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Role of digital technologies to enhance the human integration in industrial cyber–physical systems

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ABSTRACT

In the digital transformation era, and particularly in Industry 5.0, humans play an active role in industrial cyber–physical systems (CPS) since they are the most flexible piece in such automated systems. However, their integration is not easy and constitutes a relevant challenge, presenting different requirements according to the activities they execute and the related integration levels, i.e., Human-in-the-Loop (HitL) and Human-in-the-Mesh (HitM). Besides the use of human-centric design approaches, the use of digital technologies, namely Internet of Things, Artificial Intelligence, virtual and augmented reality and collaborative robotics, can contribute to empower humans to perform their operations in a faster and more efficient manner. This paper discusses how emergent digital technologies can enhance a more symbiotic integration of humans in industrial CPS, contributing with the analysis of different aspects and concerns that must be considered to properly enable the HitL and HitM integration levels in CPS. Four experimental case studies are presented to demonstrate the feasibility of using digital technologies to enhance the human-CPS integration, covering HitL and HitM levels. Furthermore, some challenges related to the human-integration factors affected by the digital technologies in such environments are briefly discussed and pointed out as research directions.

1. Introduction

Industrial Cyber–Physical Systems (CPS) (Leitão, Colombo, & Karnouskos, 2016) constitutes a new generation of production systems, based on a network of components comprising cyber and physical counterparts that can perform autonomous decisions in a decentralized manner. CPS can act as the backbone infrastructure to implement Industry 4.0 (I4.0) compliant solutions, integrating several disruptive digital technologies, e.g., Internet of Things (IoT), Artificial Intelligence (AI), and virtual and augmented reality (VR/AR). These systems are designed according to several technological principles, serving as guidelines for their implementation, namely decentralization, modularity and service orientation, connectivity, optimized and real-time decision making, virtualization, and human integration (Colombo, Karnouskos, Kaynak, Shi, & Yin, 2017).

In contrast to the conventional perspective where the human has a passive role, mostly operating the system, in the newer approaches the human actively participates, being interconnected through complex interactions with the physical system and cyber technologies (Annaswamy & Yildiz, 2021; Sowe, Simmon, Zettsu, de Vaulx, & Bojanova, 2016). The human integration, defined as the incorporation of human factors, cognition and skills in the development and integration of automation systems (Taylor, Kruger, & Bekker, 2023), represents one of the design principles for developing Industry 4.0 compliant solutions (Kagermann, Wahlster, & Helbig, 2013). Since humans are the most flexible elements in automation systems, considering the human factors is critical for the smooth and symbiotic human integration in CPS (Fantini, Leitão, Barbosa, & Taisch, 2019).

I4.0 and CPS concepts are evolving to Industry 5.0 and human CPS (Sahinel, Akpolatg, Gorur, Sivrika, & Albayraka, 2021), where humans are prominent in the process of integrating the solutions needed for the industry in two distinct forms. In the first, robots and humans work together (Wang, 2022a), with humans focusing on tasks that require flexibility and creativity, and robots focusing on automated tasks (Demir, Doven, & Sezen, 2019). The second vision considers the intelligent and digital use of natural resources for industrial purposes,

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promoting sustainability, which will help humans to achieve a balance between ecology, industry, and economy. In this context, the new systems are centered on the human, resilience and sustainability aspects, using advances on cognition and personalized AI that enables intelligent and empathetic machines to sense the human needs and emotions in an intimately integrated way that can provide assistance at different levels to the human being (Lu et al., 2022a; Wang, 2022b).

These human CPS can reveal technological principles and be organized in a way that the involved resources can support humans in their decisions at multi-levels, from real-time to strategic goals (Ji, Yanhong, & Jiyuan, 2019). In this context, an important challenge is the integration of humans in industrial CPS through the use of human-centric design approaches, complemented with the adoption of emergent digital technologies that can contribute to empowering humans to perform their operations in a faster and more efficient manner (Lu et al., 2022b). This is supported by a Statista report (*Digital transformation*, 2023), which refers that the investment in the digital transformation reached 1.6 trillion US$ in 2022, and forecasts an investment of 3.4 trillion US$ in 2026. Among this spending, the worldwide investment in AR and VR technologies in 2024 is estimated to be 4 billion US$ dedicated to human training and another 4 billion US$ for industrial maintenance (Leonie Senn-Kalb, 2023).

In a CPS, the human can assume different roles, from the operator to the strategic manager, mapped in the Human-in-the-Loop (HitL) and Human-in-the-Mesh (HitM) levels, respectively (Fantini et al., 2019). In this context, the adoption of digital technologies should respect the human activities' needs, the decision-making phase where the human is placed, and the specific operational requirements.

Having this in mind, this paper discusses how digital technologies can contribute for a smoother and more symbiotic integration of humans in industrial CPS, particularly analyzing their applicability to support the human activities defined for the HitL and HitM levels and covering decision-making phases related to detection, determining, development and description. Four experimental case studies are used to demonstrate the feasibility of using digital technologies to empower humans during the execution of their operations, mapping decision phases with HitL and HitM levels. The use of digital technologies is not novel, but their application in industrial environments to empower human activities is innovative. However, a long path for their completely adoption in industrial environments to support the human-integration is still missing, with some challenges, e.g., lack of maturity, safety, technological literacy and confidence in these technologies, being also discussed. This paper is an extended version of (Piardi, Queiroz, Pontes, & Leitão, 2023).

The rest of the paper is organized as follows: Section 2 briefly discusses the integration of humans in industrial CPS and Section 3 presents the potentialities of using digital technologies to empower human activities. Section 4 describes four experimental case studies related to human–robot collaborative work, augmented inspection in collaborative work, monitoring of KPIs (Key Performance Indicators) and assessment of health risks. Section 5 discusses the challenges associated with the adoption of these technologies for the integration of humans in CPS. Finally, Section 6 rounds up the paper with the conclusions and points out some future work.

2. Human integration in industrial CPS

The manufacturing environment is suffering important mutations as result of the digital technologies, where the digitization increases the level of connectivity between cyber and physical components and the data-driven decision-making, as well as provides new forms of interaction between humans and machines (Pinzone et al., 2020).

The human integration in industry has undergone a progressive transformation from Industry 3.0 to Industry 5.0. In the context of Industry 3.0, machines and production lines fostered collaboration between humans and machines in integrated manufacturing processes, resulting in shared workspace and, on occasion, the utilization of some physical, cognitive, and computational resources interchangeably. However, during this era, humans and machines did not concurrently engage in integrated tasks; instead, a cooperative system exists among technologies, machines, and human operators (Lu et al., 2022a; Wang, 2022b).

Fig. 1. Factors that define and influence the human behavior.
Source: Adapted from Mughni (2016).

With the advent of Industry 4.0, digital technologies facilitated the interactive collaboration of intelligent machines with human operators within a shared workspace. The primary objective was to execute tasks through synchronized human–machine activities, fostering a team-oriented interaction (Da Silva, Sotovski, Pontes, Treinta, Leitão, Mosconi, Resende, & Yoshino, 2022). Similar to Industry 3.0, Industry 4.0 is also focused on optimizing manufacturing systems. This differs from the human-centric approach embraced by Industry 5.0, wherein advancements in cognitive science and personalized AI, initiated during Industry 4.0, enable intelligent and empathetic machines to provide assistance to humans at various levels. These machines are capable of sensing human preferences, needs, and emotions (Lu et al., 2022a). As a result, intimate human–machine interactions are poised to allow both humans and machines to enhance their capabilities, paving the way for a future characterized by continuous human–machine co-evolution (Lu et al., 2022a; Wang, 2022b).

In the light of this reality, the impact of the wide adoption of digital technologies on the work environment is very relevant and provides a significant mindset about people's roles in the industrial systems, also highlighting the importance of employing human-centric approaches. Overall, humans are endowed with the capacity for decision-making, flexibility, creativity, and the ability to perform intricate and specific tasks. Nevertheless, the human behavior is subject to various factors, as depicted in Fig. 1 which include inherent limitations, and the influence of their physical, mental, and emotional states. These factors often lead to unpredictable outcomes in their decision-making processes (Mughni, 2016).

In this context, there is a concern with the loss of human space in more intelligent manufacturing systems. In fact, according to Manyika et al. (2017), approximately 60% of the jobs currently known will be automated by 2030, and 8 to 9% of the workforce will have new jobs due to the adoption of AI and automation technologies. Nonetheless, the World Economic Forum (Leopold, 2018) refers that machines will not replace people, but will be a means to facilitate their work. This highlights the human capacity for learning, being creative and solving problems, which are unique and difficult to be transferred to a machine. In this sense, humans will continue to be at the center of processes, and their importance will remain in the digital environment. However, adaptation and new specializations need to be implemented to enhance the human capabilities and minimize the negative factors that promote their unpredictability (Müller, Kiel, & Voigt, 2018).

Based on that, the Human-Centered Design Approach (HCDA) allows the human involvement in solving problems related to industrial or community needs, by using interactive systems. This idea is corroborated by Albaba and Yildiz (2019) that coined the term Cyber–Physical and Human System, where the human is integrated in the physical

Table 1
Characterization of decision-making phases at HitL and HitM levels.

Decision-making phase	Human functions at HitL	Human functions at HitM
Detection	Visualize and monitor the machine's operation; Detect malfunctions	Identify anomalies and tendencies at earlier stage; Monitor KPIs and KBFs
Determining	Select the most appropriate operation; Identify events/causes; Adapt to condition changes	Perform diagnosis, prediction, optimization, scheduling, planning and risk analysis
Development	Perform processing, assembly, transport, inspection or maintenance operations	Launch scheduling and dispatching plans
Description	Record condition/scenarios and executed actions, and add comments	Record decisions, KPIs, deviations and comments; Explain reasons for problems and deviations

system, together with communication, computing, and other technologies that allow meeting social demands. Therefore, using disruptive technologies to provide decision support and task support to optimize the role of humans in industrial processes will build a highway to bring humans and technologies closer. The advantages of this approach are the collaboration for the creation of potential ideas, greater empathy in understanding the problem and solution, and also the experimentation itself, to verify the efficiency of the process. Considering the HCDA solutions, there is a need to better understand the human activities and their roles in industrial CPS environments.

According to Fantini et al. (2019), there are two important models aiming the integration of humans in industrial CPS: HitL, which is focused on the operational level and directed to the production process, and HitM, which is focused on the managerial level and directed to the production planning. In general, the human activities for the two referred levels can be placed in different decision-making phases (Fantini et al., 2019): (1) detect and understand a situation, (2) determine the decision-making actions to be executed based on the analysis of current conditions, (3) develop or execute tasks, and (4) describe, report and explain the executed decision-making actions. Table 1 summarizes the main functions associated with each human integration level and decision-making phase.

Regarding the HitL level, during the Detection phase, humans need to visualize and monitor the system or machine operation, interpret and analyze their states and data, and identify conditions and detect malfunctions. Many monitoring tasks can be fully automated, considerably augmenting the human decision-making capabilities that must play a supervisory role, managing alarms, or monitoring tasks where a system is not feasible or reliable, or even it is required some reasoning considering contextual information to infer and identify the system conditions. In the Determining phase, humans need to select the most appropriate actions to be executed, adapting to condition changes if necessary. Similar to the Detection phase, there are several systems that can perform diagnosis and provide a set of possible solutions (e.g., based on previous or similar cases), and planning tasks, but it is still the human responsibility to evaluate take the final decision. During the Development phase, based on detailed received information and guidance, the human performs processing, assembling, transportation, inspected or maintenance actions. Finally, in the Description phase, they need to record the performed decisions and actions according to the defined plans. Although many parameters and conditions can be automatically recorded by sensing technologies, there are still a significant amount of information that need to be recorded, such those that are produced through a deduction/reasoning process. This requires expertise combined with a wide (and long-term) observation of the scenario and its evolution along the time, which could not be obtained, even by a post-processing with advanced data analysis algorithms.

On the other hand, at the HitM level, the human needs to earlier detect the performance degradation or any problem that may affect the execution of the production schedule in the Detection phase. In the Determining phase, humans need to perform the analysis of the causes, including diagnosis and prediction, and to decide on the actions to take based on the conducted analysis. In the Development phase, humans need to execute the action, e.g., launching scheduling and dispatching plans, and finally, in the Description phase, they need to record the decisions taken and explanations for the occurred problems and deviations.

Several research works, e.g., Albaba and Yildiz (2019), Pinzone et al. (2020), also discuss the social and organizational challenges related to the integration of humans in industrial CPS, which include re-thinking about how to fully exploit the individual skills and potential of humans when facing the new work environment. Other major challenges include the work-life balance, the promotion of diversity, and the balance between physical and psychological aspects to maintain the well-being and assure data driven and mitigate biased decision-making. However, one of the biggest challenges is to improve the identification and evaluation of social aspects in the industrial environment, focusing on the interaction between managerial and operational dimensions, as well as the contribution of digital technologies for this symbiotic integration.

3. Mapping key enabling technologies across the human integration levels

Digital technologies can contribute to support the human integration in industrial CPS, enhancing the efficiency and quality of the execution of their operations. These benefits can be found in activities associated with the operator role, i.e. at the HitL level, but also to the manager role, i.e. at the HitM level. In this sense, five clusters of key technologies can be identified, namely sensing and connectivity, visualization and reporting, augmented work, collaborative work, and data analytics. Fig. 2 summarizes each cluster (top) and illustrates how they cover the different decision-making phases among the HitL and HitM levels (bottom).

3.1. Enabling technologies for sensing and connectivity

The sensing and connectivity cluster comprises technologies that enhance the real-time data acquisition, transmission and storage, considering data from machines, raw materials, products and work-in-progress, enhancing their visualization, monitoring and traceability (Zhong, Xu, Klotz, & Newman, 2017). Smart sensors, wearable devices and RFID readers assume a crucial role to collect the huge amount of data that is being generated at the shop floor, contributing to leverage the data-driven decision-making. Note that, in the case of wearable and handheld devices, besides provide indirect interfaces (e.g., sensor data collection) between human and systems, they also play an important role by enabling a more direct way to interact and provide feedback to the system. The efficient connectivity between the heterogeneous data sources and systems that will store and consume data, usually placed at cloud platforms, can be achieved by using IoT technologies (Al-Fuqaha, Guizani, Mohammadi, Aledhari, & Ayyash, 2015), in particular, WiFi, LoRa, BLE (Bluetooth Low Energy) and 5G. Beyond the traditional WiFi, LoRa allows the long-range connectivity and BLE the short-range connectivity and higher transmission rate, mainly used in energy constrained scenarios, given their very low power consumption. The 5G promises a revolution in communications as it provides a high data rate, improved quality of service (QoS), low

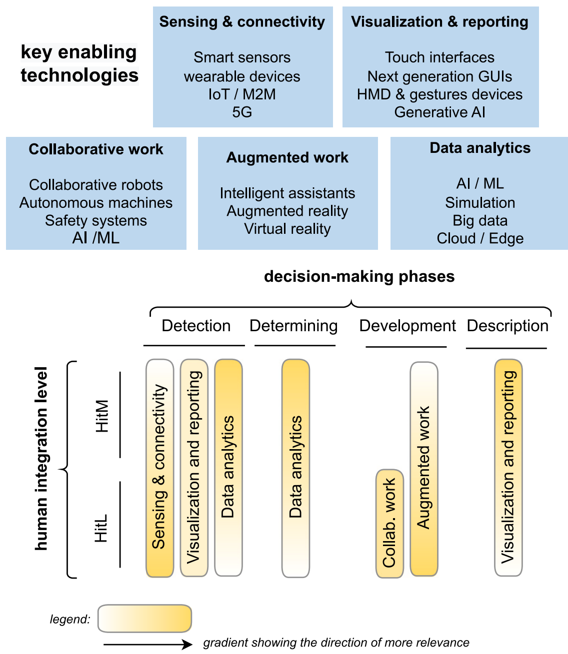

Fig. 2. Contribution of key enabling technologies along the human integration levels and decision-making phases.

latency, high coverage, high reliability, and economically affordable services. On the other hand, MQTT (Message Queuing Telemetry Transport) implements a lightweight publish/subscribe messaging schema that allows the development of loose coupled solutions, addressing the interoperability and scalability issues. In industrial environments, the OPC-UA (Open Platform Communications-Unified Architecture) technology is becoming a de-facto standard, since it provides a secure and standardized way to exchange data between machines and services. The data transmission is usually based on wireless communication that besides the advantages regarding pluggability and installation aspects, also presents connectivity issues, regarding interference and data transfer rates.

These technologies mainly support the human activities associated with the Detection phase, since they provide information regarding the related processes. Additionally, they may indirectly support the Determining phase, since the analytical models can extract information to guide operators and managers. Similarly, all the collected data together with the outputs of the analytical models can be used to support or provide additional details in the reports produced during the Description phase. Therefore, although such technologies play a major role in the Detection phase, the quality (consistency and integrity) of their outputs, i.e., the data, may affect the tasks across all the next phases.

In spite of the referred potentialities, some limitations related to use sensing and connectivity technologies for the human integration can be highlighted. As example, their usage during complex activities, e.g., handling hazardous substances, and hostile environments, e.g., inspection of equipment at the sea where the human presence is essential, is limited or affecting the accuracy of the sensors and the quality of connectivity. The reliability and security of exchanged data are issues present both at the HitL and HitM levels, as a considerable volume of data is digitized and transmitted. It is expected that advances focused on the pluggability, adaptation, and robustness of sensors and connectivity will further expand the utilization of the benefits associated with this technological cluster.

3.2. Enabling technologies for visualization and reporting

This cluster includes technologies that provide interfaces for the interaction between the human and the system. In this case, graphical interfaces are used to access and visualize the system information regarding the execution of operations, the evolution of performance indicators along the time, as well as the detection of anomalies and errors.

The combination of different technologies can provide a more intuitive interface to exchange data between humans and industrial CPS, mainly to support the data logging and the conditions report. At this stage, the bidirectional communication is usually considered, i.e., from the system to the humans for the information visualization, and from the humans to the system for the reporting activities. For this purpose, HMD (Head-mounted devices), e.g., Google Glasses and Microsoft Hololens, portable touch-screen devices, e.g., smartphones and tablets, gestures recognition devices, e.g., Leap Motion, complemented with recording comments and photos through the use of voice recorders and cameras, are examples of such user interfaces In this context, friendly and ergonomic user interfaces can be used by the operator, e.g., in a metal stamping unit to report the defects detected in the produced parts (Cachada et al., 2019). However, the selection of the communication device depends of the type of operation being performed and the role of the human. For the operator role, it is usually advised to use fixed devices on the workstation, such as touch screen, HMD or projectors, since they need to have their hands free to execute the operation, e.g., loading, unloading or assembling. On the other hand, managers are usually seated in their desks, being the computer or tablet adequate solutions. It is also important to notice that the use of HMD, usually associated with VR/AR environments, allows the visualization of information while maintaining the hands free to perform their tasks, but still remains uncomfortable solution to be used for long periods due to its weight and immersive environment. Therefore, an incorrect device assigned to the operator, or a polluted interface can hinder the development of the task, and result in human dissatisfaction in the technological integration.

Besides the hardware devices, regarding the interaction between human and systems, this cluster of technologies also considers the most advanced Human-agent interaction technologies. Recently, such technologies are mainly based on Large Language Models in the domain of generative AI, that enable the advanced natural language processing (interaction/conversation). Such tools can assist users by retrieving and summarizing information from documents and databases, e.g., with manuals, directives, lessons learned and reports, that can be used to support the decisions regarding the Determining phase related-tasks. Similarly, these tools can also automate most of the reporting related tasks of the Description phase (Jeblick et al., 2023; Kar, Varsha, & Rajan, 2023). In spite of that, such technologies still present some open issues, including hallucination, i.e., producing outputs that makes no sense, as well as requiring powerful computing resources and high amount of electricity to train the models and produce results in a timely manner, thus restricting their application in some scenarios.

3.3. Enabling technologies for augmented work

Intelligent personal assistant (IPA), VR and AR technologies can promote a more symbiotic integration of humans in industrial CPS through augmenting their capabilities to perform the operations in a faster and more efficient manner (Romero, Stahre, Wuest, Noran, Bernus, Fast-Berglund, & Gorecky, 2016). These technologies usually address the Development phase of the decision-making process and mainly focusing on the HitL level, e.g., by supporting the operators during the installation, operation and maintenance.

IPA is a guidance software system that supports the execution of operations or services (Romero et al., 2016), facilitating the interaction between operators and machines or computers through the use of contextual information, images, video and voice commands. The use of IPA contributes to improve the productivity and efficiency of the operator, particularly in the execution of complex operations, e.g., assembly of customized products. As example, maintenance technicians can improve the execution of their interventions by using an IPA that provides useful real-time information on the machine condition status and recommended actions to be taken. At the HitM level, such assistants combined with process automation tools can assist with the management and supervision of assets, workflows and schedules.

VR is an immersive and interactive computer simulation environment that digitally replicates the environment, allowing the operator to interact with real-time feedback (Romero et al., 2016). AR is the direct or indirect real-time view of a physical environment, where its elements are augmented through computer-generated elements, e.g., sound, video or graphics (Romero et al., 2016), improving the exchange of information between digital and real worlds. VR and AR constitute excellent tools for supporting the integration of humans at HitL and HitM levels (Fraga-Lamas, Fernández-Caramés, Blanco-Novoa, & Vilar-Montesinos, 2018), e.g., during the execution of inspection tasks, maintenance interventions (Lamberti et al., 2014), assembly operations (Paelke, 2014), and safety and security training (Frigo, da Silva, & Barbosa, 2016). Based on that, these technologies can be part of the Digital Twins, not only to provide information to the users, but effectively making them part of the loop.

Despite these potentialities, this technological cluster presents limitations primarily related to the complexity of use and adaptation by the operator to these new virtual environments provided by augmented and virtual environments, as well as the establishment of trust on the part of the operator in the intelligence and advice of IPA. In addition, the costs associated with the integration of this technology may restrict its application to large industries or only to certain sectors. Future trends may be associated with training methodologies to teach and introduce operators with little technological affinity to use these equipment, as well as the popularization of this technological cluster resulting in a cost reduction for implementation in small and medium-sized industries.

3.4. Enabling technologies for collaborative work

At the HitL level, the collaborative work is an important way to integrate humans in industrial CPS, namely using autonomous machines/vehicles and collaborative robots (cobots) that share the workspace side-by-side with operators to execute related tasks.

Manipulators have been widely used in the manufacturing industry to execute repetitive, heavy or dangerous tasks (Variz, Piardi, Rodrigues, & Leitão, 2019). However, such robotic systems are not able to work collaboratively with humans, being required protection and safety approaches to enable them to share safely the space with humans (Robla-Gómez, Becerra, Llata, Gonzalez-Sarabia, Torre-Ferrero, & Perez-Oria, 2017). The new generation of manipulators, called cobots, can perceive the human presence without the need of hard training and programming, to guarantee safety factors for the collaborative operation, e.g., reducing the speed and even planning collision-free routes with humans.

Another technology that provides a collaboration experience between humans and machines is the autonomous mobile robot (AMR). These type of robots can, e.g., prevent the humans from making excessive efforts and reduce the physical strain, being widely introduced in logistics warehouses, to optimize the internal transportation of goods and collaborate with humans in tasks like transportation, allocation, and dispatching (Bogue, 2016).

In this sense, smart sensors, 3D LiDAR sensors, Machine Learning (ML) and computer vision algorithms are frequently used to ensure safety without the need of the traditional protection measurements, e.g., safety barriers (Robla-Gómez et al., 2017) , as well as enabling the coexistence and environment sharing between these robots and humans, as robots can re-plan their routes when detecting the presence of humans.

The implementation of robot–human interaction can positively affect the efficiency and quality of a given operation, supporting humans during the Development phase. The robots perform the heavy duty and most repetitive activities while the operator performs meticulous and dynamic tasks, thus being able to improve quality and working conditions. In spite of being increasingly adopted in industry, e.g., electronics and automotive, there are still open challenges, especially related to safety, user interaction and design methods (Villani, Pini, Leali, & Secchi, 2018), where computer vision and ML techniques have presented promising solutions. In addition, cobots need to break the barriers of automation and become adaptive to different situations, e.g., by keeping a knowledge model of the environment (machines, processes, humans and their capabilities) where it is inserted, combined with sensors and mechanisms for perception and cognition, such as those based on semantic web.

Nevertheless, this technological cluster encounters limitations associated with predicting behaviors (e.g., abrupt movements or distractions) and physical and emotional states (e.g., fatigue) of operators to foresee more accurate actions and navigation, leading to adaptive and symbiotic collaboration. Advances in the field of smart sensors and AI algorithms tailored to predict human behavior aim to mitigate this gap.

3.5. Enabling technologies for data analytics

This cluster includes technologies, namely ML, Big data, cloud and simulation, that support the human functions associated with the Detection and Determining phases. These technologies permit the execution of data analysis to extract knowledge and provide actionable information to support and enhance the execution of tasks and decision-making. In this context, data analysis can take advantage of the huge amount of produced data combined with affordable computational resources and recent advances in ML algorithms to provide new business opportunities and keep companies competitive in an ever-changing market.

These functionalities address the human activity needs at HitL and HitM levels, enhancing the human decision-making, among others, in predictive manufacturing (Lee, Kao, & Yang, 2014) and quality control (Tao, Qi, Liu, & Kusiak, 2018). As example, an operator can benefit from the continuous monitoring to identify anomalies and guide the execution of tasks, especially when facing dynamic condition changes. On the other hand, the manager can take advantage of this capability to identify and diagnose undesirable performance levels or problems, receiving diagnosis reports and recommendations for suitable solutions. Furthermore, it can provide process planning and optimization, as well as test in advance, e.g., through what-if simulation, possible scenarios and conditions.

Also in this context, besides Cloud computing, the Edge computing comprises an emerging complementary technology that enables data processing closer or at the data sources. It is suitable to handle many industrial scenarios constrained by responsiveness and data privacy, providing local data analysis capabilities and consequently more intelligent and autonomous devices/machines. In this sense, it mainly supports the Detection phase of the HitL level contributing to equip operators with more powerful mobile devices and sensors that are less dependent on Cloud services, and constrained by latency and network issues.

In this cluster of technologies, the limitations are related to ethical policies and practices for dealing with data, as well as responsibility for decisions and actions of the outputs provided by AI algorithms. Furthermore, achieving continuous improvement in obtained solutions with massive volumes of data in an efficient and scalable manner is required, since the integration of data from different heterogeneous sources and the achievement of correlations in the data analysis can be complex.

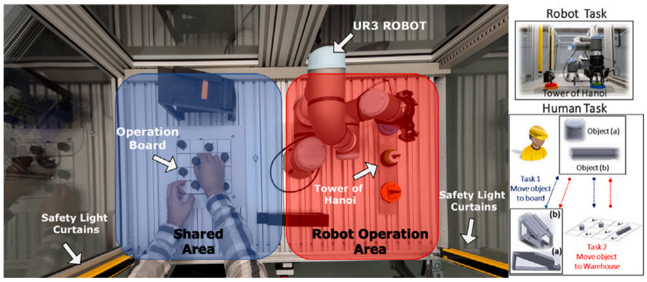

Fig. 3. Human–robot collaborative workbench, highlighting the operating and sharing workspace.

4. Experimental examples

As previously referred, emergent digital technologies can significantly enhance the seamless symbiotic integration of humans into industrial CPS, resulting in advantages for individuals, management, and productivity. This section showcases four case studies that illustrate the potential of using digital technologies for supporting both HitL and HitM in industrial systems. The first two focus on enhancing human capabilities at the HitL level, while the last two concentrate on the HitM level.

4.1. Human–robot collaborative work

The first example considers the use of cobots for the collaborative work with the operator, focusing on the HitL layer and the Development decision-making phase. To achieve this objective, as depicted in Fig. 3, both the operator and the cobot share the same workspace while carrying out their tasks. The robot is engaged in a repetitive task, while the operator is responsible for arranging items in the workbench. A critical concern is to maintain safety and prevent collisions between the robot and the operator.

To enhance collaboration while adhering to safety requirements, an intelligent interaction system was implemented, as illustrated in Fig. 4. A safety light curtain is responsible for detecting the presence of the operator, albeit without determining the operator's precise spatial position. To address this, a Kalman Filter (KF) algorithm is employed for the pose estimation, which analyzes the data captured by an Intel RealSense camera, strategically positioned on the top of the shared workspace, to provide accurate real-time data regarding the operator's hand placement. The developed algorithm, implemented in Python and adopting the OpenCV library, performs the image processing to estimate the spatial coordinates of the operator's hands and their distance to the robot. This approach facilitates the safe coexistence of the collaborative robot with operators, significantly mitigating the risk of injury by dynamically adjusting the cobot's speed based on the operator's proximity (García-Esteban, Piardi, Leitão, Curto, & Moreno, 2021).

The collaboration between the operator and the robot is extended with the capability of the operator to use gestures to communicate with the robot aiming to request its support in the execution of the operator tasks. For example, in case the operator signalizes an "1" with the fingers, the robot pauses the execution of its repetitive operation and will assist the operator in completing the assembly of the board (pick and place). After completing the collaborative activity, the robot will resume its continuous operation task. For this purpose, after detecting the spatial position, the *gesture detection* module is responsible to identify the gesture performed by the operator using his fingers. In this case, a Python script was developed to analyze the acquired image by using the OpenPose library (Simon, Joo, Matthews, & Sheikh, 2017) and the Part Affinity Fields method, being able to recognize and classify the performed gestures. Particularly, this script can detect 21 key-points for each user's hand, and due to the OpenPose database, it is possible to estimate the position of the fingers that are hidden. Knowing the relative position of the 21 key-points of the hand that represents the gesture "1" or "2", the matching is carried out to identify and classify for which operation (assembly or pick and place respectively) the operator is requesting the help of the cobot. If the operator does not request the collaboration of the robot, the system adjusts the speed of the robot, via Modbus, according to the distance from its joints to the operator, maintaining the human safety. In case of a possible collision, the robot immediately stops its movement.

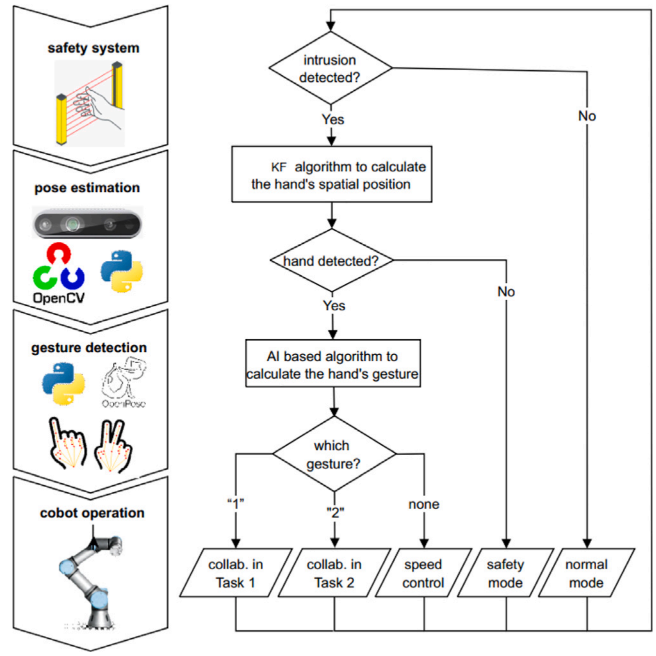

Fig. 4. Algorithm to ensure safety in human–robot collaboration.

The developed solution ensures the efficient collaboration with significant improvements in terms of accuracy for understanding the gestures performed by the operator and in terms of avoiding collisions. More details can be consulted in García-Esteban et al. (2021).

4.2. Augmented inspection in collaborative work

The second example illustrates the use of IPA and AR technologies to support operators during the quality control of parts produced in a steel cold stamping factory plant, focusing on the HitL level and *Detection* and *Development* decision-making phases. In this example, operators use a gauge tools and a testing bench to inspect the geometry compliance of parts, as shown in Fig. 5.

Traditionally, operators use a paper-based tutorial to support the execution of visual and geometric inspections, which provides a systematic guide for carrying out the inspection process. The results of the inspection are manually registered in a paper spreadsheet, which also provides details on the non-conformity found during the inspection. Using the spreadsheet, the quality control manager will use the registered data to calculate metrics and mitigate production problems. The main problems associated with this approach are the time-consuming execution of the tasks and the errors that may occur, mainly due to difficulties in memorizing the inspection sequences for the different part references. If the operator accepts error as a true procedure, it can be persistently repeated or replicated multiple times, and the current procedure is unable to identify the operator's errors or rectify them in real-time. Additionally, the use of paper to record data can be misleading since the recorded data may be wrong or incomplete,

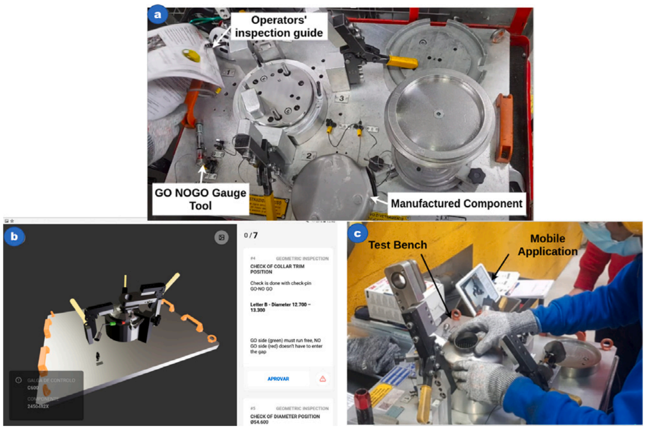

Fig. 5. Deployment of the virtual assistant system: (a) test bench, (b) virtual assistant, and (c) real industry usage.

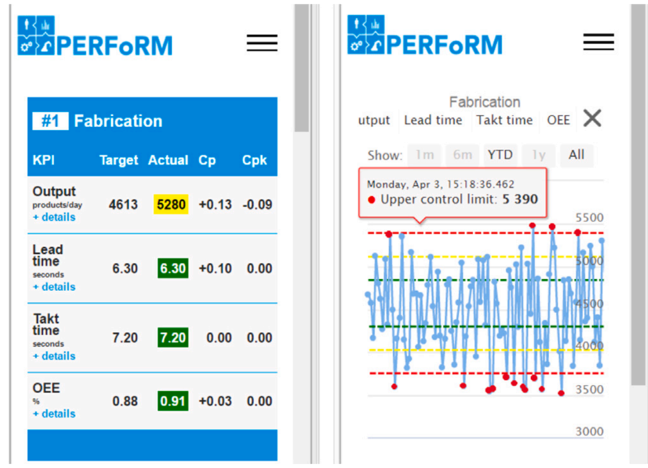

Fig. 6. KPIs monitoring dashboard.

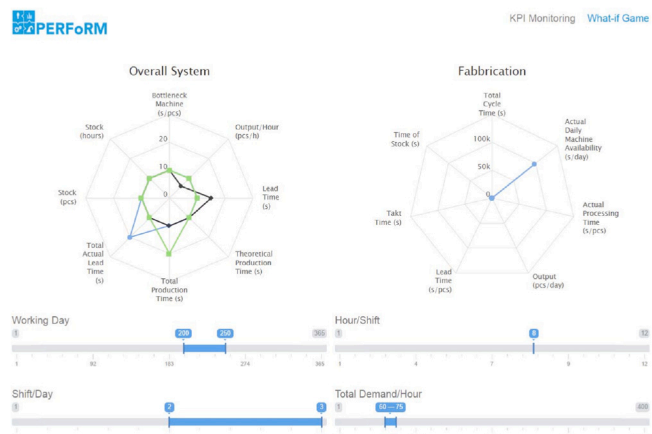

Fig. 7. What-if game dashboard.

needing future treatment to register more efficiently in a digital means, which is also time consuming.

Digital technologies can speed up the inspection time and learnability (Davanzo, Piardi, Junior, Leitão, & Pellegri, 2021), and increase the operator ergonomics, especially when used in a 3D environment to make the parts inspection easier to understand, as shown in Fig. 5. For this purpose, an augmented intelligent assistant guides the operator to carry out the operations by providing step-by-step instructions, using computer vision, AI techniques, and AR technologies. This system can be embedded in Mobile Apps and Web Apps, being portable and simple to use. In addition, it provides an automatic reporting functionality that compiles information from the inspection process, including images of the visual non-conformity. The collected data can be accessed in real-time by quality control department to visualize and analyze the results aiming to better understand non-conformities, contributing to identify earlier failure trends and proceed with the implementation of mitigation actions.

During the testing and operation period, the operators accepted well and quickly adapted to the use of the augmented intelligent assistant, and the quality control managers pointed out an increase of efficiency in the development of the inspection routine, as well as facilitating the mitigation of failures, as shown in Fig. 5-c.

4.3. KPIs visualization and monitoring

Manufacturing companies are continuously facing unpredictable internal and external condition changes that usually causes a performance degradation, reflected in loss of productivity, delay of deliveries and penalties to be paid. In this context, the analysis of the evolution of the KPIs and KBFs (Key Business Factors) for tactical and strategical decision support assumes a crucial importance. The third example explores the use of IoT for data collection and AI for the data analysis to develop a computational tool that allows the dynamic visualization and monitoring of several KPIs (Fantini et al., 2019). This tool focuses the HitM and supports the strategic managers to follow-up the real-time evolution of the system performance, to design new strategies for mitigating possible deviations and to optimize the system operation to face business opportunities, i.e. focusing on the *Detection* and *Determining* decision-making phases.

The KPIs visualization requires the real-time collection of heterogeneous data coming from different data sources, e.g., machinery and operators disposed along the production line, and databases, using IoT and M2M technologies. The use of data analytics, and particularly ML techniques, allows the execution of real time monitoring that enables the earlier detection of deviations and trends of the KPIs evolution along the time. The correlation between KBFs and KPIs, calculated according to pre-defined formulas and fed with data from business, products and consumer, takes advantage of the digitization of the production system. As a result, managers can visualize KPIs, as illustrated in Fig. 6, e.g., throughput, lead-time and Takt time, through an user interface, that provides an intuitive and comprehensive presentation of the target and actual KPIs values for each production station, as well as their trends, whether positive or negative. A control chart for each KPI is accessible by opening a new UI, displaying its timed evolution, as also shown in Fig. 6 (right).

In addition to its capability to detect problematic situations, this tool can also formulate and assess alternatives, as part of the human activities involved in the *Determining* decision-making phase. Particularly, strategic managers can leverage the support of a what-if analysis that enables the simulation of changes in critical parameters and evaluates their impacts on KPIs for a specific production station or system.

As illustrated in Fig. 7, the data is presented in a spider diagram manner, aggregating all the relevant KPIs into one graphical display (on the left, the overall what-if KPIs results, and on the right, other levels of granularity by searching KPIs at the production station level). The decision maker, can change the desired KBFs by adjusting the sliders located at the lower part, being showed new solutions allowing a thorough impact assessment of these adaptations.

4.4. Assessment of health risks in the workplace

Manufacturing companies are continuously facing the need to assess the workers' health and safety, to avoid a deterioration in their

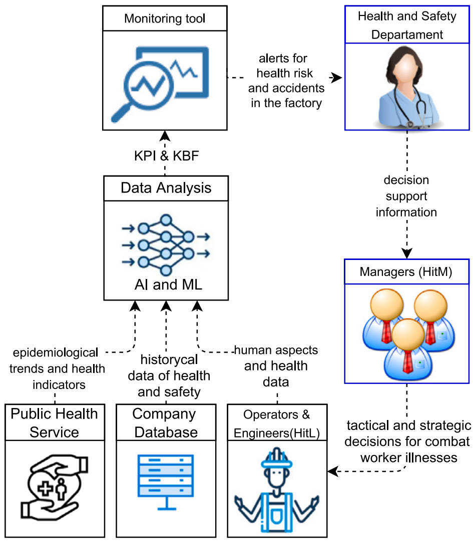

Fig. 8. Supporting the strategic and tactical decision in HitM to prevent workers illnesses.

performance, an increase in turnover and absenteeism, which can lead to a loss of motivation and reduction of productivity. In this context, the analysis and prioritization of information on occupational and individual risks, using indicators to support tactical and strategic decision-making is of crucial importance.

This case study explores the use of AI-based data analysis for predicting the worker illnesses based on data related to the occurrence of occupational and epidemiological illnesses, which should allow the dynamic visualization and monitoring of various risk indicators for absenteeism and periodic worker illnesses. This tool, illustrated in Fig. 8 and currently in the phase of designing and testing the data models, should support strategic managers, at the HitM level, to monitor the evolution of occupational risks in the workplace, designing new strategies to prevent serious illnesses in workers, improving the health and resilience of workers, improving the system productivity.

Briefly, after defining the variables with the greatest impact on the risk of absenteeism and periodic illness from the point of view of the company's decision-makers, the data analysis algorithm processes the available internal and external data to generate alerts of health risks and accidents in the factory. The analyzed data comprises, among others, the historical workers health data provided by the company database and the epidemiological trends and health indicators provided by the public health service repositories. The application is employing a supervised neural networks algorithm to analyze the generated dataset, considering the pre-defined weights, supporting the decision-making and reporting of managers.

The dashboard should establish the interface with the user, allowing to define which data have major impact on the possible health risks or periodic illnesses of workers that generate absenteeism, and providing the results of the data analysis, i.e. identifying potential illnesses and workers who are at greater risk of falling ill. Having this information, managers can take tactical and strategical decisions to prevent illnesses, e.g., the identified workers can be followed up in advance to avoid or reduce the effects of a possible health problem, reducing absenteeism, improving productivity, resilience and the quality of life of workers.

5. Discussion

As previously discussed and illustrated with the four case studies, the use of digital technologies can augment humans to perform their operations, as well as contribute for a symbiotic integration in industrial CPS, covering the HitL and HitM levels. Despite the identified benefits, the adoption of these digital technologies for the human integration raise several challenges that should be addressed to overcome obstacles and complexities, e.g., regarding technological, social and economical aspects. Besides the challenges, there are also ongoing discussion and research works, contributing to the development and evolution of solutions, standards and best practices. Some of them comprise open issues that have not yet been fully addressed and requires a particular attention.

Fig. 9. Cross-cutting areas for research opportunities with an example regarding the integration of humans with digital technologies and legacy systems.

These aspects are summarized in Table 2 and briefly discussed along this section. Moreover, depending on the context and the extent to which the solutions have been implemented, some of them can be viewed as both, an open issue and a challenge. For instance, the third major challenge of the first key aspect (see Table 2) comprises an open issue regarding to searching approaches to bridge the skills gap, with no universally accepted solution yet. On the other hand, it represents a challenge regarding the need for concrete actions and effective strategies for training the workforce, to address the evolving needs. These challenges and open issues raise several opportunities and potential research directions that can be explored by different players, like industries/organizations, policymakers and researchers.

Such opportunities can be identified in several areas regarding the major challenges. For this purpose, Fig. 9 presents the main cross-cutting areas for the research opportunities accompanied by an illustrative example considering the first challenge of the second aspect (see Table 2). Briefly, in the area of Human-Centric Design, researchers can explore how user interfaces, interaction principles, and the overall user experience can be designed to reduce the complexity and enhance the user adoption. Moreover, in the Training and Education area, the research can focus on adaptive training programs combined with diverse learning styles and skill levels, while, in the Ethical and Social Implications area, frameworks for responsible technology usage can be explored.

Since this paper does not intend to provide an in-depth analysis for each identified challenge, next sub-sections only discuss the key aspects and major challenges associated to the adoption of digital technologies for the human integration.

Table 2
Challenges for adopting digital technologies to enhance the human integration in industrial CPS.

Key aspect	Major challenges
Technology Literacy & Skilled Workforce	– Resistance of employees to accept the changes brought by digital technologies. – Effective change management strategies to gain buy-in from the workforce. – Managing and mitigating the consequences of the digital transformation, like the lack of workforce's multidisciplinary and digital skills. – Implementation of innovative training programs for re-qualification and up-skilling of active workforce. – Certification of continuous learning processes and adoption of microcredentials.
Smooth Technology Integration	– Complexity and cost for integrating humans with digital technologies and legacy systems. – Methodologies for the proper selection and application of digital technologies, considering the different integration levels and decision-making phases. – Regulations and policies to handle excess and misuse of digital technologies. – Continuous evolution of technology to enhance human skills.
Augmented decision-making and collaboration	– Development of personal and intelligent assistants integrating feedback loops. – Development of self-reconfigurable and collaborative mechanisms between humans and automated systems to augment the human capabilities. – Data analysis and collaboration models that consider human uncertainty and emergent behavior. – Balance/harmonize the human and AI-based machine intelligence. – Technologies and methods to understand, model and capture the human behavior, knowledge and intentions aiming to collaborate better and evolve together. – Handle the complex interaction between human, physical system and cyber technologies. – Enhance the human participation in data analysis related tasks, from the final decision-making to continuous feedback for data models improvement.
Trust and Safety	– Provide explainability and robustness of AI solutions to enhance confidence and reduce skepticism on the use of digital technologies. – Development of safety procedures in human–machine collaborative environments. – Compliance with industrial standards and certification of the technological solutions regarding safety and predictable behaviors.
Sustainability, Ethics and Data Privacy	– Development of environmental footprint of digital technologies, including energy consumption and electronic waste. – Development of eco-friendly design principles and sustainable manufacturing processes. – Consider data protection issues related to job displacement, surveillance, and privacy concerns. – Protecting customer and employee data, addressing data collection and usage. – Discrimination and bias in data algorithms/models.

5.1. Technology literacy & skilled workforce

Although these emergent digital technologies are very helpful in supporting operators to execute their tasks, currently in some situations, there is a technological literacy of the active workforce in using them, constituting a critical barrier to the expected increase of the digital maturity level. Based on the PwC survey performed in 2022, only 10% of companies have fully implemented digital factory solutions or are currently in the final phase. Whereas nearly two-thirds of companies that participate in the survey can only show partial results or are at the beginning of their digitalization journey (Droste et al., 2022). The increase of this digitization level is strongly dependent on the skills that the workforce can have in the different dimensions of the new multidisciplinary vision, particularly in enabling digital technologies. For this purpose, the re-qualification and up-skilling of the existing workforce are crucial to address the digital transformation. This requires the implementation of strategies and innovative training programs that consider the immersive perspective of daily problems in a lifelong learning perspective. These training programs and models should be based on customized and short actions, preferentially performed in-site and complemented with online content, distinguished for managers and operators, and properly certified.

By exploring these research opportunities, organizations must identify the necessary skills and work together with policymakers on strategies and investments in educational and training programs to ensure that the workforce will have the necessary multidisciplinary and digital skills. Researchers can contribute with the understanding and assessment of effective strategies for managing and mitigating the consequences of the digital transformation.

5.2. Smooth technology integration

In some situations, the technology is not mature enough for proper and comfortable use by the workers. One illustrative example is the use of HMD devices, that allows humans to be immersed in a virtual environment, as well as to easily access useful information related to the real system, providing the ability to perform their operations and minimize the errors during the process. However, the use of these devices still present some problems, namely the headsets ergonomics and their weight, that limits the maximum session time, as extended periods create discomfort, motion sickness, e.g., provoking nausea and disorientation, and the reduced field of view. These problems can be solved over time with the technology maturation, as well as more realistic simulations and animations developed for the virtual environment. Also at this point, the proper selection of the technology to be used is crucial, considering the human activity and the operational requirements. For example, the gestures' devices are very useful but they require the use of the hands, which is an obstacle in cases where the operators need them for other tasks; also, the use of voice commands is useful in situations where the hand iteration is difficult, but in industrial environments could not be possible due to the typical noisy environment.

In this context, organizations must be committed to find practical solutions that balance the benefits of digital technologies with the existing infrastructure and human factors, while researchers can contribute with approaches for selecting and adoption of the proper digital technologies. Meanwhile, policymakers must work on regulatory frameworks to ensure the responsible use of digital technologies.

5.3. Augmented decision-making and collaboration

Industrial CPS are becoming increasingly complex system, due to its highly distributed nature, with the human integration and collaboration being another aspect that contributes for this complexity. Humans cannot be considered as an isolated element that operate or use the system, but instead they need to be included in the CPS development process, improving its design, mainly regarding the aspects related to the interconnection and complex interactions between human and the automated system. This requires the establishment of proper methodologies and tools that are capable to combine and complement both counterparts in a symbiotic manner and allow the augmentation of the human skills and knowledge, but also, enable both to co-evolve in a collaborative environment.

The use of AI to support data analytics constitutes an important paramount of opportunity to support human activities regarding the majority of the decision-making phases at HitL and HitM levels. In general, the use of such algorithms can augment the human capabilities to analyze data and take decision, supporting more informed decisions, also complementing/overcoming the limited attention, as well as the cognitive biases inherent of human behavior. On the other hand, especially in dynamic systems and environments, such models must be constantly updated to address the changes, which requires great efforts from AI and software engineers. In this context, there are some challenges regarding the adoption of approaches for continuous learning and training the models with the integration of the users in the process.

However, the application of AI techniques should consider the implementation of proper data analysis algorithms that are simultaneously powerful to process the huge amount of collected data but also fast enough to support the continuous monitoring and the earlier detection of problems. In particular, an effort should be devoted to properly select the most adequate ML algorithms according to the applications' requirements, e.g., desired response time, the volume of data, bandwidth in the communication infrastructure and quality of the computed solution. Note that more complex algorithms usually provide more accurate outputs, but also require more computing resources and time.

Digital technologies, and particularly AI algorithms can be used to understand, model and capture the human behavior and intentions, in order to enhance the customized collaboration but also supporting the achievement of better decision-making recommendation, considering the humans' expertise and experience, perception and reasoning, since these represents main aspects that guide them in the execution of their tasks. Note that these algorithms should consider the human uncertainty, like some data analysis models, humans comprise a source of uncertainty that may pose complexities to the system. This can provide better personal assistants that can provide features beyond the traditional recommendation of optimal solutions, e.g., dynamic explanation and argumentation about the related aspects.

Also, important challenges at this level are related to the identification of correlation among the operational parameters, which are usually hidden, and difficult to extract in a simple and efficient manner, and the data visualization, being critical to selecting the proper way to transmit the collected information, in a simple, intuitive and comprehensive manner to the user.

In this cluster, researchers represent the main players that must contribute to the continuous improvement of intelligent systems, making them more adaptive, user-friendly, and effective in meeting the specific needs of users, i.e., that better understand, model, and capture human behavior, knowledge, and intentions. Meanwhile, policymakers must ensure the compliance with ethical issues related to privacy, trust, and the responsible use of automated systems.

5.4. Trust and safety

An important concern is related to trust and safety issues. The wider adoption of these emergent technologies requires that humans trust and be confident in using them. As example, the data analysis, reflected in the different human activities, requires confidence in the ML outputs, since these techniques consider more situations and actions that an user can project. Aiming to contribute to reduce the skepticism on the use and performance of disruptive technologies, and particularly AI, the system must provide explainability and transparency regarding control, robust and security aspects.

Another challenge is to ensure safety in robot–human collaborative environments, respecting the available international standards, e.g., ISO/TS 15066. However, it is necessary to improve methods and techniques to provide collaborative machines and robots with perceptions and information related to the prediction of future human intentions and movements, to control the machines' actuators, e.g., the speed and force exerted by exoskeletons, aiming to improve the collaboration effectiveness, and consequently avoid collisions with humans in the shared space. In this sense, the use of smart sensors, AI algorithms, and systems capable of identifying the human presence in real-time and predicting the movements of robots to avoid collision and damage to the operator are relevant challenges.

By exploring these opportunities and research directions, researchers must work on systems that are more transparent, robust, trustworthy and follow safety procedures, thereby fostering a safer and more trustworthy integration of humans and machines. Meanwhile, policymakers and industrial organizations must work together to establish certification, standardization, and mechanisms for ensuring that the technological solutions meet safety and predictable behaviors.

5.5. Sustainability, ethics and data privacy

In this field, the implementation of AI techniques raises ethical dilemmas (Stamatis, 2018). In fact, the lack of determinism of certain AI algorithms raises a trust problem, where an autonomous system may present emergent behavior that is undesired. Additionally, the use of such algorithms promotes ethical re-think about decisions related to social and human dimensions, both at the strategical and operational levels, about professional responsibilities, and raising awareness of the use of autonomous and intelligent systems. In this context, besides the definition of policies that the system should follow, it is also necessary to define proper certification processes for these algorithms. The research on ethical challenges at the individual and organizational levels is also important, based on the new reality focused on AI, CPS and Industry 4.0 (Pinzone et al., 2020; Piteira, Aparicio, & C., 2019).

Another aspect concerns the deployment of AI algorithms closer to the data sources, regarding both, machines and humans, not only to address scenarios constrained by responsiveness, network/mobility, but also the humans data privacy and even the user experience (i.e., how it interacts with the systems). In this context, Edge computing is an emerging technology, complementary to Cloud, that can contribute to address the related challenges, balancing the trade-offs of distributing the intelligence along Cloud and Edge layers. In a similar context, the environmental impact, especially regarding the energy consumption to build and run some algorithms (e.g., in the Cloud), but also the electronic waste (e.g., regarding IoT and Edge devices) raises concerns, and demands the adoption of a circular economy strategy and a sustainable development.

Addressing these challenges requires collaborative efforts involving organizations, policymakers and researchers to develop and implement sustainable practices, standards, and technologies that minimize the environmental impact of digital technologies. Additionally, policymakers must establish ethical, privacy-preserving, and responsible approaches to safeguard the data protection. Meanwhile, researchers must establish robust guidelines and practices that minimize bias and discrimination in algorithmic decision systems, fostering trust, transparency, and equitable outcomes, ensuring the inclusive access and benefits for everyone.

6. Conclusions

In the Industry 4.0 context, and particularly in Industry 5.0, the human integration in industrial CPS is fundamental since they are considered as the most flexible pieces of industrial automated systems. Although its integration is not straightforward, it can strongly benefit from the adoption of digital technologies. This paper discussed how emergent digital technologies can contribute to a smooth and symbiotic integration of humans in industrial CPS. This analysis is focused on determining their suitability for empowering the execution of the human activities associated with the HitL and HitM levels, and covering the several decision-making phases. The use of these digital technologies as key enablers for the human integration were discussed, being clear the advantages they provide for sensing and connectivity, visualization and reporting, collaborative work, augmented work, and data analytics.

Four experimental examples were provided to highlight the importance of disruptive technologies to enhance humans during the execution of their operations, two focusing on the HitL level (regarding assembly tasks and quality control) and others two focusing the HitM level (regarding decision-support systems and health risks assessment). These examples clearly show that the human remains central to the process, with digital technologies serving to significantly enhance and refine their capabilities, both at the operational and strategic levels, and simplify the integration of humans in industrial CPS, consequently contributing to the Industry 5.0 context. However, for the wide and effective adoption of these technologies, there are several challenges and open issues that should be addressed, namely the technology literacy, the trust and safety aspects of these technologies, the effort and complexity for their smooth integration to enable and augment the human tasks, as well as, the decision-making and collaboration with industrial CPS.

Future work will focus on providing an in-depth analysis for the identified challenges, aligning with open issues and research opportunities, and particularly analyzing guidelines, policies, actions and programs intended to encourage the wider adoption of digital technologies. This covers educational and training programs for the upskilling and re-qualification of the active workforce and streamlining the intelligence distribution within industrial CPS. Additionally, the study of the impact of ethics in industrial CPS should also be considered.

Declaration of competing interest

Luis Piardi, the corresponding author of the submitted manuscript entitled "Role of Digital Technologies to Enhance the Human Integration in Industrial Cyber–Physical Systems", hereby declare no conflict of interest involving the publication of this manuscript.

I affirm that all authors of this manuscript have been informed of the content of this Declaration of Interest Statement and agree.

If any potential conflicts of interest arise after the acceptance of this manuscript, I undertake to promptly inform the editors of "Annual Reviews in Control".

Data availability

No data was used for the research described in the article.

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