Towards human-centric industrial training

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Abstract. Digital transformation of industrial training processes is still an ongoing process. The transformation requires a specific training model to be applied to an already structured context, to experienced workers, sometimes with their needs and specific skills, and the solution is designed considering a series of boundary conditions. To design a new training model that the industry will accept, it is important to consider the design space offered by technology, but at the same time, to consider human complexity. This paper proposes a methodology to analyze current training strategies in the industrial sector to design new tools according to a digital transformation logic that considers the underlying principle of the human centricity of Industry 5.0.

Keywords: Industry 5.0 · Digital transformation · Industrial training.

1 Introduction

Digital transformation in modern industry refers to the integration of digital technologies into all areas of business, fundamentally changing how companies operate. This process involves adopting technologies, including artificial intelligence (AI), the Internet of Things (IoT), big data analytics, and cloud computing to enhance efficiency, innovation, and competitiveness [1]. In the process of industrial transformation, Industry 5.0 is a philosophy that places humans at the center of industrial processes. This approach recognizes the value of human capabilities, creativity, and intuition, combined with advanced technologies to promote innovation, productivity, and sustainable development [2]. In contrast to previous industrial revolutions that focused on automation and efficiency, Industry 5.0 emphasizes the importance of improving the quality of work and promoting meaningful collaboration between humans and machines [3]. Furthermore, it prioritizes the well-being and growth of individuals within the industrial context. In this setting, the irreplaceable value of human skills, such as problem-solving, critical thinking, adaptability, and emotional intelligence, are recognized and highly valued. Rather than replacing human workers with machines, the goal is to empower them by leveraging technology to increase their capabilities and allow them to focus on higher-value tasks that require human creativity and judgment [4].

However, the introduction of product or process innovations in socio-technical manufacturing systems impacts how work is conducted, effectively altering the roles and activities of the individuals involved. The guiding principle of Industry 5.0 is to promote and support the development of new technologies with consideration for the people who will use them and the organizational contexts in which they will be applied. This becomes particularly important when introducing technologies that automate entire processes, as these changes require workers to adapt to new roles, often in collaboration with the automated systems introduced. For instance, in decision-making processes, we can imagine an AI algorithm performing complex data analyses from sensors distributed in the production environment and production management software, offering a series of options for an operator to choose from. To prevent individuals from becoming the weak link in the production process, innovations must be understandable by those participating in the work activities (e.g., explainable AI). Additionally, training programs are essential to enable people to learn new roles, including collaboration with the newly introduced technological innovations.

Considering this, industry 5.0 recognizes that the rapid pace of technological change requires continuous learning and upskilling among workers [5]. Yet, the mere digitalization of training processes, based on the possibility of producing scalable digital material, may inadvertently overload workers by imposing continuous updates. Consequently, such training programs run the risk of being perceived as overly generic, time-intensive, and inadequately tailored to individual worker requirements, prioritizing scalability and economic efficiency rather than emphasizing customization to meet specific worker needs, ultimately posing the danger of diminishing worker motivation toward such activities. Moreover, standardized training programs, which often focus more on explaining tool features rather on how and why to use them, are frequently ineffective for day-to-day application, as they mostly focus on the lowest levels of the Bloom's taxonomy (i.e. knowledge and possibly comprehension) rather than on the application skills and eventually on judgement abilities. This ineffectiveness derives from the fact that such programs are not designed with user experience in mind but are instead based on the functional structure of the tool itself. In response to this critical point, human centricity involves promoting a culture of lifelong learning and professional development within organizations, providing individuals with the tools, resources, and support they need to adapt to evolving technologies [6]. Here, the diversity among individuals in terms of skills, preferences, and attitudes entails the need for tailored training programs that can take advantage of innovative technologies such as AI, eXtended Reality (XR), and big data analytics to adapt and improve the efficacy of upskilling and reskilling processes.

In this paper, we suggest a method to analyze the current state of training in the industrial world and offer training solutions with low impact regarding workers' effort required to acquire and consolidate knowledge. In this new approach, we propose integrating two technologies, namely XR and AI, as a possible technological solution. However, the transformation cannot ignore the learner, who can trust or not the contents presented. If this aspect is not considered, the solution will be promptly abandoned.

2 Human centric training - steps

Salas and Cannon-Bowers [7] report the basic principles of training and make some considerations regarding the technologies capable of bringing improvements. Their work describes needs analysis, antecedent training conditions, training methods plus instructional strategies, and post-training conditions as the essential elements to consider that guarantee efficient and effective training. Based on a simplification of this scheme (Fig.1), we will consider (i) the assessment the initial situation (i.e., the AS-IS condition) in order to plan a specific training program; (ii) the identification of the basic training aspects to meet users' needs and requirements; (iii) the deployment of tech innovations to facilitate data collection and promote long-term adaptability, and finally (iv) we will underline the importance of increasing trust in new technologies to maximize training effectiveness and overcome the inertia that usually accompanies tech innovations.

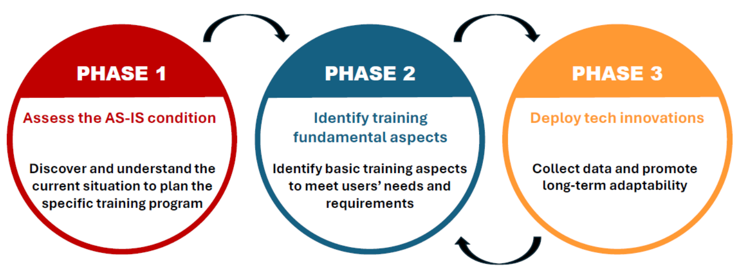

Fig. 1. The three phases approach proposed in the current paper to define human-centered training programs. The measures collected in Phase 3 promote an iterative process where the data can be used to periodically calibrate needs and requirements in light of the improvements obtained.

2.1 Understanding human needs: assess the AS-IS condition

An understanding of users' needs is essential to define effective requirements to design and plan a supportive and adaptable training path. The assessment of the current AS-IS condition is achieved through a two-pronged approach. First, an initial discovery phase focuses on gaining a comprehensive understanding of each use case through a high-level overview of the operations accompanied by interviews with individuals directly involved. Subsequently, it is possible to gain a deeper understanding of the interactions between the key roles identified and the current working context, encompassing both human competences and technical components in their surrounding environment. Inspired by EUROCONTROL [3], this process includes six relevant categories for industrial scenarios, detailed in Figure 2.

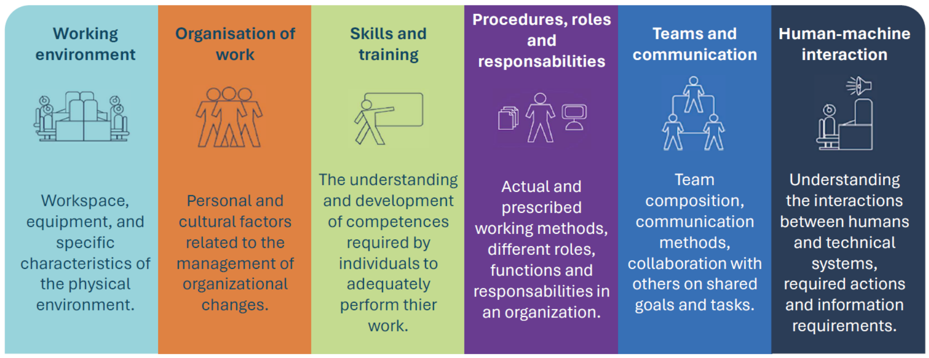

Fig. 2. The six relevant categories to understand the AS-IS condition in industrial scenarios.

2.2 Fundamental training aspects

Once the AS-IS situation has been assessed, it is necessary to organize a training program able to catch and operate on the fundamental aspects that allow both contents and methods to be adapted to the needs arising from the initial analysis of the AS-IS context and the characteristics of the worker involved. This section proposes some of the most important aspects that must be considered in order to create tailored training for the worker and thus facilitate the acquisition of new competencies.

Experience and expertise One of the first crucial aspects to consider is the workers' level of experience and expertise. Training content, difficulty level, and complexity should be adjusted to align with their existing knowledge and skill sets. Experienced workers may require advanced training materials or specialized courses to further enhance their capabilities and support upskilling processes, while novice employees may benefit from fundamental training programs to build a solid understanding of core concepts.

Learning styles and objectives Understanding the diverse learning styles of workers is essential for designing effective training programs. Visual, auditory, kinesthetic, and reading/writing preferences should be taken into consideration. Kolb's Learning Styles Model [8] provides a useful framework for categorizing workers'

[3] https://www.eurocontrol.int

learning preferences that can be differentiated in four orientations (i.e., Concrete Experience, Reflective Observation, Abstract Conceptualization, and Active Experimentation). By considering the different learning styles, training programs can be tailored to accommodate the diverse needs and preferences of workers, ultimately optimizing the learning experience, and simultaneously facilitate the best approach required for the type of information or activity object of training. Furthermore, clearly defined learning objectives are fundamental for guiding the direction of industrial training programs. By identifying specific skills, knowledge, and competencies that workers need to acquire or improve upon, training content can be structured to meet these objectives effectively.

Competence gap An increasingly automated environment, and many of the major changes brought by this swing, have a significant impact on the skills required to accomplish everyday tasks. Humans acquire a new role in terms of managing processes, machines and components with increasing and variant complexity and autonomy. The identification of gaps in skill-sets is needed at both organizational and operational levels, for example to prepare for working with data to perform descriptive diagnostics, or to increase ICT knowledge, including multimodal interaction with advanced Human-Machine Interactions in scenarios where the team would be composed of both humans and advanced automation.

Time availability Another critical factor to consider is the time availability of workers for training activities. Scheduling training sessions at convenient times and durations, and offering flexible training options, such as self-paced online courses or on-the-job training opportunities, allows workers to balance training commitments with their other responsibilities, facilitating their acceptance and ultimately improving the overall efficacy of the entire training program.

Feedback and evaluation Implementing a robust feedback and evaluation mechanism is essential for monitoring the progress of workers and gathering insights into the effectiveness of training programs from the recognition of the proposed topic to its comprehension and acquisition of applications skills. Here, XR simulations and AI-enabled training platforms can collect vast amounts of data about learners' interactions, performance, and progress. This data can be analyzed to monitor the assimilation by the trainees of the skills required to perform certain tasks, distinguishing between psychomotor skills (i.e., requiring coordination of cognitive and motor processes), procedural skills (i.e., related to the execution of sequences to accomplish a given task), decision-making or problem-solving skills (i.e. when several alternative options are available and there is not an established criterion on how to proceed), and spatial skills (i.e., the capacity to understand the visual and spatial relations among objects or space) [9].

Interests and motivations Understanding the interests and motivations of workers regarding training is essential for maintaining engagement and relevance. By conducting surveys, interviews, or assessments, organizations can gather valuable insights into what topics or areas workers are most interested in and what motivates them to participate in training activities. Incorporating real-life scenarios, case studies, or examples relevant to their industry or job role can enhance motivation and make training content more relatable and impactful.

2.3 Deploy tech innovations for tailored training programs

XR technologies offer immersive training environments that simulate real-world scenarios and tasks. For experienced workers, XR can provide advanced simulations and scenarios that challenge their skills and expertise, allowing them to practice complex procedures or problem-solving exercises in a risk-free environment. These simulations can be customized to reflect the workers' level of experience, incorporating realistic challenges and scenarios that are relevant to their specific roles and responsibilities. Most importantly, XR environments offer the possibility of collecting a large amount of data that is difficult to obtain in classic training contexts [9]. The data collected can focus both on the workers and the interaction with the environment around them. For instance, in XR training simulations for manufacturing assembly tasks, sensors embedded in the VR headset can track the worker's eye movements, hand gestures, and body posture in real-time, providing insights into the worker's level of engagement, attention, and proficiency in performing various assembly steps [10]. Additionally, XR environments can capture detailed metrics related to the worker's performance, such as task completion times, error rates, and movement trajectories. XR technologies also enable the recording and analysis of interactions between the worker and virtual objects or equipment within the simulation, providing the chance to investigate also ergonomics-related aspects linked to those interactions. For example, in an augmented training scenario, the headset can track the worker's interactions with digital overlays and simulated equipment components, allowing the blend of physical and digital contents to explore multimodal interaction and identify the most suitable method to provide the necessary information by adapting to the user's preferences and learning style [9,10]. This data can then be used by AI-powered adaptive learning systems to assess the workers' understanding of maintenance procedures, their level of experience and expertise, and to identify areas for improvement to tailor the next training interventions accordingly. Based on this assessment, the AI system can team up with the adaptability of XR environments to dynamically adjust the difficulty level, pace, and content of the training materials, according to the individual's skill level. For example, the interaction with the environment can be managed with the aim of delivering different kinds of information involving different sensory modalities, maximizing support to guide novice learners and reducing it as proficiency increases. The way and the amount of information delivered could also be adapted to meet trainees' needs, allowing them to freely move on a continuum that goes from fully guided programs to on-demand support.

2.4 Fighting inertia and creating trust

The implementation of highly innovative technologies in work contexts is not always a linear process and often has to face initial opposition from workers who may have different motivations [11]. The reluctance of workers to embrace new technologies can stem from a variety of factors, some of which may be rooted in genuine concerns and others influenced by perceptions or misunderstandings. One of the most common reasons for resistance to new technologies is the fear of job loss or displacement [12]. Workers may worry that automation or advanced technologies will make their jobs redundant, leading to unemployment or reduced job security. Some may resist innovative technologies because they perceive them as threatening their sense of control or autonomy in the workplace. This can be particularly true in industries where workers are accustomed to having a high degree of control over their tasks or where new technologies introduce greater oversight or surveillance. Moreover, workers may also resist new technologies if they perceive that their implementation will lead to increased workload, stress, or pressure to perform. Another major reason behind the resistance of workers in front of innovative technologies may be linked to difficulties in understanding how to properly use them.

Addressing this challenge requires a comprehensive approach that goes beyond simply providing technical training. Trust is a critical factor in human-machine interactions, directly influencing how people use and rely on technology. Innovations such as AI assistance also allow for increasingly natural interaction between humans and machines, making the monitoring of trust between the parties involved even more relevant. Properly calibrated trust ensures that users are able to exploit the full capabilities of the machines, while both excess and lack of trust pose significant risks both in terms of security and efficiency. Overtrust occurs when users place excessive trust in the technology they interface with, reducing the active monitoring machine performance and resulting in malfunctions that could cause serious consequences. on the other hand, undertrust occurs when users do not trust the machine and therefore limit or avoid its use altogether. this reluctance can make innovations useless, as the benefits of the technology are not fully used [13]. Therefore, balancing trust is essential to maximize the efficiency and safety of human-machine interactions, ensuring that technology serves as an effective tool rather than a source of new problems.

In conclusion, the approach proposed in the current paper not only addresses the immediate training needs but also establishes a dynamic and responsive training environment. By continuously integrating feedback and performance data, the training structure evolves alongside the organizational needs, supporting not only short-term transitions but promoting long-term adaptability in response to the ongoing technological evolution.

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