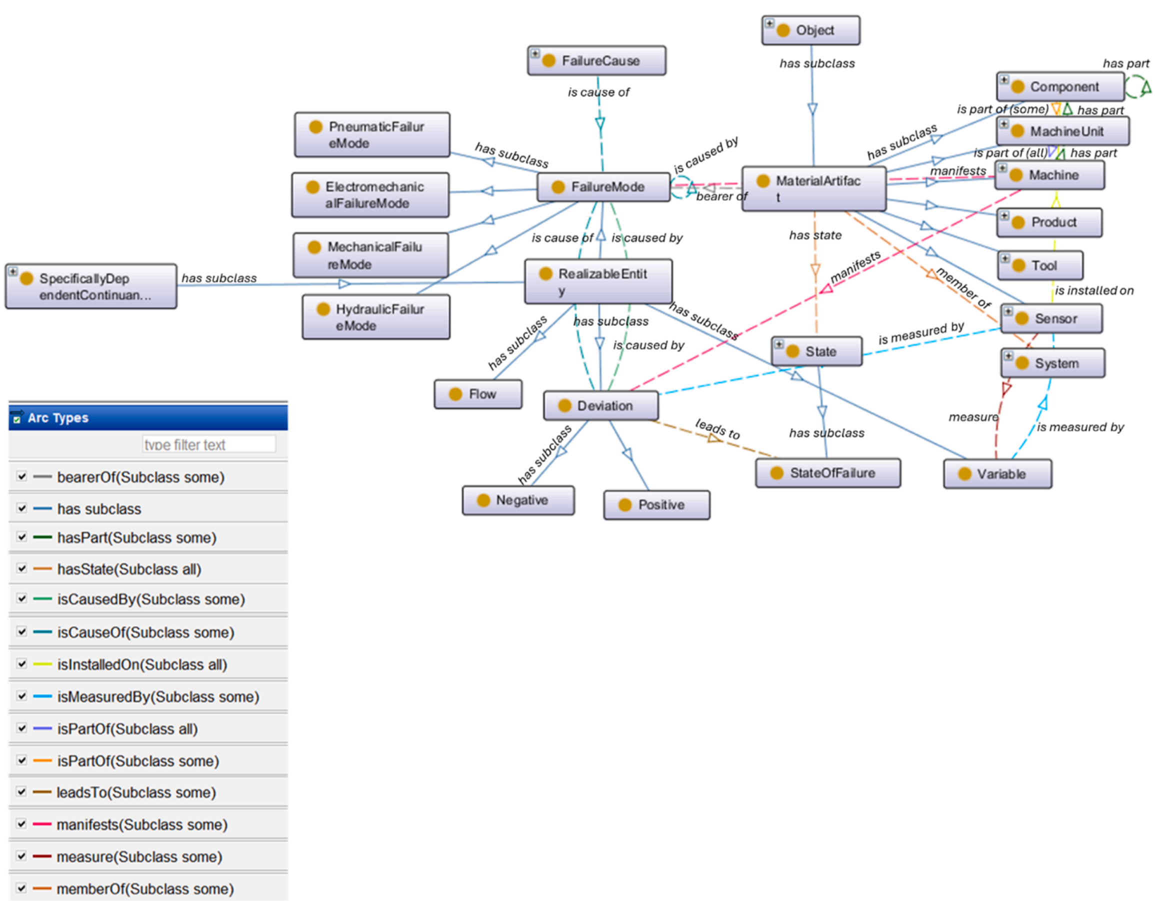

Fig. 6. FMEA and HAZOP classes of the ontology for FDD and their object properties (Protégé OntoGraf View).

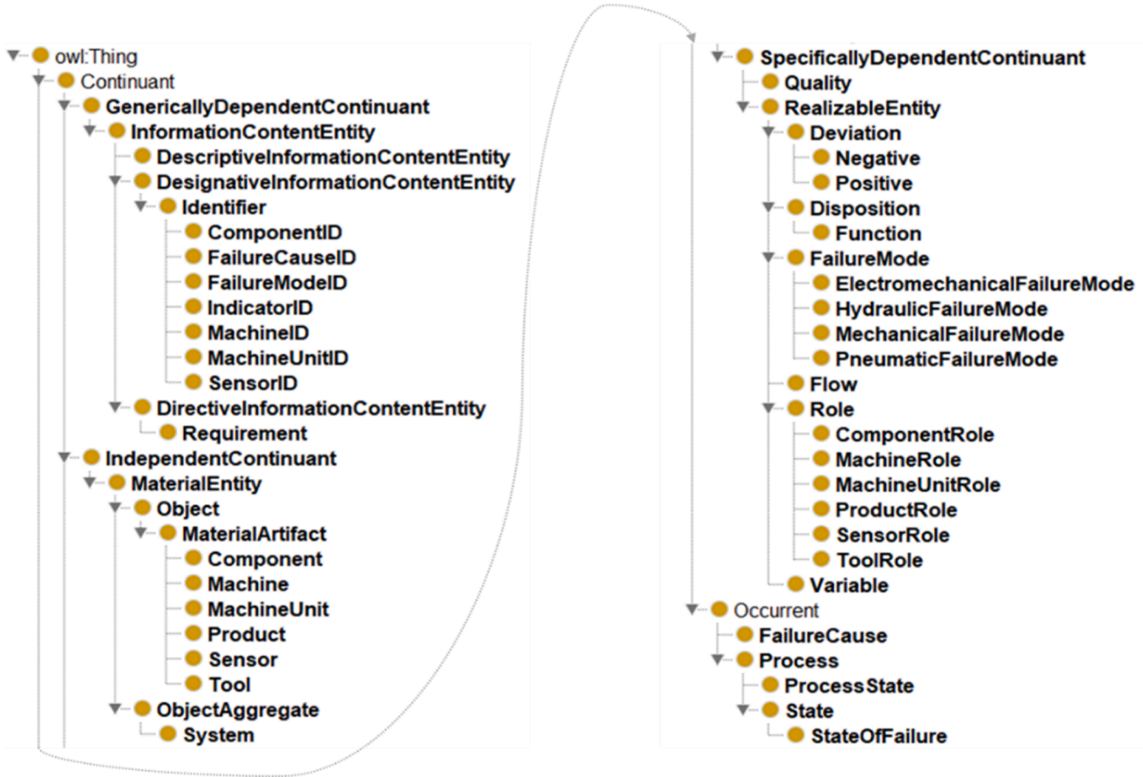

Fig. 7. FDDO hierarchy.

3.2.2.2. Data analytics. The second technological component enabling the implementation of the CDT framework revolves around the use of data analytics. These algorithms provide analytics and synchronization capabilities that support both the ontology and the maintenance staff during the FDD process. In this proposed solution, five key data analytics algorithms, each equipped with its respective HMI facilitating the interaction of the maintenance staff with the technology, have been developed:

1. Data Acquisition algorithm: it is responsible for gathering real-time data from the physical asset through sensor integration and makes the collected data available in a structured format via the OPC UA server. From the server, the high amount of collected time-evolving variables can be integrated and input into the NoSQL database, which allows for their flexible storage and retrieval for further elaborations.
2. Database Querying algorithm: it is responsible for extracting relevant stored data for further processing, on user-defined intervals, aimed at retrieving significant information for the FDD process (e.g., control limits for the identification of the health state of the physical asset).
3. Statistical Computation algorithm: as the ontology for FDD is required to identify the health state of the asset and detect the occurrence of a fault, this algorithm calculates key statistical parameters (such as the mean and standard deviation) for relevant variables, which are then modelled as data properties into the ontology.
4. Visualization algorithm: the ontology provides time-updated semantic information to the maintenance staff, allowing them to be aware of the behavior of the asset. Visualization algorithms are a beneficial addition for the maintenance staff to gain meaningful insights into the evolving (past and current) behaviour of the asset.
5. Ontology Integration (update ontology) algorithm: it is ultimately responsible for feeding the data into the ontology for FDD, enabling timely, event-driven, updates and alignment with the knowledge base.

This suite of data analytics algorithms collectively facilitates efficient data handling, processing, and integration with the CDT framework, supporting both human operators and the ontology.

Fig. 8 reports the functioning of the data analytics algorithms and their respective HMIs.

4. Application of the CDT framework in a laboratory setting

The CDT framework was implemented in a laboratory setting with a platform built ad-hoc [*whose details will be disclosed upon eventual paper acceptance as a matter of anonymity*] for maintenance-related experiments. The platform is equipped with sensors and connected to the OPC UA server, supporting the recording and access to all process data at each stage of the process, thus allowing insights into the asset in the maintenance area. In detail, the platform is composed of two overlapping and independent systems (Fig. 9):

- The first system is a continuous press/punching production process. This system can be found in industries like automotive manufacturing, in car body parts production, or in the paper industry. This system can be summarized into three main subsystems: (i) the coil changing subsystem which is in charge of providing the input material in the form of a coil (once the coil is finished, a new one is equipped), (ii) the unwinding subsystem which is in charge of unrolling the raw material and conveying the product in the form of a band to the entrance of the vertical press, and (iii) the advancement and pressing/punching subsystem which is in charge of providing the band in the right position at the entrance of the press and of pressing/punching it in the final product.
- The second system is made of two magnetic brakes, placed in correspondence to the two motors, that allow the creation of degradation and symptoms of failure on the machine. The management of the operation of the brakes is performed by a Programmable Logic Controller (PLC), ensuring precise control and functionality. In addition, several actuators are integrated into the system to emulate

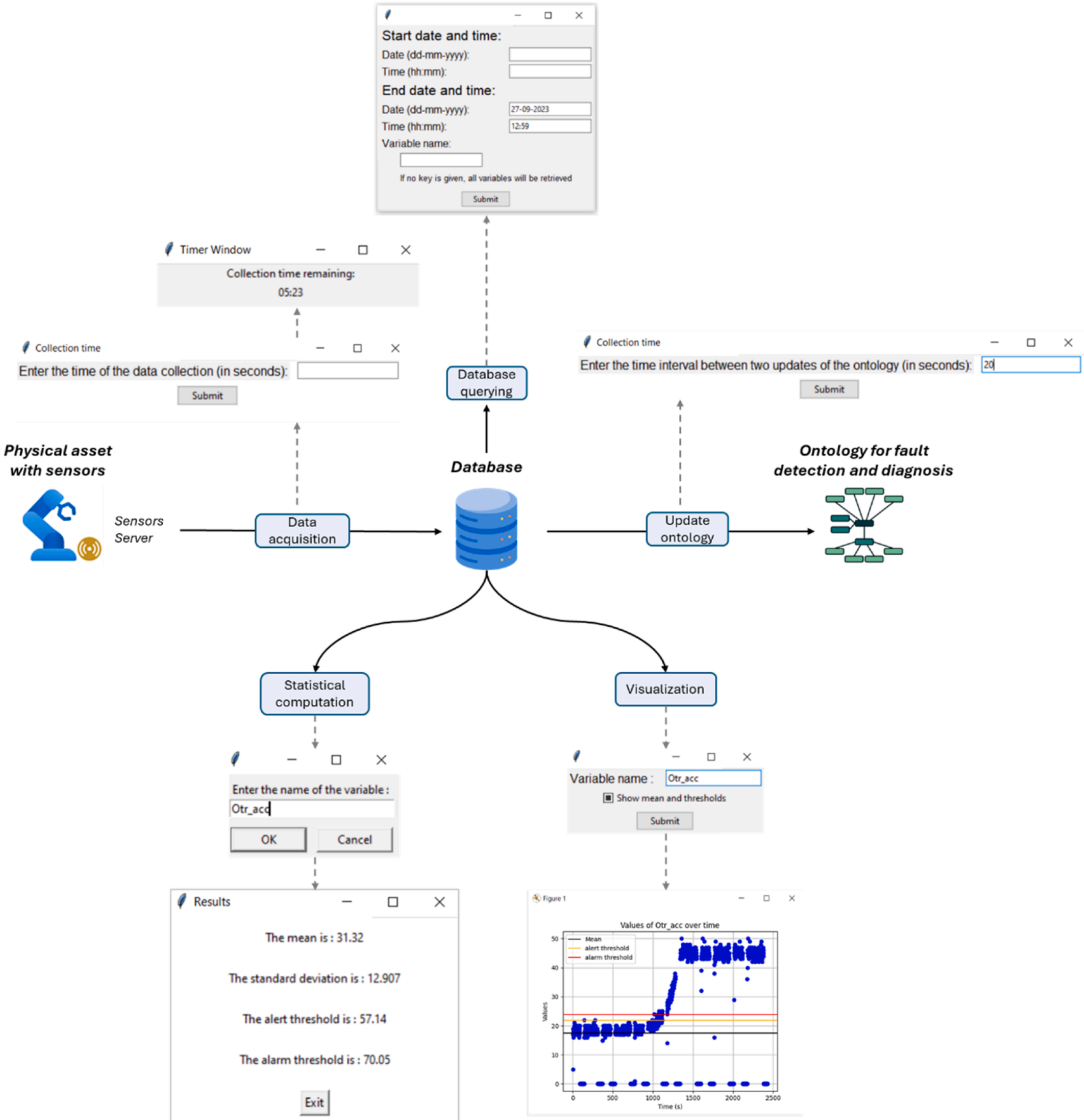

Fig. 8. Data analytics algorithms and HMIs of the Cognitive Digital Twin framework for fault detection and diagnosis decision-making support.

various fault scenarios, enabling robust testing and validation of FDD processes.

In detail, the application case consists of the implementation of the degradation scenario *bearings deterioration caused by wear by friction and fatigue* affecting the accumulator motor of the unwinding subsystem.

Provided the overview of the functioning of the platform, Section 4.1 will disclose the instantiation of the degradation scenario into the ontology for FDD and its validation, whereas Section 4.2 will discuss the output from the implementation of the framework.

4.1. *Ontology for fault detection and diagnosis: instantiation on the platform*

To lower the ontology at the application level, this requires being instantiated with instances related to the scenario under analysis. Besides the knowledge related to the machine and its process, the knowledge related to the degradation scenario needs to be formalized to allow the identification and localization of the anomaly within the system and how the process is affected by it. With this purpose, information regarding the causes of the degradation or failure, its modes, and the affected artifacts, both at component and machine-unit levels, was retrieved from the FMEA of the platform. Instead, the sequence of process deviations and the associated variables and affected components of the subsystem were retrieved from the HAZOP of the platform. Both FMEA and HAZOP are a result of the asserted knowledge formalization from experts. Afterward, the information has been integrated into a sort of ETA (Event Tree Analysis), illustrated in Fig. 10, on which basis the relationships and rules of the ontology have been modelled and implemented habilitating reasoning.

In detail, starting from the information that the primary failure cause of the bearing's deterioration is the wear by friction and fatigue, through the FMEA it has been possible to identify the mechanical modes of the failure at a component level. At a machine unit level, the secondary mechanical failure modes resulting from the propagation of the degradation to the other components have been identified. From the process standpoint, according to the HAZOP, starting from the bearings, the degradation propagates at the process level, causing a succession of deviations in the process according to a waterfall effect affecting the entire subsystem. The classes of the ontological model were thus

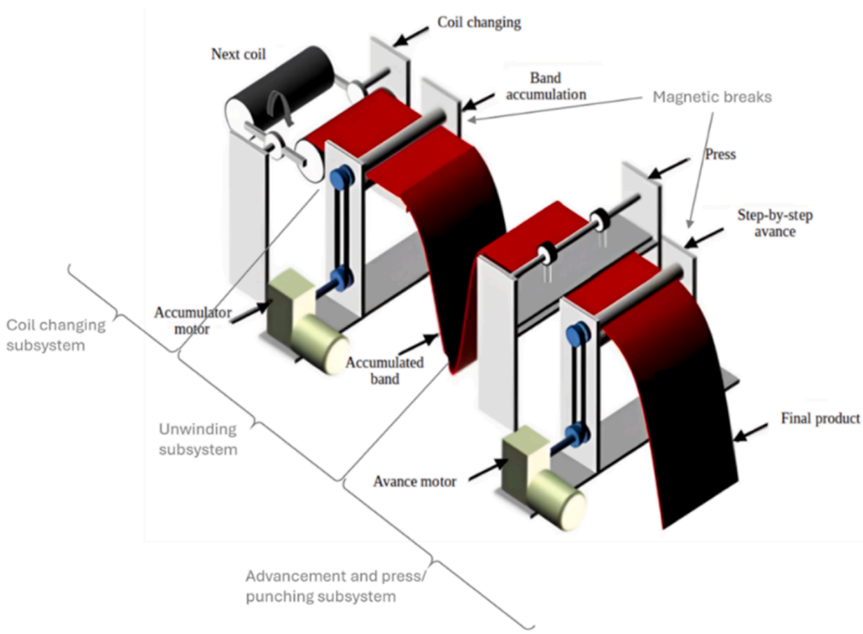

Fig. 9. Elements specification of the platform.

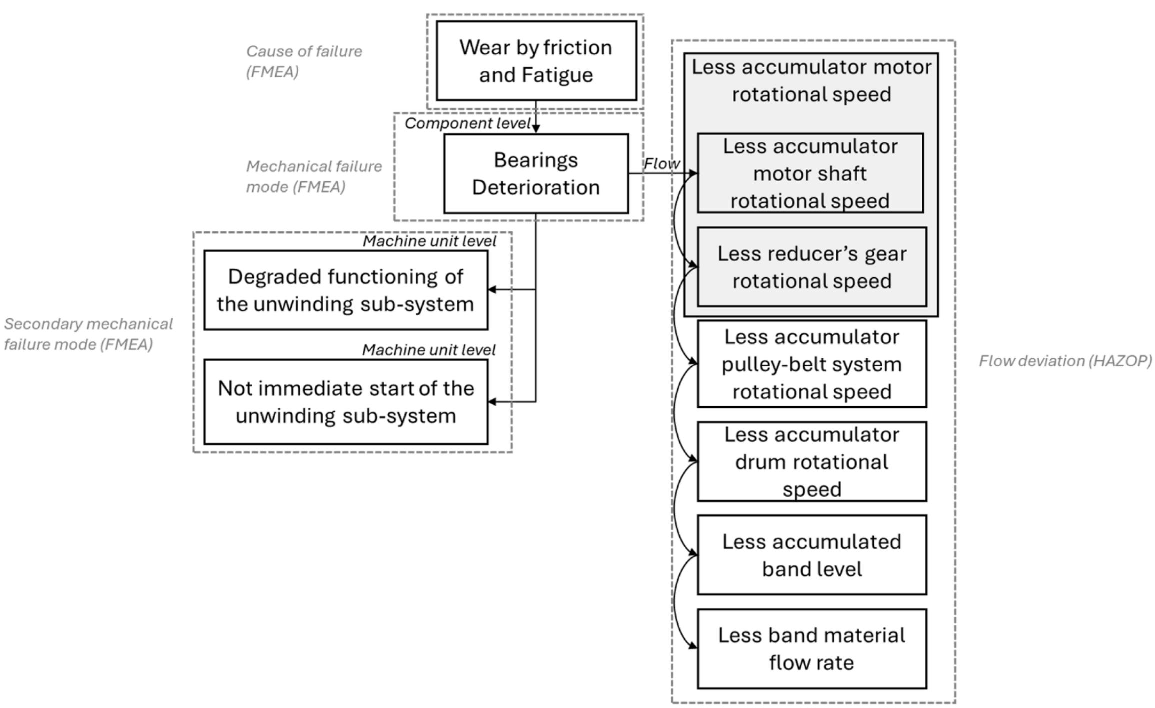

Fig. 10. ETA of the platform for the scenario 'bearings deterioration caused by wear by friction and fatigue'.

instantiated and related through data properties (e.g., the numerical values of the health, alert, and alarm thresholds) and object properties between instances, as well as through asserted (continuant line) and inferred (dashed line) SWRL rules in Protégé. A summary of the implemented SWRL rules, along with their corresponding logical functions within the diagnostic process, is provided in Table 6 to concretely illustrate the inference mechanisms enabled by the FDDO.

Fig. 11 shows an extract of the ontology for FDD modelling from *OntoGraph* in Protégé (asserted properties in continuant lines and inferred properties in dashed lines) and an example of its validation through competency questions (CQs).

Once the ontology for FDD is modelled, the full implementation of the CDT framework requires transforming the ontology into a Knowledge Graph (KG).

This transformation allows the ontology to be populated with case-specific instances and continuously updated with data from the monitored system. The process begins with the instantiation of the ontology, where the key components, failure modes, variables, and operational states relevant to the specific use case are defined as individuals. To ensure the KG remains current with the status of the system in a timely manner, the dedicated "update ontology" algorithm retrieves sensor data from the database, updates the corresponding data properties of the instantiated individuals in the FDDO, and activates the rule-based reasoning engine. Based on the previously formalized relationships

Table 6
Competency questions of the ontology for fault detection and diagnosis (FDDO).

Number	SWRL rule	SWRL rule description
1	Variable(?V1) ^ Component(?C1) ^ hasHorizontalPosition(?V1, false) ^ Variable(?V2) ^ hasVerticalPosition(?V2, true) ^ Identifier(?I1) ^ hasID(?C1, ?I1) ^ hasIDvalue(?I1, 'Bob1') -> isChanging(?C1, true)	Coil changing condition
2	Variable(?V1) ^ Component(?C1) ^ hasHorizontalPosition(?V1, true) ^ Variable(?V2) ^ hasVerticalPosition(?V2, false) ^ Identifier(?I1) ^ hasID(?C1, ?I1) ^ hasIDvalue(?I1, 'Bob1') -> isChanging(?C1, false)	Coil not changing condition
3	State(?S1) ^ hasLabel(?S1, 0) ^ Variable(?V1) ^ Component(?C1) ^ greaterThan(?A, 0) ^ hasCurrentValue(?V1, ?A) ^ lessThanOrEqual(?A, ?B) ^ hasAlertThreshold(?V1, ?B) ^ Identifier(?I1) ^ hasID(?C1, ?I1) ^ hasIDvalue(?I1, 'M1') -> hasState(?C1, ?S1)	Healthy state
4	State(?S1) ^ hasLabel(?S1, 1) ^ Variable(?V1) ^ Component(?C1) ^ hasAlertThreshold(?V1, ?B) ^ hasAlarmThreshold(?V1, ?C) ^ greaterThan(?A, ?B) ^ hasCurrentValue(?V1, ?A) ^ lessThanOrEqual(?A, ?C) ^ Identifier(?I1) ^ hasID(?C1, ?I1) ^ hasIDvalue(?I1, 'M1') -> hasState(?C1, ?S1)	Alert state
5	State(?S1) ^ hasLabel(?S1, 2) ^ Variable(?V1) ^ Component(?C1) ^ hasAlarmThreshold(?V1, ?C) ^ greaterThan(?A, ?C) ^ hasCurrentValue(?V1, ?A) ^ Identifier(?I1) ^ hasID(?C1, ?I1) ^ hasIDvalue(?I1, 'M1') -> hasState(?C1, ?S1)	Alarm health
6	State(?S1) ^ hasLabel(?S1, 0) ^ Variable(?V1) ^ Component(?C1) ^ equal(?A, 0) ^ hasCurrentValue(?V1, ?A) ^ Component(?C2) ^ isChanging(?C2, true) ^ Identifier(?I1) ^ hasID(?C1, ?I1) ^ hasIDvalue(?I1, 'M1') -> hasState(?C1, ?S1)	Zero value of the monitored variable because the coil is changing
7	State(?S1) ^ hasLabel(?S1, 3) ^ Variable(?V1) ^ Component(?C1) ^ equal(?A, 0) ^ hasCurrentValue(?V1, ?A) ^ Component(?C2) ^ isChanging(?C2, false) ^ Identifier(?I1) ^ hasID(?C1, ?I1) ^ hasIDvalue(?I1, 'M1') -> hasState(?C1, ?S1)	Zero value of the monitored variable without coil changing
8	Variable(?V1) ^ Component(?C1) ^ isMeasureOf(?V1, ?C1) ^ PrimaryFailureCause(?FC1) ^ occursIn(?FC1, ?C1) ^ MechanicalFailureMode(?FM1) ^ isCauseOf(?FC1, ?FM1) ^ MechanicalFailureMode(?FM2) ^ isCauseOf(?FM1, ?FM2) ^ Negative(?D1) ^ resultsIn(?FM2, ?D1) ^ Flow(?F1) ^ hasFlow(?C1, ?F1) -> hasDeviation(?F1, ?D1)	Negative deviation condition

(captured through SWRL rules and the class hierarchy), the KG dynamically infers contextual information about the process through reasoning [68]. The KG is therefore able to distinguish the operational status of the process, whether it is active or inactive. When active, it can infer whether the system is in setup mode (e.g., coil change) or material processing. In the processing phase, the monitoring of key variables allows the KG to semantically determine the state of health of the monitored component, identify deviations, and support fault diagnosis. Conversely, when the system is inactive, the KG may associate this with a confirmed faulty state.

The process from ontology modelling to KG update is illustrated in Fig. 12, where the tasks highlighted in blue indicate the activities that

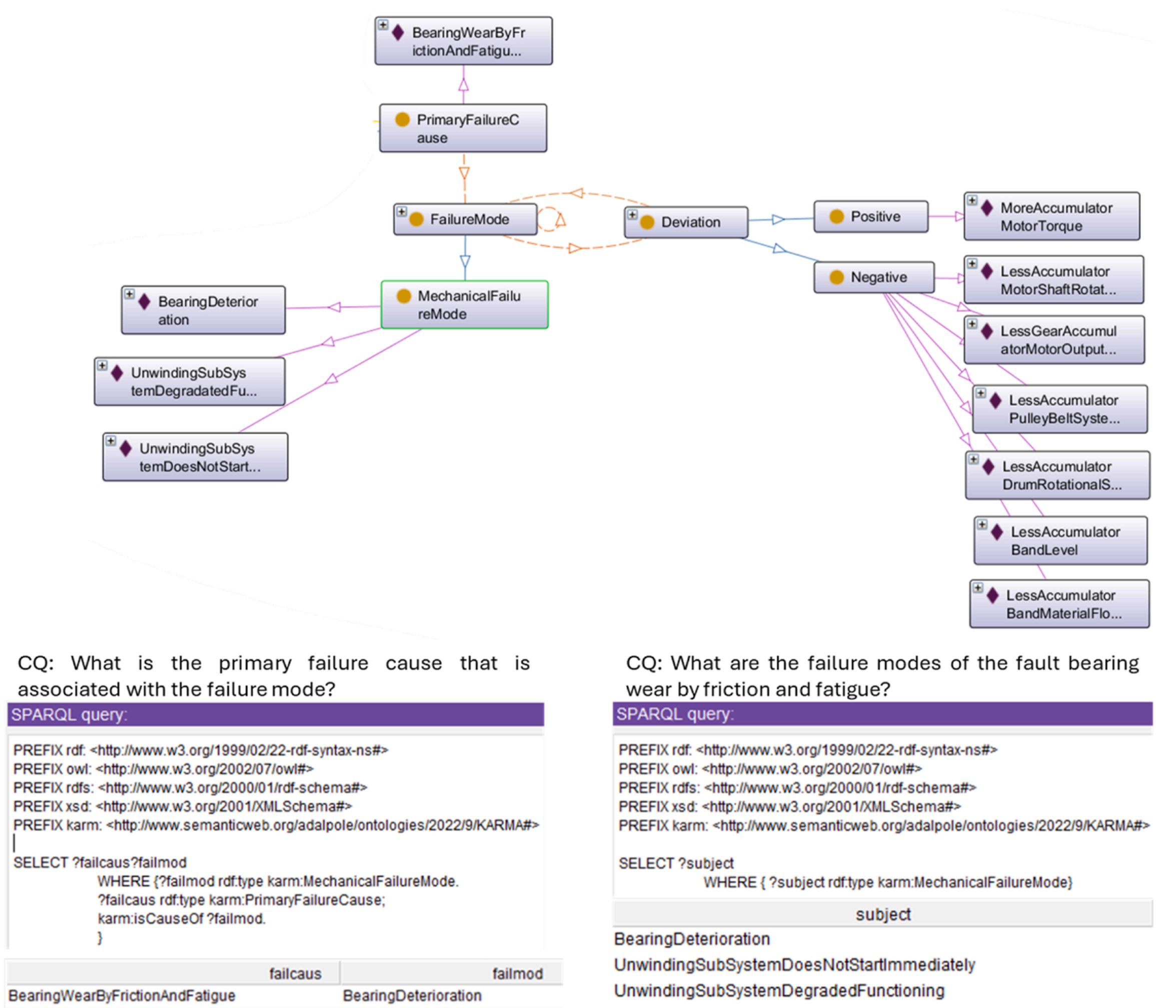

Fig. 11. Extract of the ontology for FDD of the platform from Protégé (up-hand side) and of its validation through competency questions (down-hand side).

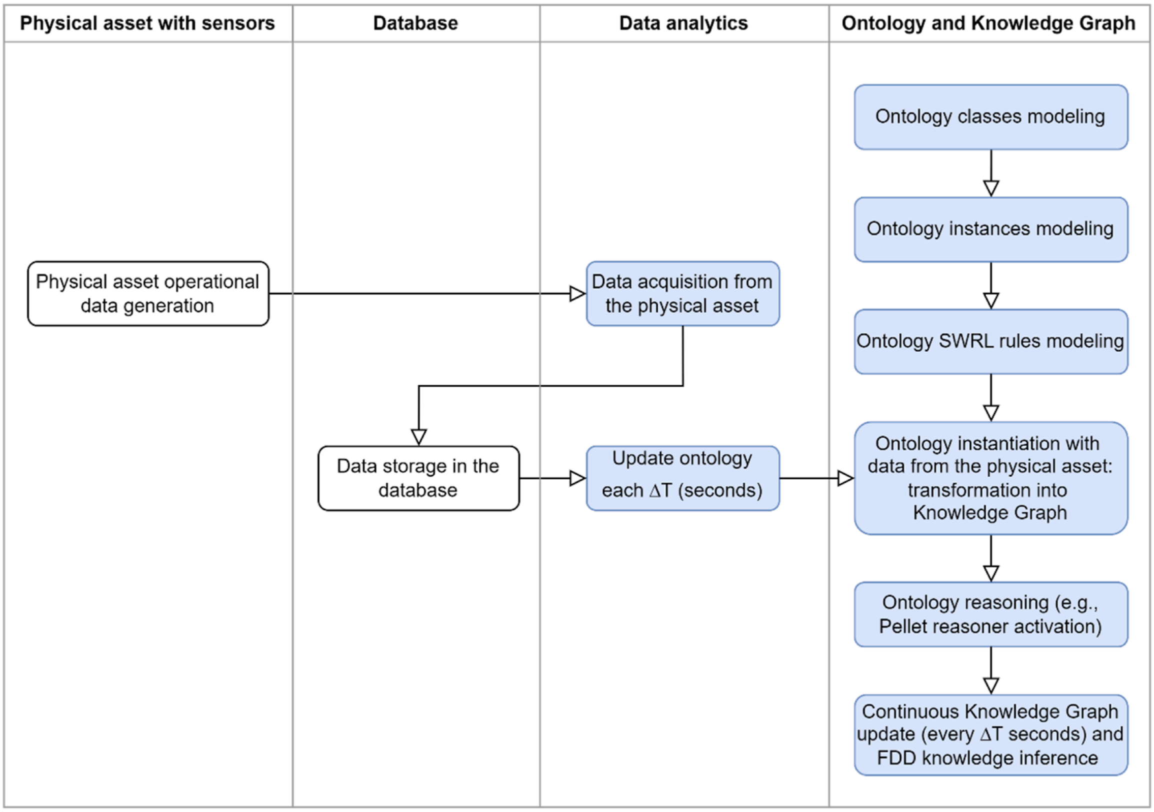

Fig. 12. Flow chart of the transformation process from Ontology to Knowledge Graph.

correspond directly to nodes already presented in the flowchart of Fig. 4 (Section 3.2.2), thus showing the connection and continuity between the two representations. In detail:

- The node “Data acquisition from the physical asset” of Fig. 12 corresponds to the node “Acquire data from the physical asset” of Fig. 4
- The node “Update ontology each ΔT (seconds)” of Fig. 12 corresponds to the node “Update data into the ontology” of Fig. 4
- The nodes “Ontology classes modelling”, “Ontology instances modelling”, “Ontology SWRL modelling” of Fig. 12 correspond to the node “Model and update the ontology-Knowledge Graph and SWRL” of Fig. 4
- The node “Ontology instantiation with data from the physical asset: transformation into Knowledge Graph” of Fig. 12 corresponds to the node “Instantiate the ontology with data (transform into Knowledge Graph)” of Fig. 4
- The node “Ontology reasoning (e.g., Pellet reasoner activation)” of Fig. 12 corresponds to the node “Run reasoning” of Fig. 4
- The node “Continuous Knowledge Graph update (every ΔT seconds) and FDD knowledge inference” of Fig. 12 corresponds to the nodes “Display asserted and inferred FDD knowledge” and “Model and update the ontology-Knowledge Graph and SWRL” of Fig. 4.

4.2. Output of the implementation of the CDT framework

The CDT framework implementation shows that maintenance staff is supported during the FDD process through dynamic insights about subsystem health and degradation, inferred by the KG. Using data from the accumulator motor torque and coil position, mapped into the KG, five states characterizing the modelled scenario were successfully assessed (Fig. 13):

- State 1 – No processing due to setup: when the coil is changed, the torque assumes the value of zero. The setup state is associated with the healthy state of the component as it is not possible to establish whether the degradation is occurring without the process performing. Once the change is completed, the platform resumes operation and it will be possible to precisely determine its state of health.
- State 2 - Healthy state of the accumulator motor: when the machine is not performing the setup and the values of the torque of the accumulator motor are below the alert threshold (no zero values), the component is identified as healthy and able to provide its function. Therefore, the maintenance staff is not required to perform any inspection action nor to intervene in the process, but just to continue monitoring the behaviour of the significant variables.
- State 3 – Alert state of the accumulator motor: when the machine is not performing the setup and the values of the torque of the accumulator motor are between the healthy and alarm limits the machine is processing with a partial degradation state. Therefore, the maintenance staff is provided with a contextualization of the values assumed by the torque by displaying relevant information regarding the alert state of health of the component and the deviations affecting the process. This knowledge can therefore be of support in the evaluation of the optimal time to perform the inspection process before the expansion of the degradation from the component to the machine unit level of the platform.
- State 4 – Alarm state of the accumulator motor: when the machine is not performing the setup and the values of the torque of the accumulator motor exceed the alarm threshold, the machine is processing at an advanced level of degradation. The maintenance staff is therefore provided with a contextualization of the values assumed by the torque by displaying relevant information regarding the alarm state of health of the component and the deviations affecting the process. Contrary to the previous scenario where there was still a time margin on the failure, herein the torque is not anymore able to

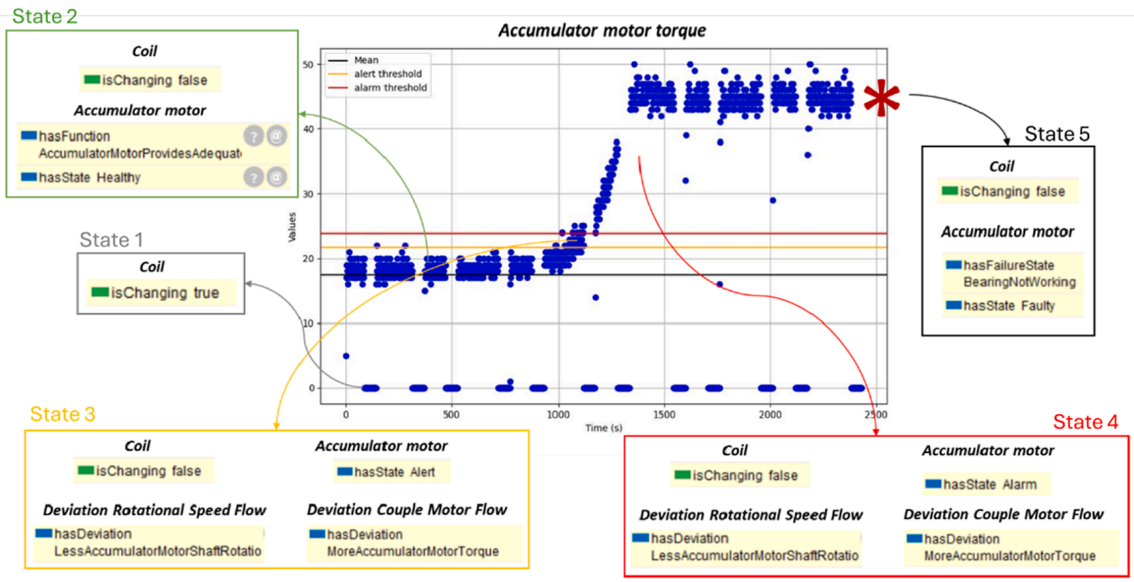

Fig. 13. Output of the implementation of the CDT framework on the platform.

compensate for a decrease in the rotational speed of the component which is consequently reaching its total state of failure. Hence, the maintenance staff is suggested for an immediate intervention in the performance of the inspection and diagnosis activities.

- State 5 – Total state of failure of the accumulator motor: when the value of the accumulator motor torque is zero and no setup is performed, the platform is not processing due to the total state of failure of the component. Hence, the maintenance staff is provided with knowledge regarding the faulty state of the motor and the specific fault state that can be useful for technicians to perform post-failure analysis on the machine. However, since the platform has been programmed to never reach total failure because the motor's torque is always able to compensate for the rotational speed reduction, it has been simulated ('* symbol' in Fig. 13).

These outputs reflect the framework's primary aim to engineer a structured and consistent FDD process that supports operator decisions.

5. Discussion and managerial implications

Building on the results presented in Section 4 and grounded in the conceptual framework introduced in Section 3, this section provides a broader discussion on the significance and implications of the proposed CDT framework. While the laboratory implementation served to test and demonstrate the feasibility of the approach, several transferable insights emerged regarding how cognitive technologies can support knowledge-driven FDD in maintenance. The discussion is structured in three parts: Section 5.1 describes the key findings from the implementation of the CDT framework in support of FDD decision making, Section 5.2 provides the lessons learnt from the application of the CDT framework in a laboratory setting, and Section 5.3 discusses the managerial implications.

5.1. Discussion from results

Drawing upon the results obtained in Section 4, this subsection highlights the main findings that demonstrate the value and feasibility of the proposed CDT framework, particularly in supporting knowledge-driven FDD activities:

- It is verified the potential of the ontology to include tacit and unstructured knowledge about FDD applications in support of the maintenance staff. This latter is indeed promptly informed about the operative state of the process, as well as the state of health of the monitored components of the system. If anomalies are detected, the maintenance staff is also provided with specific information regarding the occurring degradation/failure, such as the primary failure cause, the failure modes, and the deviations in the process.
- It is demonstrated the ability of the proposed framework to effectively integrate expert knowledge within technological models in support of humans in the engineering process of FDD. Specifically, the accuracy of data analytics algorithms and the interoperability and context awareness provided by the ontology - combined in a unified decision-support framework - allow supporting FDD decision-making process.
- It is proven the possibility of the framework to enable CDT in the maintenance domain. Indeed, the human-technology collaboration enables the six cognitive capabilities of attention, perception, memory, reasoning, learning, and problem-solving (previously defined in Section 3), thus leading to a first CDT implementation in FDD.

5.2. CDT framework for FDD implementation replicability

The CDT framework's viability has been demonstrated in a controlled environment, with the potential to extend it to real industrial systems. The application experience provided not only technical validation but also the opportunity to abstract a generalizable set of requirements and development insights. These inputs do not constitute a prescriptive methodology, but rather a set of operational lessons learned to support future replication and scaling of the framework in diverse contexts.

Although the proposed CDT framework was applied to a single degradation scenario (bearing wear) in a laboratory setting, its conceptual architecture is intentionally designed for generalization and adaptation to a broader range of degradation scenarios and, potentially, to diverse industrial contexts. This framework represents a foundational engineering solution for the development of CDTs in FDD, where the primary objective is to establish a methodologically valid, reusable structure that integrates expert knowledge and ontology reasoning capabilities into the decision-support process.

Therefore, from this first application, a set of technological and knowledge requirements (Section 5.2.1), implementation steps for replicability (Section 5.2.2), and scalability considerations (Section 5.2.3) have been outlined. These elements represent operational lessons learned, aimed at guiding replication efforts and bridging the theoretical underpinnings of the CDT with its concrete application in FDD.

Unlike general DT implementation procedures proposed in the literature (e.g., [69–71]), the insights derived here are specifically tailored to the development of CDT for FDD applications.

5.2.1. Technological and knowledge requirements

The successful deployment of the CDT framework in any new use case relies on the presence of key technological and knowledge requirements.

Technological requirements include:

- Sensorization of the physical asset, which enables the timely monitoring of variables related to degradation and operational status.
- Suitable data infrastructure, typically a server layer (e.g., OPC UA), to support the acquisition, storage, and transmission of continuous data streams from the physical asset.

Knowledge requirements include:

- Comprehensive understanding of the system structure and functioning, including its operational workflows and interdependencies.
- Expert knowledge about critical components, associated failure causes, modes, and potential process deviations, which serve as essential inputs for conducting the FMEA and HAZOP dysfunctional analyses.

5.2.2. CDT framework implementation procedure

Once the technological and knowledge requirements are in place, the CDT framework can be implemented by following a six-step procedure derived from the current study:

1. Analyse the system: conduct a comprehensive analysis of the system and operational workflows to understand the functioning of the system.
2. Execute FMEA/FMECA and HAZOP studies: systematically identify potential failure modes, causes, effects, and process deviations that will constitute the knowledge base of the FDD engineering process.
3. Identify critical components and variables: prioritize system components with the highest relevance for reliability, safety, or performance impact.
4. Instantiate and extend the ontology: reuse the upper-level structure of the FDDO (based on BFO and aligned with CCO and IOF standards), and adapt it (if needed) by adding new classes, subclasses, and instances that reflect the system-specific taxonomy (e.g., new components, failure modes, deviations).
5. Define SWRL rules and reasoning logic: translate expert knowledge and diagnostic rules into formal logic expressions, allowing inferred knowledge to support the decision-making process.
6. Implement data analytics: implement ad-hoc algorithms (data acquisition, querying, statistical computation, visualization, and ontology update) for use case-specific variables, thresholds, and server configurations.

5.2.3. Generalizability and scalability

The CDT framework is built on a conceptual foundation that ensures reusability and extensibility:

- The FDDO structure is modular and hierarchical, allowing the reusability of upper-level classes (e.g., Component, FailureMode, Deviation), while scenario-specific knowledge can be captured by adding subclasses and populating them with new instances.
- The SWRL rules are general in structure but must be contextually adapted to reflect the fault logic and causal dependencies of the specific use case.
- The data analytics algorithms' function (e.g., threshold computation, data collection), and their logical connection (Fig. 8) remain generalizable, although input parameters, signal types, and server addresses will need to be adjusted.
- The ontology-based knowledge graph construction workflow is replicable: once the ontology is instantiated and linked to equipment data via the data analytics layer, reasoning is activated through rule-based engines, producing semantically enriched, contextualized output for maintenance staff.

In summary, the CDT framework, though tested in a single, lab-scale scenario, is built to be scalable and transferable. By combining structured expert knowledge, semantic reasoning, and modular data processing, it provides a pathway for future implementations in real-world industrial systems.

5.3. Managerial implications

From a managerial perspective, possible impacts, to be intended as medium-to-long-term actions, resulting from the implementation of the CDT framework are:

- *De-fragmentation of diagnostic knowledge*: the fragmentation of diagnostic knowledge is a relevant industrial challenge. While fault identification may often be handled by embedded systems or automated tools, fault diagnosis typically remains reliant on external experts or scattered documentation, leading to delayed decisions and divided responsibilities. This was also evident in the application case presented in this study, where diagnostic understanding resided in different sources - technical documents, spreadsheets, and personnel expertise. By consolidating this dispersed knowledge into a formal, reusable ontology, the framework enhances traceability, consistency, and accessibility of diagnostic reasoning. Although no quantitative performance metrics were assessed, the framework shows potential to contribute meaningfully to reducing time-to-repair (TTR) by making fault diagnosis more structured and accessible, thus supporting operators more effectively within their existing workflows.
- *Efficient Monitoring and maintenance*: the technological support provided by the CDT framework facilitates easier monitoring, inspection, and maintenance. Operators can manage maintenance activities more efficiently by leveraging technology-driven insights about system health and operational status.
- *Improved maintenance and production scheduling*: the integration of real-time health and operational data could allow for more flexible and coordinated scheduling of production and maintenance activities. It also reduces human error during FDD tasks by offering technological guidance.
- *Economic and operational considerations*: To implement the proposed solution, organizations must address the costs related to training, equipment, and infrastructure. This will ensure that the workforce is equipped to fully utilize the technological and cognitive capabilities offered by the framework.
- *Rethinking employee purpose*: the framework enhances employee capabilities, requiring a reconsideration of their roles to ensure optimal collaboration with technologies.

6. Conclusions

This research work contributes to the existing literature by enabling CDT through a framework that has been proposed and assessed in a laboratory setting. Its originality lies in how ontology and data analytics are combined into a cohesive system that enables cognitive decision support specifically for FDD in maintenance.

The CDT in the domain of maintenance is an emerging concept, and besides its potential to address the current maintenance needs for resiliency, dynamism, broad vision of the system, and responsiveness, implementations of CDT solutions in the current literature remain scarce. While some studies provide general definitions of CDT and its cognitive capabilities, there is still a lack of shared understanding when it comes to defining these capabilities specifically in the maintenance domain. Therefore, this paper provides a new definition of the cognitive capabilities of attention, perception, memory, reasoning, learning, and problem-solving by adapting the definitions of Zheng et al. (2022) and Eirinakis et al. (2022) in the domain of FDD, highlighting the main human and technological enablers.

In the proposed solution, technologies are seen as an important support for maintenance staff for the accomplishment of the activities, but no longer as the main means. As a matter of fact, this paper contributes to overcoming the identified gap from the SLR about the integration of human knowledge with advanced technologies to develop intelligent and adaptive solutions capable of understanding and addressing complex scenarios and making informed decisions. Focusing on FDD, a crucial task in maintenance that typically requires human expertise, this research work identifies data analytics and asserted-knowledge embedded ontology as a key enabler for implementing CDT, integrated in a novel framework to support cognitive capabilities in a practical maintenance setting.

The main research contributions can be therefore summarized as follows:

- Development of a SLR for the identification of the state-of-the-art DT in the domains of maintenance and asset management, aimed at analyzing CDT contributions in maintenance.
- Elaboration of a new definition of the cognitive capabilities of the CDT applied to the domain of FDD and their enabling technologies.
- Proposal of a CDT framework in the domain of FDD in support of the decision-making process in maintenance. The synergistic employment of human knowledge and the technologies of ontology, algorithms, and database allows for the enabling of the cognitive capabilities of attention, perception, memory, reasoning, and problem-solving, leading towards the implementation of a CDT in maintenance FDD.
- Development of a novel ontology for FDD (FDDO) based on the taxonomy proposed by Franciosi et al. (2022). The formalization and integration of the FMEA and HAZOP dysfunctional analyses concepts and classes allowed the development of a common knowledge base that can be reused for different applications that aim to verify the health status of systems and determine the causes of failure, the modes of failure, and its effects on the process.
- Implementation and assessment of the CDT framework at laboratory scale.

6.1. Limitations and further research

Despite its innovative and pioneering approach in relation to CDT, this work can be improved. As a novel topic, the CDT doesn't present a shared definition. Despite an elaboration and adaptation of the definition of the cognitive capabilities in the maintenance domain of FDD is provided, still, a more generic, shared definition of the CDT in the domain of maintenance is missing. Secondly, the implementation of the CDT framework requires the adoption of a blend of technologies. In this regard, the algorithm responsible for updating the ontology with data from the physical asset does not support continuous real-time synchronization. Instead, it operates in an event-driven manner, where updates are triggered only by relevant changes in the monitored variables. While this approach has proven sufficiently responsive for the specific FDD scenario addressed in this study, future enhancements of the update mechanism could further improve the reactivity of the system, particularly for applications requiring higher-frequency data integration or more dynamic process conditions. Moreover, the instantiation of the ontology at the application level is assessed with one degradation scenario only. Hence, the result of implementing other scenarios can allow improvements in the ontology to make it more flexible in recognizing different anomalies and providing related diagnosis information. Additionally, the performance of the data analytics algorithms (responsible for data acquisition, querying, statistical computation, and ontology integration) was not the central focus of this study and was not evaluated in terms of computational efficiency or scalability. Future work should assess the behavior of these algorithms under large-scale, high-frequency industrial data streams, and identify potential trade-offs between performance, responsiveness, and system complexity.

Building on the results obtained in this study, future developments should focus on validating the CDT framework across additional fault scenarios and applying it to other laboratory and industrial systems. This is essential to assess and enhance the adaptability and robustness of the proposed approach, and to extend its applicability to a broader range of maintenance contexts and operational environments, thus addressing current limitations and advancing toward industrial-scale implementation. Moreover, future work should explore how human feedback gathered from real diagnostic activities can be systematically incorporated to evolve the ontology and improve system performance over time, strengthening the learning capability of the CDT. In this regard, particular attention could be given to hybrid approaches that continue to integrate human reasoning and learning within the ontology, to enhance its adaptability and evolution.

In addition, an extension of the CDT framework could be developed by proposing other combinations of technologies aimed at addressing maintenance applications. Last, further research on the function of the CDT in supporting information flows aimed at optimizing the management of the assets (not limited to maintenance) along their life cycle would be beneficial.

CRediT authorship contribution statement

Sofia Zappa: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Chiara Franciosi:** Writing – review & editing, Visualization, Validation, Software, Methodology, Formal analysis, Conceptualization. **Adalberto Polenghi:** Writing – review & editing, Visualization, Validation, Software, Methodology, Formal analysis, Conceptualization. **Alexandre Voisin:** Writing – review & editing, Visualization, Validation, Supervision, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors report there are no competing interests to declare.

Acknowledgments

This work is supported by the MODAPTO project (MODULAR MANUFACTURING AND DISTRIBUTED CONTROL VIA INTEROPERABLE DIGITAL TWINS) funded by the European Union's Horizon 2022 (grant agreement No 101091996).

Appendix

Annex 1
Mapping of the papers with respect to cognitive capabilities defined by Zheng et al. (2022) with references.

Cognitive capabilities	Definition of the cognitive capabilities by Zheng et al. 2022	Papers	Enabling technologies
Perception	Capability of forming useful representations of data related to the physical twin and its physical environment	All papers	Data analytics, semantic technologies, simulation tools, ML models
Attention	Capability of focusing selectively on a task or a goal or certain sensory information either by intent or driven by environmental signals and circumstances	All papers	Data analytics, ML models, IoT
Memory	Capability of encoding information, storing and maintaining information, and retrieving information	All papers	Database, semantic technologies, cloud
Reasoning	Capability of drawing conclusions consistent with a starting point	[1,10,11,16,18,25,26,29,30,32–35,37–41,44,72–88]	Semantic technologies, ML models, data analytics
Problem-solving	Capability of finding a solution for a given problem or achieving a given goal	[1,10,25,26,32,40,86,88,89]	Data analytics, ML models
Learning	Capability of transforming the experience of the physical twin into reusable knowledge for a new experience	[1,10,16,18,29,30,32,33,35,37–41,44,74,75,77,83,84,86–88]	Data analytics, ML models

Annex 2
Reference definitions of the cognitive capabilities by Zheng et al. (2022) and Eirinakis et al. (2022), and the proposed FDD-specific definitions.

Cognitive capabilities	Definition by Zheng et al. (2022)	Definition by Eirinakis et al. (2022)	Proposed FDD-specific definition
Perception	Capability of forming useful representations of data related to the physical twin and its physical environment	Capability of identify/predict anomalies and events, which can be implemented through data analytics on various data streams.	Capability of forming structured human and machine-readable representations of data related to the physical twin and its physical environment, to allow the identification and prediction of anomalies and events in the system.
Attention	Capability of focusing selectively on a task or a goal or certain sensory information either by intent or driven by environmental signals and circumstances	Capability that focuses on handling the identified/predicted anomalies and events. It is enabled by anomaly detection tools, therefore, tools that emulate the behavior of the asset and hence can identify abnormalities.	Capability of focusing selectively on a task or information either by intent or driven by environmental signals. It allows a prompt and proper reaction to the identification of an anomaly, triggering diagnosis activity involving the appropriate tools.
Memory	Capability of encoding information, storing and maintaining information, and retrieving information	Capability consisting of encoding and retrieving all the appropriate information. Memory enables the evocation of stored past knowledge and experience, and in turn manipulation of the needed information to execute complex cognitive tasks. It can be enabled by production data or domain knowledge (e.g., ontologies) and persistent technologies (e.g., databases).	Capability of encoding information, storing and maintaining information, and retrieving information. It allows the storage of relevant fault diagnosis information for the correct functioning and modelling of the technologies employed in support of the activity and for the performance of offline analysis of the fault.
Reasoning	Capability of drawing conclusions consistent with a starting point	The process by which we derive conclusions that can be enabled by root cause analysis tools and simulation tools.	Capability of deriving knowledge and conclusions (fault diagnosis) about the state of the system and the fault, and its causes.
Problem-solving	Capability of finding a solution for a given problem or achieving a given goal	The overall output upon the completion of a task can become new knowledge and induce learning. DT and Knowledge Graph models can enable this process.	The ability to convert established and new derived knowledge gained by experience and the CDT during the FDD process into reusable insights for future applications.
Learning	Capability of transforming the experience of the physical twin into reusable knowledge for a new experience	Process that requires the mental representation of an initial state of the problem, a goal state, and the possible intervening states (problem space), as well as the strategies for moving through the problem space towards the end goal state. Problem-solving can be enabled by optimization for obtaining optimal responses, and by simulation for evaluating the corresponding activities.	Capability of finding a solution for a given problem or achieving a given goal and acting back on the real system.

Data availability

Data will be made available on request.

References

[1] P. Eirinakis, et al., Cognitive Digital Twins for resilience in production: a conceptual framework, Information 13 (1) (2022), https://doi.org/10.3390/info13010033. Jan.
[2] D.M. Upton, The management of manufacturing flexibility, Calif. Manage. Rev. (1994) 72–89.
[3] C. Semeraro, M. Lezoche, H. Panetto, M. Dassisti, Digital twin paradigm: a systematic literature review, Comput. Ind. 130 (2021), https://doi.org/10.1016/j.compind.2021.103469. Sep.
[4] H. Li, H.C. Pangborn, I. Kovalenko, A system-level energy-efficient Digital Twin framework for runtime control of batch manufacturing processes. IEEE International Conference on Automation Science and Engineering, IEEE Computer Society, 2023, https://doi.org/10.1109/CASE56687.2023.10260642.
[5] F. Tao, B. Xiao, Q. Qi, J. Cheng, P. Ji, Digital twin modeling, Elsevier B.V (2022), https://doi.org/10.1016/j.jmsy.2022.06.015.
[6] E. Negri, L. Fumagalli, M. Macchi, A review of the roles of Digital Twin in CPS-based production systems. Procedia Manufacturing, Elsevier B.V., 2017, pp. 939–948, https://doi.org/10.1016/j.promfg.2017.07.198.

[7] C. Chen, H. Fu, Y. Zheng, F. Tao, Y. Liu, The advance of digital twin for predictive maintenance: the role and function of machine learning, Elsevier B.V (2023), https://doi.org/10.1016/j.jmsy.2023.10.010.
[8] S. Acharya, A.A. Khan, T. Päivärinta, Interoperability levels and challenges of digital twins in cyber–physical systems, Elsevier B.V (2024), https://doi.org/10.1016/j.jii.2024.100714.
[9] F. Tao, J. Cheng, Q. Qi, M. Zhang, H. Zhang, F. Sui, Digital twin-driven product design, manufacturing and service with big data, Int. J. Adv. Manuf. Technol. 94 (9–12) (2018) 3563–3576, https://doi.org/10.1007/s00170-017-0233-1. Feb.
[10] R.D. D'Amico, J.A. Erkoyuncu, S. Addepalli, S. Penver, Cognitive Digital Twin: An Approach to Improve the Maintenance Management, Elsevier Ltd, 2022, https://doi.org/10.1016/j.cirpj.2022.06.004. Aug. 01.
[11] M. Arena, V. Di Pasquale, R. Iannone, S. Miranda, S. Riemma, A maintenance driven scheduling cockpit for integrated production and maintenance operation schedule, Adv. Manuf. 10 (2) (2022) 205–219, https://doi.org/10.1007/s40436-021-00380-z. Jun.
[12] M.A. Navas, C. Sancho, J. Carpio, Disruptive maintenance engineering 4.0, Int. J. Qual. Reliab. Manage. 37 (6–7) (2020) 853–871, https://doi.org/10.1108/IJQRM-09-2019-0304. Nov.
[13] A. Al-Yacoubb et al., "Investigating the impact of Human in-the-loop digital twin in an industrial maintenance context," *SSRN Electronic Journal*, Oct. 2020, doi: 10.2139/ssrn.3717797.
[14] J. Cárcel-Carrasco, J.A. Cárcel-Carrasco, Analysis for the knowledge management application in maintenance engineering: perception from maintenance technicians, Appl. Sci. 11 (2) (2021) 1–16, https://doi.org/10.3390/app11020703. Jan.
[15] F. Psarommatis, G. May, V. Azamfirei, Envisioning maintenance 5.0: insights from a systematic literature review of industry 4.0 and a proposed framework, Elsevier B.V. (2023), https://doi.org/10.1016/j.jmsy.2023.04.009.
[16] C. Avornu, S.D. Akama, E.K. Avornu, V. Aveyom, Data fusion for predictive maintenance of industrial assets using digital twin, in: *International Conference on Electrical Engineering, Computer Science and Informatics (EECSI)*, Institute of Electrical and Electronics Engineers Inc, 2022, pp. 115–121, https://doi.org/10.23919/EECSI56542.2022.9946575.
[17] F. Di Cosmo, A. Polenghi, I. Roda, M. Macchi, Proposal and test of a configurable production system Digital Model to support energy-based asset management. IFAC-PapersOnLine, Elsevier B.V., 2022, pp. 133–138, https://doi.org/10.1016/j.ifacol.2022.09.196. Jul.
[18] B.D. Deebak, F. Al-Turjman, Digital-twin assisted: fault diagnosis using deep transfer learning for machining tool condition, Int. J. Intell. Syst. 37 (12) (2022) 10289–10316, https://doi.org/10.1002/int.22493. Dec.
[19] S. Abburu, A.J. Berre, M. Jacoby, D. Roman, L. Stojanovic, N. Stojanovic, COGNITWIN - hybrid and cognitive digital twins for the process industry, in: Proceedings - 2020 IEEE International Conference on Engineering, Technology and Innovation, ICE/ITMC 2020, 2020, https://doi.org/10.1109/ICE/ITMC49519.2020.9198403.
[20] X. Zheng, J. Lu, D. Kiritsis, The emergence of cognitive digital twin: vision, challenges and opportunities, Int. J. Prod. Res. 60 (24) (2022) 7610–7632, https://doi.org/10.1080/00207543.2021.2014591.
[21] H. ElMaraghy, W. ElMaraghy, Adaptive Cognitive Manufacturing System (ACMS)–a new paradigm, Int. J. Prod. Res. 60 (24) (2022) 7436–7449, https://doi.org/10.1080/00207543.2022.2078248.
[22] D. Tranfield, D. Denyer, and P. Smart, "Towards a methodology for developing evidence-informed management knowledge by means of systematic review," 2003. doi: 10.1111/1467-8551.00375.
[23] A. Polenghi, I. Roda, M. Macchi, A. Pozzetti, Information as a Key Dimension to Develop Industrial Asset Management in Manufacturing, Emerald Group Holdings Ltd., 2022, https://doi.org/10.1108/JQME-09-2020-0095. Jun. 28.
[24] S.R. Newrzella, D.W. Franklin, S. Haider, 5-Dimension cross-industry digital twin applications model and analysis of digital twin classification terms and models, IEEE Access 9 (2021) 131306–131321, https://doi.org/10.1109/ACCESS.2021.3115055.
[25] A. Mohammed, A. Chaimae, B.-A. Hussain, A smart decision making system for the optimization of manufacturing systems maintenance using digital twins and ontologies [Online]. Available, www.ijacsa.thesai.org, 2022.
[26] J. Guo, Z. Yang, C. Chen, W. Luo, W. Hu, Real-time prediction of remaining useful life and preventive maintenance strategy based on digital twin, J. Comput. Inf. Sci. Eng. 21 (3) (2021), https://doi.org/10.1115/1.4049153. Jun.
[27] O. Davies, A. Makkattil, C. Jiang, M. Farsi, A digital twin design for maintenance optimization. Procedia CIRP, Elsevier B.V., 2022, pp. 395–400, https://doi.org/10.1016/j.procir.2022.05.268.
[28] P. Aivaliotis, K. Georgoulias, G. Chryssolouris, The use of Digital Twin for predictive maintenance in manufacturing, Int. J. Comput. Integr. Manuf. 32 (11) (2019) 1067–1080, https://doi.org/10.1080/0951192X.2019.1686173. Nov.
[29] S. Wang, Y. Wang, X. Liu, J. Wang, Z. Wang, Health State assessment of industrial equipment driven by the fusion of digital twin model and intelligent algorithm, Comput. Intell. Neurosci. 2022 (2022), https://doi.org/10.1155/2022/7324121.
[30] N. Dallaora, K. Alamin, E. Fraccaroli, M. Poncino, D. Quaglia, S. Vinco, Digital transformation of a production line: network design, online data collection and energy monitoring, IEEE Trans. Emerg. Top. Comput. 10 (1) (2022) 46–59, https://doi.org/10.1109/TETC.2021.3132432.
[31] F. Abdoune, M. Nouiri, O. Cardin, P. Castagna, An enhanced methodology of fault detection and diagnosis based on Digital Twin. IFAC-PapersOnLine, Elsevier B.V., 2022, pp. 43–48, https://doi.org/10.1016/j.ifacol.2022.09.181. Jul.
[32] I.O. Olalere, O.A. Olanrewaju, Optimising production through intelligent manufacturing, in: *E3S Web of Conferences*, EDP Sciences, 2020, https://doi.org/10.1051/e3sconf/202015203012. Feb.
[33] G. Gao, D. Zhou, H. Tang, X. Hu, An intelligent health diagnosis and maintenance decision-making approach in Smart manufacturing, Reliab. Eng. Syst. Saf. 216 (2021), https://doi.org/10.1016/j.ress.2021.107965. Dec.
[34] S. Cho, G. May, D. Kiritsis, A semantic-driven approach for industry 4.0, in: *Proceedings - 15th Annual International Conference on Distributed Computing in Sensor Systems, DCOSS 2019*, Institute of Electrical and Electronics Engineers Inc, 2019, pp. 347–354, https://doi.org/10.1109/DCOSS.2019.00076. May.
[35] Y. Wang, W. Ren, Y. Li, and C. Zhang, "Complex product manufacturing and operation and maintenance integration based on digital twin," 2021, doi: 10.1007/s00170-021-07350-6/Published.
[36] A.El. Adl, "The cognitive digital twins: vision, architecture framework and categories," 2016.
[37] M. Kaji, J. Parvizian, H.W. van de Venn, Constructing a reliable health indicator for bearings using convolutional autoencoder and continuous wavelet transform, Appl. Sci. 10 (24) (2020) 1–21, https://doi.org/10.3390/app10248948. Dec.
[38] J. Zenisek, J. Wolfartsberger, C. Sievi, M. Affenzeller, Modeling sensor networks for predictive maintenance. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), Springer Verlag, 2019, pp. 184–188, https://doi.org/10.1007/978-3-030-11683-5_20.
[39] A. Barthelmey, E. Lee, R. Hana, J. Deuse, Dynamic digital twin for predictive maintenance in flexible production systems, in: *45th Annual Conference of the IEEE Industrial Electronics Society (IECON2019)*, in IEEE Industrial Electronics Society. 345 E 47TH ST, NEW YORK, NY 10017 USA: IEEE, 2019, pp. 4209–4214.
[40] S. Khan, M. Farnsworth, R. McWilliam, J. Erkoyuncu, On the requirements of Digital Twin-driven autonomous maintenance, Elsevier Ltd (2020), https://doi.org/10.1016/j.arcontrol.2020.08.003.
[41] M. Dhada, M.P. Hernandez, A. Salvador Palau, A.K. Parlikad, Comparison of agent deployment strategies for collaborative prognosis, in: *2021 IEEE International Conference on Prognostics and Health Management, ICPHM 2021*, Institute of Electrical and Electronics Engineers Inc, 2021, https://doi.org/10.1109/ICPHM51084.2021.9486628. Jun.
[42] M. Macchi, et al., Operations-aware novelty detection framework for CNC machine tools: proposal and application, Int. J. Adv. Manuf. Technol. 128 (9–10) (2023) 4491–4512, https://doi.org/10.1007/s00170-023-12158-7. Oct.
[43] P.K.R. Maddikunta, et al., Industry 5.0: a survey on enabling technologies and potential applications, Elsevier B.V. (2022), https://doi.org/10.1016/j.jii.2021.100257.
[44] S.M.R. Naqvi, M. Ghufran, S. Meraghni, C. Varnier, J.M. Nicod, N. Zerhouni, Human knowledge centered maintenance decision support in digital twin environment, J. Manuf. Syst. 65 (2022) 528–537, https://doi.org/10.1016/j.jmsy.2022.10.003. Oct.
[45] J. Yang, et al., A digital twin-assisted intelligent fault diagnosis method for hydraulic systems, J. Ind. Inf. Integr. 42 (2024), https://doi.org/10.1016/j.jii.2024.100725. Nov.
[46] M. Vathoopan, M. Johny, A. Zoitl, A. Knoll, Modular Fault Ascription and Corrective Maintenance Using a Digital Twin, Elsevier, B.V., 2018, pp. 1041–1046, https://doi.org/10.1016/j.ifacol.2018.08.470. Jan.
[47] G. Medina-Oliva, A. Voisin, M. Monnin, J.B. Leger, Predictive diagnosis based on a fleet-wide ontology approach, Knowl. Based. Syst. 68 (2014) 40–57, https://doi.org/10.1016/j.knosys.2013.12.020.
[48] M. Jasiulewicz-Kaczmarek, S. Legutko, P. Kluk, Maintenance 4.0 technologies - new opportunities for sustainability driven maintenance, Manage. Product. Eng. Rev. 11 (2) (2020) 74–87, https://doi.org/10.24425/mper.2020.133730. Jun.
[49] F. Ameri, D. Sormaz, F. Psarommatis, D. Kiritsis, Industrial ontologies for interoperability in agile and resilient manufacturing, Int. J. Prod. Res. 60 (2) (2022) 420–441, https://doi.org/10.1080/00207543.2021.1987553.
[50] H. Kościelniak, A. Puto, Big data in decision making processes of enterprises. Procedia Computer Science, Elsevier, 2015, pp. 1052–1058, https://doi.org/10.1016/j.procs.2015.09.053.
[51] J. Bhogal, I. Choksi, Handling big data using NoSQL, in: *Proceedings - IEEE 29th International Conference on Advanced Information Networking and Applications Workshops, WAINA 2015*, Institute of Electrical and Electronics Engineers Inc, 2015, pp. 393–398, https://doi.org/10.1109/WAINA.2015.19. Apr.
[52] Q. Qi, F. Tao, Digital Twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison, IEEE Access 6 (2018) 3585–3593, https://doi.org/10.1109/ACCESS.2018.2793265. Jan.
[53] P. Eirinakis, et al., Enhancing cognition for Digital Twins, in: Proceedings - 2020 IEEE International Conference on Engineering, Technology and Innovation, ICE/ITMC 2020, 2020, https://doi.org/10.1109/ICE/ITMC49519.2020.9198492.
[54] E. Curry, S. Auer, A.J. Berre, A. Metzger, M.S. Perez, and S. Zillner, "Technologies and applications for big data value," 2022.
[55] B. Liu, Z. Ding, J. Wu, L. Yao, Ontology-based fault diagnosis: a decade in review, in: *ACM International Conference Proceeding Series*, Association for Computing Machinery, 2019, pp. 112–116, https://doi.org/10.1145/3307363.3307381. Jan.
[56] C. Franciosi, A. Polenghi, M. Lezoche, A. Voisin, I. Roda, and M. Macchi, "Semantic interoperability in industrial maintenance-related applications: multiple ontologies integration towards a unified BFO-compliant taxonomy," 2022. Accessed: Mar. 26, 2024. [Online]. Available: https://doi.org/10.5220/0011560800003329.
[57] A. Polenghi, I. Roda, M. Macchi, A. Pozzetti, H. Panetto, Knowledge reuse for ontology modelling in maintenance and industrial asset management, J. Ind. Inf. Integr. 27 (2022), https://doi.org/10.1016/j.jii.2021.100298. May.
[58] "ISO 21838," 2021.
[59] G. Savić, M. Segedinac, Z. Konjović, M. Vidaković, R. Dutina, Towards a domain-neutral platform for sustainable Digital Twin development, Sustainability 15 (18) (2023), https://doi.org/10.3390/su151813612. Sep.

[60] C. Franciosi, Y. Eslami, M. Lezoche, A. Voisin, Ontologies for prognostics and health management of production systems: overview and research challenges, J. Intell. Manuf. 36 (4) (2025) 2223–2253, https://doi.org/10.1007/s10845-024-02347-w. Apr.
[61] International Electrotecnical Commission, “IEC 60812:2018,” 2018.
[62] International Organization for Standardization, “ISO 14226:2006,” 2006.
[63] International Electrotecnical Commission, “IEC 60300-3-11:2009,” 2009.
[64] M.H. Karray, F. Ameri, M. Hodkiewicz, T. Louge, ROMAIN: towards a BFO compliant reference ontology for industrial maintenance, Appl. Ontol. 14 (2) (2019) 155–177, https://doi.org/10.3233/AO-190208.
[65] J.J. Montero Jiménez, R. Vingerhoeds, B. Grabot, S. Schwartz, An ontology model for maintenance strategy selection and assessment, J. Intell. Manuf. 34 (3) (2021) 1369–1387, https://doi.org/10.1007/s10845-021-01855-3. Mar.
[66] Industrial Ontologies, “Industrial ontologies foundry,” www.industrialontologies.org.
[67] M. Giardina, M. Morale, Safety study of an LNG regasification plant using an FMECA and HAZOP integrated methodology, J. Loss. Prev. Process. Ind. 35 (2015) 35–45, https://doi.org/10.1016/j.jlp.2015.03.013. May.
[68] X. Chen, S. Jia, Y. Xiang, A Review: Knowledge Reasoning Over Knowledge Graph, Elsevier Ltd., 2020, https://doi.org/10.1016/j.eswa.2019.112948. Mar. 01.
[69] Y. Qamsane, et al., A methodology to develop and implement digital Twin solutions for manufacturing systems, IEEE Access 9 (2021) 44247–44265, https://doi.org/10.1109/ACCESS.2021.3065971.
[70] D. Adamenko, S. Kunnen, R. Pluhnau, A. Loibl, A. Nagarajah, Review and comparison of the methods of designing the Digital Twin. Procedia CIRP, Elsevier B.V., 2020, pp. 27–32, https://doi.org/10.1016/j.procir.2020.02.146.
[71] F. Psarommatis, G. May, A Literature Review and Design Methodology for Digital Twins in the Era of Zero Defect Manufacturing, Taylor and Francis Ltd, 2023, https://doi.org/10.1080/00207543.2022.2101960.
[72] A. Werner, N. Zimmermann, J. Lentes, Approach for a holistic predictive maintenance strategy by incorporating a Digital Twin. Procedia Manufacturing, Elsevier B.V., 2019, pp. 1743–1751, https://doi.org/10.1016/j.promfg.2020.01.265.
[73] D. Kibira, G. Shao, B.A. Weiss, Buiding a digital twin for robot Workcell prognostics and health management, in: *Proceedings - Winter Simulation Conference*, Institute of Electrical and Electronics Engineers Inc, 2021, https://doi.org/10.1109/WSC52266.2021.9715501.
[74] M.A. Bermeo-Ayerbe, C. Ocampo-Martinez, J. Diaz-Rozo, Data-driven energy prediction modeling for both energy efficiency and maintenance in smart manufacturing systems, Energy 238 (2022), https://doi.org/10.1016/j.energy.2021.121691. Jan.
[75] W. Booyse, D.N. Wilke, S. Heyns, Deep digital twins for detection, diagnostics and prognostics, Mech. Syst. Signal. Process. 140 (2020), https://doi.org/10.1016/j.ymssp.2019.106612. Jun.
[76] L. Li, C. Mao, H. Sun, Y. Yuan, B. Lei, Digital Twin driven green performance evaluation methodology of intelligent manufacturing: hybrid model based on fuzzy rough-sets AHP, multistage weight synthesis, and PROMETHEE II, Complexity 2020 (2020), https://doi.org/10.1155/2020/3853925.
[77] A. Mubarak, M. Asmelash, A. Azhari, T. Alemu, F. Mulubrhan, K. Saptaji, Digital Twin enabled industry 4.0 predictive maintenance under reliability-centred strategy, in: *2022 1st International Conference on Electrical, Electronics, Information and Communication Technologies, ICEEICT 2022*, Institute of Electrical and Electronics Engineers Inc, 2022, https://doi.org/10.1109/ICEEICT53079.2022.9768590.
[78] Q. Qiao, J. Wang, L. Ye, R.X. Gao, Digital twin for machining tool condition prediction. Procedia CIRP, Elsevier B.V., 2019, pp. 1388–1393, https://doi.org/10.1016/j.procir.2019.04.049.
[79] I. Rojek, D. Mikołajewski, E. Dostatni, Digital twins in product lifecycle for sustainability in manufacturing and maintenance, Appl. Sci. 11 (1) (2021) 1–19, https://doi.org/10.3390/app11010031. Jan.
[80] I.T. Christou, N. Kefalakis, J.K. Soldatos, A.M. Despotopoulou, End-to-end industrial IoT platform for Quality 4.0 applications, Comput. Ind. 137 (2022), https://doi.org/10.1016/j.compind.2021.103591. May.
[81] P. Aivaliotis, K. Georgoulias, Z. Arkouli, S. Makris, Methodology for enabling digital twin using advanced physics-based modelling in predictive maintenance. Procedia CIRP, Elsevier B.V., 2019, pp. 417–422, https://doi.org/10.1016/j.procir.2019.03.072.
[82] Y. Qamsane, J.R. Phillips, C. Savaglio, D. Warner, S.C. James, K. Barton, Open process automation- and digital twin-based performance monitoring of a process manufacturing system, IEEE Access 10 (2022) 60823–60835, https://doi.org/10.1109/ACCESS.2022.3179982.
[83] S. Mi, Y. Feng, H. Zheng, Y. Wang, Y. Gao, J. Tan, Prediction maintenance integrated decision-making approach supported by digital twin-driven cooperative awareness and interconnection framework, J. Manuf. Syst. 58 (2021) 329–345, https://doi.org/10.1016/j.jmsy.2020.08.001. Jan.
[84] Bruno. Castanier, Marko. Čepin, David. Bigaud, Christophe. Bérenguer, in: Proceedings of the 31st European Safety and Reliability Conference (ESREL 2021) : 19 - 23 September, Research Publishing (S), Angers, France, 2021, p. 2021.
[85] IEEE Technology Engineering and Management Society., Institute of Electrical and Electronics Engineers, in: Proceedings, 2019 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC) : Sophia Antipolis Innovation Park, France, 17-19 June, 2019.
[86] IEEE Technology Engineering, Management Society., Institute of Electrical and Electronics Engineers, in: Proceedings, 2020 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC) : virtual conference, 15 -17 June, 2020.
[87] P. IEEE Industrial Electronics Society, Conference (45th : 2019 : Lisbon, Universidade Nova de Lisboa, Institute of Electrical and Electronics Engineers, and IEEE Industrial Electronics Society, in: Proceedings, IECON 2019-45th Annual Conference of the IEEE Industrial Electronics Society : Convention Center, Lisbon, Portugal, 14-17 October, 2019.
[88] Á. Bányai, T. Bányai, Real-time maintenance policy optimization in manufacturing systems: an energy efficiency and emission-based approach, Sustainability 14 (17) (2022), https://doi.org/10.3390/su141710725. Sep.
[89] Á. Bányai, Energy consumption-based maintenance policy optimization, Energies 14 (18) (2021), https://doi.org/10.3390/en14185674. Sep.