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Research article

Digital Twin Learning Ecosystem: A cyber–physical framework to integrate human-machine knowledge in traditional manufacturing

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ABSTRACT

As Industry 4.0 enablers, digital twins of manufacturing systems have led to multiple interaction levels among processes, systems, and workers across the factory. However, open issues still exist when addressing cyber–physical convergence in traditional manufacturing small and medium-sized enterprises. The problem for both traditional operators and the existing infrastructure is how to adapt knowledge to the increasing business needs of manufacturing plants that demand high efficiency, while reducing production costs. In this paper, a framework that implements the novel concept of Digital Twin Learning Ecosystem in traditional manufacturing is presented. The objective is to facilitate the integration of human-machine knowledge in different industrial cyber–physical contexts and eliminate existing technological and workforce barriers. This adaptive approach is particularly important in meeting the requirements to help small and medium-sized enterprises build their own interconnected Digital Twin Learning Ecosystem. The contribution of this work lies in a single digital twin learning framework for different traditional manufacturing scenarios that can work from scratch using a light infrastructure, reusing the knowledge and common condition-based methods well-known by skilled workers to rapidly and flexibly integrate existing legacy resources in a non-intrusive manner. The solution was tested using real data from a milling machine and a currently operating induction furnace with a maximum power of 12 MW in a foundry plant. In both cases, the proposed solution proved its benefits: first, by providing augmented methods for maintenance operations on the milling machine and second, by improving the power efficiency of the induction furnace by approximately 9 percent.

1. Introduction

The emergence of connected platforms has provided manufacturing with a learning ecosystem oriented towards exploiting knowledge from the integration of physical and digital worlds. Digital twins, as Industry 4.0 enablers, represent an abstraction of the reality of manufacturing systems, allowing for multiple integration levels between processes, systems, and workers within the virtual space [1]. Essentially, the potential of this cyber–physical convergence [2] has closed the loop between systems and workers' interactions [3], while manufacturing processes have taken advantage of a digital twin representation of heterogeneous assets in real-time. As digital twin technology advances, it is expected to become a decision-making solution to provide manufacturing workers with a deeper understanding and skills development [4].

However, open issues still exist in the literature regarding digital twin learning approaches in manufacturing environments. For example, the lack of crossed knowledge from academia and real factories towards the empowerment of workforce skills and

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competences [5], limited data availability for control and scheduling in participatory-adaptive ways [6], and the necessity of constructing flexible solutions standardized for cyber–physical convergence [1]. Despite the advent of Industry 4.0, which provided Small and Medium-sized Enterprises (SMEs) with a new digital transformation movement linking machines and humans [7], it is not clear in the industry what features a digital twin should have or how it should work in different human-machine ecosystems. Factories should first learn how to overcome connectivity barriers and apply current-enabling technologies for digital twins [8]. This is the case in traditional manufacturing environments, which are still common among SMEs. They still lack technological approaches regarding the digitization of operators and legacy systems that are not yet aligned with Industry 4.0 [9]. In addition, it should be noted that there is a lack of Industry 4.0-trained experts to conduct fieldwork in human-machine collaboration frameworks [10]. Human knowledge is still indispensable for maintaining and improving the manufacturing systems, while the causes of the problems that may occur are identified and solved to prevent them in the future. Consequently, programs to develop specific lifelong learning scenarios for reskilling and upskilling the workforce are insufficient, particularly those associated with operating traditional manufacturing processes.

One way SMEs can overcome legacy barriers is to update workers and old industrial systems simultaneously with human–machine digital twin strategies and proactive management environments. This actually lays the foundation for human-machine collaborative methodologies in SMEs, as demonstrated in [11]. Concerning challenges for the integration of workers and digital twins in the industry, the recent definition of Digital Twin Learning Ecosystem [12] provides augmented cyber–physical means to achieve bidirectional interaction, understanding, and learning between processes, systems, and workers. This approach can support human-machine learning ecosystems, however the process of modeling reality in a digital twin is a complex task, particularly when using traditional approaches involving sensors and different types of sources, models, and services. Based on the recent literature [8,13–17] two research gaps in cyber–physical human-machine integration when applied to traditional manufacturing processes in SMEs have been identified. First, there is a crucial need for seamless integration and cooperation between humans and connected machines towards Human-Cyber–Physical Systems [18]. New technologies can help reduce production costs efficiently, dynamically, and intelligently. However, there are many common scenarios in which the manufacturing systems are equipped with old machinery. Under this legacy approach, application-based services for controlling production, such as monitoring, are limited without a bidirectional connection to interchange information between a digital twin and its physical counterpart [6]. One method to mitigate this is retrofitting legacy machines, ensuring that data are not wasted and that old machines can have some form of analytics [8]. In this way, digital twins can enable the transfer of learning to generate knowledge of manufacturing systems [19]. Second, human factors and workers' skills should be considered to understand existing complex manufacturing systems. A comprehensive framework is required to facilitate full-stack solutions by incorporating expert knowledge [14]. Therefore, both technological and training issues are inherent in providing workers of SMEs with resources and skills for more appropriate and effective knowledge of human-machine interactions. Specifically, when SMEs seem to struggle to adapt and implement modern technologies [20]. Despite this, digital twins provide workers of SMEs with a cyber–physical-assisted interface to simulate and test real-world operations [21]. Following this idea, a comprehensive digital representation on a factory-wide level arises in the context of adaptive digital twin frameworks [22], which are capable of making decisions based on information about their environment or situation [14]. Therefore, the existing challenges for workers, such as lifelong learning, may be addressed by digital twin advancements in learning capabilities, skills, and expertise that workers do not yet possess [23]. In summary, the future and effective interoperability of digital twins faces the challenges of building and supporting new technical and digital infrastructure, while workers' skill development eventually manages to handle digital change. Consequently, significant research effort is required to combine digital twins, systems and workers in traditional manufacturing processes.

The present paper contributes to the understanding of how the novel concept of Digital Twin Learning Ecosystem facilitates the integration of human-machine knowledge in different contexts of traditional manufacturing SMEs. This is achieved by providing a learning framework based on three non-intrusive interconnected digital twin layers, in which a demonstration of the retrofitted cyber–physical convergence of legacy production systems and skilled workers is adaptively managed in different organizations with a minimal set of changes. The integration process was carried out in two different SME case studies to examine the convergence of existing physical and human resources for knowledge-generation. For this purpose, this paper extends previous work on the adoption of digital twins in industry, in which the authors have already presented practical applications for building connected human-machine learning frameworks in traditional manufacturing [11] and a literature review concerning specific human and technological challenges [12], such as cyber–physical convergence and digital skills development. Consequently, this work aims to provide new insights adapted to different traditional manufacturing scenarios for the successful integration of skilled workers and legacy systems. This approach is particularly important for meeting the requirements to help SMEs build their own interconnected digital twin learning infrastructure at different traditional manufacturing levels. Therefore, real data from a Nicolas Correa CF20 milling machine and a currently operating medium-frequency induction furnace with a maximum power of 12 MW in a foundry plant were used to test the solution. In both cases, the proposed solution proved its benefits: first, by providing augmented methods for maintenance operations on the milling machine and second, by improving the power efficiency of the induction furnace by approximately 9 percent.

The remainder of this paper is organized as follows. Section 2 explores related work on knowledge-based improvements and learning opportunities offered by digital twins in manufacturing. Section 3 describes the developed Digital Twin Learning Ecosystem framework and knowledge generation in traditional manufacturing. Section 4 presents two real case studies on manufacturing SMEs to facilitate the integration of human-machine knowledge. These include improvements in the maintenance operations and traditional manufacturing processes. Section 5 discusses the results of the proposal. Finally, Section 6 presents the conclusions derived from this work.

2. Literature background

The concept of digital twin has emerged as one of the most disruptive innovations for exploiting data-enabling industrial technologies [2]. Simultaneously, digital twins have been improved in manufacturing using different approaches and definitions [24] and refined for learning, optimization, and control [25]. However, traditional manufacturing is in the midst of the cyber–physical convergence towards Industry 4.0 [6]. This section reviews previous studies on digital twin learning applications. The aim is to understand the existing barriers and enablers to providing traditional manufacturing with an additional layer of knowledge, specifically for maintenance strategies and process monitoring. In addition, different Digital Twin Learning Ecosystems and current challenges in SMEs are studied to determine how traditional manufacturing systems must deal with the integration between humans and heterogeneous machines.

2.1. Digital twins for knowledge-based improvement

Digital twins provide an intelligent data approach capable of managing previously acquired information over their lifecycle, such as fault prediction [19]. Tao et al. [26] pointed out that the ability to offer seamless integration between cyber and physical spaces enables their implementation to improve the performance of products and processes in the physical space. Moreover, this work also defined a digital twin as *"a digital representation that can depict the production process and product performance"* and summarized the state-of-the-art of digital twin research and its application as a reference guide in different industries such as aerospace engineering, electric grid, car manufacturing, petroleum industry, and healthcare.

Owing to the cyber–physical connection process, digital twins have attracted the interest of industries regarding maintenance strategies. Specifically, the manufacturing industry is the sector in which most research on the implementation of digital twins is focused [27]. Concerning digital twin use in manufacturing, Madni et al. [28] considered maintenance to be a major contribution area for digital twins, both helping organizations transition from schedule-based to condition-based maintenance and reducing system maintenance costs, while also enhancing its availability. In a different study, Fuller et al. [8] identified a range of publications with particular growth in the health of machines and predictive maintenance from small to large scale plants and industrial processes, which are tangible with the development of digital twins. In addition, Kritzinger et al. [29] provided a categorical literature review of digital twins in manufacturing. The review, which is broader in scope, described maintenance as a main discipline of production systems with the common target of increasing competitiveness, productivity, and efficiency, supported by four applications of the digital twin: (i) state changes in production systems, (ii) anticipatory maintenance measures, (iii) condition based maintenance, and (iv) the machine's health condition.

Several authors have presented papers concerning the applicability of maintenance strategies based on digital twins and their associated learning models. For instance, Madni et al. [28] presented an overall vision and rationale for incorporating digital twin technology into model-based system engineering (MBSE), including updated performance, maintenance, and health status data throughout the life cycle of physical systems. Cai et al. [30] presented the integration of manufacturing data into developing "digital-twins" virtual machine tools for the health status of a milling machine. Aivaliotis et al. [31] presented a methodology for advanced physics-based modeling to enable the digital twin concept in predictive maintenance applications. Mi et al. [32] proposed a digital twin-driven cooperative awareness and interconnection framework to improve the accuracy of fault diagnosis, prediction, and support, thereby creating a maintenance plan with higher accuracy and reliability. Huang et al. [33] proposed a digital twin-driven online anomaly detection framework for an automation system based on edge intelligence for the early detection of potential failures of industrial systems and proactive maintenance schedule management. Xu et al. [34] presented a two-phase digital-twin-assisted fault diagnosis method and framework to achieve smart manufacturing using deep transfer learning, which realizes fault diagnosis in both development and maintenance phases. In another study based on deep learning, Booyse et al. [35] presented a Deep Digital Twin (DDT) for prognostics and health monitoring (PHM), which was used for the automation of predictive maintenance scheduling directly from operational data.

2.2. Digital twin learning ecosystems and current challenges in manufacturing SMEs

Industry 4.0 presents opportunities for enabling Digital Twin Learning Ecosystems in academic and industrial scenarios. The development of next-generation Information Technologies has provided manufacturing with digital twin-based approaches that can be applied to cyber–physical convergence [2]. However, industry faces the challenges of building and supporting new digital infrastructures and skills, while academia faces the challenges of providing technological research programs and experts to prepare a new generation workforce equipped with interdisciplinary skills [22].

In the manufacturing context, the convergence of digital twins with diverse technologies in learning ecosystems has been studied over the last years. Fuller et al. [8] presented the status, applications, and enabling technologies for Artificial Intelligence (AI), Internet of Things (IoT) and digital twins to improve manufacturing processes. The study evidences that digital twin runs in parallel with AI and IoT technology to gain knowledge in manufacturing. Furthermore, in a different work, Lu et al. [36] reviewed the development and advancement of digital twin-driven smart manufacturing with other technologies, such as industrial communications and protocols, simulation, cyber–physical systems, IoT, and Big Data. It presents the rapid growth and challenges of integrating Information Technologies and Operation Technologies in the industry, where digital twin-driven applications for social manufacturing and sustainability are called to change the fundamentals of manufacturing systems and operations. Consequently, the use of different technologies in digital twin learning ecosystems enables smart decisions to be made at every point in manufacturing operations. For example: (i) digital twins and modular artificial intelligence algorithms to dynamically reconfigure manufacturing systems [37], (ii) digital twins assisted by augmented reality for futuristic human-centric industry transformation [38], (iii) a digital twin of the manufacturing process with an immersive virtual reality interface for multi-robot manufacturing cell commissioning [39], or (iv) a digital twin-based cyber–physical production system for autonomous manufacturing in smart shop floors [40].

As a future trend in the industry, production factories will be presented with multiple digital twins representing their complete production system [41]. In this way, different manufacturing phases can be addressed using digital twins. Virtual factory replication and the Learning Factory concept [42] allow the implementation of complex scenarios and frameworks for testing and training in a diversity of collaborative levels as digital twin learning ecosystem enablers. Focusing on new learning approaches in manufacturing, Raza et al. [43] presented the Festo Cyber–Physical Factory (CPF), which collects IoT data and replicates the processes of the CPF real production line for product assembly at different stages of the product's lifecycle. This system, coupled with the proposed digital twin framework, interlinks cyber–physical data that are used to enable predictive maintenance, operational information for design and performance improvements, and contributes to workers' lifelong learning. With regard to the manufacturing systems configuration and validation, using learning data during the design phase can enable a digital twin-based cyber–physical commissioning approach. Therefore, there is an opportunity to enhance the early development phase and ensure correct decision-making guidance [44]. For example, Qamsane et al. [45] presented a digital twin framework to improve control reconfiguration, self-organizing and learning in a manufacturing flow-shop. In another phase, the digital twin learning ecosystem can improve the cyber–physical interaction of manufacturing systems for the intelligent organization of resources. In this context, Leng et al. [46] proposed a digital twin-driven manufacturing cyber–physical system (MCPS) framework that discusses how the digital twin applies in optimizing system behavior in a demonstrative implementation of the digital twin-driven parallel controlling of board-type product smart manufacturing workshop.

By promoting the digital twin areas of research already under way, new approaches for transforming existing production and control methods may emerge towards intelligent cyber–digital interfaces and smart decision support models. This is the case of the interaction between skilled workers and the production environment, allowing digital twins to offer a context-aware approach for supporting decision making and learning [14]. A standardized framework to develop a digital twin in manufacturing, such as ISO 23 247, which partitions a digital twin system into layers, can facilitate the acceptance of the digital twin concept [47]. However, Shao and Helu [48] remarked that there remains much confusion about digital twins and how different solutions can be implemented in real manufacturing systems, especially among SMEs. Digital twins depend on the context and viewpoint required for a specific use case and require a good understanding of the scope and constraints of the use case to avoid enormous costs. Recent experiments made in EU funded projects address digital technologies for learning in industry. For example, the FACTLOG project [49] develops a real-time processing layer combined with digital twins, where observations, knowledge and experience interoperate to understand the control behavior of a complex system to accomplish the cognitive factory for process industries. In a different approach, the RETROFEED project [50] develops a Decision Support System for aluminum melting furnaces through the retrofitting of core equipment and the implementation of an advanced monitoring and control system based on machine learning and digital twin.

Existing related works of Digital Twin Learning Ecosystems based on frameworks have been identified in the literature, as shown in Table 1. Some frameworks provide digital twin learning features for manufacturing at conceptual, proof-of-concept or laboratory level. David et al. [51] proposed a digital twin framework of a flexible manufacturing system for production engineering courses at the university level. Caldarola et al. [52] implemented the concept of Teaching Factory using knowledge-based systems and a framework for social manufacturing. Malik and Bilberg [53] presented a framework to support computer simulations to develop a experimental setup of a human–robot collaborative work environment for assembly work. Yildiz et al. [54] presented a digital twin-based Virtual Factory in a proof-of-concept in a wind turbine manufacturing plant, which is integrated with multi-user virtual reality simulation for learning/training in a close collaboration with shop floor workers and engineers. Friederich et al. [56] proposed a conceptual data-driven framework in laboratory for automated generation of simulation models as basis for digital twins for smart factories. Liu et al. [57] proposed a digital thread-driven distributed collaboration mechanism between digital twin manufacturing units at experimental level. This environment was verified in a manufacturing workshop to manage the product quality information during the manufacturing process. On the other hand, considering a practical approach, frameworks exist that provide digital twin learning features and real-world verification. Qamsane et al. [45] proposed a novel digital twin learning framework for the real-time monitoring of large-scale smart manufacturing systems to improve control reconfiguration, self-organizing. This framework, evaluated in a manufacturing flow-shop, enables flexible control of smart manufacturing systems using unified and standardized protocols such as OPC-UA and interfaces for communications with the Manufacturing Execution System (MES) and the Enterprise Resource Planning (ERP). Kong et al. [55] showed a data-driven digital twin framework that uses a non-intrusive add-on method via low cost edge computing devices (Raspberry Pi, Arduino and Nvidia Jetson) to tune physical assets as IoT-enabled for monitoring through the Internet. It offers emulation and human-asset interaction with operational decision support accross multiple open devices in several use cases (embedded system, integrated Frequency Modulated and UR5-based collaborative-robot system) for better understanding of remaining useful life of assets. Kumbhar et al. [58] developed a digital twin framework to track and diagnose for decision-making in a complex manufacturing system in real-time. The framework was automated using open-source software in a fully-automated manufacturing facility for assembled bearings. Mo et al. [37] constructed a simulation environment combining digital twins and modular artificial intelligence algorithms to dynamically reconfigure manufacturing systems. The framework was validated in a real use case, resulting in a process time improvement of approximately 10%.

It is observed that most processes still depend on human intervention and expert knowledge [3], and digital twins data are highly dependent on the specific goals of the system in place [59]. In particular, in the case of SMEs, despite the development of Industry 4.0-enabling technologies, digital twins face a lack of digital resources concerning data acquisition [60], while workers' skill

Table 1
Examples of digital twin learning ecosystems in manufacturing based on frameworks.

Approach	Features	Domain	Application	Reference
Reconfiguration framework for manufacturing systems based on digital twins and AI.	Dynamical reconfiguration	Optimization	Simulation	[37]
Framework for real-time monitoring and evaluation of smart manufacturing systems.	Self-organizing and learning	Monitoring	Flow-shop	[45]
Pedagogical digital twin framework to educate students on manufacturing systems.	Learning experiences	Pedagogical learning	Laboratory test	[51]
Conceptual framework for social manufacturing.	Quality of life	Social sustainability	Conceptual	[52]
Framework to support the design, building and collaborative environment for assembly.	Human-machine cooperation	Production setting	Simulation	[53]
Framework architecture for supporting factory life-cycle processes.	Workers' training	Collaborative learning	Virtual factory	[54]
Interactive data-driven digital twin framework for asset management.	Human-asset interaction	Asset management	Decision support	[55]
Digital twin research framework for data-driven simulation modeling in assembly line.	Automated generation	Simulation models	Conceptual	[56]
Framework for distributed collaboration between digital twin manufacturing units.	Thread-driven models	Quality control	Workshop model	[57]
Digital twin based framework for improvement of complex manufacturing systems.	Detection and diagnosis	Sustainability	Assembly	[58]

development eventually includes the increased complexity of industrial processes [61]. It should be noted that SMEs are generally less prepared to adopt digital technologies [62] and maturity models [63]. Although collaborative human-machine models [64] and maintenance trends have evolved collaboratively [65], only a few SMEs have the capacity to implement the latest advances in maintenance strategies [66].

Focusing on digital twins convergence, some studies have presented solutions to augment legacy-based production equipment without incurring expensive resources. For instance, Orellana and Torres [67] proposed a retrofitted method using monitored sensors within cyber–physical systems to upgrade legacy production systems while reducing costs. Similarly, Lins and Oliveira [68] focused on reusing existing equipment with the addition of new technologies installed independently of the system, upgrading to cyber–physical production systems as a rapid and low-cost solution. Pantelidakis et al. [69] considered a cost-efficient digital twin ecosystem used to provide legacy equipment with digital twin capabilities, collect historical data, generate analytics, and establish an ecosystem with bidirectional information flow in a simulated virtual environment. In particular, the authors presented in [11] a framework and architecture for retrofitting traditional manufacturing systems with digitized scenarios in a non-intrusive manner. This paper integrated a modular multitier cyber–physical convergence approach with diverse heterogeneous systems. The implemented solution focuses on a rapid and flexible human–machine collaborative environment to interact with and visualize the health condition of legacy systems. The resulting knowledge models provide bidirectional information in an augmented visualization layer. However, this convergence can be improved by following adaptive development according to productive and specific manufacturing requirements, thereby generating an adaptive learning framework that seamlessly integrates workers, systems, and processes into knowledge modeling. To the best of our knowledge, there is no adaptive framework and architecture approach standardized for traditional manufacturing SMEs that can integrate both heterogeneous legacy production systems and skilled workers into a Digital Twin Learning Ecosystem in real production conditions. Therefore, this work aims to provide an adaptive and bidirectional human-machine framework that demonstrates its applicability from scratch and capacity of replication in traditional manufacturing processes.

3. Developed framework and knowledge generation in traditional manufacturing

This work addresses the rising demand for the integration of human-machine knowledge in traditional manufacturing SMEs [70, 71]. Currently, the problem for both traditional operators and legacy infrastructure is how to adapt expert knowledge to the increasing business needs of manufacturing plants that demand high efficiency in industrial production while reducing production costs [13]. In this case, Industry 4.0 transformation is facing a lack of skilled personnel and a low adoption rate of digital technologies

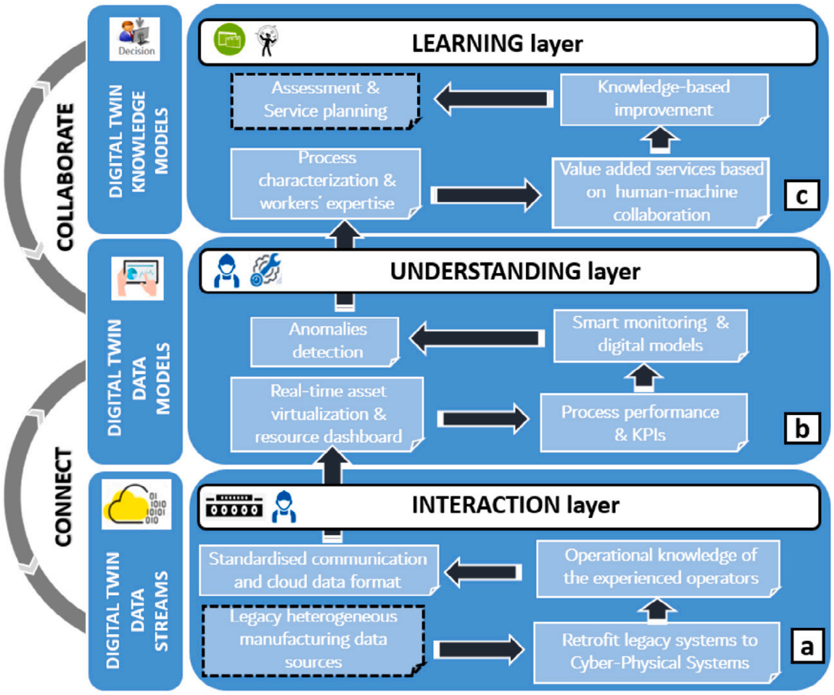

Fig. 1. Overview of the concept of Digital Twin Learning Ecosystem proposed in traditional manufacturing and its three conceptual layers.

and maturity models [20]. Therefore, current challenges in a changing manufacturing industry have led to the need to develop adaptive cyber–physical frameworks that combine expert knowledge and legacy systems to overcome the lack of connected data infrastructure [72].

In this paper, a framework that implements the novel concept of Digital Twin Learning Ecosystem in traditional manufacturing is presented. Overall, this concept poses common requirements to facilitate a real and effective integration of human-machine knowledge in currently operating traditional manufacturing SMEs [12]. According to its definition, the Digital Twin Learning Ecosystem consists of three conceptual layers: *Digital Twin Data Streams*, *Digital Twin Data Models* and *Digital Twin Knowledge Models*, which are depicted in Fig. 1. The behavior of each layer is determined by a hardware and software stack implemented in a three-tier model architecture. Consequently, the methodology used in this paper is based on an adaptive application under the production conditions of these three interconnected bidirectional layers.

It must be noted that there exist diverse frameworks, as presented in Section 2.2, that apply the digital twin concept to manufacturing systems for learning. In such cases, there are challenges pending to facilitate the integration of human-machine knowledge: (i) to enhance the workforce skills and competencies in manufacturing, (ii) to manage adaptability under different tasks in manufacturing systems, (iii) to understand processes and data science, and (iv) to extract the corresponding simulation models using expert knowledge. In comparison with the studied digital twin frameworks, the proposed Digital Twin Learning Ecosystem provides the following unique features:

- It works from scratch in traditional manufacturing for workers and machines simultaneously, regardless of maturity and level of digitization.
- It contributes to an adaptive and non-intrusive bidirectional cyber–physical approach in response to the requirements of very different retrofitted traditional scenarios, always under production conditions.
- It offers new models of collaboration between the workforce and industrial processes that include enablers required for future human-technology integration in manufacturing [13].
- It provides the creation of standardized communication paths and service infrastructure according to human-machine interactions to manage and generate industrial knowledge in SMEs [7].
- It generates a human-machine digital twin learning framework using a light infrastructure that seamlessly integrates existing resources via knowledge modeling, which is supported by workers' expertise.
- It reuses the knowledge that highly skilled operators usually have and contributes to workers' lifelong learning and training in traditional manufacturing.

In this way, traditional manufacturing SMEs that are increasingly dependent on highly skilled workers and digital changes to improve their working methods can take advantage of bidirectional knowledge [73]. Regarding architecture, the framework provides customizable services that are valid for different traditional SMEs, as described below. These include: (i) IIoT hardware and software, (ii) industrial protocols and sensors, (iii) human-machine interfaces, (iv) edge and cloud software stacks, and (v) analytic software and dashboards, intended to rapidly and flexibly integrate the resources already existing in a non-intrusive manner. In summary, this contribution lies in a common digital twin framework architecture and knowledge modeling process that can be implemented in diverse organizations with a minimal set of changes.

3.1. Digital twin data streams

The *Digital Twin Data Streams* conceptual layer, also referred to as the *Interaction* layer, manages the physical interaction between skilled workers and legacy industrial systems [67]. It provides the digital twin framework with real-time information from systems and workers via heterogeneous manufacturing multiple data sources, as depicted in Fig. 1a. Currently, in traditional environments, the interconnection of the manufacturing process must be considered, reflecting the specific legacy systems, applications, or data sources needed to define the most straightforward solution. In this context, a step-by-step digital upgrade is proposed to address a non-intrusive retrofit approach supported by standardized hardware, communications and software tools. Simultaneously, meetings with key human resources involved in the manufacturing process are conducted to gain first-hand knowledge of the work cycles and procedures involved in the operation of the systems. These workers are also provided with human–machine interface devices to include further information that may be relevant to the process [14]. Following a digital paradigm, the retrofitted approach enables a specific client/server model [74]. This stream converts the knowledge of workers and physical measurements gathered from legacy systems into time-series values as the input source for the digital twin. The upgrade, oriented towards accomplishing a cyber–physical production system, results in a standardized common IIoT communication layer that connects the data of the manufacturing process in the virtual world [68].

3.2. Digital twin data models

The *Digital Twin Data Models* conceptual layer, also referred to as the *Understanding* layer, manages the way the retrofitted-based manufacturing systems data are imported, stored, and presented in real-time as shown in Fig. 1b. This furthers a virtual representation and understanding of the specific behaviors of production resources [75]. Process performance is analyzed using a tailored cloud service to visualize and monitor selected measurement inputs, providing relevant information to workers regarding the connected objects of the physical layer. This cloud-based service infrastructure manages data availability in real-time, setting up a cyber–physical connection that enables synchronization of real-world activities to the virtual space [24]. Subsequently, both the management dashboard and data processing modules are implemented to enable the digital twin visualization of manufacturing systems. The dashboard is customized to assist workers in responding to the detection of anomalies regarding incidents, such as changes in the manufacturing cycle and changes in a trend; it also assists in modeling some properties related to the health status of the manufacturing systems, such as operational parameters and knowledge-based techniques [33]. Therefore, this layer meet the requirements of enabling predictive maintenance applications [31] and the identification of patterns and/or indicators for the detection of anomalies [45], presenting a flexible solution to generate the data models needed to understand the behavior of the systems and processes.

3.3. Digital twin knowledge models

The *Digital Twin Knowledge Models* conceptual layer, also referred to as the *Learning* layer, manages the characterization of manufacturing processes, including workers' expertise and feedback. The aim is to generate a non-intrusive and adaptive learning ecosystem as shown in Fig. 1c. The sum of all available data previously collected and analyzed on the other layers, such as the interaction between skilled workers and legacy systems across the factory, is processed in a data analysis module. This step brings with it invaluable information, which can help with the generation of data-driven models in proactive decision-making [76]. Consequently, the learning process is accelerated, while encompassing the ecosystem as a whole. Furthermore, selected operational processes that bring initial knowledge through the discovery stage are characterized and combined with the transfer of knowledge of skilled workers, enabling value-added services based on human–machine collaboration for continuous improvement [3]. Finally, a set of well-known visual methods and human-machine interface applications are linked to the digital twin dashboard to assess the impact of changes in process performance [77], while workers diagnose the condition status of systems based on physical indicators (temperature, frequency, vibration, energy consumption, etc.). In general, this upper layer of the digital twin framework aims to integrate machine learning through adaptive modeling strategies, which facilitates root cause analysis and the prediction of changes to address manufacturing planning [28].

3.4. Framework system architecture

The overall framework system architecture, depicted on the left-hand side of Fig. 2, has been designed to seamlessly integrate the three layers of the Digital Twin Learning Ecosystem. The corresponding data flow is also presented on the right-hand side of Fig. 2, and is described in more detail below. From this perspective, the framework has been built by integrating a hardware and software stack around the interconnections of different tiers, as shown separated by a red line. Together, they work as learning enablers, entailing close cooperation among workers, systems, and processes. Consequently, the proposed architecture includes non-intrusive

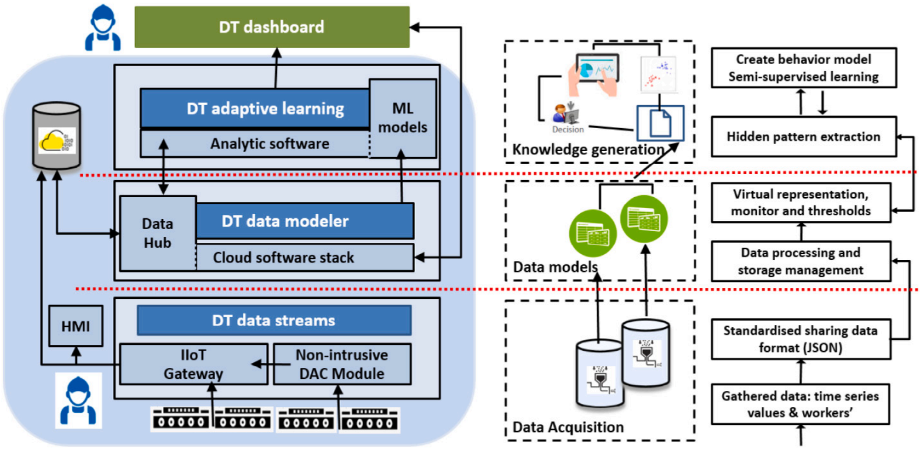

Fig. 2. The overall Digital Twin system architecture (left), and the corresponding data flow (right).

methods and solutions, such as retrofitting and supervisory human-machine interfaces, to address the bidirectional cyber–physical convergence of all layers presented. All the digital twin components of the framework architecture: (i) DT data streams, (ii) DT data modeler, and (iii) DT adaptive learning, are provided as adaptive modular services without interfering with the existing working conditions.

3.4.1. DT data streams

This tier is nearest to the sensors, machines, and workers, enabling real-time information from systems and workers via multiple heterogeneous manufacturing data sources. With respect to the fact that traditional SMEs still have inherent limitations to enable Industry 4.0 human-machine integration [78], in these cases, the framework can include an external non-intrusive industrial acquisition device with specific sensors plug-and-play/wireless, and human-machine interface software such as Web applications. Consequently, this module has been designed to integrate an IIoT gateway and a wide range of industrial communication protocols, such as Modbus TCP/IP, OPC-UA, and HTTP for data acquisition [79]. Particularly in traditional manufacturing, establishing standardized communication provides the lowest level of digitization services necessary to implement retrofitting techniques between legacy systems and the cloud infrastructure towards cyber-phisical systems [68]. Thus, the data flow input to the digital twin defines a common method that transforms the data capture process of legacy systems into time-series values. Overall, information is shared using the JSON standardized data format [22]. In this way, skilled workers have immediate real-time data access through a human-machine interface device to manage process control indicators, such as input voltage, acceleration, and temperature, among others.

3.4.2. DT data modeler

This tier is based on a cloud software stack that exchanges JSON data streams from manufacturing systems to a REST API hub storage [7]. An authenticated API uses the HTTPS protocol to access digitized data managed by the IIoT gateway and enables virtual connection between workers, machine data, and third-party systems, such as augmented reality devices. In this way, the visualization and modelization of real-time data and historical data are supported by a set of human-machine interface software tools, time series data graphics, and web-based widgets. On top of them, an interactive analytic DT dashboard module manages the visualization of the target systems, consisting of real-time machine variables, performance indicators, and modeled thresholds. The data flow of this module presents real-time data processing and storage management, which are required to understand the key performance indicators and determine the operational thresholds for real-time monitoring and building data models [80]. Data visualization includes alarms to alert workers about incidents triggered via anomaly detection or behavior fault models related to the health status of systems or processes [28].

3.4.3. DT adaptive learning

This tier allows characterization of the adaptive behavior of a system or process using condition-based knowledge [81]. In this manner, the analytic software allows historical data to be retrieved while learned manufacturing models are visualized on the DT dashboard. This module communicates with a large amount of data from different industrial systems and assists workers via augmented human-machine interface tools. Specifically, machine learning libraries and data models are used to extract patterns associated with the different tasks involved in the studied manufacturing cycles [82]. The data flow address the process of knowledge generation through the extraction of hidden patterns and the creation of unsupervised algorithms that are used to cluster data samples into behavior models [83]. Furthermore, to accelerate the learning process, supervised learning strategies are used according to the historical data of each system and feedback provided by experienced workers.

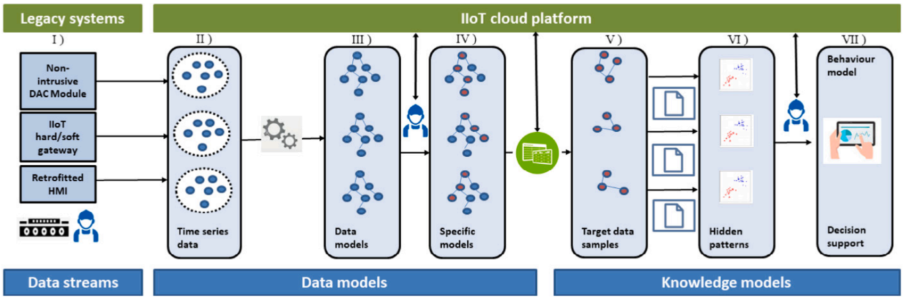

Fig. 3. Knowledge modeling process including a step-by-step diagram for the proposed digital twin approach.

3.5. Knowledge modeling process

The starting point of this work focuses on the context of traditional manufacturing SMEs, where skilled workers usually make operative decisions on a decentralized basis based on their experience. Thus, the exploration of systems' behavior and workers' learning patterns can ease their adaptation to changes in manufacturing and develop new ways to convert past experiences into precise guidelines [51]. In addition, workers play a significant role in the overall efficiency of the systems as well as the evolution of the manufacturing process [3] and are an integral part of the industrial ecosystem. Human–machine interactions and their associated learning processes are key challenges in the development and implantation of digital twins in manufacturing applications [1]. Therefore, the proposed knowledge modeling process is the result of the integration of consecutive stages based on the interaction, understanding, and learning among workers, systems, and manufacturing processes. The proposed framework architecture supports the sequence of steps shown in Fig. 3. The entire process is described as follows:

- Step I: Deployment of retrofitted hardware or software gateways, diverse non-intrusive data acquisition modules, and human-machine interface devices. They provide IIoT communications protocols and the user interface to set up the measurement parameters characterized by type and properties. All digitized systems are converted into an individualized time series of data objects automatically retrieved.
- Step II: Connection and storage of time-series data gathered from different retrofitted systems into cloud-based service architecture. All attributes of the different measurement data points, such as accelerometers, resistance temperature detectors, three-phase current transducers, and weight sensors, are classified according to the manufacturing system properties.
- Step III: Visualization of data models using a dashboard interface and data cleansing. All objects from Step II are fixed, labeled and configured manually using drag-and-drop widgets that provide several out-of-the box graphics and data tables, building their visual representation of the process performance indicators in real-time.
- Step IV: Determination of specific working cycles or phases involved in the manufacturing process. Skilled workers model the operational status of the systems and set customized threshold levels based on their personal experience. Certain properties related to their health status can be modeled (dynamic behavior, virtual sensors, and operational parameters), enabling an improved understanding of systems based on their state changes.
- Step V: Selection of the data samples containing physical measurement point values using time series data snapshots corresponding to each individual working cycle or phase defined by skilled workers. The data set values are normalized in the range of 0 to 1 before comparing the results.
- Step VI: Extraction of hidden information from the different data samples related to the health status of the analyzed system using Python 3.x open-source tool kits, such as Numpy, Pandas, Matplotlib, Scipy, and Scikit-learn, a free software machine learning library. An unsupervised clustering algorithm is used to minimize the amount of labeled data in the system to obtain the based-condition models.
- Step VII: Classification of the extracted patterns learned from Step IV and checking by workers to build an initial reference behavior model. Consequently, the sum of all the models constitutes a behavior model and determines the trends and detection thresholds necessary for the development of adaptive human-machine learning.

4. Case studies

To verify the effective implementation, replicability, and learning derived from the proposed digital twin framework, two industrial case studies are presented to facilitate the integration of human-machine knowledge in traditional manufacturing. This work focuses on traditional material processing in SMEs, specifically in a machining workshop and a foundry plant. Both cases contribute to manufacturing materials in the automotive industry supply chain [84]. Currently, traditional European manufacturing SMEs remain an important source of employment and wealth creation [85].

The selected traditional industry scenario is governed by Operational Technologies (OT) and manufacturing legacy systems. Typical OT control hardware for manufacturing machines include Programmable Logic Controllers (PLC), Distributed Control

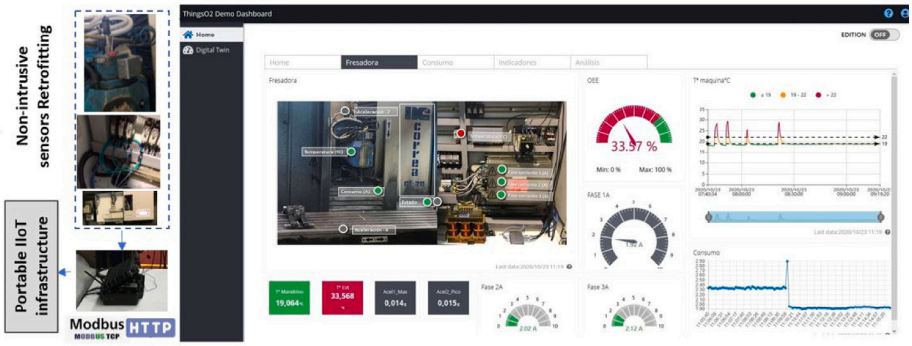

Fig. 4. (a) Portable IIoT gateway and non-intrusive sensors. (b) ThingsO2 cloud platform hosting the digital twin visualization of the milling machine.

Systems (DCS), human-machine interface devices, Supervisory Control And Data Acquisition Systems (SCADAS), and MES. Most are integrated by diverse commercial industrial systems that often own data sources with proprietary access [86] and heterogeneous communication interfaces for which the data architecture is unknown. This perspective is crucial for integrating complex heterogeneous scenarios in manufacturing, where systems, processes, and workers are simultaneously involved in operations at the same time. Despite the increasing digital skills and the accelerating transformation of work, traditional highly skilled jobs will always be needed by industry [87]. In this case, an effective human-machine interaction involves expert knowledge as well as smart production systems and tools. On the other hand, human-technology integration by the use of cyber–physical systems enables new work ecosystems [13]. Consequently, the implementation of novel concepts such as Digital Twin Learning Ecosystem is a valid approach to provide a cyber–physical framework, allowing tailored knowledge integration of legacy manufacturing systems and skilled workers.

In summary, this paper provides the literature with new valuable insights and human-machine integration paths. They can be used to examine its feasibility in other manufacturing scenarios for building new knowledge and digital twin infrastructure as well as reskilling and upskilling the workforce. In particular, the proposed industrial scenarios validated the common framework and knowledge generation process to provide augmented maintenance operations in a milling machine and improve the power efficiency of an induction furnace. The enablement of more straightforward cyber–physical systems and the empowerment of workforce skills [88] mark an additional step in the adoption of Industry 4.0 in traditional SMEs.

4.1. Case study 1: machining workshop

This section presents a case study conducted using an older three-axis milling machine, Nicolas Correa CF20, at Fundación Cidaut. This non-digitized production milling machine, which is more than 25 years old, is used in the machining workshop to shape slots and drill solid material workpieces using a rotating cutter. All the manufacturing orders are manually programmed. The milling machine is started and stopped every working day by an experienced worker, whereas the maintenance strategies are preventive or corrective without monitoring. In this type of situation, sensors for monitoring daily changes in energy consumption can help detect repetitive technical issues in a short period of time towards enhanced learning in maintenance processes. This measurement tool was previously applied in a similar study to register abnormal current consumption patterns [11]. Regarding these recurring patterns, the start-up process of the milling machine was considered a suitable environment to address the study on the basis of real consumption data.

4.1.1. Knowledge modeling process

All the steps presented in Section 3.5 were followed to build the knowledge modeling process to meet the requirements of a tailored Digital Twin Learning Ecosystem for the milling machine. The first tier of the digital twin framework, supported by a portable industrial gateway IIoT TWave T8-L, was used to develop retrofitting approaches on the milling machine without interfering with the working conditions. The gateway provides a customizable industrial acquisition device that integrates plug-and-play connectors and common sensors. Specifically, these components were used: (i) accelerometers with a magnetic mounting base, (ii) a pt100 magnetic resistance temperature detector, and (iii) an open-ended Rogowski three-phase AC current transducer, as depicted in Fig. 4a. This type of infrastructure is intended for applications that require a monitoring solution within a very short time. Embedded web-based and industrial communication agents, such as HTTPS and Modbus-TCP, were used to convert the physical measurements associated with the start-up of the milling machine into objects characterized by type and properties. All information managed during the manufacturing process was registered on a cloud-based architecture provided by ThingsO2, as shown in Fig. 4b. This second tier is aimed at detecting activity patterns. Digital tools adapted to the shop floor were used to enable cyber—physical and bidirectional human–machine interactions. Thus, the proposed digital twin dashboard monitored the start-up of the milling machine and synchronized real-time data in JSON format. In particular, time series data regarding energy consumption every second, between December 2019 and March 2020, were stored, as shown in Table 2.

Table 2
Detail of start-up power consumption values (Three-Phase Amperage) at every second registered in the milling machine.

Date	Time	T-PC1(A)	T-PC2(A)	T-PC3(A)
01/13/2020	08:09:50	0.68	0.09	0.58
01/13/2020	08:09:51	0.68	0.09	0.58
01/13/2020	08:09:52	2.15	1.75	2.63
01/13/2020	08:09:53	2.15	1.75	2.63
01/13/2020	08:09:54	2.15	1.75	2.63
01/13/2020	08:09:55	3.61	3.51	3.71
01/13/2020	08:09:56	3.81	3.51	3.81
01/13/2020	08:09:57	3.81	3.51	3.81
01/13/2020	08:09:58	3.51	3.61	3.81
01/13/2020	08:09:59	3.51	3.61	3.81

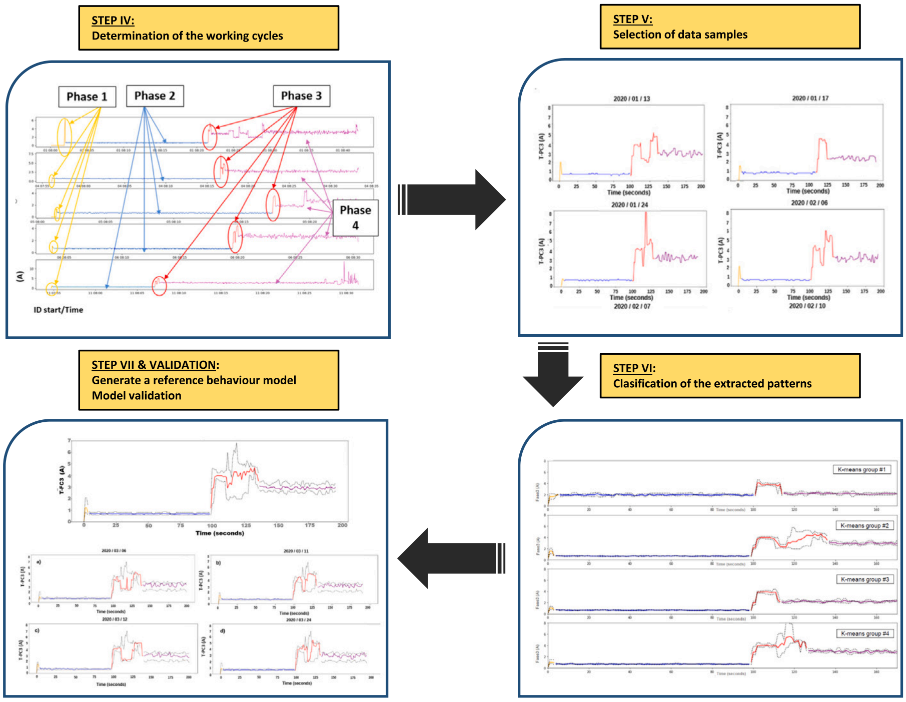

Fig. 5. Steps of the knowledge modeling process on the milling machine.

Collecting daily data over multiple start-ups provides repetitive behavioral patterns over a short period of time. Detection and learning were performed at the beginning of the day to generate power consumption data samples. In this way, the experienced worker was able to set the correspondence between the data and label four different operation phases depicted in Fig. 5: (i) power-up from scratch, (ii) PLC running cycle, (iii) engine start, and (iv) engine warm-up, as well as provide lessons learned about anomalies based on other characterizations of past events, such as overheating or excess consumption. Because the human-machine interaction managed during the engine start depends on a variable moment in which the worker manually releases the milling machine's emergency button, the timeline for phase 2 (end of the PLC running cycle) was adjusted up to 95 s. in all data series and interpolated using average values to have comparable start-up datasets without substantial change.

Specifically, data samples containing physical measurement values were selected for 19 days, between January and February 2020. Data models supporting decision making for maintenance operations were built using this dataset. The unsupervised k-means clustering algorithm [89] from the Scikit-learn Python library was used to accelerate the extraction of patterns, while minimizing the amount of labeled data. Next, the elbow method [90] was used to determine four as the number of different clusters for each type of start-up in the dataset, as shown in Table 3.

Subsequently, the minimum, maximum, and average values from all data samples in each individual resulting cluster were processed to generate the threshold limits in the four data models. With the aim of building a single initial reference model as shown in the entire start-up process, the four groups modeled were checked with the support of an experienced worker. In this manner, the admissible threshold data values for each model were adjusted and supervised by considering the learned behavior when starting the machine. This was achieved through real-time monitoring using a human-machine interface device (Android

Table 3
Group clusters obtained from CNC start-up analysis.

Date	K-means group	Date	K-means group
01/13/2020	2	02/03/2020	2
01/16/2020	1	02/04/2020	2
01/17/2020	3	02/05/2020	1
01/21/2020	3	02/06/2020	2
01/22/2020	1	02/07/2020	1
01/24/2020	4	02/10/2020	1
01/27/2020	3	02/11/2020	4
01/29/2020	4	02/13/2020	3
01/30/2020	4	02/14/2020	3
01/31/2020	2		

tablet). Hence, an aggregated model implementing the common patterns labeled by the worker was proposed as a digital twin input for the detection of abnormal start-ups, as shown in Fig. 5.

4.1.2. Model validation

In particular, the aim of the Digital Twin Learning Ecosystem is to provide workers who interact with legacy manufacturing systems with a bidirectional decision-making approach, such as these human-machine augmented models in real time. To evaluate the improvement in maintenance strategies in this traditional manufacturing scenario, the usefulness of the proposed digital twin-based model was tested using new start-up data samples supervised by different workers. During the assessment, operational data from the milling machine were collected in March 2020 (March 6th, March 11th, March 12th, and March 24th). Regarding each individual phase of the start-up process, the data tests presented only minor deviations beyond the upper threshold for Phase 3 (engine start), as shown in Fig. 5. Therefore, after three months of work assisted by digital twin data, the expert operator considered the implemented learning environment as a valid approach for diagnosing anomalies that depend on the asset condition, such as those triggered by the measurement of power consumption related to threshold values.

4.2. Case study 2: foundry plant

The second case study was conducted at a foundry plant in the SME sector. Lingotes Especiales plant located in Valladolid (Spain) has several induction furnaces used for casting gray iron parts. In particular, 80 per cent of the energy input is used for the cast iron manufacturing process. Because it is an electrointensive industry, electricity is a primary factor in its production process. Specifically, during 2021, the electricity consumption recorded in the factory was around 100 MM kWh. Therefore, human–machine interaction has become a critical aspect in reducing the cost of production because the induction furnace uses a high-voltage electrical source (up to 12 MW) for the casting of gray iron. This case study was selected because it is a repetitive process in a legacy manufacturing system that is suitable for understanding a Digital Twin Learning Ecosystem in different contexts. In this way, it is possible to retrofit real available data while reusing known measurement tools and conducting expert worker interviews to validate data patterns generating human-machine knowledge models.

During the process, experienced workers manage the production orders and quality of cast iron using a MES and visual displays. However, they did not have predictive analysis models for enhanced learning based on a comparison of data from the Key Performance Indicators (KPIs). In this respect, the charge of the raw materials for each heating cycle in the induction furnace is added (steel, tin, cast iron shavings, iron, scrap, etc.), and the maximum power is continuously applied. Then, the required casting temperature is gradually controlled to 1500 °C and the process ends when the cast iron is poured.

4.2.1. Knowledge modeling process

The implementation of the proposed Digital Twin Learning Ecosystem was evaluated with the aim of improving the efficiency of the gray iron casting process in an induction furnace. All the steps presented in Section 3.5 were applied. First, a non-intrusive gateway software was deployed to retrofit the isolated proprietary data capture system that operates plant process monitoring. Using a tailored IIoT data connector, the software was configured to gather physical values from the MES solutions Olanet and Circutor Powerstudio, and send them to the digital twin cloud data hub via authenticated HTTPS API. Thus, real-time monitoring of the operating patterns of the induction furnace, shown on the left-hand side of Fig. 6, was allowed as the input for the digital twin. In particular, several data streams were registered every minute between July 2021 and December 2021, such as the values of energy consumption, temperature, and iron mass, which were processed as time-series data (Table 4).

The cloud-based infrastructure used the JSON format to communicate data streams between legacy systems and the data hub. Next, digital twin visualization and the data modeler were configured, as shown on the right-hand side of Fig. 6. Both were presented through a web browser interface to the workers. Simultaneously, historical data samples from the furnace were processed between January 2021 and June 2021.

The assistance of two experienced workers was required to analyze the samples of the heating cycles. These workers' skills facilitated the acquisition of digital patterns according to plant operating procedures. In this respect, the workers used data from digital twin dashboard to determine up to four different working phases for the furnace's heating cycle: (i) initial iron mass charge,

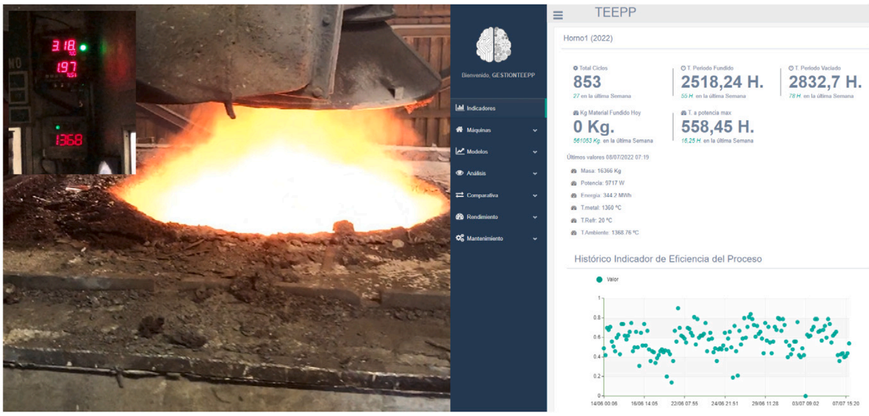

Fig. 6. Induction furnace for the cast iron manufacturing process (left). TEEPP digital twin dashboard (right).

Table 4
Detail of mass and power consumption values acquired in the induction furnace.

Date	Time	m (kg)	P (kW)	I (A)
01/10/2021	07:52:00	815	2811	1620.28
01/10/2021	07:53:00	822	2824	1634.20
01/10/2021	07:54:00	949	2840	1886.68
01/10/2021	07:55:00	944	2855	1880.48
01/10/2021	07:56:00	937	2871	1866.53
01/10/2021	07:57:00	923	2886	1884.99
01/10/2021	07:58:00	913	2902	1815.11
01/10/2021	07:59:00	901	2917	1794.82
01/10/2021	08:00:00	900	2932	1789.26
01/10/2021	08:01:00	905	2947	1799.21

Table 5
Group clusters obtained from induction furnace analysis.

Date	K-means group
01/10/2021 04:55	2
02/01/2021 00:00	1
02/21/2021 20:56	1
03/14/2021 22:20	1
04/04/2021 11:58	1
04/18/2021 21:15	1
05/09/2021 20:51	1
06/20/2021 21:06	1

(ii) raw material ramp-up, (iii) raw material charge ending and casting of gray iron, and (iv) ramp-down of cast iron. The correlation between each specific phase and a collection of time-series values associated with this foundry plant was established. In particular, the detection of the first phase change depends on the increase in the charge of the raw material in the induction furnace. This change make it possible to determine its duration and thus obtain comparable datasets for heating cycles.

Next, as in the previous case study, the k-means clustering algorithm was used to group the data samples extracted from the heating cycles into clusters. Eight data samples were selected to investigate the four working phases of the induction furnace. The elbow method was used to determine two as the number of different clusters for the heating cycles. Most of the data samples were grouped into the same cluster. Only one data sample dated October 01/10/2021 was placed in the other cluster, as shown in Table 5.

After investigation with the help of the experienced workers, this singularity of the iron casting process was confirmed as an abnormal heating cycle after a long scheduled outage. From this point on, after validating the extracted patterns and comparing the KPIs supervised by the plant manager, an initial behavior model was built. The visual representation of this model, depicted in Fig. 7, includes the average curve of the data corresponding to the heating cycles from cluster 1, and the standard deviation of these data to determine the detection thresholds.

4.2.2. Model validation

The applicability of the proposed approach was evaluated to measure the impact of the human-machine learning process on improving the energy efficiency associated with the casting of gray iron. Between January 2022 and May 2022, foundry plant operators used a digital twin knowledge model connected to real-time data. These process operators were provided with the

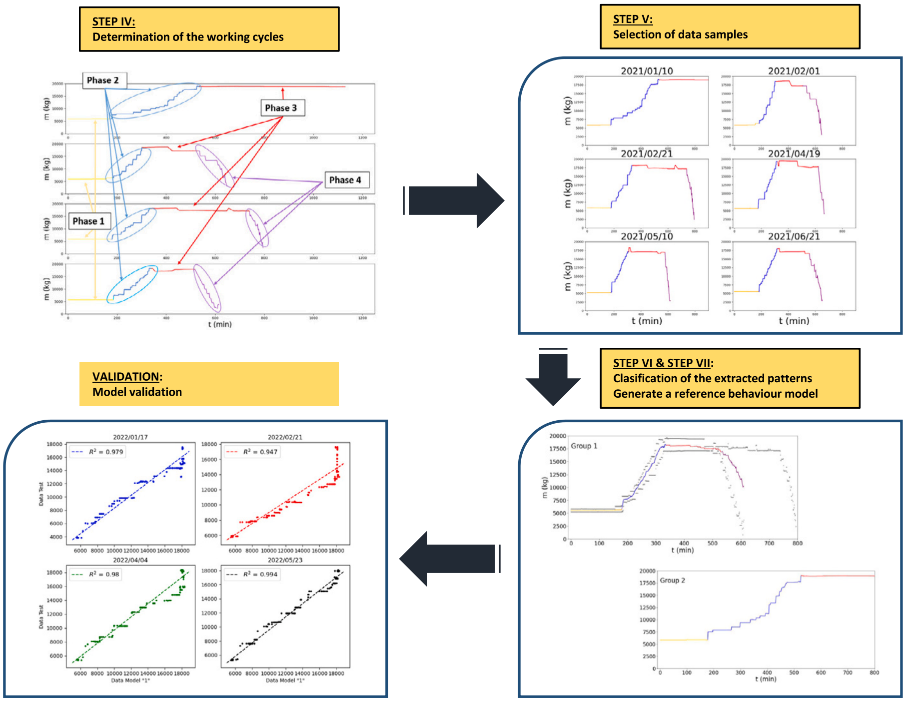

Fig. 7. Steps of the knowledge modeling process on the induction furnace.

visualization of KPIs in real-time, such as the iron mass and power consumption, as well as the heating cycle state of the induction furnace in comparison with the threshold models obtained for the planning of the production cycles. Thus, some improvements were successfully applied during the model-fitting process associated with the digital twin. An R-squared statistical parameter (Eq. (1)) was selected to determine the correlation between the behavior model of the studied furnace and the subsequent production data series tested.

$$R^2 = \left(\frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2(y_i - \overline{y})^2}}\right)^2 \tag{1}$$

The R-square results obtained by the comparison between the proposed heating cycle model of the furnace and four different and random iron casting production processes in 2022 were 0.979 (2022/01/17), 0.947 (2022/02/21), 0.98 (2022/04/04), and 0.994 (2022/05/23). These values show a strong correlation between the model data and subsequent process data samples. Therefore, during the tests, it was considered that the learned model represents a good approach to determine if the heating cycle process is in line with acceptable thresholds or whether a possible anomaly must be investigated to implement predictive maintenance plans. Additionally, a measure of the impact of the learning process is discussed in Section 5.

5. Discussion

This work presents a new adaptive and non-intrusive digital twin learning framework to facilitate the integration of human-machine knowledge in traditional manufacturing SMEs from scratch. In particular, using this framework, has been demonstrated the applicability and replication capacity of the common methodology, architecture, and knowledge-modeling process presented. The outcomes of this study contribute real data from two relevant case studies linking machines and humans to evaluate and illustrate the benefits of the proposed adaptive learning ecosystem for traditional manufacturing SMEs. Eliminating existing technological and workforce barriers in processes not yet aligned with Industry 4.0 provides the literature with new valuable insights that can be used to design similar learning scenarios or build new technical and digital infrastructures. In this way, the requirements of a tailored Digital Twin Learning Ecosystem are validated in these two currently operating traditional manufacturing SMEs. Therefore, this work presents an opportunity to help SMEs operating traditional processes build their own interconnected learning infrastructure at different manufacturing levels, focusing on non-intrusive twinned interactions between skilled workers and legacy systems. Consequently, all existing and required resources can be adaptively integrated, even if they vary for each industrial scenario.

5.1. Comparative study

Table 6 compares the proposed Digital Twin Learning Ecosystem against four existing scenarios in outstanding productive centers and research institutions in the literature. The comparison is carried out using different dimensions concerning digital twin-based learning approaches related to fault diagnosis, anomaly detection, and decision-making strategies, particularly for traditional manufacturing SMEs. The columns describe the features (approach, asset, sensors, digital twin model, scenario, aim, data, automated learning type, and results) and metrics (number of samples and accuracy) to enable data-driven knowledge models in these manufacturing systems.

From Table 6, it can be noted that one of the key points in which Digital Twin Learning Ecosystem is focused is a rapid bidirectional human-machine knowledge integration using small labeled samples for pattern recognition. Comparing industrial digital twin learning approaches, Xia et al. [91] considers that the process of obtaining sufficient labeled data to train models is expensive and laborious in industrial applications. Furthermore, Netzer et al. [92] also uses a pattern recognition system to detect anomalies in a test series (10 individual tests in three repetitive machining segments) and applies a “human-in-the-loop approach” after anomalies are detected to further enhance the system. Villalonga et al. [93] conducts the decision making about the process condition or state by analyzing residuals (difference between the actual output and the output estimated by the model), while Özen et al. [50] exposes that detailed simulations of the whole process using Computational Fluid Dynamics method are extremely computationally time consuming. Despite significant advances in intelligent data-driven methods, it is found that factories require human resources and data automation levels to support the vision of Industry 4.0.

To verify the results, complex heterogeneous scenarios governed by Operational Technologies in traditional manufacturing are presented. In particular, Cimino et al. [6] has demonstrated that the use of the digital twin closes the loop with MES, thereby enhancing the availability of field data for more consistent autonomous decision-making. For this purpose, Villalonga et al. [93] has described the digital twin implemented in a MES-equipped assembly line, which is focused on monitoring machine states and energy consumption in a practical laboratory environment. Nevertheless, digital twins are dependent on interaction and an exchange of data and information, where some operations are conducted manually and operational data are incomplete or missing due to a lack of acquisition systems, specifically in SMEs. Instead, the Digital Twin Learning Ecosystem proposes an alternative bidirectional non-intrusive digital twin approach based on generated data through an augmented interaction between workers, MES and legacy equipment to avoid data dependence on proprietary systems. In this way, the visualization of the digital twin has the feedback of the skilled workers and simultaneously offers in real-time knowledge-based decisions regarding the production orders and the health status of the manufacturing systems. Özen et al. [50] has presented a study carried out in the ASAŞ Aluminum Factory at Turkey which includes a future decision support system based on machine learning and digital twin models. It provides the simulation capabilities of a real furnace, where all models are intended to replicate the real process in the digital platform as closely as possible. The model will be used for day-by-day processes using fresh data from ASAŞ’s DCS system, to predict billet’s quality of real batches in quasi real-time. Thus, the application of human-machine knowledge-based operations in traditional SMEs has proven to be a key factor in the Digital Twin Learning Ecosystem, enabling both the efficiency of the manufacturing process and workers’ learning by integrating existing resources in a short period of time.

5.2. Machining workshop benefits achieved

In the first case study, the knowledge modeling process introduced in a traditional machining workshop helps a worker perform augmented maintenance operations from scratch in three months by detecting abnormal start-ups in a milling machine. In this industrial scenario, as shown in Fig. 8, the human–machine interaction allows a rapid and flexible digital twin to be built, based on the time series of working data and state changes from the physical counterpart. Despite the possibility of a false positive result in the training stage, as evidenced by an adaptive human–machine interaction during the process, the involvement of a skilled worker allowed the use of augmented human–machine interface devices to integrate expert knowledge. The worker facilitated the assessment of physical values in real time, anomaly labeling, and its association with datasets for further analysis using a semi-supervised learning process. This digital twin bidirectional approach minimizes downtimes using a fully digitized context-aware operator.

The use of human-machine interfaces and augmented procedures to monitor alarm thresholds in real time introduces an advanced diagnosis well-known by the operator. When applied to the milling process, the diagnosis was useful for saving time and improving the performance by interacting with the operational knowledge of the experienced operator. Both workers and industrial systems were simultaneously updated with a framework learning, which validated an example of the effective implementation and proved the operational capability of the integration of existing legacy systems and human resources, as well as the value generated using this approach.

5.3. Foundry plant benefits achieved

In the second case study, the same system architecture and knowledge modeling process is used to replicate a custom-built digital twin enhancing human-machine learning in a traditional foundry plant. Problems concerning the current coexistence of different technology levels in factories, such as legacy control systems that operate plant process monitoring, are now well known. Consequently, the framework can be reused and all existing and required resources, such as humans or systems, can be adaptively integrated.

Table 6
Digital Twin Learning Ecosystem compared with existing scenarios in outstanding productive centers and research institutions.

Ref.	Digital Twin-based approach	Asset	Digital twin model	Scenario	Aim	Human-machine learning	Data acquisition
Ours	Digital Twin Learning Ecosystem	Older non-digitized three-axis milling machine, Nicolas Correa CF20	Start-up process of a CNC milling machine	Machining workshop	Provide workers with an augmented decision-making approach to evaluate maintenance strategies (predictive)	Yes	Retrofitted three-phase current values. Time series every second
Ours	Digital Twin Learning Ecosystem	Induction furnace with a high-voltage electrical source (up to 12 MW)	Heating cycles of an induction furnace, used for casting gray iron parts	Foundry plant	Assist plant staff in making decisions in real time to improve the iron casting process	Yes	Retrofitted data from MES (energy consumption, temperature and iron mass). Time series every minute
[91]	Digital twin-enhanced fault diagnosis framework	Motor mounted on a Drivetrain Dynamics Simulator	Induction motor simulated using COMSOL Multiphysics software	Experimental machinery fault simulator (Drivetrain Dynamics Simulator platform)	Predict fault categories	No	Three-phase stator current signals
[92]	Machine tool process monitoring	DMG 6-axis milling center	Extraction of patterns from available time series and retrieval during machine operation	wbk Institute of Production Science, Karlsruhe, Germany	Anomaly detection for indirect tool condition monitoring	Yes	13 individual signals from Milling head position, Spindle position, Current, Spindle current and Torque.
[93]	Distributed digital twin framework for manufacturing processes	Simplified mobile phone prototype assembly line. Station (2) "Front Cover"	Fault detection and maintenance scheduling developed in MATLAB	Industry 4.0 Laboratory at the School of Management of Politecnico di Milano	Improvement in decision making about abnormal situations at local level	Yes	Pressure signal in the station 2
[50]	Decision support system based on machine learning and digital twin models	Melting furnaces	Operative digital twin model for the, melting process using ANSYS Twin Builder v2021R1	ASAŞ Aluminum Factory	Provide simulation capabilities of the real furnace to test beforehand possible process modifications or improvements	No	Company's MES or DCS platforms

Ref.	Dataset	Supervised learning	Unsupervised learning	Knowledge transfer	Clustering-based learning	Results	Real-time	Sensors
Ours	19 days (at the beginning), 200 s	Pattern recognition. Four different working phases and thresholds labeled by operator using limits and threshold values	19 samples	Collaborative augmented learning	K-means	4 samples tested. 75% by thresholds defined for each phase	Yes	Current sensors
Ours	8 heating cycles	Pattern recognition. Four different working phases and thresholds labeled by operator using limits and threshold values	8 samples	Collaborative augmented learning	K-means	4 samples tested by R-squared statistical parameter (0.979, 0.947, 0.98 and 0.994)	Yes	Current sensors, temperature sensors, weight sensors
[91]	2000 samples (real motor signals) 500 for each health state	Small labeled dataset (10%)	Large unlabeled dataset (90%)	DDA, Adversarial training	K-means	76% with only 1 labeled sample of each category	Yes	Current sensors

(continued on next page)

Table 6 (continued).

[92]	10 individual milling tests (x3)	By pattern recognition, 40 sub-sequences were detected as part of the milling process	Mean-Shift Clustering	Pattern recognition	Mean-Shift Clustering	N/A	No	Integrated in the milling machine
[93]	41 operations and 410 samples	Decision making about the process condition or state is conducted by analyzing residuals. Threshold are used corresponding to normal operating conditions	N/A	Adaptive learning	N/A	Able to detect abnormal conditions. Weighted sum of the square of the residuals (WSSR)	Yes	Pressure sensors
[50]	729 casting processes	Ridge Regression model, Random Forest Regression, Support Vector Regression, Artificial Neural Network 1-deep layer network 8 neurons	N/A	Decision support strategies	N/A	Preliminary test results for ASAŞ' raw material management process (Si, Mg, C, Fe, Cr)	No	Furnace sensors

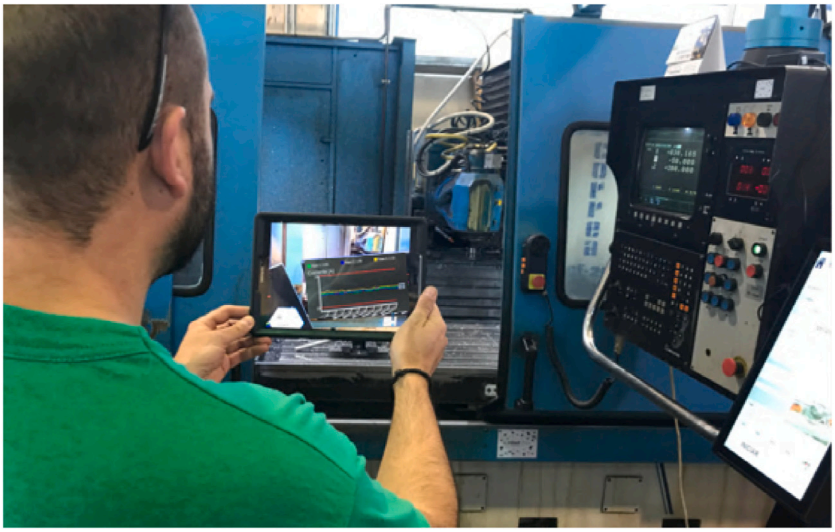

Fig. 8. Worker putting into practice augmented maintenance operations by detecting abnormal start-ups of a legacy milling machine.

In this industrial scenario, owing to the communication restrictions on proprietary supervisory systems, effective human-machine interaction became possible only when a fully operational three-tier digital twin was deployed. This non-intrusive knowledge example proved to be less demanding on resources and more flexible towards cloud solutions than other proprietary supervisory or MES systems. Therefore, using this legacy approach means that digital twin services, providing a bidirectional connection to interchange information between the digital twin and skilled workers, effectively overcome connectivity barriers in traditional processes.

Knowledge modeling provided production staff with both digital twin-based models and indicators of manufacturing processes, as shown in Fig. 9. Thus, the digital twin visualization that compares data with KPIs and workers' expert knowledge to assist decisions in real time allowed the staff to significantly improve the iron casting process. The interaction of workers and the integration of digital information with the real environment provided enhanced human-machine learning, empowering workers' skills, and building up digital twin data flows.

The learning ecosystem allowed experienced workers to apply changes in heating cycles and improve them, thereby reducing the cost of production. In particular, in the short period between January and July 2022, there was an improvement in the power efficiency indicator in the induction furnace by approximately 9 percent, as shown on the right-hand side of Fig. 10, whereas the amount of cast iron mass remained within normal values, as shown on the left-hand side of Fig. 10.

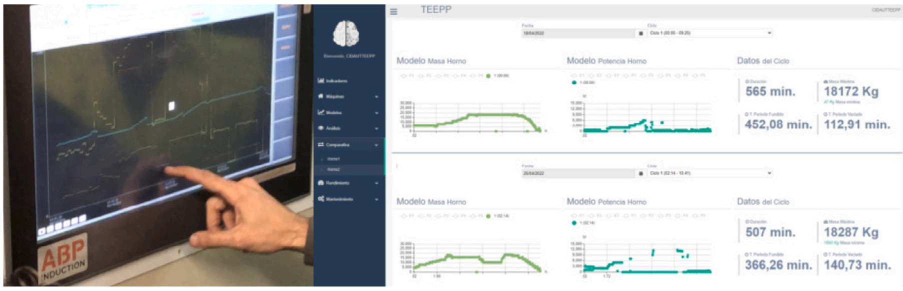

Fig. 9. (a) Induction furnace's SCADA. (b) Custom-built online digital twin for the foundry production staff.

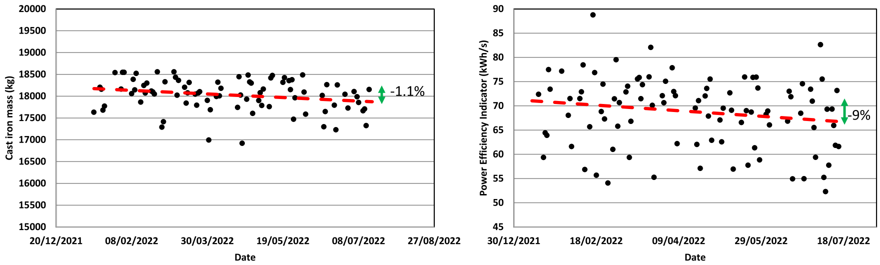

Fig. 10. KPIs comparison in the induction furnace between January and July 2022 of cast iron mass (left) vs. power efficiency indicator (right).

6. Conclusion

For decades, the traditional manufacturing industry has relied on skilled workers for the supervisory control of systems and processes. In fact, the increasing business needs motivated by enhancing factors over the entire manufacturing life-cycle, are making these same workers already face Industry 4.0 challenges. However, there is a lack of Industry 4.0-trained experts to conduct fieldwork in human-machine collaboration frameworks. This represents a source of concern for industries that have not yet reached a sufficient level of digital maturity. Consequently, existing case studies and Industry 4.0 programs to develop specific lifelong learning scenarios for reskilling and upskilling the workforce, particularly those associated with operating traditional manufacturing processes, are still sparse.

In general, there are limitations to sharing captured data of proprietary industrial equipment, commonly managed by automation systems such as MES or SCADA. Moreover, the maintainability of the entire production process must be addressed before transforming legacy manufacturing systems into smart manufacturing systems [94]. Thus, the convergence between legacy manufacturing systems and next-generation Information Technologies such as cyber–physical systems, artificial intelligence, and digital twins in SMEs remains an open challenge for continuous improvement. On the other hand, research on flexible and low-cost retrofitting techniques effectively promotes the convergence of the physical and digital worlds. Therefore, it is possible to extend digital twins in a non-intrusive way to manage different types of industrial ecosystems in SMEs, while also offering flexible opportunities to overcome actual knowledge limitations for smart manufacturing in traditional processes.

To this end, this work contributes to a cyber–physical knowledge for human-machine bidirectional interaction, focusing on adaptive digital twins [95], which can provide industrial systems with tailored cyber–physical convergence at different integration levels, such as retrofitting, monitoring and human-machine learning. Knowledge-based improvements can be applied to traditional SMEs, where there are many outdated systems, starting from scratch. Following this idea, this work also proposes the implementation of a three-layer digital twin-based framework that meets cyber–physical requirements for human–machine integration at different levels of the manufacturing process. Therefore, the implementation of digital twins, integrated seamlessly in a non-intrusive way, contributes to human-machine adaptive learning to characterize systems and processes via knowledge modeling supported by workers' expertise. The validation and replication of the digital twin framework in two industrial SMEs (a machining workshop and a foundry plant) demonstrated the same human-machine knowledge generation by applying a rapid and flexible semi-supervised learning method, which models the physical values monitored from diverse retrofitted manufacturing systems, while also receiving feedback from the workers.

As seen in these SME environments, there is a possibility of overcoming both legacy and workforce barriers. Digital twins have proven to be effective in enhancing workers' 4.0 skills to avoid technological exclusion risks. This approach is especially important for traditional SMEs to learn tasks that require experienced plant-process knowledge that highly skilled operators usually have and who are difficult to replace upon retirement. Although resistance to change can be an obstacle to innovation, particularly when new technologies are tested and introduced in traditional SMEs, further research should consider the workers' learning process to cope with upcoming digital technologies. The removal of older workers from their jobs owing to lack of knowledge and confidence in new technologies poses a risk to their employment in the future. As reflected in the research findings, the available insights from workers and their work methods could be adapted to other learning scenarios in a Digital Twin Learning Ecosystem and introduced into teaching programs that concern workers' lifelong learning and training in the manufacturing sector.

CRediT authorship contribution statement

Álvaro García: Conceptualization, Investigation, Methodology, Resources, Validation, Visualization, Writing – original draft, Writing – review & editing. **Anibal Bregon:** Conceptualization, Visualization, Writing – review & editing. **Miguel A. Martínez-Prieto:** Conceptualization, Visualization, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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References

[1] C. Semeraro, M. Lezoche, H. Panetto, M. Dassisti, Digital twin paradigm: A systematic literature review, Comput. Ind. 130 (2021) 103469, http://dx.doi.org/10.1016/j.compind.2021.103469.

[2] T.P. Raptis, A. Passarella, M. Conti, Data management in industry 4.0: State of the art and open challenges, IEEE Access 7 (2019) 97052–97093, http://dx.doi.org/10.1109/ACCESS.2019.2929296.

[3] P. Fantini, M. Pinzone, M. Taisch, Placing the operator at the centre of Industry 4.0 design: Modelling and assessing human activities within cyber-physical systems, Comput. Ind. Eng. 139 (2020) 105058, http://dx.doi.org/10.1016/j.cie.2018.01.025.

[4] K. Kokkonen, L. Hannola, T. Rantala, J. Ukko, M. Saunila, T. Rantala, Preconditions and benefits of digital twin-based business ecosystems in manufacturing, Int. J. Comput. Integr. Manuf. 36 (5) (2023) 789–806, http://dx.doi.org/10.1080/0951192X.2022.2145022.

[5] K. Wärmefjord, R. Söderberg, B. Schleich, H. Wang, Digital twin for variation management: A general framework and identification of industrial challenges related to the implementation, Appl. Sci. (Switz.) 10 (10) (2020) http://dx.doi.org/10.3390/APP10103342.

[6] C. Cimino, E. Negri, L. Fumagalli, Review of digital twin applications in manufacturing, Comput. Ind. 113 (2019) 103130, http://dx.doi.org/10.1016/j.compind.2019.103130.

[7] H. Han, S. Trimi, Towards a data science platform for improving SME collaboration through Industry 4.0 technologies, Technol. Forecast. Soc. Change 174 (2022) 121242, http://dx.doi.org/10.1016/j.techfore.2021.121242.

[8] A. Fuller, Z. Fan, C. Day, C. Barlow, Digital twin: Enabling technologies, challenges and open research, IEEE Access 8 (2020) 108952–108971, http://dx.doi.org/10.1109/ACCESS.2020.2998358.

[9] F. Doyle, J. Cosgrove, Steps towards digitization of manufacturing in an SME environment, Procedia Manuf. 38 (2019) 540–547, http://dx.doi.org/10.1016/j.promfg.2020.01.068.

[10] L. Li, Reskilling and upskilling the future-ready workforce for industry 4.0 and beyond, Inf. Syst. Front. (2022) http://dx.doi.org/10.1007/s10796-022-10308-y.

[11] Á. García, A. Bregon, M.A. Martínez-Prieto, A non-intrusive Industry 4.0 retrofitting approach for collaborative maintenance in traditional manufacturing, Comput. Ind. Eng. 164 (2022) 107896, http://dx.doi.org/10.1016/j.cie.2021.107896.

[12] Á. García, A. Bregon, M.A. Martínez-Prieto, Towards a connected Digital Twin Learning Ecosystem in manufacturing: Enablers and challenges, Comput. Ind. Eng. 171 (2022) 108463, http://dx.doi.org/10.1016/j.cie.2022.108463.

[13] C. Cimini, A. Lagorio, S. Cavalieri, O. Riedel, C.E. Pereira, J. Wang, Human-technology integration in smart manufacturing and logistics: current trends and future research directions, Comput. Ind. Eng. 169 (2022) 108261, http://dx.doi.org/10.1016/j.cie.2022.108261.

[14] K. Hribernik, G. Cabri, F. Mandreoli, G. Mentzas, Autonomous, context-aware, adaptive Digital Twins—State of the art and roadmap, Comput. Ind. 133 (2021) 103508, http://dx.doi.org/10.1016/j.compind.2021.103508.

[15] J. Wilhelm, C. Petzoldt, T. Beinke, M. Freitag, Review of digital twin-based interaction in smart manufacturing: Enabling cyber-physical systems for human-machine interaction, Int. J. Comput. Integr. Manuf. 34 (10) (2021) 1031–1048, http://dx.doi.org/10.1080/0951192X.2021.1963482.

[16] M. Liu, S. Fang, H. Dong, C. Xu, Review of digital twin about concepts, technologies, and industrial applications, J. Manuf. Syst. 58 (November) (2021) 346–361, http://dx.doi.org/10.1016/j.jmsy.2020.06.017.

[17] W. Hu, T. Zhang, X. Deng, Z. Liu, J. Tan, Digital twin: a state-of-the-art review of its enabling technologies, applications and challenges, J. Intell. Manuf. Spec. Equip. 2 (1) (2021) 1–34, http://dx.doi.org/10.1108/jimse-12-2020-010.

[18] J. Zhou, Y. Zhou, B. Wang, J. Zang, Human–cyber–physical systems (HCPSs) in the context of new-generation intelligent manufacturing, Engineering 5 (4) (2019) 624–636, http://dx.doi.org/10.1016/j.eng.2019.07.015.

[19] B. Maschler, D. Braun, N. Jazdi, M. Weyrich, Transfer learning as an enabler of the intelligent digital twin, Procedia CIRP 100 (June) (2021) 127–132, http://dx.doi.org/10.1016/j.procir.2021.05.020, arXiv:2012.01913.

[20] J. Stentoft, K.W. Jensen, K. Philipsen, A. Haug, Drivers and barriers for industry 4.0 readiness and practice: A SME perspective with empirical evidence, in: Proceedings of the 52nd Hawaii International Conference on System Sciences, Vol. 6, 2019, pp. 5155–5164, http://dx.doi.org/10.24251/hicss.2019.619.

[21] D. Grube, A.A. Malik, A. Bilberg, SMEs can touch Industry 4.0 in the smart learning factory, Procedia Manuf. 31 (2019) 219–224, http://dx.doi.org/10.1016/j.promfg.2019.03.035.

[22] I. Onaji, D. Tiwari, P. Soulatiantork, B. Song, A. Tiwari, Digital twin in manufacturing: conceptual framework and case studies, Int. J. Comput. Integr. Manuf. 35 (8) (2022) 831–858, http://dx.doi.org/10.1080/0951192X.2022.2027014.

[23] A. Berisha-Gawlowski, C. Caruso, C. Harteis, The concept of a digital twin and its potential for learning organizations, in: D. Ifenthaler, S. Hofhues, M. Egloffstein, C. Helbig (Eds.), Digital Transformation of Learning Organizations, Springer International Publishing, Cham, 2021, pp. 95–114, http://dx.doi.org/10.1007/978-3-030-55878-9_6.

[24] E. Negri, L. Fumagalli, M. Macchi, A review of the roles of digital twin in CPS-based production systems, Procedia Manuf. 11 (June) (2017) 939–948, http://dx.doi.org/10.1016/j.promfg.2017.07.198.

[25] C. Cronrath, L. Ekstrom, B. Lennartson, Formal properties of the digital twin-implications for learning, optimization, and control, in: IEEE International Conference on Automation Science and Engineering, Vol. August, 2020, pp. 679–684, http://dx.doi.org/10.1109/CASE48305.2020.9216822.

[26] F. Tao, H. Zhang, A. Liu, A.Y.C. Nee, Digital twin in industry: State-of-the-art, IEEE Trans. Ind. Inform. 15 (4) (2019) 2405–2415, http://dx.doi.org/10.1109/TII.2018.2873186.

[27] I. Errandonea, S. Beltrán, S. Arrizabalaga, Digital Twin for maintenance: A literature review, Comput. Ind. 123 (2020) 103316, http://dx.doi.org/10.1016/j.compind.2020.103316.

[28] A. Madni, C. Madni, S. Lucero, Leveraging digital twin technology in model-based systems engineering, Systems 7 (1) (2019) 7, http://dx.doi.org/10.3390/systems7010007.

[29] W. Kritzinger, M. Karner, G. Traar, J. Henjes, W. Sihn, Digital Twin in manufacturing: A categorical literature review and classification, IFAC-PapersOnLine 51 (11) (2018) 1016–1022, http://dx.doi.org/10.1016/j.ifacol.2018.08.474, 16th IFAC Symposium on Information Control Problems in Manufacturing INCOM 2018.

[30] Y. Cai, B. Starly, P. Cohen, Y.S. Lee, Sensor data and information fusion to construct digital-twins virtual machine tools for cyber-physical manufacturing, Procedia Manuf. 10 (2017) 1031–1042, http://dx.doi.org/10.1016/j.promfg.2017.07.094.

[31] P. Aivaliotis, K. Georgoulias, Z. Arkouli, S. Makris, Methodology for enabling digital twin using advanced physics-based modelling in predictive maintenance, Procedia CIRP 81 (2019) 417–422, http://dx.doi.org/10.1016/j.procir.2019.03.072.

[32] 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 (August) (2021) 329–345, http://dx.doi.org/10.1016/j.jmsy.2020.08.001.

[33] H. Huang, L. Yang, Y. Wang, X. Xu, Y. Lu, Digital Twin-driven online anomaly detection for an automation system based on edge intelligence, J. Manuf. Syst. 59 (October) (2021) 138–150, http://dx.doi.org/10.1016/j.jmsy.2021.02.010.

[34] Y. Xu, Y. Sun, X. Liu, Y. Zheng, A digital-twin-assisted fault diagnosis using deep transfer learning, IEEE Access 7 (2019) 19990–19999, http://dx.doi.org/10.1109/ACCESS.2018.2890566.

[35] W. Booyse, D.N. Wilke, S. Heyns, Deep digital twins for detection, diagnostics and prognostics, Mech. Syst. Signal Process. 140 (2020) 106612, http://dx.doi.org/10.1016/j.ymssp.2019.106612.

[36] Y. Lu, C. Liu, K. Wang, H. Huang, X. Xu, Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues, Robot. Comput.-Integr. Manuf. 61 (April) (2020) 101837, http://dx.doi.org/10.1016/j.rcim.2019.101837.

[37] F. Mo, H.U. Rehman, F.M. Monetti, J.C. Chaplin, D. Sanderson, A. Popov, A. Maffei, S. Ratchev, A framework for manufacturing system reconfiguration and optimisation utilising digital twins and modular artificial intelligence, Robot. Comput.-Integr. Manuf. 82 (2023) 102524, http://dx.doi.org/10.1016/j.rcim.2022.102524.

[38] Y. Yin, P. Zheng, C. Li, L. Wang, A state-of-the-art survey on Augmented Reality-assisted Digital Twin for futuristic human-centric industry transformation, Robot. Comput.-Integr. Manuf. 81 (2023) 102515, http://dx.doi.org/10.1016/j.rcim.2022.102515.

[39] L. Pérez, S. Rodríguez-Jiménez, N. Rodríguez, R. Usamentiaga, D.F. García, Digital twin and virtual reality based methodology for multi-robot manufacturing cell commissioning, Appl. Sci. 10 (10) (2020) http://dx.doi.org/10.3390/app10103633.

[40] K. Ding, F.T.S. Chan, X. Zhang, G. Zhou, F. Zhang, Defining a Digital Twin-based Cyber-Physical Production System for autonomous manufacturing in smart shop floors, Int. J. Prod. Res. 57 (20) (2019) 6315–6334, http://dx.doi.org/10.1080/00207543.2019.1566661.

[41] S. Suuronen, J. Ukko, R. Eskola, R.S. Semken, H. Rantanen, A systematic literature review for digital business ecosystems in the manufacturing industry: Prerequisites, challenges, and benefits, CIRP J. Manuf. Sci. Technol. 37 (2022) 414–426, http://dx.doi.org/10.1016/j.cirpj.2022.02.016.

[42] N. Tvenge, O. Ogorodnyk, N.P. Østbø, K. Martinsen, Added value of a virtual approach to simulation-based learning in a manufacturing learning factory, Procedia CIRP 88 (2020) 36–41, http://dx.doi.org/10.1016/j.procir.2020.05.007, 13th CIRP Conference on Intelligent Computation in Manufacturing Engineering.

[43] M. Raza, P.M. Kumar, D.V. Hung, W. Davis, H. Nguyen, R. Trestian, A digital twin framework for industry 4.0 enabling next-gen manufacturing, in: ICITM 2020 - 2020 9th International Conference on Industrial Technology and Management, 2020, pp. 73–77, http://dx.doi.org/10.1109/ICITM48982.2020.9080395.

[44] J. Leng, D. Wang, W. Shen, X. Li, Q. Liu, X. Chen, Digital twins-based smart manufacturing system design in Industry 4.0: A review, J. Manuf. Syst. 60 (May) (2021) 119–137, http://dx.doi.org/10.1016/j.jmsy.2021.05.011.

[45] Y. Qamsane, C.Y. Chen, E.C. Balta, B.C. Kao, S. Mohan, J. Moyne, D. Tilbury, K. Barton, A unified digital twin framework for real-time monitoring and evaluation of smart manufacturing systems, in: IEEE International Conference on Automation Science and Engineering, IEEE, 2019, pp. 1394–1401, http://dx.doi.org/10.1109/COASE.2019.8843269.

[46] J. Leng, H. Zhang, D. Yan, Q. Liu, X. Chen, D. Zhang, Digital twin-driven manufacturing cyber-physical system for parallel controlling of smart workshop, J. Ambient Intell. Humaniz. Comput. 10 (3) (2019) 1155–1166, http://dx.doi.org/10.1007/s12652-018-0881-5.

[47] G. Shao, Use Case Scenarios for Digital Twin Implementation Based on ISO 23247, in: Advanced Manufacturing Series (NIST AMS), National Institute of Standards and Technology, Gaithersburg, MD, 2021, http://dx.doi.org/10.6028/NIST.AMS.400-2.

[48] G. Shao, M. Helu, Framework for a digital twin in manufacturing: Scope and requirements, Manuf. Lett. 24 (2020) 105–107, http://dx.doi.org/10.1016/j.mfglet.2020.04.004.

[49] J. Lu, X. Zheng, A. Gharaei, K. Kalaboukas, D. Kiritsis, Cognitive twins for supporting decision-makings of internet of things systems, in: L. Wang, V.D. Majstorovic, D. Mourtzis, E. Carpanzano, G. Moroni, L.M. Galantucci (Eds.), Proceedings of 5th International Conference on the Industry 4.0 Model for Advanced Manufacturing, Springer International Publishing, Cham, 2020, pp. 105–115, http://dx.doi.org/10.1007/978-3-030-46212-3_7.

[50] Z.T. Özen, H.B. Taşkın, I.A. Sarı, B. Arkan, G. Özçelik, A. Fernández, S. Muiños, M. Pozzi, A. Gordini, L. Ferrari, J. Hercog, A. Kiedrzyńska, B. Glot, Development of decision support system based on machine learning and digital twin for aluminium melting furnaces, in: 6nd International Conference on Material Science and Technology in Cappadocia, IMSTEC'21, Zenodo, 2022, http://dx.doi.org/10.5281/zenodo.5897240.

[51] J. David, A. Lobov, M. Lanz, Learning experiences involving digital twins, in: IECON 2018 - 44th Annual Conference of the IEEE Industrial Electronics Society, 2018, pp. 3681–3686, http://dx.doi.org/10.1109/IECON.2018.8591460.

[52] E.G. Caldarola, G.E. Modoni, M. Sacco, A knowledge-based approach to enhance the workforce skills and competences within the Industry 4.0, in: eKNOW 2018 : The Tenth International Conference on Information, Process, and Knowledge Management, 2018, pp. 56–61.

[53] A.A. Malik, A. Bilberg, Digital twins of human robot collaboration in a production setting, Procedia Manuf. 17 (2018) 278–285, http://dx.doi.org/10.1016/j.promfg.2018.10.047.

[54] E. Yildiz, C. Møller, A. Bilberg, Virtual factory: Digital twin based integrated factory simulations, Procedia CIRP 93 (2020) 216–221, http://dx.doi.org/10.1016/j.procir.2020.04.043, 53rd CIRP Conference on Manufacturing Systems 2020.

[55] L.C.W. Kong, S. Harper, D. Mitchell, J. Blanche, T. Lim, D. Flynn, Interactive digital twins framework for asset management through internet, in: 2020 IEEE Global Conference on Artificial Intelligence and Internet of Things, GCAIoT 2020, 2020, pp. 1–7, http://dx.doi.org/10.1109/GCAIoT51063.2020.9345890.

[56] J. Friederich, D.P. Francis, S. Lazarova-Molnar, N. Mohamed, A framework for data-driven digital twins of smart manufacturing systems, Comput. Ind. 136 (2022) 103586, http://dx.doi.org/10.1016/j.compind.2021.103586.

[57] S. Liu, Y. Lu, X. Shen, J. Bao, A digital thread-driven distributed collaboration mechanism between digital twin manufacturing units, J. Manuf. Syst. 68 (2023) 145–159, http://dx.doi.org/10.1016/j.jmsy.2023.02.014.

[58] M. Kumbhar, A.H.C. Ng, S. Bandaru, A digital twin based framework for detection, diagnosis, and improvement of throughput bottlenecks, J. Manuf. Syst. 66 (2023) 92–106, http://dx.doi.org/10.1016/j.jmsy.2022.11.016.

[59] M. Grieves, J. Vickers, Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems, in: F.-J. Kahlen, S. Flumerfelt, A. Alves (Eds.), Transdisciplinary Perspectives on Complex Systems: New Findings and Approaches, Springer International Publishing, Cham, 2017, pp. 85–113, http://dx.doi.org/10.1007/978-3-319-38756-7_4".

[60] T.H.J. Uhlemann, C. Lehmann, R. Steinhilper, The digital twin: Realizing the cyber-physical production system for industry 4.0, Procedia CIRP 61 (2017) 335–340, http://dx.doi.org/10.1016/j.procir.2016.11.152, The 24th CIRP Conference on Life Cycle Engineering.

[61] S. Mittal, M.A. Khan, D. Romero, T. Wuest, A critical review of smart manufacturing & Industry 4.0 maturity models: Implications for small and medium-sized enterprises (SMEs), J. Manuf. Syst. 49 (2018) 194–214, http://dx.doi.org/10.1016/j.jmsy.2018.10.005.

[62] D. Horváth, R.Z. Szabó, Driving forces and barriers of Industry 4.0: Do multinational and small and medium-sized companies have equal opportunities? Technol. Forecast. Soc. Change 146 (March) (2019) 119–132, http://dx.doi.org/10.1016/j.techfore.2019.05.021.

[63] C. Semeraro, N. Alyousuf, N.I. Kedir, E.A. Lail, A maturity model for evaluating the impact of Industry 4.0 technologies and principles in SMEs, Manuf. Lett. 37 (2023) 61–65, http://dx.doi.org/10.1016/j.mfglet.2023.07.018.

[64] T. Zonta, C.A. da Costa, R. da Rosa Righi, M.J. de Lima, E.S. da Trindade, G.P. Li, Predictive maintenance in the Industry 4.0: A systematic literature review, Comput. Ind. Eng. 150 (2020) 106889, http://dx.doi.org/10.1016/j.cie.2020.106889.

[65] J. Bokrantz, A. Skoogh, C. Berlin, T. Wuest, J. Stahre, Smart Maintenance: a research agenda for industrial maintenance management, Int. J. Prod. Econ. 224 (2020) 107547, http://dx.doi.org/10.1016/j.ijpe.2019.107547.

[66] S.H. Dolatabadi, I. Budinska, Systematic literature review predictive maintenance solutions for smes from the last decade, Machines 9 (9) (2021) http://dx.doi.org/10.3390/machines9090191.

[67] F. Orellana, R. Torres, From legacy-based factories to smart factories level 2 according to the industry 4.0, Int. J. Comput. Integr. Manuf. 32 (4–5) (2019) 441–451, http://dx.doi.org/10.1080/0951192X.2019.1609702.

[68] T. Lins, R.A.R. Oliveira, Cyber-physical production systems retrofitting in context of industry 4.0, Comput. Ind. Eng. 139 (2020) 106193, http://dx.doi.org/10.1016/j.cie.2019.106193.

[69] M. Pantelidakis, K. Mykoniatis, J. Liu, G. Harris, A digital twin ecosystem for additive manufacturing using a real-time development platform, Int. J. Adv. Manuf. Technol. 120 (9) (2022) 6547–6563, http://dx.doi.org/10.1007/s00170-022-09164-6.

[70] H. Kroll, G. Copani, E. Van de Velde, M. Simons, D. Horvat, A. Jäger, A. Wastyn, G. PourAbdollahian, M. Naumanen, An Analysis of Drivers, Barriers and Readiness Factors of EU Companies for Adopting Advanced Manufacturing Products and Technologies, European Union, 2016, pp. 1–93, http://dx.doi.org/10.2873/715340.

[71] Deloitte, Preparing Tomorrow's Workforce for the Fourth Industrial Revolution. For Business: A Framework for Action, Global Business Coalition for Education, 2018, pp. 1–58.

[72] Q. Qi, F. Tao, Y. Zuo, D. Zhao, Digital twin service towards smart manufacturing, Procedia CIRP 72 (2018) 237–242, http://dx.doi.org/10.1016/j.procir.2018.03.103.

[73] V. Toivonen, M. Lanz, H. Nylund, H. Nieminen, The FMS Training Center - A versatile learning environment for engineering education, Procedia Manuf. 23 (2017) (2018) 135–140, http://dx.doi.org/10.1016/j.promfg.2018.04.006.

[74] Q. Li, Q. Tang, I. Chan, H. Wei, Y. Pu, H. Jiang, J. Li, J. Zhou, Smart manufacturing standardization: Architectures, reference models and standards framework, Comput. Ind. 101 (April) (2018) 91–106, http://dx.doi.org/10.1016/j.compind.2018.06.005.

[75] H. Jiang, S. Qin, J. Fu, J. Zhang, G. Ding, How to model and implement connections between physical and virtual models for digital twin application, J. Manuf. Syst. 58 (2021) 36–51, http://dx.doi.org/10.1016/j.jmsy.2020.05.012, Digital Twin towards Smart Manufacturing and Industry 4.0.

[76] M. Kunath, H. Winkler, Integrating the Digital Twin of the manufacturing system into a decision support system for improving the order management process, Procedia CIRP 72 (2018) 225–231, http://dx.doi.org/10.1016/j.procir.2018.03.192.

[77] M. Albano, E. Jantunen, G. Papa, U. Zurutuza, The MANTIS Book Cyber Physical System Based Proactive Collaborative Maintenance, River Publishers, 2018, pp. 1–626, http://dx.doi.org/10.13052/rp-9788793609846.

[78] A. Amaral, P. Peças, SMEs and Industry 4.0: Two case studies of digitalization for a smoother integration, Comput. Ind. 125 (2021) 103333, http://dx.doi.org/10.1016/j.compind.2020.103333.

[79] H. Ramesh, S.A.E. Xavier, R.P. Kumar, S.J. Fusic, Case study on server–client protocols of industrial controllers, in: S. Rawat, A. Kumar, P. Kumar, J. Anguera (Eds.), Proceedings of First International Conference on Computational Electronics for Wireless Communications, Springer Nature Singapore, Singapore, 2022, pp. 241–257, http://dx.doi.org/10.1007/978-981-16-6246-1_21.

[80] M.J. Kaur, V.P. Mishra, P. Maheshwari, The convergence of digital twin, IoT, and machine learning: Transforming data into action, in: M. Farsi, A. Daneshkhah, A. Hosseinian-Far, H. Jahankhani (Eds.), Digital Twin Technologies and Smart Cities, Springer International Publishing, Cham, 2020, pp. 3–17, http://dx.doi.org/10.1007/978-3-030-18732-3_1.

[81] J. Liu, H. Zhou, X. Liu, G. Tian, M. Wu, L. Cao, W. Wang, Dynamic evaluation method of machining process planning based on digital twin, IEEE Access 7 (2019) 19312–19323, http://dx.doi.org/10.1109/ACCESS.2019.2893309.

[82] F. Ansari, S. Erol, W. Sihn, Rethinking human-machine learning in industry 4.0: How does the paradigm shift treat the role of human learning? Procedia Manuf. 23 (2017) (2018) 117–122, http://dx.doi.org/10.1016/j.promfg.2018.04.003.

[83] Z. Huang, Y. Shen, J. Li, M. Fey, C. Brecher, A survey on AI-driven digital twins in industry 4.0: Smart manufacturing and advanced robotics, Sensors 21 (19) (2021) http://dx.doi.org/10.3390/s21196340.

[84] A. Orlowicz, M. Mróz, M. Tupaj, A. Trytek, Materials used in the automotive industry, Arch. Foundry Eng. 15 (2) (2015) http://dx.doi.org/10.1515/afe-2015-0042.

[85] D. Radicic, G. Pugh, D. Douglas, Promoting cooperation in innovation ecosystems: evidence from European traditional manufacturing SMEs, Small Bus. Econ. 54 (1) (2020) 257–283, http://dx.doi.org/10.1007/s11187-018-0088-3.

[86] D. Baglee, U. Gorostegui, E. Jantunen, P. Sharma, J. Campos, How can SMES adopt a new method to advanced maintenance strategies?: A case study, in: I. Sherrington, A. Onsy, R. R., H. Brooks, J. Philip (Eds.), COMADEM 2017, University of Central Lancashire, United Kingdom, 2017, pp. 155–162, 30th International Conference on Condition Monitoring and Diagnostic Engineering Management.

[87] J. Morgan, M. Halton, Y. Qiao, J.G. Breslin, Industry 4.0 smart reconfigurable manufacturing machines, J. Manuf. Syst. 59 (2021) 481–506, http://dx.doi.org/10.1016/j.jmsy.2021.03.001.

[88] I. Graessler, A. Poehler, Intelligent control of an assembly station by integration of a digital twin for employees into the decentralized control system, Procedia Manuf. 24 (2018) 185–189, http://dx.doi.org/10.1016/j.promfg.2018.06.041.

[89] M.S. Packianather, A. Davies, S. Harraden, S. Soman, J. White, Data mining techniques applied to a manufacturing SME, Procedia CIRP 62 (2017) 123–128, http://dx.doi.org/10.1016/j.procir.2016.06.120.

[90] M.A. Syakur, B.K. Khotimah, E.M.S. Rochman, B.D. Satoto, Integration K-means clustering method and elbow method for identification of the best customer profile cluster, IOP Conf. Ser.: Mater. Sci. Eng. 336 (1) (2018) 012017, http://dx.doi.org/10.1088/1757-899X/336/1/012017.

[91] P. Xia, Y. Huang, Z. Tao, C. Liu, J. Liu, A digital twin-enhanced semi-supervised framework for motor fault diagnosis based on phase-contrastive current dot pattern, Reliab. Eng. Syst. Saf. 235 (2023) 109256, http://dx.doi.org/10.1016/j.ress.2023.109256.

[92] M. Netzer, Y. Palenga, J. Fleischer, Machine tool process monitoring by segmented timeseries anomaly detection using subprocess-specific thresholds, Prod. Eng. 16 (5) (2022) 597–606, http://dx.doi.org/10.1007/s11740-022-01120-3.

[93] A. Villalonga, E. Negri, L. Fumagalli, M. Macchi, F. Castaño, R. Haber, Local decision making based on distributed digital twin framework, IFAC-PapersOnLine 53 (2) (2020) 10568–10573, http://dx.doi.org/10.1016/j.ifacol.2020.12.2806, 21st IFAC World Congress.

[94] R. Burke, A. Mussomeli, S. Laaper, M. Hartigan, B. Sniderman, The Smart Factory, Deloitte University Press, 2017, pp. 1–22, URL https://www2.deloitte.com/content/dam/insights/us/articles/4051_The-smart-factory/DUP_The-smart-factory.pdf.

[95] J.A. Erkoyuncu, I.F. del Amo, D. Ariansyah, D. Bulka, R. Vrabič, R. Roy, A design framework for adaptive digital twins, CIRP Ann. 69 (1) (2020) 145–148, http://dx.doi.org/10.1016/j.cirp.2020.04.086.