Accepted version of the article published in: Computers and Industrial Engineering, 2022, vol. 171
https://doi.org/10.1016/J.CIE.2022.108463

# Towards a Connected Digital Twin Learning Ecosystem in Manufacturing: Enablers and Challenges

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**Abstract**

The evolution of digital twin, leveraged by the progressive physical-digital convergence, has provided smart manufacturing systems with knowledge-generation ecosystems based on new models of collaboration between the workforce and industrial processes. Digital twin is expected to be a decision-making solution underpinned by real-time communication and data-driven enablers, entailing close cooperation between workers, systems and processes. But industry will need to face the challenges of building and supporting new technical and digital infrastructures, while workers' skills development eventually manages to include the increased complexity of industrial processes. This paper is intended to reach a better understanding of learning opportunities offered by emerging Industry 4.0 digital twin ecosystems in manufacturing. Diverse learning approaches focused on the potential application of the digital twin concept in theoretical and real manufacturing ecosystems are reviewed. In addition, we propose an original definition of Digital Twin Learning Ecosystem and the conceptual layered architecture. Existing key enablers of the digital twin physical-digital convergence, such as collaborative frameworks, data-driven approaches and augmented interfaces, are also described. The role of the Learning Factory concept is high-

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lighted, providing a common understanding between academia and industry. Academic applications and complex demonstration scenarios are combined in line with the enablement of connected adaptive systems and the empowerment of workforce skills and competences. The adoption of digital twin in production is still at an initial stage in the manufacturing industry, where specific human and technological challenges must be addressed. The research priorities presented in this work are considered as a recognised basis in industry, which should help digital twin with the objective of its progressive integration as a future learning ecosystem.

*Keywords:* Digital Twin, Learning Ecosystem, Manufacturing,
Human-machine collaboration, Learning Factory, Cyber-physical system

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## 1. Introduction

With the empowerment of workers' digital-based skills in manufacturing environments, human-machine collaborative ecosystems supported by Digital Twins (DT) will ultimately be a trend. Today, the digital twin concept is called to accomplish the integration between physical and digital worlds in manufacturing as one of the most promising Industry 4.0 (I4.0) enabling technologies (Liu et al., 2021), (Kritzinger et al., 2018). By the physical-digital convergence, digital twin is able to represent an abstraction of manufacturing systems' reality that allows for multiple interaction levels between processes, systems, and workers within the virtual space (Semeraro et al., 2021), building complex virtual models. In this way, a virtual model acts as a point of knowledge (Tao et al., 2019b) by providing direct access to existing plant-process information in real-time, as an integral part of a Digital Twin Learning Ecosystem (DTLE). Thus, the interaction of workers and the integration of digital information with the real environment, provides the plant ecosystem with the cyber-physical connections and digital twin data flows. At the same time, all the required counterpart relationships that collect data as input to agile methods, adaptive learning, process simulation and service planning, among others, are represented. During this time, the manufacturing industry has taken advantage on the digital twin learning opportunities presented by the development of new generation of information technologies applied to physical-digital convergence (Raptis et al., 2019). However, an important consideration when discussing lifelong learning and training in industry is that they are increasingly dependent on highly skilled workers and digital changes to improve the working methods (Toivonen et al., 2018). In this context, the potential of digital twin and its real-time cooperation between machines and human resources offer continuous learning opportunities to clear away obstacles in technological environments (Berisha-Gawlowski et al., 2021). Through the combination of such factors as the human-machine learning (Ansari et al., 2018), as well as the Learning Factory (LF) concept (Tvenge et al., 2020), physical and virtual environments are set to improve the skill set of the future workforce, which includes all processes, products, resources and categories of people in different manufacturing activities, regardless of age, gender and social status. Moreover, in line with the building process of a connected Digital Twin Learning Ecosystem, many different angles of the manufacturing context can be explored on all the aforementioned levels interacting at the same time.

In the cyber-physical connection process, a paradigm shift was imposed to manufacturing plants where data operations can be gathered in real time through new smart sensors supported by Industrial Internet of Things (IIoT) gateways. In that regard, the concept of digital twin is not really new in manufacturing. Originally, Grieves conceived digital twin on a conceptual level linked to Product Lifecycle Management (PLM) in 2003 (Grieves, 2003), (Grieves & Vickers, 2017). He defined a conceptual model that contains three main parts: the *Real Space* (physical products), the *Virtual Space* (virtual products) and the bidirectional data flow links between them, including virtual sub-spaces. Later, (Grieves, 2014) extended his own digital twin concept in manufacturing through Virtual Factory Replication, where the physical product and the virtual product can be viewed and compared at the same time in a closed-loop. In this way, towards the comprehension of new physical-digital learning enablers and challenges in the Industry 4.0 era, next-generation manufacturing systems are supported by adopting digital twin frameworks (Pérez et al., 2020), and theoretical and practical Learning Factories knowledge models (Baena et al., 2017), (Prinz et al., 2016).

During the last decade, the digital twin role has been improved with different approaches and definitions focused on the manufacturing domain, considering that digital twin is still mainly in an early concept stage (Kritzinger et al., 2018). Furthermore, (Negri et al., 2017) remarked the need for future digital twin research on relevant industrial applications, in order to express their potential through effective demonstrations for Industry 4.0 manufacturing contexts. Regarding current studies for realising digital twin in Industry 4.0, (Tao et al., 2019b) summarises the state-of-the-art of digital twin research and its application in different industries as a reference guide. In addition, the paper poses many pressing issues, such as a unified digital twin modeling method, which should be addressed to enhance a rapid digital twin evolution in practice. In a different work, (Lu et al., 2020) reviews the connotations, application scenarios, and research issues of digital twin-driven smart manufacturing in the context of Industry 4.0. Some digital twin aspects focused on manufacturing assets, people, factories and production networks are presented as playing a crucial role in the vision of smart manufacturing.

The purpose of our research is to reach a better understanding of the holistic approach offered by Industry 4.0 Digital Twin Learning Ecosystems in a collaborative way. Some of the main outputs concerning the physical-digital learning explored are aligned with worker training programs oriented towards appropriate digital skills. The rest of the paper is organized as follows (Figure 1). Section 2 describes the research methodology. Section 3 addresses a literature review to understand the learning opportunities offered by digital twin in manufacturing under the Industry 4.0 paradigm. Section 4 presents different enablers of knowledge in Industry 4.0 manufacturing systems. Section 5 describes the main digital twin learning challenges and research priorities that need to be met in manufacturing. Finally, Section 6 presents the findings and conclusions derived from this work.

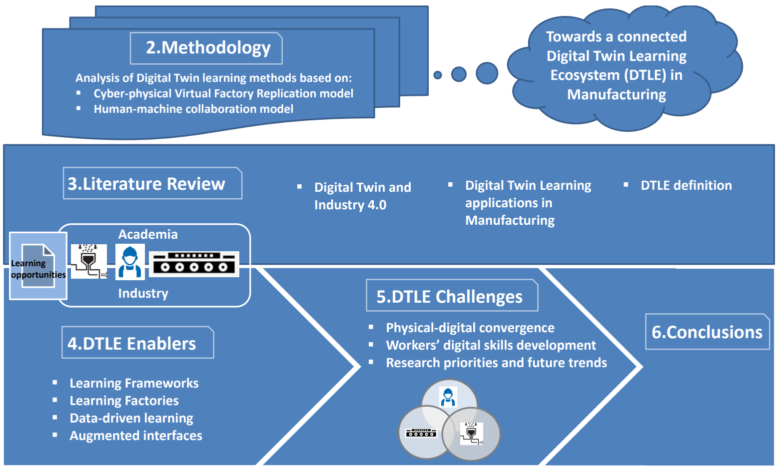


Figure 1: Scope of the research

## 2. Methodology

This research is motivated by the digital twin concept presented by Grieves and focused on a connected physical-virtual model. Existing technical articles and scientific research on industrial digital twin ecosystems are considered to study human-machine interaction methods based on applications, frameworks and collaboration models used for decision-making and training in manufacturing. Apart from this, in this work we also analyse the current enablers and challenges found in the physical-digital convergence.

Figure 2 describes the research methodology conducted in this paper. Two literature databases were considered. First, Scopus is used as the main database, while, Google Scholar is used to complete and enrich the Scopus results. We filtered papers by their publication year, starting in 2015 (this review aims to show the latest advances, so older papers are not considered) and finishing in 2021.

Since we focus on the digital twin concept in manufacturing environments, all our searches always included the so called domain keywords in Figure 2, which are **“Digital Twin”** and **“manufacturing”**. Then, we proceeded with our search in different phases, by adding selected keywords following the main objectives of the paper:

1. Reviewing Industry 4.0 driven applications of digital twin, which offer human-machine cooperation opportunities in smart manufacturing ecosystems from both academia and industry.
2. Understanding the emerging Digital Twin Learning Ecosystems, focusing the research topic on both theoretical virtual factories and connected real collaborative ecosystems in manufacturing.
3. Reviewing the current enablers, challenges and research priorities in developing Industry 4.0 Digital Twin Learning Ecosystems.

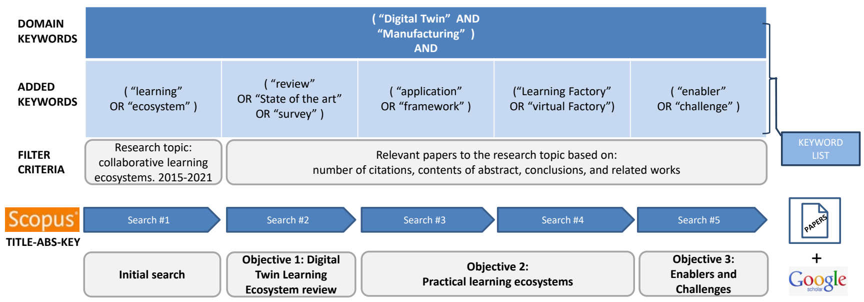


Figure 2: Iterative search methodology conducted

First, we proposed an initial search *(search #1)* based on the research topic: Digital Twin Learning Ecosystems in Manufacturing, composed as follows: *“Digital Twin” AND “manufacturing” AND (“learning” OR “ecosystem”)*. As a result, 271 papers were found. However, only 9 of those papers were useful for our review. For the remaining papers, the filter criteria did not provide practical manufacturing digital twin applications in the context of a cyber-physical human-machine collaboration as intended in the review, others presented a digital twin limited contribution, and 115 papers were not publicly available. Because of this, we reoriented our search strategy by using more general keywords, following the intended objectives of the review, and then selecting the most relevant papers to the research topic based on: (i) number of citations, (ii) abstract' content, (iii) conclusion' content, and (iv) related works.

For the first objective, survey-type papers were searched *(search #2)* composed as follows: *"Digital Twin" AND "manufacturing" AND ("review" OR "State of the art" OR "survey").* We found 212 papers, of which some preliminary literature findings were identified, underpinning the research topic in the context of the Digital Twin Learning Ecosystem. Table 1 shows the 7 selected most relevant papers together with Grieves' paper. On that basis, the detailed digital twin context, related Industry 4.0 enabling technologies, learning ecosystem approaches and human-machine collaboration enablers, were examined in order to validate the scope and retrieval strategy.

For the second objective, two different searches were performed looking for practical learning ecosystems. The list of keywords was improved to include applications and connected frameworks, having a third search *(search #3)* composed as follows: *"Digital Twin" AND "manufacturing" AND ("application" OR "framework")*, selecting the most representative papers (20), from 761 results. Then, we included "Learning Factory" and "virtual factory" strings for and additional search *(search #4)* composed as follows: *"Digital Twin" AND "manufacturing" AND ("learning factory" OR "virtual factory")*, selecting the most representative papers (7), from 30 results, and completing the selection of works for this second objective.

Finally, for the third objective, we added the keywords for digital twin "enablers" and "challenges", having a fifth search *(search #5)* composed as follows: *"Digital Twin" AND "manufacturing" AND ("enabler" OR "challenge").* The identified papers (13), from 294 results, had already been selected in previous searches.

Additionally, Google searches using the list of selected keywords, helped to complete our iterative search, including some new technical and original articles. We found over 60 documents from Google search, to grasp the digital twin learning opportunities emerging from the collaboration between industry and academia.

## 3. Literature Review

This section aims to contribute with diverse learning approaches applying the digital twin concept in theoretical and existing manufacturing ecosystems in line with Industry 4.0 physical-digital convergence. Through the revision of scientific literature and original articles, the paper is aligned to derive knowledge from both the research community and real scenarios in the manufacturing industry.

In addition, our work proposes an original definition of Digital Twin Learning Ecosystem in the manufacturing domain.

### *3.1. Digital Twin and the Industry 4.0*

At the beginning of 2015, the general Industry 4.0 definition and its main design principles (*interoperability*, *virtualization*, *decentralization*, *real-time capability*, *service orientation*, and *modularity*) were presented in (Hermann et al., 2015) as a "how to do" Industry 4.0. The definition already includes the four Industry 4.0 key components: *CPS*, *IoT*, *IoS* and *Smart Factory*. The integration of these components is standardised in the "Reference Architecture Model Industrie 4.0" (RAMI 4.0) as a service-oriented architecture for the development of Industry 4.0 applications and the development of models for smart manufacturing ecosystems (Adolphs et al., 2015). Also, in 2015, the term "Smart Manufacturing" (SM) was introduced in the United States to deploy the new technologies in manufacturing, such as IIoT and Artificial Inteligence (AI). The National Institute of Standards and Technology (NIST) defined SM as *"fully-integrated, collaborative manufacturing systems that respond in real time to meet changing demands and conditions in the factory, in the supply network, and in customer needs"* (Tantawi et al., 2019).

| References | Digital Twin Context | Related Industry 4.0 enabling technologies | Learning Ecosystem | Human-machine collaboration enablers |
|---|---|---|---|---|
| (Grieves, 2014) | Focused on the connection between the physical product and the virtual product. It changes the way of understanding manufacturing processes from digital factory simulation model (prediction), to digital factory replication model (production) | Physical non-destructive sensing technologies | Virtual factory replication model, using conceptualization, comparison and collaboration capabilities as human-knowledge tools | Synchronization between physical product data and virtual product information |
| (Kritzinger et al., 2018) | Production science providing a holistic overview of the enabling technologies and areas of Digital Twin application, as basis for further work | Simulation, communication protocols, IoT, cloud computing, big data | Data-driven models applied in simulation, process control and condition-based maintenance | Simulation and optimization of the production system |
| (Tao et al., 2019b) | Enabling technologies for the Digital Twin based on data modeling-simulation, data-driven and cyber-physical fusion | Cyber-physical manufacturing system | Cyber-physical manufacturing system with information about a real-world situation and operating status analytical assessment for predictive diagnosis, and performance optimization | Interaction and collaboration using physical data, virtual data, connection data, service data, and data fusion |
| (Lu et al., 2020) | Current status and advancement of Digital Twin-driven smart manufacturing | Industrial communications and protocols, simulation, CPS, IoT, Big Data | Convergence of the digital-physical worlds enabling smart decisions | Manufacturing systems augmented with cognitive intelligence. Understanding strategies of human state at workforce to increase the physical and psychological health of workers, as well as achieving best production performance |
| (Tao et al., 2019a) | Integration between physical and cyber/digital worlds using a model-based systems-engineering approach that emphasizes data and models | CPS | Creation of high-fidelity virtual models to realistically reproduce physical properties, behaviors, and rules of the physical world, and usage of a bidirectional dynamic mapping where the physical entities and virtual models co-evolve | Real-time interaction and organization integration |
| (Fuller et al., 2020) | Status of Digital Twins with IoT/IIoT and data analytics to optimise the manufacturing processes | IoT/IIoT | Real-time simulation-based to learn and monitor simultaneously applying machine learning algorithms | Health of the machines and predictive maintenance |
| (Cimino et al., 2019) | Degree of integration between Digital Twin and a physical control system through a Manufacturing Execution Systems (MES) based on the Automation Pyramid | CPS, industrial communication protocols | Simulation model at assembly laboratory line that focuses on monitoring machine states and the energy consumption. Data can be analysed to understand the steps performed | Real-time replication of the machine states of each station in laboratory |
| (Qi & Tao, 2019) | Improvement of different levels of shop floor intelligence supported by three-way real-time applications with high availability in a cloud-based smart manufacturing paradigm | Cloud computing, fog computing, edge computing | Digital twin shop-floor framework. Real-time service collaboration layer using a "Human-Machine-Material-Environment" approach to constantly acquire the status data of the physical resources | Users are connected with the manufacturing shop-floor through cloud services to complete the task collaboratively |

Table 1: Selection of relevant review papers in the context of Digital Twin Learning Ecosystem

Nowadays, the most representative terms of these definitions and technologies have been adopted globally by industry and academia. Overall, their key characteristics and technologies (Mittal et al., 2019) serve as a guide to the implementation of I4.0-enabled manufacturing systems. In a scenario led by the cyber-physical convergence of Industry 4.0 ecosystems (Qi et al., 2018b), the concept of digital twin emerges as one of the most disruptive innovations to exploit data enabling industrial technologies (Raptis et al., 2019). Owing to their growing relevance, Gartner Hype Cycle (Dedehayir & Steinert, 2016) named digital twin as one of the "Top 10 Strategic Technology Trends" from 2017 to 2019 (Qi et al., 2019). There is a paradigm shift moving from the traditional product-oriented manufacturing to service-oriented manufacturing (Moghaddam et al., 2015). This landscape allows value to be added through connected services, specialized skills, learning tools to support new collaborative business models, and hybrid digital twin data-driven approaches such as monitoring, diagnostic and prediction (Lu et al., 2020). Even though the digital twin concept has been improved in manufacturing with different approaches and definitions (Negri et al., 2017), and refined in system theoretical terms for learning, optimization, and control (Cronrath et al., 2020), it is certainly true that several works show that research outcomes for digital twin in this domain are mainly on a conceptual level. In this regard, many articles are of a foundational nature (Holler et al., 2016), some works are recent (Negri et al., 2017), and many researchers are starting to derive the first steps of digital twin in practice (Kritzinger et al., 2018).

Academia and industry have different visions about how to understand and apply digital twin as a tool of knowledge responding to dynamic changes in manufacturing processes (Parrott & Warshaw, 2017). However, it is a fact that a standardised framework to develop a digital twin in manufacturing, such as the ISO 23247 (Shao & Helu, 2020), can help the acceptance of the digital twin concept (Shao et al., 2021). In the meantime, technological vendors have their own interpretation of the digital twin concept (Schleich et al., 2017) and continue with its research and development in accordance with their customers and business models. For example, General Electric (GE, 2016) provides a cloud-based platform with analytic models. ANSYS[2], ALTAIR[3] and ESI GROUP[4] have their origins in Computer Aided Engineering (CAE) supporting physics-based simulation and virtual prototyping. Moreover, the ESI GROUP‘s "Hybrid Twin" concept introduces a complementary physics-based virtual model to describe cause-effect relationships (Chinesta et al., 2020). Another different solution implemented by SOFTWARE AG[5], PTC[6] and Siemens[7] provides a PLM-based platform supporting AR and IoT management cloud. Enabling technologies like AR in digital twin ecosystems derives added value for human-machine interface integration, visualization and learning of the digital twin data (Zhu et al., 2019). Thus, the advent of connected digital twin models in manufacturing has enhanced the development of collaborative skills 4.0 and training capabilities (Fantini et al., 2020), providing workers with direct access to existing plant-process knowledge to perform technical tasks, or using their inputs as part of the learning process (Graessler & Poehler, 2018b).

### *3.2. Digital Twin learning applications in manufacturing*

New digital twin learning applications are emerging in a virtual space to provide manufacturing ecosystems' reality with an additional knowledge layer. It is with this perspective that the connected digital twin enables different applications and ways to collaborate between humans and automated production systems. Moreover, distributed learning gives opportunities for modelling the multiple interactions between processes (Kunath & Winkler, 2018), systems

[2]https://www.ansys.com/products/systems/digital-twin

[3]https://www.altair.com/resource/altair-digital-twin-platform

[4]https://www.esi-group.com/blog/hybrid-twin-vs-digital-twin-well-tell-you-the-difference-and-which-can-save-the-life-of-your-asset

[5]https://www.softwareag.com/en_corporate/platform/iot/iot-digital-twins.html

[6]https://www.ptc.com/en/product-lifecycle-report/what-is-digital-twin-technology

[7]https://www.plm.automation.siemens.com/global/en/our-story/glossary/digital-twin/24465

(Reid & Rhodes, 2016), and workers' skills (Graessler & Poehler, 2018a).

As a result, three categories reporting digital twin applications in manufacturing environments are presented discussing learning opportunities in academia and industry below. These are as follows: *human-machine interaction applications*, *training applications* and *data-driven applications*. Table 2 summarises several articles classified in these three dimensions by the digital twin approach used for learning (in the second column), as well as a summary of the aims, features and benefits presented.

### *3.2.1. Human-machine interaction applications*

Towards the concept of a learning ecosystem (Burke et al., 2017), digital twin offers bidirectional interaction in real-time dealing with different data sources in order to transform information into valuable knowledge (Uhlemann et al., 2017a). The use of human-machine interfaces is therefore promoting the implementation of digital twin applications oriented to collaborative environments (see Table 2). A context-aware and adaptive digital twin model (Hribernik et al., 2021) offers human-machine complex interactions related to manufacturing processes, while they are involved in an intelligent data space. In this collaborative context, a social-based framework of interconnected manufacturing systems of workers, assets and services also takes place. Virtual, physical and social worlds are integrated around a Cyber-Physical-Social System (CPSS) approach, on the concept of social manufacturing (Leng et al., 2020).

Collaborative learning models, present strategies for evaluating workers' skills in CPS environments, enable local or remote interaction services and provide intuitive augmented applications to monitor and control processes. For example, studies such as (Graessler & Poehler, 2018b) show a conceptual approach of a digital twin application involving workers and CPS devices in an experimental assembly station of a production laboratory, in fully automated decision-making processes. In addition, there are other studies focused on the

| Dimension | DT approach | Aims | Features | Benefits | References |
|---|---|---|---|---|---|
| **Human-machine interaction applications** | Experimental production setup | Automated computational decision processes | Learning through the evaluation of workers‘ skills | Intuitively interaction of workers with technical devices in CPS environments | (Graessler & Poehler, 2018b) |
| | Knowledge fruition as a service | Enable a Smart Factory 4.0 with augmented interfaces | Interaction service between operators working in-situ or remotely and CPPS | Industrial performances in terms of productivity and process quality standards | (Padovano et al., 2018) |
| | Comprehensive visualisation of augmented information | HMI to improve workers‘ efficiency | Intuitive AR application to monitor and control a machining process | Taking advantage of operative data to perform efficient decision-making and higher level machine control | (Zhu et al., 2019) |
| **Training applications** | Learning Factories | Competence development | Path towards Industry 4.0 into an academic context | Convergence of the real world and cyber physical system | (Baena et al., 2017) |
| | | Practical learning | Workplace-integrated learning system for knowledge-based manufacturing | Transfers learned knowledge directly to the own workplace | (Prinz et al., 2016) |
| | | Training in similar research fields of conventional physical learning factories | Planning and simulation activities | Digital and virtual environment for providing added value for the education of the production of the future | (Abele et al., 2017) |
| | | Manufacturing education | Cognitive process when working in, or with, VR/AR learning environments | Interlinkage between the digital and physical twin concerning cognition and learning | (Tvenge et al., 2020) |
| | Enhanced interaction framework | Create an augmented and interactive environment | Immersive and multi-perception interaction experience brought by VR/AR/MR | Augment the seamless integration between the physical and virtual worlds | (Ke et al., 2019) |
| **Data-driven applications** | Manufacturing cyber-physical system (MCPS) | Dynamic autonomous system to co-create personalized products | Bi-level online intelligence in proactive decision making for the organization and operation of manufacturing resources | Enable continous improvement based on an intelligent optimisation engine | (Leng et al., 2019) |
| | Machining process evaluation (DT-MPPE) | Methods for dynamic change of the machining condition and uncertain available manufacturing resources | Maintaining consistency of processing quality for the machined parts | Improvement of the machining efficiency by integrating the cyber and physical space in manufacturing | (Liu et al., 2019) |
| | Assisted fault diagnosis method using deep transfer learning (DFDD) | Fault diagnosis both in the development and maintenance phases | Transfer simulation results learned from the virtual space to the physical space without training the model from scratch | Enhance fault diagnosis in virtual space and physical space to be more transparent, flexible, and efficient | 6 (Xu et al., 2019a) |

Table 2: Classification of Digital Twin learning applications in manufacturing

usefulness of augmented interfaces. (Padovano et al., 2018) presented a DT-based application designed to enable a knowledge as a service approach in a real factory floor producing carton packaging boxes. The digital twin prototype provides workers with a real time CPPS-based 4.0 knowledge navigation service linked to an Android application with a QR code. The workers can use this application, a screen interaction or a vocal message to request specific knowledge, keeping their attention directly on the physical system. Another collaborative scenario, based on an AR human-machine interface for the visualization of digital twin data, is presented in (Zhu et al., 2019). An AR application is used to provide workers with comprehensive information to monitor and control a CNC milling machine in a real manufacturing environment. The connected framework also allows the worker to interact and manage digital twin data in order to improve the process efficiency through an augmented approach.

#### *3.2.2. Training applications*

It is known that workers' knowledge is improved by different backgrounds and outcomes in training processes. Likewise, experienced workers are necessary to guide others with little experience. Nevertheless, training applications of digital twin in manufacturing require a collaborative learning framework as the basis for generating knowledge towards decision support systems. In this way, learning factories offer a path towards Industry 4.0 in an academic context, while promoting the integration of learning systems in the workplace by transferring lessons learned for knowledge-based manufacturing, through the convergence of the real world. Apart from this, training in virtual environments encourages the cognitive process when working in immersive and multi-perception environments with augmented learning.

Some studies included in (Table 2) show that the Learning Factory concept is evolving in manufacturing to support Industry 4.0 enabling technologies (Baena et al., 2017) and practical learning activities (Prinz et al., 2016), as a promising training and research environment where digital twin combines both industrial scenarios and academic applications (Abele et al., 2017). The communication and interaction between teams of engineers and researchers establishes a two-way knowledge to bring real industrial environments to teaching programmes and research laboratories to factories. Also, in a Learning Factory context, the digital twin concept offers learning opportunities for the representation and visualisation through mapping of real processes in digital and virtual models (Tvenge et al., 2020). AR/VR technologies also provide workers with enhanced interaction frameworks and augmented interfaces (Ke et al., 2019).

### *3.2.3. Data-driven applications*

(Kunath & Winkler, 2018) defines digital twin *"as the sum of all available data, i.e. engineering data and operational data, of all elements of the manufacturing system that reflect the historical and actual state of the system in real-time"*. In the context of industrial applications, therefore, digital twin provides a connected data infrastructure able to help with the generation of data-driven models in proactive decision making, maintaining process & product quality and transferring results learned - from simulations in the virtual space to the physical space - without training the model from scratch.

Some different real-time data-driven learning applications can be found in the literature based on the digital twin approach (see Table 2). For example, in (Leng et al., 2019) a systems engineering-based approach of a digital twin to co-create personalised products is presented. A demonstrative implementation scenario is characterised by a DT-driven manufacturing CPS for parallel control of a smart manufacturing workshop. Through the analysis of a dynamic process execution, digital twin provides workers with the status of manufacturing operation and enables continuous improvement with an intelligent optimisation engine. Another different solution is proposed in (Liu et al., 2019) using a DT-based process planning evaluation method with real-time data status. The implementation is addressed in a manufacturing workshop of key parts of the marine diesel engines, where planning evaluation is required to ensure consistency of processing quality of manufactured parts. IoT and digital twin technologies allow the improvement of the machining efficiency by using a dynamic physical-virtual information about the process status. On the other hand, data analysis enables behaviour-based applications focused on CPS. For example, a DT-assisted fault diagnosis method for real-time monitoring and predictive maintenance is presented in (Xu et al., 2019a). The case study is implemented in a car body-side production line, where a Programmable Logic Controller (PLC) allows data interconnection and interaction. Through a two-phase using deep transfer learning, the application of digital twin in virtual and physical spaces transforms fault diagnosis patterns in knowledge for both development and maintenance phases, thus reducing the risk of accidental breakdowns.

### *3.3. Definition of Digital Twin Learning Ecosystem*

This paper aims to identify and define a Digital Twin Learning Ecosystem. In this way, (Gartner, 2017) defines Digital Ecosystem as *"an interdependent group of actors (enterprises, people, things) sharing standardized digital platforms to achieve a mutually beneficial purpose"*. In a manufacturing production plant, for instance, those interdependent groups of actors can be represented by processes, systems and workers. Another definition, focused on the Digital Learning Ecosystem, is proposed by (Ficheman & de Deus Lopes, 2008) as *"the set of all relationships between biotic factors (consisting of hardware, software, network and database technologies as well as pedagogies) and abiotic factors (human specie and digital specie)"*. According to this, it is the abiotic factor which provides the environment that supports interactions between biotic factors. In addition, a different definition of Learning Ecosystems is proposed by (García-Holgado & García-Peñalvo, 2017), as *"a type of technological ecosystems focused on learning management processes"*, where the technological ecosystems are *"the evolution of the traditional information systems, providing support to* *information and knowledge management in heterogeneous environments.”*. As mentioned above, digital twin applications in manufacturing will provide workers with learning services in order to augment their working experience and performance. However, without a bidirectional and adaptive physical-digital synchronisation at a factory wide-level, this knowledge would not be effective (Padovano et al., 2018).

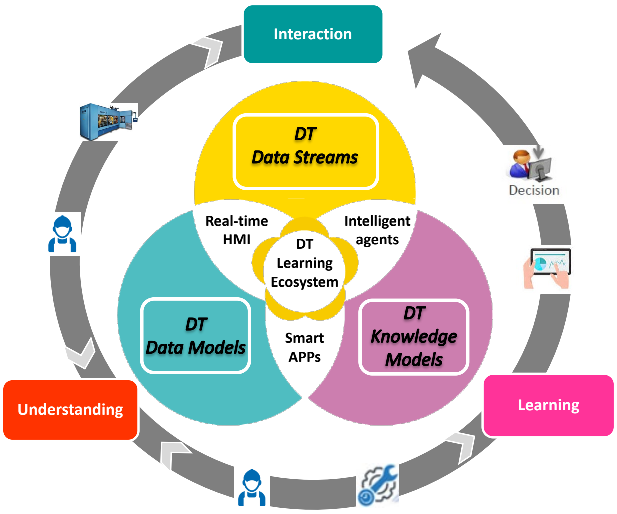


Figure 3: Proposed three-layer Digital Twin Learning Ecosystem

To the best of our knowledge, there is no specific definition for a Digital Twin Learning Ecosystem in Manufacturing. After successful completion of previous R&D studies carried out and tested in our lab[8], we define three feedback conceptual layers focused on the generation of an adaptive learning framework. They are oriented to human-machine collaborative ecosystems in the context of Industry 4.0 as digital twin input (see Figure 3), providing a physical-digital

[8]Due to the requirements for anonymized manuscript submissions at Computers & Industrial Engineering, the work is not cited in this version of the paper

connection, smart human-machine interfaces, and cognitive skills:

- **DT Data Streams**. Real-time information from systems and workers via multiple and heterogeneous manufacturing data sources, such as measuring devices, augmented human-machine interface devices, industrial automation middleware, process control systems or other software programmes, using a standardised data format.
- **DT Data Models**. Management, monitoring and virtualization services applied to manufacturing data that will be used further as datasets by high-level AI applications, building digital objects of all ecosystem resources to extract valuable information about the whole production life cycle.
- **DT Knowledge Models**. Variability of smart views providing a complete immersion in a knowledge-based augmented human-machine manufacturing ecosystem, where a virtual representation of all actors of the manufacturing environment is set through intelligent agents, describing their real world counterparts to model decision-making actions, based on learned data.

Therefore, as a result, we propose the definition of a Digital Twin Learning Ecosystem in Manufacturing as follows:

**Definition 3.1** (**Digital Twin Learning Ecosystem**). An augmented physical-digital way of bidirectional interaction, understanding and learning between workers, systems and processes in a framework integrated by virtual and real Intelligent Manufacturing Ecosystems.

## 4. Enablers

(Grieves, 2014), anticipated the advances in computing capabilities as an important enabler of the future knowledge potential for the digital twin concept in manufacturing. Furthermore, he proposed a *cyber-physical Virtual Factory*

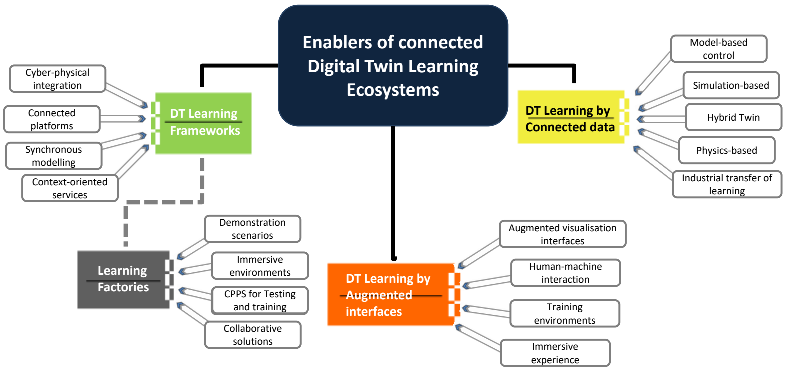


Figure 4: Digital Twin Learning Ecosystems enablers and main properties

*Replication model*, advancing the digital twin concept forward in human knowledge through the fusion of three of its skills: *conceptualization*, *comparison* and *collaboration*. Thus, this section presents different Digital Twin Learning Ecosystem scenarios as enablers of knowledge in Industry 4.0 manufacturing systems. The main properties of these digital twin enablers are summarised in Figure 4. Some approaches comprising connected collaborative digital twin frameworks and their key features are described and, in addition, the role of the Learning Factory concept is examined. In a similar way, digital twin data-driven approaches to enable knowledge models are presented. Finally, digital twin augmented interfaces driven by human-system interaction to enable learning capabilities in manufacturing environments are discussed.

### *4.1. Digital Twin Learning Ecosystems frameworks*

The emergence of connected platforms supporting digital twin frameworks, provides manufacturing with a learning ecosystem oriented towards exploiting knowledge from the integration of physical and digital worlds. Figure 5, describes an example of a connected digital twin learning framework at Research and Development Centre labs[9], which has been designed and tested for the proactive collaborative maintenance (local and remote) of manufacturing assets. The framework is focused on the generation of a non-intrusive and fully two-way adaptive human-machine collaborative ecosystem, supporting workers' training and enhanced learning. In addition, the proposed real-time Augmented Reality (AR) and Virtual Reality (VR) augmented frameworks for visualising digital twins enable the development of skills 4.0, while providing direct access to existing manufacturing-process knowledge bridged through smart sensors.

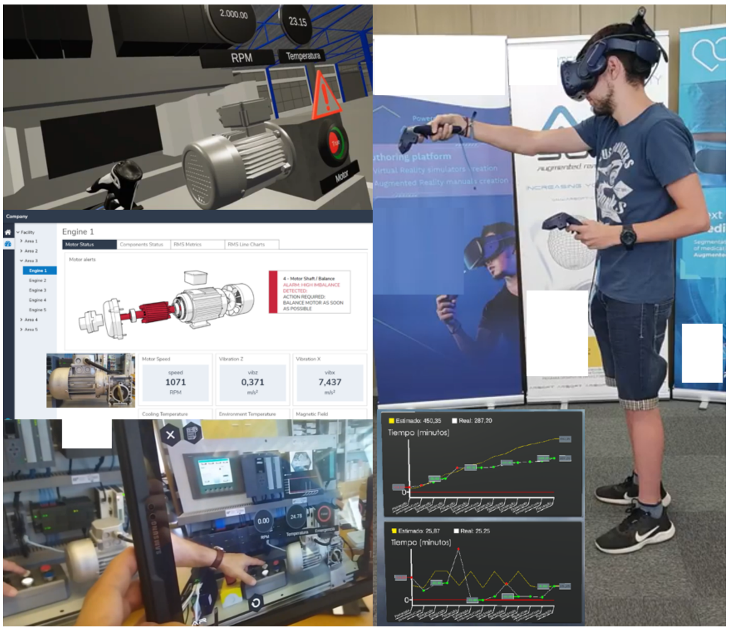


Figure 5: Example of a Digital Twin framework to enable learning ecosystems at Research and Development Centre labs

[9]Due to the requirements for anonymised manuscript submissions at Computers & Industrial Engineering, the name of the research center is not mentioned in this version of the paper

In the literature, some Digital Twin Learning Ecosystems based on frameworks are identified and discussed below. Table 3 summarises these frameworks, whose learning features aims to enable effective competences (David et al., 2018), enhanced skills (Caldarola et al., 2018), more efficient engineering solutions (Yildiz et al., 2020), improved human-asset interaction (Kong et al., 2020), synchronous modeling (Zhuang et al., 2021), human-robot collaborative systems (Malik & Bilberg, 2018), improved quality and resources (Qamsane et al., 2019) and support fault diagnosis (Mi et al., 2021). As a result, Digital Twin Learning Ecosystems enable a distributed approach focused on achieving a connected learning model of a product (Tao et al., 2018), process or industrial service (Tao et al., 2019b). It is thus necessary for a real-time replicated representation of the physical world to be built for understanding purposes, while the technological frameworks offer its own digitised data and fully bidirectional interaction capabilities (Qi et al., 2019).

Different teaching methodologies proposed in (David et al., 2018) can allow a learning framework involving digital twin in the context of manufacturing pedagogy. Methodologies and tools are investigated to educate university students in a pedagogical digital twin framework of production-based engineering environments, using engineering model outcomes and evaluating student performance. The learning experiences are evaluated in three scenarios: *passive learning in classroom*, *experimental learning in laboratory and physical site*, and using a *situational awareness approach* for a better understanding of workers' process perception.

(Caldarola et al., 2018) proposed a different solution, based on a conceptal framework for social manufacturing sustainability 4.0. A knowledge-based approach supported y CPS, intelligent software and AR/VR systems, allows the skills and competences of the workforce to be enhanced focusing on the production process of wooden furniture. The digital twin concept is underpinned by representational models ensuring continuous learning about the whole factory: a *digital factory model* of the entire production system, a *virtual individual model*

| DTLE enablers | Aims | Approach to the acquisition of knowledge | Process / Product / Service | References |
|---|---|---|---|---|
| Pedagogical digital twin framework to educate university students on manufacturing systems | Effective development of learning experiences and competences | Practical application of the acquired knowledge or skill in different flexible manufacturing environments | Flexible Manufacturing System (FMS) Training Centre | (David et al., 2018) |
| Conceptual framework for social manufacturing | Enhance skills and competences of the workforce | Continuous learning about the whole factory | Process of Wooden furniture | (Caldarola et al., 2018) |
| Framework architecture for supporting Factory life-cycle processes | Implement more efficient engineering solutions | Evaluation of manufacturing systems | Wind turbine manufacturing plant (Vestas) | (Yildiz et al., 2020) |
| Interactive data-driven digital twin framework for asset management | Improve human-asset interaction and decision making | Understanding of assets' lifecycle and operational decision support | Offshore energy assets | (Kong et al., 2020) |
| Framework of assembly data management and process traceability for complex products | Synchronous modelling of the product, and management | Participatory approach managing each stage of the product lifecycle | Satellite assembly process | (Zhuang et al., 2021) |
| Framework to support the design, building and control of human-machine cooperation | Human-robot collaborative system for assembly work | Simulation of the behaviour of the system by creating virtual models of physical objects | Human-robot collaborative (HRC) system | (Malik & Bilberg, 2018) |
| Framework to improve control reconfiguration, self-organizing and learning | Improve quality and optimise production resources | Monitor and evaluate large-scale SM systems | Manufacturing flowshop | (Qamsane et al., 2019) |
| Cooperative awareness and interconnection framework for predictive maintenance | Support fault diagnosis and prediction with higher accuracy and reliability | Decision-making approach | Large vertical mill | (Mi et al., 2021) |

Table 3: Examples of Digital Twin Learning Ecosystems based on frameworks

of the workers' profiles, and a *skills virtual model* based on workers' capabilities. The framework facilitates the implementation of a user-centred approach where workers interact with systems and processes to develop context-oriented services useful for a smart workplace.

Another collaborative solution is presented in (Yildiz et al., 2020), in which a concept of a DT-based virtual factory shows the integration between product, process and system. The digital twin framework architecture supports factory life-cycle processes in a wind turbine manufacturing plant (Vestas) employing collaborative VR learning and training scenarios. Both factory data -from real systems- and generated data -from simulation systems-, are integrated for the evaluation of manufacturing systems, bringing potential to implement more efficient engineering solutions.

A different problem addressing human-machine interaction is presented in (Kong et al., 2020). An interactive data-driven digital twin framework is used to improve human-asset interaction and decision making for offshore energy assets. The complete digital twin framework uses embedded and front-end sensors which can capture, synchronise and exchange physical-digital data. Data-driven digital twin methods allow events between the environment, workers and assets to be simulated, enabling a better understanding of the life-cycle of the assets. This digital twin framework also provides intuitive interfaces to enhance workers' knowledge oriented to operational decision support.

Another example is also proposed in (Zhuang et al., 2021). This work is characterised by a DT-based framework for assembly data management and process traceability approach. A participatory approach to produce complex products such as satellites, means that each stage of the product lifecycle is managed for all the components and has the electronic feedback of workers. The digital twin application provides the assembly process with a synchronous modelling of the product, hierarchical management and traceability data, reflecting human-computer interactions.

A different assembly application, characterised by a digital twin interconnected framework to develop a human-robot collaborative system, is presented in (Malik & Bilberg, 2018). In this case, a digital twin of an assembly workstation allows a virtual commissioning approach to test, validate and optimise the behaviour of the dynamic system by creating virtual models of physical objects.

In addition, predictive maintenance techniques and monitoring systems are widely extended in smart manufacturing as valuable human-machine interfaces for decision-making frameworks. For example, in (Qamsane et al., 2019), a digital twin framework to improve control reconfiguration, self-organizing and learning in a manufacturing flow-shop is presented. The digital twin framework is based on a novel architecture to monitor and evaluate large-scale SM systems. It includes historical and real-time data to provide comprehensive digital twin capabilities such as prediction, anomalies detection, monitoring and health state. The construction of a global view of the SM system helps to improve quality and optimise production resources.

Another framework example, focused on predictive maintenance and fault diagnosis, is presented in (Mi et al., 2021). A digital twin driven cooperative awareness and interconnection framework for predictive maintenance, is applied to the decision-making approach of a large vertical mill. Digital twin is used to support fault diagnosis and prediction with higher accuracy and reliability through a comprehensive analysis method. The framework is designed to share data models and knowledge models in order to obtain more accurate and detailed information of the diagnosis across multiple organizations.

#### *4.1.1. Learning Factories*

Digital twin learning approaches in Learning Factories combine academic applications and demonstration scenarios. In this way, virtual factory replication and the Learning Factory concept also allow the implementation of complex scenarios and frameworks for testing and training in a diversity of collaborative levels as Digital Twin Learning Ecosystem enablers. Table 4 summarises six exemplary scenarios existing in outstanding research and educational institutions, as described in some works below. Researchers, experts in the use of next gen-

| **Exemplary scenarios** | **DTLE enablers** | **Aims** | **Benefits** | **Research groups** | **References** |
|---|---|---|---|---|---|
| Pilot Factory Industry 4.0 | Platform for research and demonstration of mutual human-machine learning | New human-machine learning patterns in highly digitised industrial work scenarios | Development of multi and interdisciplinary skills for Industry 4.0 | TU Wien University, Austria | (Ansari et al., 2018) |
| Chair Manufacturing and Remanufacturing Technology | SME Cyber Physical Production System (CPPS) oriented to experiential training and learning experience | Demonstrate the potentials and advantages of real time data acquisition and subsequent simulation based data processing | Analysis and modification of production systems experienced by workers in practical training sessions | Bayreuth University, Germany | (Uhlemann et al., 2017b) |
| Advanced Manufacturing Research Centre (AMRC Factory 2050) | Immersive environment to suit the application highlighting the varied nature of different sectors | Understanding the technical challenges for a robust production system at different levels | Added value of immersive approaches for business cases to the manufacturing sector | University of Sheffield, UK | (Eyre & Freeman, 2018) |
| Enterprise Service Bus (ESB) Logistics Learning Factory | Cloud- and app-based software that builds on a dynamic, multidimensional data and information model | Collaborative mobile digital shop-floor management system | Human centre management and mobile digital shopfloor meetings | Reutlingen University, Germany | (Brenner & Hummel, 2017) |
| Smart Learning Factory (SLF) at SDU Mads Clausen Institute | Collaborative Factory by embedding the use of discrete event simulation connected with physical objects | Interaction and cooperation between university researchers and industry experts | Smart Learning Factory to enable manufacturing SMEs to capture the benefits of highly complex tools and enablers | University of Southern Denmark | (Grube et al., 2019) |
| Festo Cyber-Physical Factory (CPF) | Develop the digital counterpart of this Industry 4.0 system to replicate its functionalities, data, communications, feedback, emergency and safety aspects | Replicate processes of the Cyber-Physical Factory real production line for product assembly at different stages of the product's lifecycle | Enable predictive maintenance and prognostics services, design and performance improvements, workers' life-long learning | Middlesex University, UK | (Raza et al., 2020) |

Table 4: Examples of Digital Twin Learning Ecosystems based on Learning Factories.

eration information technologies and industry, are already working together to develop learning platforms for research and demonstration (Ansari et al., 2018), experiential CPPS environments for training and learning (Uhlemann et al., 2017b), immersive environments for different applications and sectors (Eyre & Freeman, 2018), collaborative software (Brenner & Hummel, 2017), collaborative factory environments (Grube et al., 2019) and new Industry 4.0 learning approaches in manufacturing (Raza et al., 2020).

In (Ansari et al., 2018), the challenges of a bidirectional process of human-machine learning in the *TU Wien Pilot Factory Industry 4.0*, are addressed. The term "mutual learning" is defined by considering the smart factory as a learning environment and explored in the context of new learning patterns in highly digitised manufacturing work scenarios.

(Uhlemann et al., 2017b) presented a resource efficiency oriented towards a learning environment built up by *The Chair of Manufacturing and Remanufacturing Technologies at Bayreuth University.* This work introduces a Learning Factory concept supported by the digital twin of a production system. It shows the benefits of real-time data acquisition technologies that can be experienced by workers in practical training sessions.

In (Eyre & Freeman, 2018), a different solution is implemented using the digital twin concept to investigate the benefit of immersive applications at the *Advanced Manufacturing Research Centre (AMRC Factory 2050, University of Sheffield, UK).* This work presented three prototypes dedicated to conducting collaborative research with the aim of understanding the technical challenges for a robust production system at different levels using diverse methodologies: (i) a monitoring application exploring the ability to provide a contextual view information for engineers to better understand the current working parameters, (ii) a highly realistic training scenario providing an emulated monitoring digital twin, improving health and safety for workers and also recognising new issues thanks to their expertise, and (iii) augmented monitoring on a reconfigurable fixture cell, integrating real-time simulation of processes into Siemens Plant

Simulation software[10] to enable a closed feedback loop providing workers with contextual information.

A collaborative solution is described in (Brenner & Hummel, 2017) based on a digital twin prototype of an Enterprise Service Bus *(ESB) Logistics Learning Factory at Reutlingen University*. Diverse prototypes of this digital twin, as a digital copy available in real-time, provide a global shop floor meeting concept for workers with the latest information and methods to all their subsystems. It enables an innovative and collaborative mobile digital shop-floor management system based on a cloud app-based software.

Another collaborative approach is described in (Grube et al., 2019). A digital twin to simulate a physical factory layout for manufacturing SMEs in a *Smart Learning Factory (SLF) at SDU Mads Clausen Institute (University of Southern, Denmark)*, allows interaction and cooperation between university and industry experts, building data-driven conclusions. The digital twin concept provides SME' workers with an Industry 4.0 assisted interface for simulating and testing real world operations in the SLF well known by them, such as assembly, laser welding and soldering.

Focused on new Industry 4.0 learning approaches in manufacturing, a digital twin framework replica of the *Festo Cyber Physical Factory (CPF)* is presented in (Raza et al., 2020). The digital twin framework, located at *Middlesex University*, collects IoT data and replicates 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 physical-digital data that is used to enable predictive maintenance and prognostics services, operational information for design and performance improvements, and contributes towards workers' life-long learning.

[10]https://www.plm.automation.siemens.com/global/es/products/manufacturing-planning/plant-simulation-throughput-optimization.html

| DT learning approach | Focus | Reference |
|---|---|---|
| Model based and data driven | Accelerate engineering phase of modern manufacturing systems | (Jaensch et al., 2018) |
| Model-based system engineering (MBSE) | Explore failure modes, leading to progressive design improvements over time | (Madni et al., 2019) |
| Hybrid twin | New paradigm within simulation-based engineering sciences (SBES) using dynamic data-driven application systems (DDDAS) | (Chinesta et al., 2020) |
| Advanced physics-based modeling | Predictive maintenance applications | (Aivaliotis et al., 2019) |
| Industrial transfer learning | Fault prediction training algorithm‘s behaviour for events involving (rare) faults | (Maschler et al., 2021) |
| Assisted fault diagnosis using deep transfer learning (DFDD) | Fault diagnosis both in the development and maintenance phases | (Xu et al., 2019b) |
| Deep generative models | Prognostics and Health Management (PHM) | (Booyse et al., 2020) |

Table 5: Digital twin learning approaches focused on enabling intelligent data models in SM systems.

### *4.2. A Digital Twin learning ecosystem driven by connected data*

Digital twin can enable the transfer of learning to generate knowledge of manufacturing systems by providing an intelligent data approach able to manage the information previously acquired over their lifecycle (Maschler et al., 2021). A way towards enabling these connected ecosystems is digitising industrial processes. As mentioned earlier, digital twin can integrate frameworks which encompass SM systems in a new way to capitalise on knowledge generated with the interaction between workers and CPPS data. Table 5 summarises several digital twin learning approaches which can be used to enable data-driven knowledge models in SM systems. They are focused on the enhancement of manufacturing processes through modeling, simulation, predictive maintenance and fault diagnosis, which are described below.

Machine Learning (ML) is becoming increasingly adopted to enhance digital twin with predictive modelling and intelligence by using data-driven approaches, where both real-time captured data and production historical data help to improve human-machine interactions and decision-making processes. A solution to integrate ML with model-based and data-driven methods, in order to build a digital twin, is proposed in (Jaensch et al., 2018) to control complex manufacturing systems. Two digital twin interfaces are provided in a circular approach throughout the engineering tasks. The first, manages ML-based data processing extracted from the real production system, and the second, manages the AI environment for reinforcement learning algorithms. As a result, this solution offers a digital twin with an autonomous problem-solving approach and data-based learning methods for enhanced modelling.

Simulation has been taken as a widespread approach to provide digital twin with enhanced learning. Broad operational data is incorporated to predict the behaviour of the real world. According to this learning model, in (Madni et al., 2019) simulation and MBSE are presented as DT-modelling enablers of a variety of manufacturing applications, such as predictive maintenance and design.

Creating behaviour models from scratch is expensive or even difficult to collect. However, a hybrid twin paradigm for a real-time decision-making next generation digital twin, that combines data analytic, ML, and physics-based models for predictions, is presented in (Chinesta et al., 2020). Through this hybrid approach, two models are used to perform the modelling framework. The first based on the physics and the second on the AI-based prediction.

In a similar way, the creation of digital models in manufacturing systems requires a computational effort to deal with complex environments. Nevertheless, (Aivaliotis et al., 2019) presented an advanced physics-based modelling methodology as a guide to create a description of a system or process using simplified data models to enable the digital twin concept. In this work, some properties of an industrial robot environment were modelled (*dynamic behaviour*, *virtual sensors*, and *parameters*), enabling the digital twin concept in predictive maintenance applications, so as to calculate the Remaining Useful Life (RUL) of machine components. In a complementary way, intelligent transfer learning approaches in manufacturing can provide the digital twin concept with new abilities, such as fault prediction (Maschler et al., 2021).

A two-phase digital-twin-assisted fault diagnosis method, based on deep transfer learning, is presented in (Xu et al., 2019b). This work aims to make fault diagnosis more applicable in the dynamic changing manufacturing process. In a first phase called *Intelligent Development Phase*, potential failures and how to prevent them are explored; while, in a second one called *Proactive Maintenance Phase*, the application of digital twin uses deep transfer learning to transform fault information from virtual to the physical space through an immersed experience. This approach extends the fault diagnosis along the entire product lifecycle through proactive and preventive maintenance.

A different solution based on Prognostics and Health Management was presented in (Booyse et al., 2020), providing deep learning strategies to generate asset health models without relying on historical failure data. In this way, condition-based approaches are very valuable to represent a real-time health state of a manufacturing system, as well as to generate learning about its behaviour. Thus, the knowledge is enabled by the increasing data collection systems and ML algorithms. In addition, this work poses the concept of Deep Digital Twin (DDT) to produce a health indicator in an experimental diagnostic environment, consisting of intermediate shaft bearing parts. The DDT uses deep generative models to learn the distribution of healthy data, estimating the health status of parts under both stationary and non-stationary conditions monitored by Integrated Circuit Piezoelectric (ICP) accelerometers.

### *4.3. Augmented interfaces for Digital Twins*

Industry 4.0 requires workers to be better prepared to meet the increased complexity of industrial tasks in dynamic working environments. Visualisation interfaces of digital twin data, driven by human-system interaction in manufacturing, have become one of the ways of enabling a better support for workers in learning and training processes. A digital twin powered by AR/VR technologies can be used to build autonomous and highly-efficient training environments

| DT learning approach | Focus | Reference |
|---|---|---|
| Augmented instructions | AR instruction generation adaptive to the shop floor operators' level of experience | (Mourtzis et al., 2019) |
| | AR assistance step-by-step to accomplishing the work according operators' skills and the operation to be performed | (Caldarola et al., 2018) |
| Content-based environments | VR visualization as testbed to allow operators' interaction with production processes (robots) in totally safe environments | (Pérez et al., 2020) |
| | AR contents to augment operators' skills and abilities for the development of human skills 4.0 to perceive and act within the working environment | (Longo et al., 2017) |
| Virtual-physical collaboration | Confront human–machine challenges with improvements to collaboratively update workers and industrial systems with augmented digital strategies based on AR and Web services | (García et al., 2022) |
| | Cyber-Physical System model with an AR system and Web services to enable users to easily access product, simulation and manufacturing data in real-time | (Schroeder et al., 2016) |

Table 6: Digital twin learning approaches focused on enabling augmented interfaces.

for workers (Egger & Masood, 2020). Moreover, augmented interfaces enable collaborative environments that can allow a physical object to be modelled and dynamically adjusted based on instructions learned from a virtual model (Tao et al., 2019b). Thus, the roles of the workforce are changing due to the use of user-facing technologies (Ras et al., 2017), leading to agile production and improved quality of products and processes. Table 6 presents several learning approaches visualising the digital twin, such as *augmented instructions*, *content-based environments* and *virtual physical collaboration*, which are described below.

*Augmented instructions*

A context-aware digital twin can use the learning capability and the ability to adapt to changing environments of the workforce to improve the knowledge of the processes. (Mourtzis et al., 2019) described AR as a promising technology to generate instructions for operators. The assistance is enabled on the shop floor according to the operators' level of experience and their skills. This augmented interaction for knowledge transfer across the factory accelerates the learning process as the instructions are skill-tailored, playing a significant role in the system's overall efficiency. A different AR approach applied to manufacturing processes which can help in implementing a smart workplace, is presented in (Caldarola et al., 2018). The skills of different operators were modelled and mapped with the operations to be performed. In this regard, AR enhances the efficiency of workers assisting the operator step-by-step to accomplish the work.

*Content-based environments*

VR applications allow workers to interact with production processes through non-intrusive technologies in order to improve their skills. This guided approach makes the training tasks more flexible and attractive by using virtual digital twin contents. In this direction, a research work integrating VR contents and intelligent systems to support workers in manufacturing operations, is presented in (Pérez et al., 2020). A digital twin of the manufacturing process includes a VR interface which enables training tasks for operators. It provides a virtual testbed for enhanced production processes before the physical implementation. Another learning approach that relies on AR contents is described in (Longo et al., 2017). The solution, applied on a CNC milling machine, has a real impact on worker learning curves by making use of AR contents suited to augmenting their skills. Through an intelligent personal digital assistant with vocal interaction capabilities, the proposed approach provides workers with a learning framework for the smart operator concept.

*Virtual-physical collaboration*

The integration of the digital twin information within the real environment of the worker is therefore crucial to connect and define all real-time relationships and behaviour between systems, users and processes. An augmented learning model of a CNC milling machine, using AR and Web Services in real-time, is presented in (García et al., 2022). This solution provides a human-machine collaborative approach to interact and visualise the health-condition status of those machine components that are more susceptible to failures. Moreover, non-intrusive data acquisition and human-machine knowledge models, provide bidirectional information to the digital twin visualisation layer. In (Schroeder et al., 2016), another case study based on Web Services, using an AR system as a digital twin data interface, is presented. A Web browser provides workers with easy access and visualisation of oil and gas processing in an offshore oil platform. The solution can be used on portable devices and showed using an AR system to get product, simulation, and manufacturing data from digital twin.

## 5. Challenges

The previous sections addressed how the impact of digital twin is closing the loop between physical and digital worlds in current manufacturing environments. However, how to bring about the future and effective interoperability, managing different types of human-machine ecosystems and enabling the intelligent operation of this physical-digital convergence, is still one of the open challenges towards SM (Qi et al., 2018a).

Industry 4.0 presents opportunities for enabling Digital Twin Learning Ecosystems in academic and industrial scenarios. However, at the same time, industry faces the challenges of building and supporting new technical and digital infrastructures, while workers' skills development eventually manages to handle the digital change. In the process, a change in the fundamentals of manufacturing systems and operations is required (Lu et al., 2020). In the same way, academia faces the challenges of providing technological research programmes and experts in line with complex manufacturing life cycle processes. Both these challenges, focused on the *physical-digital convergence* and *digital skills development*, are explored below.

### *5.1. Physical-digital convergence*

One of the Intelligent Manufacturing System (IMS) requirements, in order to enable adaptive systems and learning capacities, is the empowerment of connected ecosystems. Furthermore, digital twin is expected to be a decision-making solution underpinned by real-time communication and cooperation between workers, systems and processes (Zhong et al., 2017). Thus, manufacturing companies need to resolve the issue of capturing human and implicit knowledge in digital twin (Jari Kaivo-oja et al., 2020). However, mayor digital twin challenges on the manufacturing-related learning that impact on systems and processes can be classified in the four classes defined below.

*Lack of standards where digital solutions are not mature enough to be applied in production environments*

Manufacturing ecosystems have to deal with a complex integration to become more connected and autonomous. (Lu et al., 2020) shows how digital twin application development approaches for SM present implementation limitations through a lack of understanding of the digital twin concept, reference models, frameworks and development methods. Furthermore, the construction of a reliable digital twin in manufacturing applications depends on standardised information models, industrial communications, and is subject to strict requirements on timeliness (high-performance data processing), accuracy and reliability. In this way, (Moyne et al., 2020) shows that digital twin has a lack of behaviour, consistency and structure to integrate and maintain this technology in manufacturing systems. In addition, the necessary development of standards to align digital twin efforts with its capabilities should be considered. On the other hand, (Semeraro et al., 2021) considers the lack of standards regarding heterogeneous exchange data sources between different suppliers, manufacturers and customers as an interoperability barrier for the evolution of digital twin applications.

*Coexistence of different technology levels in the factory*

Regarding production environments, (Cimino et al., 2019) considers that digital twin faces many common scenarios where manufacturing systems are equipped with traditional machinery. This legacy approach, means that digital twin services are limited without the bidirectional connection to interchange information between the digital twin and its physical counterpart. In a similar way, (Fuller et al., 2020) considers that currently industrial infrastructure in place is behind the requirements for new technologies such as digital twin, particularly in manufacturing environments which have old machines without retrofitted or legacy ways to gather digital twin data.

*Closed and non-standardised control systems*

The great diversity of heterogeneous systems makes the deployment of digital connections slower. (Cimino et al., 2019) shows how closed proprietary production systems, such as Manufacturing Execution Systems (MES), meet the challenge to control processes and participate through a fully reactive way in decision making aspects: scheduling, energy consumption, maintenance, quality, etc. In a similar way, (Uhlemann et al., 2017a) considers that a slow standardisation of data acquisition in production systems impedes the adaptive systems implementation for digital twin, while new issues concerning data security arise.

*Traditional management approaches to gather operational data*

Traditional environments are still too common in manufacturing, particularly in SMEs. Some operations are conducted manually, and operational data is incomplete or missing due to lack of acquisition systems. (Uhlemann et al., 2017a) shows that a widely used manual data acquisition of motion data, and hence the lack of data availability in real-time, compromises digital twin for the evaluation and analysis of production systems. Therefore, the use of fully automated techniques to support planning processes is not considered as a common practice, while the information and timing with regard to manufacturing business planning (long run) comes up against manufacturing operations management (real-time) (Cimino et al., 2019). In addition, (Hu et al., 2021) considers that the integration of sensors and data acquisition technologies to achieve two-way connections has to be solved to ensure real-time data. It is also considered that data accuracy and building models in the virtual space with high fidelity of physical objects are a fundamental issue. In this way, (Semeraro et al., 2021) considers that the process of modelling the reality in a digital twin is a complex task, particularly using traditional approaches involving sensors and different kinds of sources, models and services. In regard to digital twin construction, a minimum level of data quality and a consistent data stream for efficient use is required (Fuller et al., 2020), whilst another challenge can reside in how to determine the optimal level of detail to create a digital twin model (Parrott & Warshaw, 2017). In a similar way, a major need for digital twin implementation is a fully updated 3D digital model (Wärmefjord et al., 2020).

### *5.2. Digital skills development*

The understanding of human-machine interactions, and their associated learning processes in intelligent manufacturing (also known as SM), must be researched and managed to enable the creation of digital twins as a process knowledge generation. (Semeraro et al., 2021) considers human interaction as a key challenge in the development and implantation of digital twin in manufacturing applications. In this way, the exploration of workers' learning patterns, and their associated digital twin model outcomes, can ease their adaptation to manufacturing changes and develop new ways to convert past experience into precise statements (David et al., 2018). Therefore, in manufacturing, despite progress in the Industry 4.0 paradigm, the existing cultural and workers' lifelong learning related challenges must be addressed in order to allow digital twin advancements in learning capabilities, improving the knowledge, skills and expertise that workers do not yet possess (Berisha-Gawlowski et al., 2021).

*Lack of background research, expert knowledge or trained workers with digital skills*

A previous work of research to develop learning programmes allowing the generation and consolidation of applied results at the shop floor is required. Nevertheless, on the one hand (Cimino et al., 2019) considers that, in practice, research on digital twin is still ongoing and, on the other (Lu et al., 2020) shows that there is only superficial knowledge about the research questions and challenges of digital twin, where current research outcomes are showing preliminary application examples in general. Regarding engineering students at universities, for instance, (Wärmefjord et al., 2020) points to the importance of the fact that they will need more knowledge and competencies in the future about model-based definition workflows and geometry assurance, in particular of the automotive domain. In that regard, these are major digital twin obstacles related to future skills development, even in front-running companies: the lack of Industry 4.0 specialists and digital expertise (Uhlemann et al., 2017a).

*Digital and cultural change*

Traditional environments are facing a substantial increment in the use of advanced technologies to improve the learning capability of the workforce. In that sense, a human-machine integration is necessary in order to lead the learning process and knowledge management in organisations (Jari Kaivo-oja et al., 2020). On the other hand, (Moyne et al., 2020) considered the necessary consolidation of the digital twin research for advancing technology, avoiding specific deficiencies to tackle issues such as the development and implementation of longer-term solutions. In addition, a unified and standardised development platform and tools for digital twin are required in the future (Hu et al., 2021). Also, human skills at work, as a dynamic factor during workers' learning, have to be modelled in digital twin (Ifenthaler et al., 2021). Nevertheless, a major challenge arises when digital twin comes up against organizations and workers and must verify that the generated models work as expected, and in order to ensure that they know its benefits (Fuller et al., 2020).

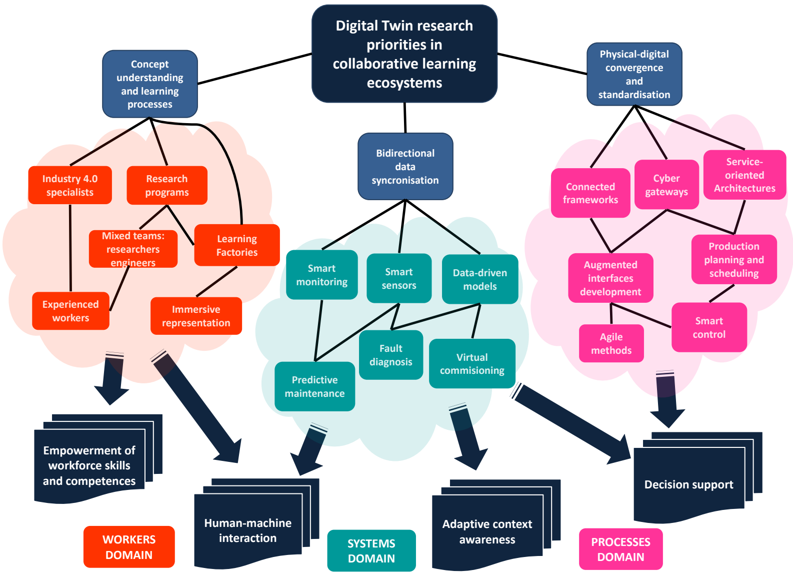


Figure 6: Digital twin research priorities and future trends in collaborative learning ecosystems

*5.3. Research priorities and future trends*

The building process of Digital Twin Learning Ecosystems requires a connected infrastructure to address the presented challenges. However, there still exist open issues described in the literature, such as part of the interconnected three-dimension ecosystem composed of workers, systems and processes. Table 7 summarises some identified barriers to be tackled, which would enable all learning approaches associated to the digital twin concept to accomplish IMS trends. In this way, the advancement in the proposed digital twin field of research cannot be regarded without a common understanding between academia and industry.

In this work, we have proposed a comprehensive definition of a Digital Twin Learning Ecosystem based on a holistic approach. This is followed by the identification of three key digital twin research priorities in the collaborative learning ecosystems described in Figure 6. Furthermore, the matching between the three aforementioned dimensions and future trends, while outlining these main research priorities and factors, are discussed below:

(i) *Digital twin concept understanding and learning.* Focused on the workers' dimension, research programmes encourage a two-way *human-machine interaction* (Abele et al., 2017). In this way, the Learning Factory concept offers a widely accepted learning approach by academia and industry. Learning Factories can be used as a training ecosystem that comprises researchers, Industry 4.0 specialists and teaching programs (Tvenge et al., 2020). As such, they represent crossed knowledge from laboratories and real factories as fully operational digital twin models towards the *empowerment of workforce skills and competences.*

(ii) *Bidirectional data synchronisation.* Focused on SM systems, data availability in real time can provide digital twin with cyber-physical connections and smart monitoring capabilities (Negri et al., 2017). In this way, *Human-machine collaborative ways* are brought forward through the use of smart sensors and data-driven approaches. Nevertheless, to enable an effective data-driven digital twin bidirectional interaction, a better understanding of the *dynamic behaviour*

| Dimension | IMS trends | Challenges for building DTs | References |
|---|---|---|---|
| **Workers** | Empowerment of digital skills (research, expert knowledge and training) | Results of research not mature enough, concept understanding | (Cimino et al., 2019)<br>(Lu et al., 2020)<br>(Moyne et al., 2020) |
| | | More knowledge required from engineering education programmes | (Wärmefjord et al., 2020) |
| | | Lack of I4.0 specialists and digital expertise | (Uhlemann et al., 2017a) |
| | | Human-machine integration issues | (Jari Kaivo-oja et al., 2020)<br>(Ifenthaler et al., 2021)<br>(Semeraro et al., 2021) |
| | | Lack of confidence in technology | (Fuller et al., 2020) |
| **Systems** | Smart sensor deployment, real-time data, and smart monitoring | Manual practices, evaluation and timing of information | (Uhlemann et al., 2017a)<br>(Cimino et al., 2019) |
| | | Two-way data acquisition, data accuracy, high fidelity models | (Hu et al., 2021)<br>(Parrott & Warshaw, 2017)<br>(Wärmefjord et al., 2020) |
| | | Data modelling, data quality, consistent data streams | (Fuller et al., 2020)<br>(Semeraro et al., 2021) |
| | Data availability for control and sheduling, in participatory-adaptive ways | Decision making (control and participation) | (Cimino et al., 2019) |
| | | Low standardisation in data acquisition, data security | (Uhlemann et al., 2017a) |
| **Processes** | Digital standards, frameworks development, and cyber gateways connection | Application development, reliable information models, industrial communications, strict requirements of operation | (Lu et al., 2020)<br>(Semeraro et al., 2021) |
| | | Capabilities, consistency, behaviour, integration and support | (Moyne et al., 2020) |
| | Convergence of the digital world and physical world | Limited traditional operation, interchange of information | (Cimino et al., 2019) |
| | | Legacy integration requirements | (Fuller et al., 2020) |

Table 7: Trends and challenges to enable digital twin learning ecosystems.

*of systems* during their life cycle is required (Malik & Bilberg, 2018). Thus, improved diagnostic methods can be promoted, and virtual models' development of physical systems can be improved. Moreover, smart manufacturing design through learning data can enable a digital twin-based semi-physical commissioning approach. In this context, there is an opportunity to enhance SM design in advance in the early development phase and ensure correct *decision guidance* (Leng et al., 2021).

(iii) *Physical-digital convergence and standardisation.* Focused on the process domains, the generation of industrial knowledge is based on the creation of standardised communication paths and service architectures, according to the convergence conditions of the real and virtual worlds (Tao & Zhang, 2017). By promoting the digital twin areas of research already under way, such as the potential in the field of verification and validation (Löcklin et al., 2020), and the development of augmented interface-based frameworks (Cimini et al., 2020), new approaches for transforming existing production and control methods may emerge towards *intelligent physical-digital interfaces* and *smart decision support models*.

## 6. Conclusions

The evolution of the digital twin concept, leveraged by the onward physical-digital convergence, has provided SM ecosystems with knowledge-generation opportunities based on new models of collaboration between workforce and industrial processes. It is a fact that the increased deployments of smart sensors to capture data powered by IIoT gateways, and current technological trends such as ML, VR and AR, are enabling workers' skills to take part in the immersive digital twin paradigm. Technology industry experts, such as the Gartner Group, ranked digital twins among the top ten technology trends for several years (Qi et al., 2019). In a similar way, a *Digital Twins in IoT: Market Strategies, Challenges & Future Outlook, 2019-2023* study from Juniper Research (Sutanto, 2019) found that digital twin operations will help human workers' skills to manage their capabilities in areas that the technology cannot address. In addition, this research forecasts Manufacturing as the fastest growing sector in potential future revenues from digital twin's market in 2023.

The rationale behind this work was to better understand the enablers and challenges involving the digital twin physical-digital convergence in manufacturing environments, to improve the development of learning strategies through the cyber-physical virtual factory replication and human-machine collaboration models. This paper reviews in detail the concept and potential application of digital twin to accomplish IMS knowledge-generation requirements by exploring the physical-digital learning fusion coupled with connected frameworks. We present literature findings which provide details on diverse framework models of digital twin learning ecosystems. In the case of Learning Factories, the digital twin concept is well integrated from both the research community and the manufacturing industry, in line with the enablement of connected adaptive systems and the empowerment of workforce skills. Nevertheless, we considered it necessary to contribute with an original definition of Digital Twin Learning Ecosystem and its conceptual layered architecture, providing a reference model to enable real-time augmented interfaces and bidirectional collaboration capabilities between workers, systems and processes. Furthermore, based on these three interconnected dimensions, we outline the main digital twin research priorities in collaborative learning ecosystems and how they can contribute to emerging trends in manufacturing.

In this way, digital twin is expected to be a decision-making solution to provide manufacturing workers with a deeper understanding and skills development. However, it is not clear in the industry what features a digital twin should have or how it should work in different ecosystems. Industry should first learn how to apply these virtual representations, taking into account a trade-off between the latest advances in scientific research and the relative maturity needed for current enabling technologies, whilst some of them are under development in manufacturing processes. In this sense, the adoption of digital twin in production is still at an initial stage in the manufacturing industry, where specific human and technological challenges must be addressed. The research priorities presented in this work are considered as a recognised basis in industry, which should help digital twin with the objective of its progressive integration as a learning ecosystem.

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