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Digital Technologies to Empower Human Activities in Cyber-Physical Systems

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Abstract: Humans play a critical role in cyber-physical systems (CPS) since they are the most flexible piece in this systems. However, their integration is not an easy task and constitutes a significant 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). This paper aims to discuss how emergent digital technologies can empower a smoother and more symbiotic integration of humans in industrial CPS. Particularly, it contributes with an analysis of different aspects and concerns that must be considered to properly enable the HitL and HitM in CPS. Three experimental case studies are presented to demonstrate the feasibility and contribution of using disruptive digital technologies to enhance the human-CPS integration, by assisting them to perform their operations in a faster and more efficient manner.

Keywords: Human-in-the-Loop, Human-cyber-physical system, Disruptive digital technologies.

1. INTRODUCTION

Industry 4.0 (I4.0) is bringing a new generation of production systems based on Cyber-Physical Systems (CPS), created as a network of components with cyber and physical counterparts that can perform autonomous decisions in a decentralized manner. CPS can act as the backbone infrastructure to implement I4.0 compliant solutions based on several disruptive 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 (Kagermann et al., 2013).

I4.0 and CPS concepts are evolving to Industry 5.0 and human CPS (Sahinel et al., 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, 2022), with humans focusing on tasks that require flexibility and creativity, and robots focusing on automated tasks (Demir et al., 2019). The second vision considers the intelligent and digital use of natural resources for industrial purposes, promoting sustainability, which will help humans to achieve a balance between ecology, industry, and economy. 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 et al., 2019). In this context, an important challenge is the integration of humans in industrial CPS through the use of human-centric design approaches.

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 aims to discuss the role of digital technologies 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, determine, development and description. For this purpose, three 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. It is crucial to notice that the use of digital technologies is not novel, but their application in industrial environments to empower human activities is innovative. In fact, there is still a long path for them to be completely adopted in industrial environments, mainly due to the lack of maturity, technological literacy, and confidence in these technologies.

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The rest of paper is organized as follows: Section 2 overviews the integration of humans in industrial CPS and Section 3 discusses the benefits of using digital technologies to empower human activities. Section 4 presents three experimental case studies and 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

Humans are at the center of manufacturing processes, since they can make decisions, have creativity and flexibility, and can execute specific and complex tasks. However, humans are exposed to several factors that influence their behavior, e.g., their limited capabilities, and physical, mental, and emotional states, usually resulting in an unpredictable decision-making outcome.

In this context, there is a concern with the loss of human space in more intelligent manufacturing systems. In fact, according to (Manyika and 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. The same report estimates that the reasoning and decision-making processes performed by humans will only be reduced from 81% to 72% from 2018 to 2022. 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 qualities and minimize the negative factors that promote their unpredictability (Müller et al., 2018).

Based on that, the Human-Centred 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 integrates the physical system, together with communication, computing, and other technologies that allow meeting social demands. 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 is 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.

Regarding the HitL level, during the Detect phase, humans need to visualize the system or machine operation and detect malfunctions. In the Determine phase, humans need to select the most appropriate actions to be executed, adapting to condition changes if necessary. During the Develop phase, the human needs to receive detailed information and guidance on how to perform 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.

On the other hand, at the HitM level, the human needs to earlier detect the performance degradation or any problem that affects the execution of the production schedule in the detection phase. In the Determine 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 Develop phase, humans need to execute the action, e.g., launching scheduling and dispatching plans, and finally, in the Describe phase, they need to record the decisions taken and explanations for the occurred problems and deviations.

3. KEY ENABLING TECHNOLOGIES

Digital technologies can provide significant support for the human integration in industrial CPS, contributing to improve the efficiency and quality of the execution of their operations. These benefits can be found in activities associated with the operator role, i.e. HitL level, but also to the manager role, i.e. 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. 1 summarizes each cluster (top) and illustrates how they cover the different decision-making phases among the HitL and HitM levels (bottom).

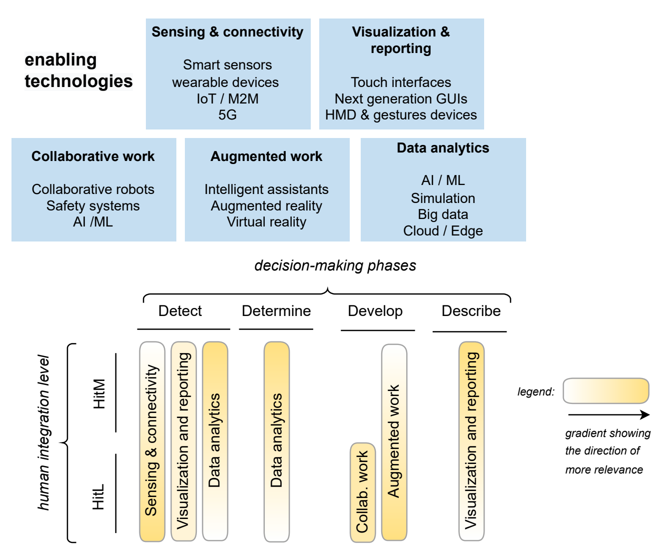

Fig. 1. Key enabling technologies along the different human integration levels and decision-making phases.

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. 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. 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 et al., 2015), in particular, MQTT (Message Queuing Telemetry Transport), LoRa, BLE (Bluetooth Low Energy) and 5G.

These technologies mainly support the human activities associated with the Detect phase, since they provide information regarding the related processes. Additionally, they may indirectly support the Determine phase, since the analytical models can extract information to guide operators and managers.

3.2 Enabling Technologies for Visualization and Reporting

This cluster comprises 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, and portable touch-screen devices, e.g., smartphones and tablets, are examples of such user interfaces. The selection of the communication device depends of the type of operation being performed and the role of the human.

3.3 Enabling Technologies for Augmented Work

Technologies like intelligent personal assistant (IPA), VR and AR, enhance 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 et al., 2016). These technologies usually address the Develop phase of the decision-making process and focus on the HitL level, supporting the operators during the installation, operation and maintenance.

IPA is a guidance software system that can support 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 about the machine condition status and recommended actions to be taken.

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 the digital and real world.

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 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. However, such robotic systems are not able to work collaboratively with humans, being required protection and safety approaches to enable that robots can share safely the same space with humans (Robla-Gómez et al., 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. In this sense, smart sensors, Machine Learning (ML) and human detection algorithms based on image processing, are usually used to ensure safety without the need of the traditional protection measurements, e.g., safety barriers (Robla-Gómez et al., 2017).

The implementation of robot-human interaction can positively affect the efficiency and quality of a given operation. The robots perform the 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 et al., 2018).

3.5 Enabling Technologies for Data Analytics

The data analytics cluster comprises technologies, namely ML, Big data, cloud and simulation, that support the human functions associated with the Detect and Determine 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 and quality control. As example, the 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.

4. EXPERIMENTAL EXAMPLES

As previously referred, emergent digital technologies can significantly contribute for the smooth and symbiotic integration of humans in industrial CPS resulting in benefits for humans, management and production efficiency. This section presents three case studies to demonstrate the feasibility of using digital technologies to support the HitL and HitM in industrial systems, with the first two to empower humans at the HitL level and the third at the HitM level.

4.1 Human-Robot Collaborative Work

The first example considers the use of cobots for the collaborative work between the operator and the robot, focusing on the HitL layer and the Development decision-making phase. For this purpose, as illustrated in Fig. 2, the operator and an UR3 robot are sharing the workspace during the execution of their operations: the robot performing a repetitive activity and the operator organizing items on a collaborative area. In such shared environment, an important challenge is to ensure the safety issues and avoid collisions between the robot and the operator.

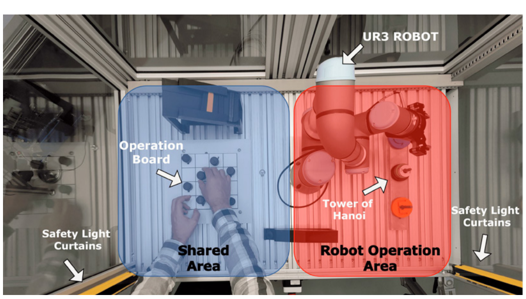

Fig. 2. Human-robot collaborative workbench.

In order to foster the collaboration with safety requirements, an intelligent interaction system was adopted. A safety light curtain detects the presence of the operator, but misses the identification of the operator's spatial position. In this way, a Kalman Filter (KF) algorithm is used to execute the *pose estimation*, analyzing the data from an Intel real sense camera, placed on the top of the shared workspace, to obtain accurate real-time information on the location of the operator's hands. The algorithm, performs the image processing to estimate the spatial position of the operator's hands and the distance to the robot by using the Kalman Filter. This approach enables the cobot to share space with the humans greatly reducing the risk of injuring them, dynamically adjusting the cobot speed according to the distance to the operator (García-Esteban et al., 2021).

4.2 Augmented Environment in Collaborative Work

The second example is related to the use of intelligent assistants and AR technology to support operators' during the execution of their tasks, focusing on the HitL level and the*Detect* and *Develop* decision-making phases. The case study considers the use of gauge tools to perform the quality control of parts produced in a steel cold stamping factory plant, where operators use a testing bench to inspect the geometry compliance, as shown in Fig 3.

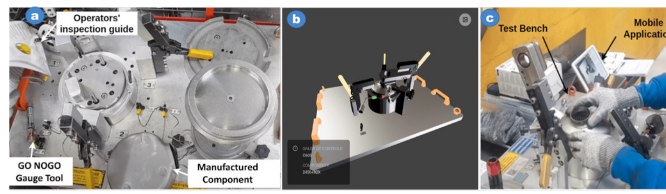

Fig. 3. Deployment of the virtual assistant system: a) test bench, b) virtual assistant, and c) real industry usage.

Traditionally, operators perform the visual and geometric inspection guided by a tutorial printed paper, which provides step-by-step information on how to proceed with the inspection. After conducting the inspection, the results are recorded in the paper spreadsheet, which also offers insights on the non-conformity found during the inspection. The main problems of the traditional approach are the time execution and errors, which are due to the operators' difficulties in memorizing the entire inspection sequence for the different part references. Once the operator takes an error as true, it can be repeated or replicated numerous times, and the current procedure is unable to point out the operator's failure or correct it in real-time.

The use of digital technologies can improve the inspection speed and the operator's perceived comfort, particularly using a 3D environment to enhance the parts inspection's learnability, as illustrated in Fig. 3 (Davanzo et al., 2021). The operator is supported by an augmented intelligent assistant that guides the operation's execution by providing step-by-step instructions, using image processing, AI techniques, and AR technologies. This system can be embedded in Mobile Apps and Web Apps, being flexible, portable and intuitive to use. Additionally, it provides a reporting functionality that automatically collects information from the inspection process without depending on operators, including the photos of visual non-conformity.

4.3 KPIs Visualization and Monitoring

The third case 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 (Key Performance Indicators) (Fantini et al., 2019). This tool supports the strategic managers to follow-up the 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 *Detect* and *Determine* decision-making phases. Fig. 4 presents the modules needed to integrate HitM into a manufacturing scenario, where decisions are made with AI and ML support, along with a tool that presents real-time information on the production process to the managers.

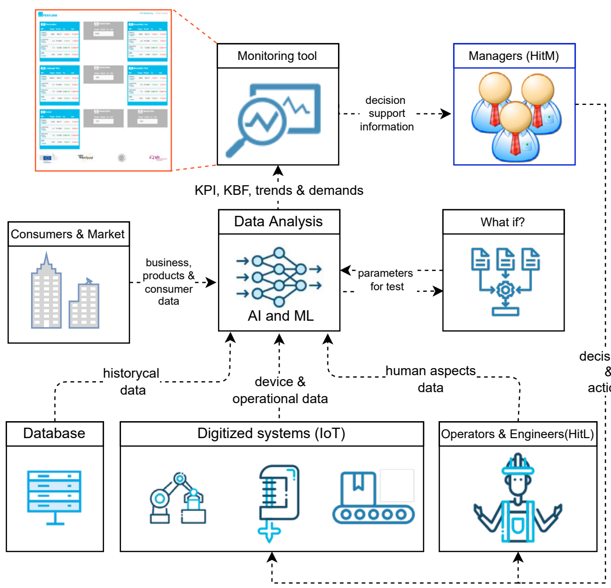

Fig. 4. Supporting the strategic decision in HitM.

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 advanced data analytics, and particularly ML techniques, i.e., the "Data Analysis" module, allows the execution of real time monitoring that allows the earlier detection of deviations and trends of the KPIs evolution along the time.

Besides being able to detect problematic situations, the tool can also formulate and test options, as part of the human activities associated with the Determine decision-making phase. In fact, the strategic manager can receive the support of a what-if analysis by simulating the change in critical parameters and assessing the impacts on the KPIs for a given production station or system. In this way, the manager can visualize the KPIs, e.g., throughput and Takt time, through an user interface, as shown in the module "Monitoring tool" of Fig. 4, which provides, in an intuitive and comprehensive manner, the target and the actual KPIs values for each production station, as well as their (positive or negative) evolution trend.

5. DISCUSSION

As previously discussed, and illustrated in Fig. 1, the use of digital technologies can empower humans to perform their operations, as well as contribute to a symbiotic integration in industrial CPS, at HitL and HitM levels. Despite the identified benefits, several challenges regarding human aspects arise with the adoption of these technologies.

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. In fact, 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 transition, through the implementation of innovative training programs that consider the immersive perspective of daily problems in a lifelong learning perspective.

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. Another challenge is to ensure safety in robot-human collaborative environments, respecting the available international standards, e.g., ISO/TS 15066. 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.

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, which 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.

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. 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.

In this field, the implementation of AI techniques rises 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.

Another aspect concerns where such algorithms should be deployed, regarding cloud and edge computing layers. Although the cloud provides virtually unlimited computing resources, it is not suitable to handle many industrial scenarios constrained by responsiveness and data privacy. On the other hand, although the edge can attend to such requirements, it suffers from constrained resources devices. Such trade-off illustrates the challenge of achieving a balance that harmonizes the distribution of intelligence along cloud and edge layers (Queiroz et al., 2019).

6. CONCLUSIONS

The integration of humans is fundamental in industrial CPS since they are considered as the most flexible pieces of an automated CPS. However, their integration is not an easy task but can benefit of using digital technologies. This paper discussed how emergent digital technologies can strongly contribute to a smooth and symbiotic integration of humans in industrial CPS. In particular, this analysis focused on their applicability to implement the human activities defined for the HitL and HitM levels and covering the different decision-making phases. From this analysis, it was clear the advantages they provide for sensing and connectivity, visualization and reporting, collaborative work, augmented work, and data analytics.

Three experimental examples were provided to support feasibility of the humans' empowerment during the realization of their activities by using digital technologies, two focusing on the HitL level and one focusing the HitM level. These examples clearly show that emergent digital technologies can significantly contribute to empower humans during the realization of their tasks and simplify the integration of humans in industrial CPS, consequently contributing to the context of HCPS and Industry 5.0. However, some challenges are still open for a wider adoption of these technologies, namely the technological literacy of humans, the trust and confidence in these technologies, the lack of maturity of some technologies and the difficulties to deploy these technologies for the use cases.

Future work will be devoted to study guidelines and actions for the wider adoption of these technologies, e.g., for training of active workforce and properly balancing the distribution of intelligence, as well as the study of the impact of ethics in industrial CPS.

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