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ORIGINAL ARTICLE

A human-cyber-physical system for Operator 5.0 smart risk assessment

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Abstract

In the context of Industry 5.0, characterized by the human-centred transformation of manufacturing processes, assessing operator risk is crucial for ensuring workplace safety and well-being. In this respect, this paper presents the development of a human-cyber-physical system (HCPS) capable of estimating operator risk by leveraging diverse sensing data. By comprehensively analysing complex patterns and interactions among physiological, environmental, and manufacturing variables, the HCPS offers an advanced approach to operator risk assessment. Through the integration of cutting-edge sensing technologies, real-time data collection, and sophisticated analytics paradigms, the HCPS accurately identifies meaningful patterns and anomalies. It dynamically adapts to changing manufacturing conditions, generating risk profiles for operators and work processes. Timely alerts and notifications enable proactive interventions, enhancing safety measures and optimizing work processes. The HCPS empowers decision-making and supporting the well-being and productivity of operators in the Industry 5.0 paradigm, while maintaining a safe working environment. A simulated case study is reported to validate the proposed framework on a variety of industrial scenarios.

Keywords Human factors · Sustainable production · Risk · System monitoring

1 Introduction

In recent years, there has been a global emphasis on people and their well-being, transcending disciplinary boundaries, with a focus on respecting the health and development of individuals [1]. This shows, in new ethical standards, legislation, trading standards, and working patterns [2]. With reference to the manufacturing context, the well-being and longevity of workers are of utmost importance to ensure that manufacturing can be sustained into future generations and industrial revolutions as well as to maintain productivity and business [3]. As a result, while Industry 3.0 emphasized the development of robotic and manufacturing automation, the shift towards Industry 4.0 and the emerging trend of Industry 5.0 prioritize and highlight the importance of placing humans at the core of manufacturing systems [4].

The increasing implementation of automation supported by Information and Communication Technology (ICT) has led to the evolution of the operator's role in the new connected manufacturing systems. In this respect, Industry 5.0 designates the realization of the so-called Resilient Operator 5.0, defined as a smart and skilled operator aided by information and technology, to overcome obstacles ensuring operative long-term sustainability and workforce well-being in the face of difficult and/or unexpected conditions [1].

In order to enhance manufacturing efficiency in this new context, it is beneficial to utilize advanced monitoring technology that takes a holistic approach, considering the manufacturing environment, workforce, and machinery. By

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implementing improved resource monitoring, manufacturers can gain better insights into manufacturing quality, reduce downtime, and improve key performance indicators (KPIs). Previous studies have demonstrated the positive impact of such monitoring on machinery and tooling health [5]. There is now opportunity to improve the wider system resources to increase manufacturing outputs, by further extending this monitoring applicability to workers [6].

In this framework, to address the challenge of estimating operator risks in a manufacturing environment, the development of a human-cyber-physical system (HCPS) is proposed in this research work. The HCPS aims to utilize a wide range of sensing data to accurately assess the level of health risk faced by operators. This is realized by integrating human physiology, environmental conditions, and manufacturing variables to gain a comprehensive understanding of the complex patterns and interactions among these factors. The HCPS employs sophisticated data analytics techniques, such as fuzzy logic, to process the collected multi-dimensional data over time.

The concept is to acknowledge the dynamic nature of the manufacturing environment by consistently monitoring and adapting to fluctuations in variables such as machine operation, task complexity, and workloads. By considering the real-time context and interdependencies between different factors, the system can provide a continuous assessment of operator risk in terms of risk profiles for individual operators on specific work processes. The system can also issue timely alerts and notifications to operators and supervisors when risk levels exceed predetermined thresholds, enabling proactive interventions and mitigations.

2 Literature survey

A review of literature and industrial practice highlights the interesting knowledge gap on how modern manufacturing tools integrate with factories and manufacturing personnel, especially in system methods, data processing algorithms, and decision-making. As automation increasingly replaces manual processing, there is a gap in operator monitoring, which is consistent with the most recent operator concept.

In fact, human roles have evolved alongside technological and industrial revolutions, moving away from the original Operator 1.0 designation. Recently, the notion of Operator 5.0 has emerged, referring to a smart and skilled operator who harnesses human skills supported by information and technology to secure the long-term sustainability of manufacturing operations and promote the well-being of the workforce in demanding or unforeseen circumstances [7].

However, in this new era of information physical systems, operators still need to complete inherent tasks, as their interaction around the robotics and automation evolves. This highlights the need to explore the concept of a healthy operator in hazardous work environments [8] to be achieved through real-time monitoring using wearable trackers and analysing the operator's interaction with big data to monitor safety and predict potential risks [9].

Although the contributions in the development of sensor systems and the IoT emphasize the wide availability of commercially available solutions, an attractive research direction comes from the lack of system methods for integrated system development applied in manufacturing environment. In addition, the limited contributions available in the literature on decision support systems have promoted the development of intelligent systems [10].

Cyber-physical systems (CPS) are computational entities that are tightly integrated with the physical world and its ongoing processes. They interact extensively with their surroundings and utilize data-accessing and data-processing services available on the Internet [11]. Efforts have been made to incorporate human factors into CPS, leading to the development of human-cyber-physical systems (HCPS). HCPS aim to enhance human capabilities in dynamically interacting with machines in both the cyber and physical realms. This is achieved by employing human-computer interaction techniques designed to cater to the cognitive and physical needs of operators.

While recent research efforts have focused on human factors in manufacturing system design, human-robot collaboration, fatigue recognition, and musculoskeletal risk prevention, the application of these efforts to transformation processes is limited [12, 13].

The integration of CPS and human-CPS approaches is gaining traction in monitoring operator health and safety. CPS combine physical elements with computational and networking components, enabling the collection and analysis of real-time data from manufacturing processes. Human-CPS focuses on the interaction between operators and CPS, considering human factors and safety considerations [14].

IoT and sensor networks have transformed the monitoring of manufacturing environments by deploying interconnected sensors to capture data on parameters like temperature, humidity, noise levels, and air quality. This data analysis helps identify hazards, monitor ergonomic conditions, and ensure safety compliance, leading to real-time alerts and notifications for risk mitigation and improved operator safety [15].

The miniaturization of sensing technology has expanded its applications, particularly in physiological monitoring. Physiological sensors, such as smartwatches, provide individuals with better access to health-related data for understanding their bodies. Extensive reviews have explored the use of physiological sensors in manufacturing and extreme environments, including health monitoring in complex systems [16–19]. Similarly, healthcare research has examined the integration of sensing technology for recovery, amputee prostheses, and soft machines [20, 21].

Physiological sensors can monitor biological/chemical states, track body positioning, and measure strain using coordinate systems and accelerometery. Monitoring surgeon postural health in healthcare performance and identifying postural risks in manufacturing are examples of their applications [22–25]. Various products exist for monitoring physiological and kinematic states, but the selection criteria depend on sensor location convenience, task risk, environmental demands, desired sampling rate, accuracy, and timely integration within a safety feedback loop [26]. While physiological sensors perform well in their designated environments, challenges arise when integrating them into larger systems, particularly concerning data transfer and appropriate hardware configuration.

In factories, environmental sensors are essential for monitoring the quality of the working environment. They provide real-time data on temperature, humidity, noise levels, and pollutants, ensuring worker well-being and productivity. Advanced technologies, including gas sensors, particulate matter sensors, and temperature/humidity sensors, enable data collection and real-time feedback. Wireless connectivity enables remote monitoring and control, facilitating prompt responses to deviations. Integration with data analytics and visualization platforms enhances the utility of environmental sensor systems by providing insights, pattern recognition, and risk prediction. Challenges in this domain include sensor calibration, data security, and standardization for interoperability [27].

In recent years, the measurement of key variables in manufacturing processes has been facilitated by innovative sensing designs allowing to deal with physical constraints and challenging operating conditions [12]. Commercial sensors like accelerometers are increasingly integrated into machine tools, providing data with high sampling rates beyond the capability of machine PLCs. Traditionally, manufacturing process data were limited to time series data (e.g. vibration, pressure, force, torque), providing temporal information for process and tool monitoring. Recent advancements in signal processing and hardware have greatly enhanced image data processing, resulting in a significant increase in image acquisition in manufacturing. Technological progress has also enabled high-speed sensing, allowing processes to be monitored with exceptional temporal resolution. Both condition monitoring data and event data can be acquired on the manufacturing machines. Condition monitoring data, measured by sensors (e.g. force, vibration, acoustic emission, temperature), reflect the current health condition or state of the machines. Event data encompasses information on machine-related incidents (e.g. installation, breakdown, overhaul) and actions taken (e.g. component change, preventive maintenance) [12, 28].

2.1 Research gap

The emergence of HCPS as a developing paradigm for comprehending and establishing intricate human-centred intelligent systems has garnered significant attention from both industry and academia, particularly in the realm of human-centric smart manufacturing. Regardless of the perspective taken, whether involving humans directly (human-in-the-loop) or excluding them (human-out-of-the-loop), advanced manufacturing technologies are conceived by humans, designed to benefit humans, and function alongside humans. Therefore, it is crucial to integrate both human and cyber elements into smart manufacturing systems instead of excluding humans from the equation. Several surveys and reviews have been published exploring the interactions between humans and cyber systems in sensing, control, Industry 4.0, and manufacturing applications. HCPS, serving as the fundamental basis of human-centric smart manufacturing, is still in the early stages of research and development [7].

While CPS can be referred as the operating system or fundamental technology for X 4.0 (e.g. Industry 4.0, Engineering 4.0, Education 4.0), HCPS and human-smart manufacturing (HSM) would serve as the theoretical foundation and operating system for the upcoming X 5.0 (e.g. Industry 5.0, Operator 5.0, Engineering 5.0, Education 5.0, and Society 5.0) [7].

The literature review emphasized the necessity of developing an integrated system capable of sensing and facilitating risk-aware decision-making regarding actions such as maintenance and scheduling, while considering operator health and safety as crucial factors.

In this respect, this work aims at developing a HCPS to assess the various health and safety-related risks for the operator by collecting, processing, and combining information from various sensing data. Such system can be used to upgrade an existing production system into an operator 5.0-compliant environment.

3 Research framework

The HCPS proposed in this paper has a multi-layered structure as illustrated in Fig. 1. A physical layer is responsible for the acquisition of human health data, working environment data, and manufacturing process data. Such acquisition is enabled by a series of specific sensing units.

The data transmission is powered by the design and realization of a network layer including a tailored ICT infrastructure, which, through diverse transmission technologies, allows for sensing data to be conveyed to the central unit for processing purposes.

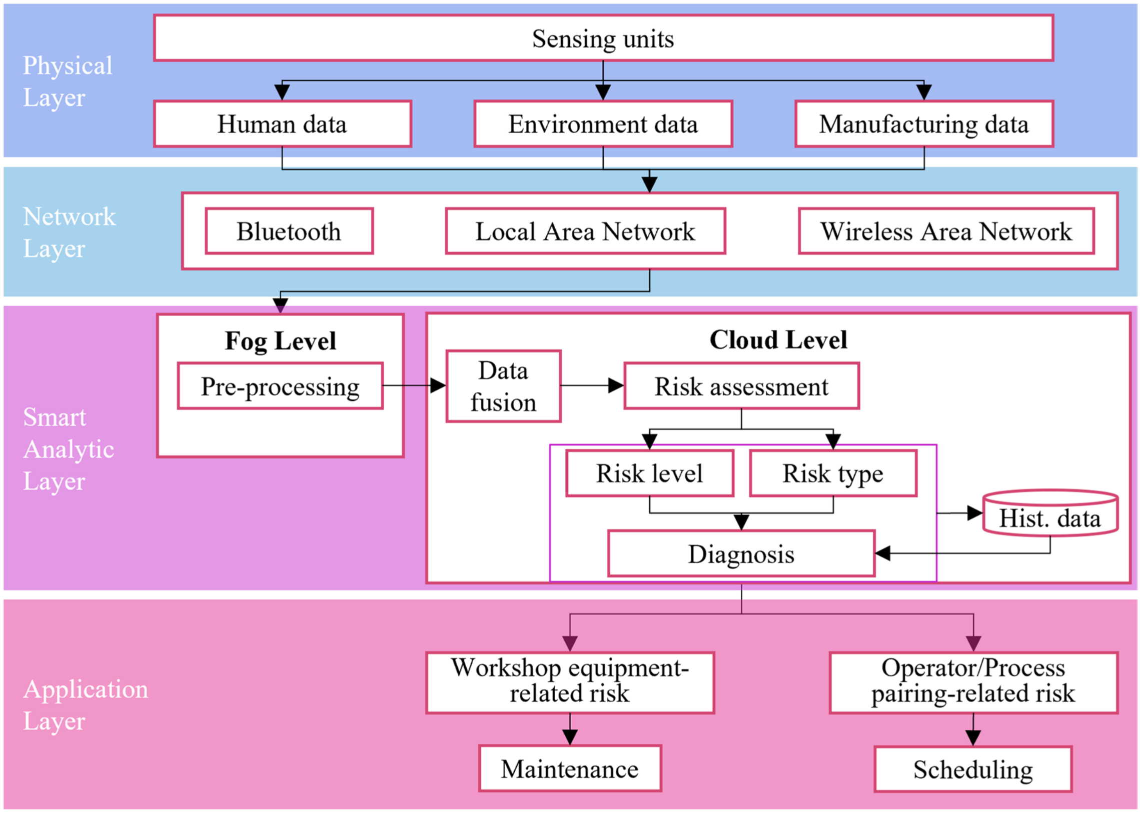


Fig. 1 Framework flow chart

The analytic layer converts data to information on a fog-cloud platform. Specifically, at the fog level, data preprocessing is performed while at the cloud level, tailored data fusion procedures carry out an intelligent risk assessment and diagnosis. In this layer, cloud-based storage is performed as data are continuously generated.

The application layer deploys the results from the analytic layer to further characterize the risks and prompt actions.

A detailed description of the various layers is reported in the following subsections.

3.1 Physical layer

In the context of a human-cyber-physical system framework, the physical layer refers to the collection of sensing units and computing elements. Real-time data collected from product sensors can be processed locally by the controller and/or transmitted to the cloud for further processing. In this paper, the physical layer is made of sensing units for the acquisition of relevant data on the physiological status of the operator, a comprehensive characterization of the workshop environment as well as a complete assessment of manufacturing process health.

3.1.1 Human physiological data

In this research context, physiological data are limited to a number of essential offline and online variables. The offline variables are manually inputted and regularly updated; such data include the following: age; body mass index (BMI), defined as the ratio of the body weight to the square of the body height; and medical history, including information on pregnancy, maternity, injury and surgery recovery, and mental health. Real-time physiological data can be acquired from wearable sensors throughout any working shift [9]. Concerning online data, wearable sensors will provide for a continuous monitoring of physiological parameters. such as blood pressure — both systolic and diastolic, respiration rate and heart rate, oxygen saturation, hydration level and body temperature, and eye-related data such as eye blink frequency and duration. Data on musculoskeletal parameters should be acquired too, such as posture, including neck posture, body vibration, and especially limb vibration.

Ultimately, data on exposure should be acquired too, possibly via GPS data which give an indication on how long a worker is exposed to various hazards; also, the number of walking steps can be useful to an overall health risk assessment.

3.1.2 Environmental data

In addition to the human data, a comprehensive environmental characterization of the workshop in which workers operate is also very important as environmental conditions often induce various diseases [9]. In this respect, basic environmental sensing units placed in the workplace can be used to acquire ambient temperature, humidity, ventilation and airflow rate, ambient lighting and noise.

Other relevant variables such as presence of chemicals particles in the air, with particular reference to priority compounds [29] such as benzene, carbon monoxide, formaldehyde, methane, ethane, naphthalene, nitrogen oxides, radon, trichloroethylene, and tetrachloroethylene. Data on perceived indoor quality can be acquired by monitoring the volatile organic compounds [15] such as acetic acid, hexanal, 2-butoxyethanol, 2-ethylhexanol, hexanoic, limonene, and phenol.

Data on the presence of dust, oxygen concentration/deficiency ambient noise including infrasounds (0.1–1 and 1–10 kHz) and ultrasounds (10–20, 20–40, and 40–400 kHz), odour [30], and ionizing radiations can be added for the construction of a more comprehensive dataset.

3.1.3 Manufacturing process data

For a comprehensive operator risk assessment, in addition to physiological data and environmental data, manufacturing processes and machines have to be monitored so as to assess any potentially dangerous scenarios in manufacturing operations. Relevant manufacturing process and machine data can be collected from diverse sources, such as machine and process monitoring systems as well as the machine control.

Recent years have seen an increase in the use of sensors in production machines to monitor machine and process status using relevant sensor signals. Although many of the acquired variables are used for tool, process, and machine condition monitoring, they also have an impact on the operator's well-being. These variables may include vibrations, noise, temperature, power consumption, and more, depending on the specific manufacturing process and machine [28].

Power consumption is commonly measured to ensure the normal operation of machines and processes and can be used to detect potential faults and related manufacturing risks. Vibrations are often measured to detect malfunctioning, which may reduce the service life of machines or lead to process failure. However, vibrations also generate noise that can pollute the environment and affect human health. Although noise emission is now regarded as a machinery quality flaw, manufacturing processes and machines are still noisy. Monitoring noise levels via different sensors can provide valuable data for the diagnosis and monitoring of machine and process health, as well as mitigate noise emissions to a level that is safe for human operators [31]. Temperature is also increasingly measured on production machines to monitor the thermal changes induced by the environment or internal heat sources, and it represents another relevant index for ensuring safe working conditions. Finally, other sensors may be employed on production machines to measure relevant variables specific to the production machine/process, such as chemicals, leaks, and fumes.

3.2 Network layer

The proposed cyber-physical system in this paper can be likened to a multi-layered Open Systems Interconnection (OSI) model, with the network layer responsible for data forwarding. Data from the physical layer are transmitted to the storage layer through a tailored network infrastructure, requiring different communication paths due to the diverse sensing units used (Fig. 2). Wearable sensors collect human physiological online data and employ a microcontroller unit (MCU) for orderly data acquisition. Real-time acquisition of certain sensor data, like respiration, requires no additional computation, while blood pressure data undergoes specific algorithms. The MCU handles pre-processing and transfers essential data to the central unit, with Bluetooth being a suitable communication technology due to its low-power requirements.

Bluetooth, operating at a transmission power of 2.5 mW and utilizing 40 channels between 2.402 and 2.48 GHz, follows a master-slave architecture in the human wearable sensing system [32]. The MCU acts as the master, sampling data from slave sensors. While Bluetooth is suitable for communication between the MCU and storage layer, longer distances beyond 10 m require more stable data transmission, making wireless area network (WLAN) a preferable choice.

WLAN, commonly known as Wi-Fi based on IEEE 802.11 standards, enables wireless communication and provides an Internet connection for firmware updates. Its longer data transfer distance makes it ideal for environmental data collection [33]. A preliminary study is necessary to optimize sensor positioning for effective data collection, especially considering the potential large number of sensors and their scattered locations within the workshop. A single WLAN can connect sensors within a workshop, while an external roaming getaway can facilitate information sharing across workshops.

However, disturbing factors like ionizing radiation and excessive heat in the air can impact WLAN data collection quality and reliability. In such cases, a wired LAN becomes a suitable solution for communication among mechanical sensors. Manufacturing data from various machines and equipment can be equipped with sensing units and monitoring dashboards that have a default LAN interface for data

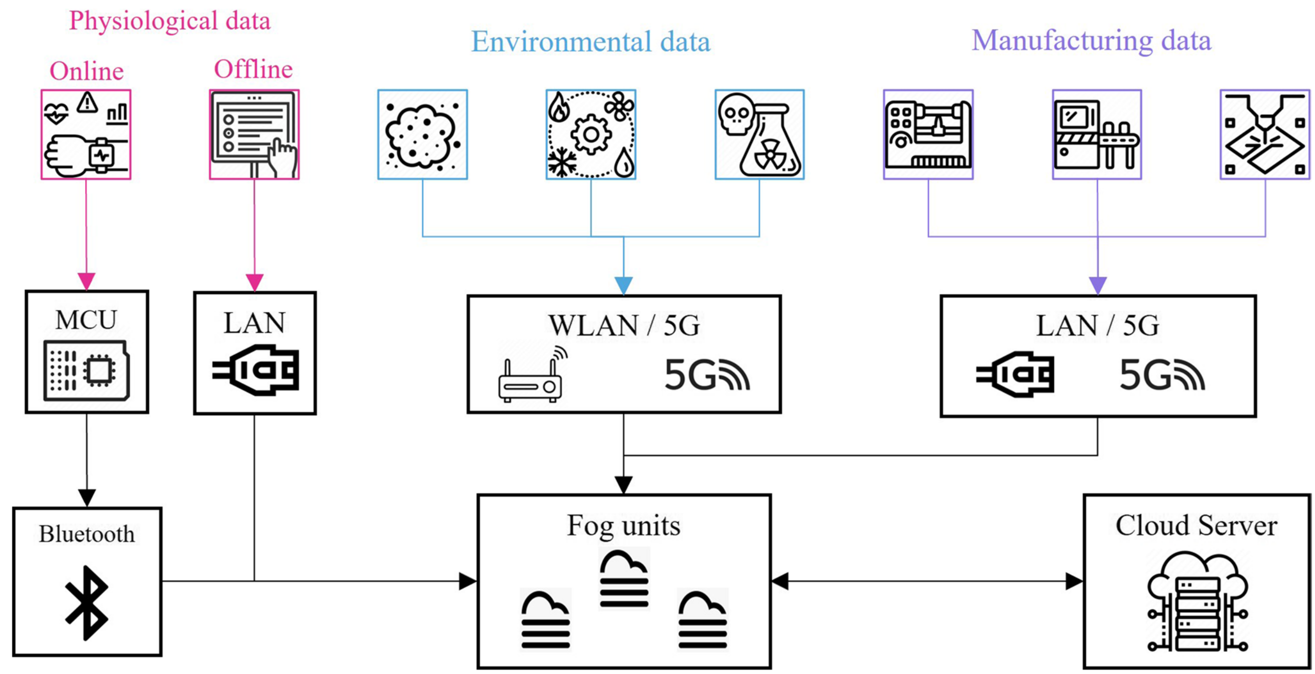


Fig. 2 Network architecture concept

transmission to the central unit. Additionally, LAN enables input and collection of offline physiological data.

The capabilities of complex manufacturing systems can be significantly enhanced by the 5th generation mobile network (5G), as it greatly improves communication capacity, data transmission rate, coverage nodes, and real-time performance. In the context of human-cyber-physical systems (HCPS), 5G plays a crucial role where numerous heterogeneous nodes communicate and generate massive data and information transmission across different layers. Furthermore, 5G is vital for enabling interactions between humans and CPS, including monitoring humans' physical and mental state, real-time task performance using VR/AR, remote control, and human-robot collaboration (HRC) [7].

3.3 Smart analytic layer

The raw data generated by the diverse sensing units need to be processed and submitted to a data fusion procedure to obtain useful information to be employed for the intelligent diagnosis executed by the proposed cyber-physical system.

In this work, a dedicated three-level architecture comprising a device layer, a fog layer, and a cloud layer is developed, forming a complex cyber-physical system where the fog layer acts as an intermediary between the physical devices and the cloud. Data originating from the physical layer at the factory level undergo pre-processing at the fog level before being transmitted to the cloud layer, which handles tasks such as data fusion, risk assessment, and intelligent diagnosis.

Fog computing aims to provide data processing and storage capabilities closer to the end devices, rather than directly sending raw data from sensors to the cloud. At the fog layer, small-scale cloud functionality is ensured through fog nodes, which are devices equipped with computing, storage, and network connectivity [34, 35]. The goal is to enhance efficiency and performance and reduce the amount of data transmitted to the cloud for processing, analysis, and storage, thereby minimizing network traffic and latency [36, 37].

The employment of cloud architectures with fog layers in smart manufacturing represents a promising approach to setup interconnected networks providing reliable and responsive computation services. The main challenges are related to the limited communication bandwidth and computation capabilities of fog nodes, requiring efforts to reduce data communication load and computation time latency. Novel approaches for manufacturing data reduction and efficient modelling and machine learning methods are a promising solution. Other challenges include supporting resource heterogeneity, scalability, fog node mobility, and interoperability, calling for the development of appropriate data and control interfaces [35]. While the implementation of cloud architectures incorporating fog layers in manufacturing is still in its early stages, some proposals have been presented in the literature [34, 37], emphasizing the associated benefits such as connectivity between physical devices and the cloud, heterogeneity and distribution of fog nodes, low and predictable network latency, secure remote access to large volumes of factory data, and high-performance computing [34].

The framework proposed in this work leverages the capabilities of both the cloud and fog to integrate complex and heterogeneous data, including human physiological data, environmental data, and manufacturing data, generated by various sensing units and computing elements.

3.3.1 Data pre-processing at fog level

The raw data generated by the diverse sensing units can be categorized into two main types, i.e. digital and analogue signals. Digital data such as temperature, time, and pressure data can be simply converted from binary to decimal. Analogue data include the voltage data which are read by analogue to digital converters (ADC) and require some signal processing program for extracting useful information. For example, a respiratory signal can be extracted from an ECG signal via independent component analysis (ICA) algorithm, which can directly separate respiratory signals from various interferences, avoiding the design of several complex filters.

Data from wearable devices have to be pre-processed by the MCU at the edge level, while other data are directly transferred to the fog nodes where pre-processing steps are carried out when necessary. Sensing units such as temperature and humidity sensors generally directly output the digital data which can be easy to read by simply conversion of binary to decimal. Position sensors generally acquire redundant data such as geographic position of latitude and longitude, time and data, as well as satellite information which are not needed in the health monitoring system. Therefore, resampling operations are required to homogenize the overall dataset. Different pre-processing steps such as data filtering, selection, normalization, encoding, transformation, and feature extraction are required, which are carried out at fog level. Afterwards, the pre-processed data are further processed at the cloud level of the analytical layer, when data fusion, risk assessment, intelligent diagnosis, and data storage tasks are carried out.

3.3.2 Knowledge base

The first step for the developed decision-making procedure is the construction of a knowledge base. In this context, the knowledge base is meant to be a summary of the relationship among the various variables. The knowledge base of this framework links together various human “states” in reference to different bodily systems that can be impacted by poor work environments. Figure 3 provides a visual of these elements and their reference to data and environmental conditions. Manufacturing roles are known for being practical and

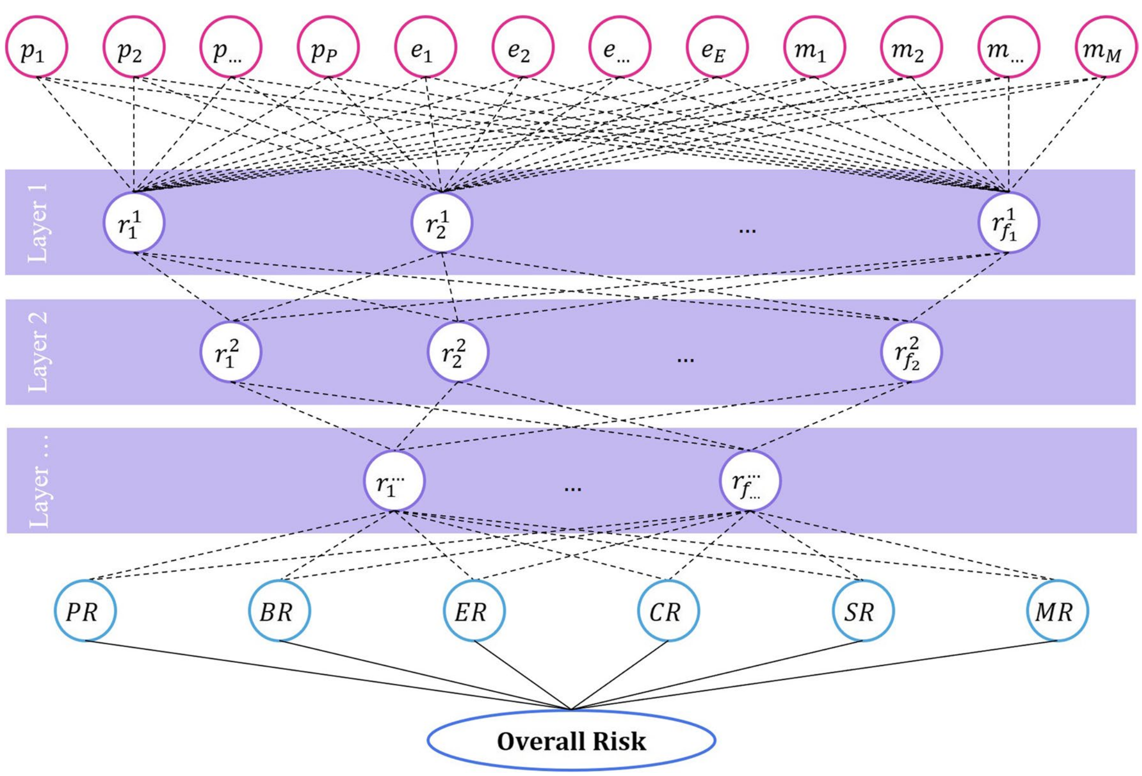


Fig. 3 Data fusion methodology

therefore physical, generally requiring a variety of strenuous work dexterous work. Both have implications on musculoskeletal state and vice versa.

More strenuous activity in manufacturing adds additional strain to the cardiovascular system which is repetitive over a longer duration increases the body temperature, leading to stress and dehydration. Lack of care to ensure operators are hydrated and have appropriate electrolytes (if necessary) can lead to fatigue, headaches, and lower physical ability.

Measuring all of these individual elements is a difficult task that often requires multiple sensing technologies or expensive sampling methods. While fitness trackers and smart watches can provide some of this information, there are concerns regarding the confidentiality and use of health data.

To properly assess these elements, multi-dimensional sensors and sensor fusion would need to report on various manufacturing levels. Operators would require feedback when physical thresholds are crossed, such as alerts to drink water if they are dehydrated or to reduce movement if the temperature increases. Over time, mapping out these processes and responses would provide a more extensive knowledge base that could be used to identify correlations or statistical relationships and recognize process limitations.

At the management level, this would enable more efficient job design, rotation, and procedures for dealing with processes that could be described as "physiological bottlenecks".

3.3.3 Fuzzy inference–based data fusion

The data fusion methodology is based on a fuzzy inference process [9] interpreting the values in the input vector (simple measured variables) and, based on some sets of rules (knowledge base), assigns values to the output vector, consisting of more complex variables representing risk factors.

Such approach aims at evaluating the interaction among physiological, environmental, and process variables, by progressively transforming groups of such simple variables into more complex risk variables, consisting in decision-making drivers to characterize the risk according to six main risk categories: physical, biological, ergonomic, chemical, safety, and mental-related risks [38].

Physical risks denote factors within the working environment that can harm the body without necessarily touching it. Biological risks are associated with working with animals, people, or infectious plant materials. Ergonomic risks indicate the type of tasks, body positions, and working conditions that can put strain on the body, for which, long-term exposure can result in serious long-term illnesses. Chemical risks are related to the exposure to any chemical compound in the workplace in any form (solid, liquid, or gas). Safety risks include unsafe conditions that can cause injury, illness, and death. Mental risks refer to the potential hazards or stressors that can negatively impact on the operator psychological well-being, cognitive functioning, and overall mental health [38].

Figure 3 shows the data fusion methodology, where p_1, p_2, $\ldots p_P$ represent the physiological variables; e_1, e_2, $\ldots e_E$ represent the environmental variables; and m_1, m_2, $\ldots m_M$ represent the manufacturing variables. The full set of such variables is fused using a fuzzy-based layer-by-layer progressive approach.

To initialize such procedure, the first step is to define the dependencies among the measured variables and then define a hierarchy which will identify the data fusion patterns.

Once identified such relationships, the full dataset of measured variables will be fused into a first layer of $r_1^1, r_2^1, \ldots, r_{f_1}^1$ risk factors, where the superscript 1 indicates the first layer and f_1 the related number of risk factors. At this point, the procedure is iterated, i.e. the dependencies among the first layer risk factors is defined and such factors are fused into a second layer consisting in $r_1^2, r_2^2, \ldots, r_{f_2}^2$ second-layer factors. There can be the need of repeating the fusion procedure over L layers. The number of layers depends on the number and types of variables and the manufacturing context.

At this point the risk factors $r_1^L, r_2^L, \ldots, r_{f_L}^L$ are eventually fused into the six risk categories physical (PR), biological (BR), ergonomic (ER), chemical (CR), safety (SR), and mental risk (MR). Analogously, a final step is then performed to define an overall indicator, i.e. the overall risk (OR) which serves as synthesis of the whole risk for the operator.

The fusion is enabled by a knowledge base, which involves occupational health expertise, company policies, and process engineering in a form of fuzzy inference rules [39]. The fuzzy inference consists in a mapping process from a set of fuzzy inputs to a crisp output based on fuzzy logic, which deals with vague and imprecise information. The fuzzy inference process includes fuzzy sets, membership functions, logical operations, and if-then rules. The mechanism is exemplified in Eq. 1 and illustrated in Fig. 4.

$$\text{IF} \left\{ I_x^l \in \tilde{I}_x * \cdots * I_y^l \in \tilde{I}_y \right\} \text{THEN } O_z^{l+1} \in \tilde{O}_z \tag{1}$$

where $I_x^l, \ldots, I_y^l$ are input variables, $\tilde{I}_x, \ldots, \tilde{I}_y$ are the fuzzy sets which the input variables belong to by the membership functions, O_z^{l+1} is the corresponding output variable in the next layer $l+1$, and $\tilde{O}_z$ is the fuzzy set which the output variable belongs to by the membership function [39]. "*" represents a logical operator, such as "AND", "OR", and "XOR".

The fuzzification process is carried out considering the specific variables and their ranges, in this respect, while for the physiological variables, medical guidelines can be followed, and for environmental variables, it is possible to refer to specific standards [40].

In specific ranges for machine tools and process equipment, the ranges have to be determined by considering the specific machine configurations and materials involved.

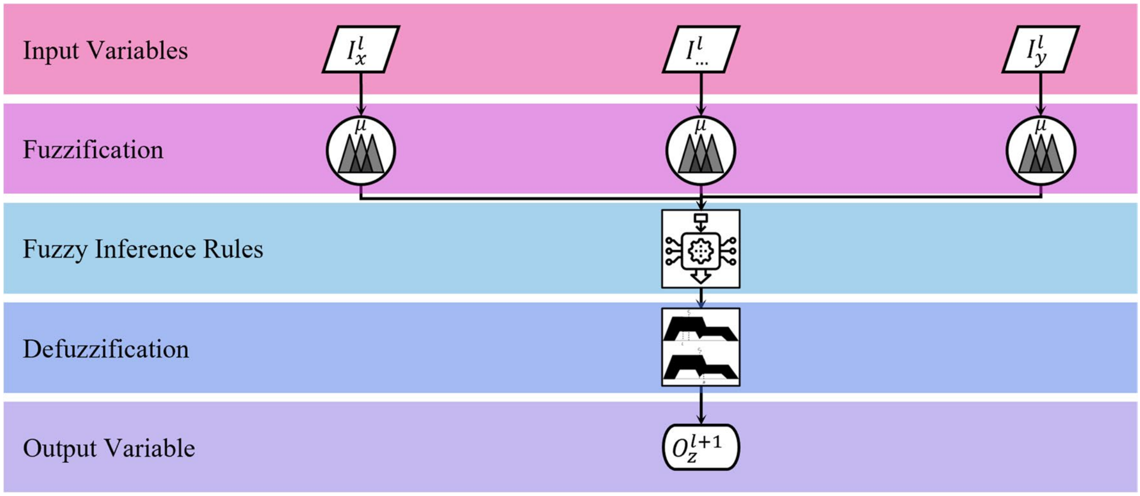


Fig. 4 Fuzzy fusion procedure

Table 1 Examples of variable ranges

Variable	Level			Units
	Low	Normal	High	
Respiratory rate	<12	12–15	>15	Times/min
Heart rate	<60	60–100	>100	Beats per minutes
Oxygen saturation	<95	95–100	100	%
Body temperature	<36.5	36.5–37.5	>37.5	°C
…	…	…	…	…
Hydration level	<50	50–60	>60	%
Ambient ventilation	<5	5–8	>8	l/s
Ambient lighting	<300	>300		lux
Ambient temperature	<16	16–34	>34	°C
…	…	…	…	…
Humidity	<20	20–60	>60	%
Oxygen deficiency	<19.5	>19.5	>23	%

An excerpt of the variables ranges adopted for the fuzzy logic–based fusion is reported in Table 1.

Concerning the inference process, a number of rules have to be set to link the fuzzy input to a fuzzy output. A defuzzification step is then carried out in order to convert the fuzzy quantities into crisp quantities. In this respect, various methods can be used, such as the max-membership method, the centroid method, the weighted average method, and the mean-max membership method [39]. The results of this step consist in a set of charts showing the risk value and trend over time. A statistical risk distribution over time can be easily computed too, as per Eq. 2.

$$RC_{i,t} = \frac{R_{i,t}}{\sum_{i=1}^{6} R_{i,t}} \bullet 100\ (\%), \forall t \quad (2)$$

where $RC_{i,t}$ represents the percentual contribution of the risk category i to the overall risk for a given time instant t, and $R_{i,t}$ is the risk level related to the risk category i.

The normalized risk values $R_{i,t}$ are generated through a fuzzy logic inference procedure and fall within the range of [0,1], where 0 signifies the lowest risk, and 1 signifies the highest risk.

To get to these results, the first step is defining the ranges for all the variables. As regards the physiological variables, ranges are defined according to medical guidelines customized upon the operator characteristics coming from offline health background data and information [13]. Concerning the working environment variables, ranges can be defined by relevant literature and by international standards such as EN 15251:2007, EN 16798-1:2019, and ASHRAE 55-2017 [41]. Similarly, the wide availability of literature and industrial practice on machine and equipment sensor monitoring can help define the proper ranges for manufacturing variables related to the specific unit/process, machine, and equipment under investigation. Once the ranges have been identified, a normalization procedure has to be carried out to "translate" them into a number of risk classes; three in this work were named as "low", "medium", and "high".

At this point, key thresholds on the risk values, such as a warning threshold and a higher critical threshold, are defined by the system administrator for diagnosis purposes. Such values are to be decided on a case-by-case basis. The procedure for setting the key thresholds involves various considerations. First of all is the identification of the risk indicators which are made available in the proposed approach through the layer-wise data fusion. Subsequently, the system administrator, in compliance with the company policy, should determine the specific risk appetite, i.e. type and amount of risk that the company is prepared to retain/

take and risk tolerance [42]. Accordingly, it is necessary to take into account the historical data, the prevention measures, the exposure, the operator training, and the company capacity to perform appropriate course of actions when and where required [43].

If the operator risk is estimated to be over the abovementioned thresholds, an online diagnosis procedure is triggered, which is carried out by a backtrack involving the analysis of all the intermediate complex variables generated by the fuzzy inference system up to the sensing data, which is helpful to distinguish different risk classes. This paper considers two risk classes, i.e. workshop equipment from operator/process pairing–related risk. From a computational perspective, the diagnosis can be powered by analytic tools such as outlier analysis and analysis of variance (ANOVA) or more refined tools such as machine learning classifiers.

3.4 Application layer

In the application layer, the output of the diagnosis is employed to support decision-making on the course of action that should be taken when a risk is identified.

Two main scenarios are envisaged in this work, described as follows:

- Workshop equipment–related risk: The risk comes from machine fault, equipment malfunctions, and environmental issues such as excessive pollution and noise.
- Operator/process pairing–related risk: The risk comes from an incompatibility between the human health state and the process.

Such scenarios imply different actions to be taken, i.e. extraordinary maintenance or equipment upgrading for workshop equipment–related risk, while different scheduling strategies in case of operator/process pairing–related risk.

4 Case study

The case study refers to a manufacturing cell where both manual and semiautomated welding processes are performed by two different operators. The welding process considered in this case study is gas tungsten arc welding, also referred to as tungsten inert gas (TIG) welding, which is an electric arc welding process that produces an arc between a non-consumable electrode and the piece being welded. In this type of welding, a shielding gas forms a protective envelope around the weld area to help protect the weld. An inert gas such as argon or helium helps protect the area from contamination. TIG welding is one of the most precise and controlled welding processes, providing a very smooth welding finish and allowing to weld a big range of metals including both ferrous and non-ferrous metals (such as copper, magnesium, aluminium). However, the main shortcoming is that TIG is a complex welding method to learn with great control and accuracy, which needs a deep arc, correct distance, and accurate manoeuvring for a better result and hence is a demanding process to master. This means that experienced operators are required to execute the TIG welding process, especially when the latter is carried out manually.

Safety concerns related to TIG welding are due to the exposure to high heat arcs (dangerous for the safety of eyes and skin) and potential radioactive gases (due to radioactivity of tungsten). The most important safety precautions for the health of operators include wearing protective gear and PPE (such as helmets, aprons, gloves, goggles, jackets, sleeves, pants, and safety shoes, to protect skin and face from impending burns), ensuring a ventilated workplace and installing appropriate fume extraction solutions (to circulate fresh air and reduce the toxicity of fumes exposure to the welder), making sure that all electrical connections are secure, the welding equipment is properly grounded and that the workplace is dry (to avoid electric shock), and ensuring that the welding area is clear of any combustible materials.

The workpieces considered in this paper are flange-pipe assemblies which require a fillet weld to be realized both outside and inside, as illustrated in Fig. 5.

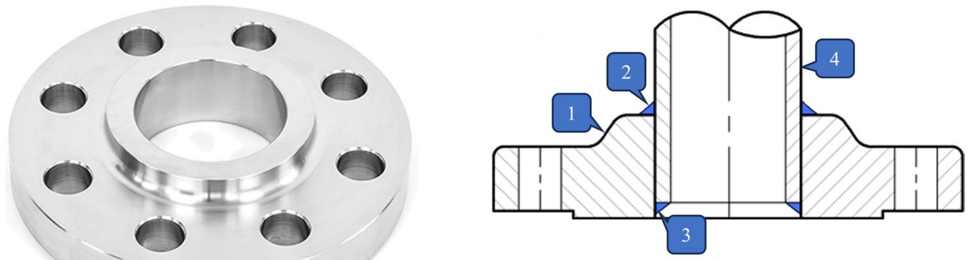
Two different processes are carried out in the manufacturing cell under study: (1) manual TIG welding and (2) semiautomated TIG welding. The description of the process steps for both processes is reported below.

4.1 Process 1: manual TIG welding

In manual TIG welding, the operator employs a handheld torch to perform welding along the joint and manually adds the filler metal to the weld area. A skilled operator is required, who is responsible for the following process steps:

1. Pre-weld parts inspection (ensure the quality of metal parts before assembling them)
2. Electrode preparation (pick and grind the electrode and insert the electrode into the collet)
3. Configuration of the proper parameter setting (e.g. select the current that is required) and set on the shielding gas chosen for the process
4. Arrangement of the welding station (cleaning and clamping of the parts)
5. Manual welding of the parts and in-process inspection
6. Removal of the completed part
7. Post-weld inspection (visual inspection to verify the integrity of the completed weld)

Table 2 shows the duration of each activity step in the manual welding process.



1. Slip on flange 2. Fillet weld outside
3. Fillet weld inside 4. Pipe

Fig. 5 Flange-pipe and assembly scheme

Table 2 Manual welding process activity breakdown

Activity		Duration (s)
Handling		300
Grinding		600
Configuration		300
Tooling		900
Welding process	Welding	15
	Inspection	15

Table 3 Semi-automatic welding process activity breakdown

Activity	Duration (s)
Handling	300
Grinding	600
Configuration	300
Tooling	900
Welding	1125
Inspection	120
Removal	600

4.2 Process 2: semi-automated TIG welding

In semi-automated welding, an operator manually loads the part(s) into the welding fixture. A weld controller then controls the torch/part motions and welding parameters to ensure a high-quality, repeatable weld. After the weld is completed, the operator then removes the completed part and the process begins again. The operator is responsible for a series of operations which include the following:

1. Pre-weld parts inspection (ensuring the quality of metal parts before assembling them)
2. Electrode preparation (pick and grind the electrode and insert the electrode into the collet)
3. Configuration of the proper parameter setting (e.g. select the current that is required) and set on the shielding gas chosen for the process
4. Arrangement of the welding station (cleaning and clamping of the parts)
5. Automatic welding of the parts: The operator ensures that the equipment is functioning properly and safely and that the welds are produced to meet the required specifications.
6. Removal of the completed part
7. Post-weld inspection (visual inspection to verify the integrity of the completed weld)

Table 3 shows the duration of each activity step in the semi-automated welding process.

To simulate the activities carried out by the operators in the manufacturing cell, an 8-h working shift was considered, with short breaks (5-10 min) after each assembly and a lunch break of 30 min.

In order to take into account the characteristics of potentially different workers involved in the welding processes, two different operators were included in the simulations, i.e. a young and fit operator and an elderly operator with cardiovascular medical history.

Two different scenarios were simulated with the aim to highlight the response of the developed HCPS in terms of risk characterization under different circumstances, with particular reference to the identification of operator-related risks and workshop equipment–related risks.

In the first scenario, the elderly operator is assigned to the manual welding process, due to his experience and skill in performing the TIG welding process. On the other hand, the younger operator is assigned to the semi-automated welding process.

In the second scenario, a malfunctioning of the ventilation system was simulated in order to assess the response of the human-cyber-physical system under changing manufacturing equipment conditions.

The variables utilized for the case study are reported in Table 4.

Each fuzzy inference process has been constructed by setting three sets of gaussian membership functions for each input and output variable, i.e. low, medium, and high.

The fuzzy-based fusion methodology has been implemented as per Fig. 6. The sensing variables are subject to a first-layer fuzzy inference for normalization purposes, i.e. assigning to each sampled value a low/medium/high class. This step facilitates the computational procedures. In this respect, the first-layer outputs are fed into a second-layer fuzzy inference, where the 58 variables are fused into 14 complex variables. Following this step, the procedure is applied to a third-layer inference which outputs the physical, ergonomic, chemical, safety, and mental risk. The biological risk has been disregarded in all the scenarios due to the non-relevance to this case study. The overall risk has been computed with the same approach.

To take into account the fatigue, each risk factor is multiplied by a fatigue coefficient, gradually increasing within each assembly task and ranging from 10% (first assembly task) to 40% (last assembly task). The fatigue coefficient represents the level of fatigue experienced by workers and reaches its maximum value at the end of each assembly task. This approach recognizes that fatigue can amplify the effects of risk factors, potentially increasing the likelihood or severity of adverse outcomes. Literature contributions report various non-linear and complex fatigue functions [44]; however, in this work, the authors have modelled the fatigue as a linear function of time to simplify the analytic processing. While it is widely acknowledged that fatigue can significantly increase the risk for factory workers, the specific percentage increase in risk due to fatigue can vary depending on the nature of the work, the individual worker health and fitness level, and other factors such as working environment conditions. In this work, the fatigue values are defined in line with relevant literature, and it is worth to remind that they are mainly thought for proof-of-concept purpose in order to demonstrate the applicability of the methodology [45, 46].

As concerns the risk diagnosis, this case study has established two thresholds to identify significant risks that trigger the appropriate course of actions. Specifically, a warning threshold of 0.7 and a critical threshold of 0.8 have been defined.

When considering the threshold settings, it is important to account for the unique characteristics of each company. For instance, a company characterized by lower capacities in terms of equipment and resources and longer response times should set lower key thresholds (i.e. corresponding to lower levels of risk) compared to a company which is able to timely and effectively mitigate high-risk circumstances. From an analytical perspective, it is essential that each threshold is determined on a case-by-case basis by following the guidelines mentioned in Section 3.3. Furthermore, from a system usage standpoint, the proposed HCPS can adapt to variable threshold values set by the system administrator, both for online assessment and for scenario simulation.

Table 4 Sensing variables utilized in the case study

ID	Variable	ID	Variable	ID	Variable
p_1	Age	$e_1 \ldots e_9$	Priority compounds	m_1	Heat source
p_2	BMI			m_2	Radiant heat flux
p_3	Medical history			m_3	Mechanical vibrations
p_4	Mental health	$e_{10} \ldots e_{16}$	Volatile organic compounds	m_4	Power consumption
p_5	Pregnancy + maternity			m_5	Machine overload
p_6	Gender			m_6	Electromagnetic radiations
p_7	Systolic blood pressure	e_{17}	Ambient ventilation	m_7	Ultraviolet light
p_8	Diastolic blood pressure	e_{18}	Ambient lighting	m_8	Blue light
p_9	Respiratory rate	e_{19}	Ambient temperature	m_9	Infrared light
p_{10}	Heart rate	e_{20}	Dust	m_{10}	Ionizing radiations
p_{11}	O_2 saturation	e_{21}	Humidity		
p_{12}	Body temperature	e_{22}	O_2 deficiency		
p_{13}	Sitting posture	$e_{23} \ldots e_{25}$	Ultrasounds		
p_{14}	Neck posture	$e_{26} \ldots e_{28}$	Infrasounds		
p_{15}	Eye blink frequency	e_{29}	Noise		
p_{16}	Eye blink duration				
p_{17}	Body vibrations				
p_{18}	Hand-arm vibration				
p_{19}	Hydration level				

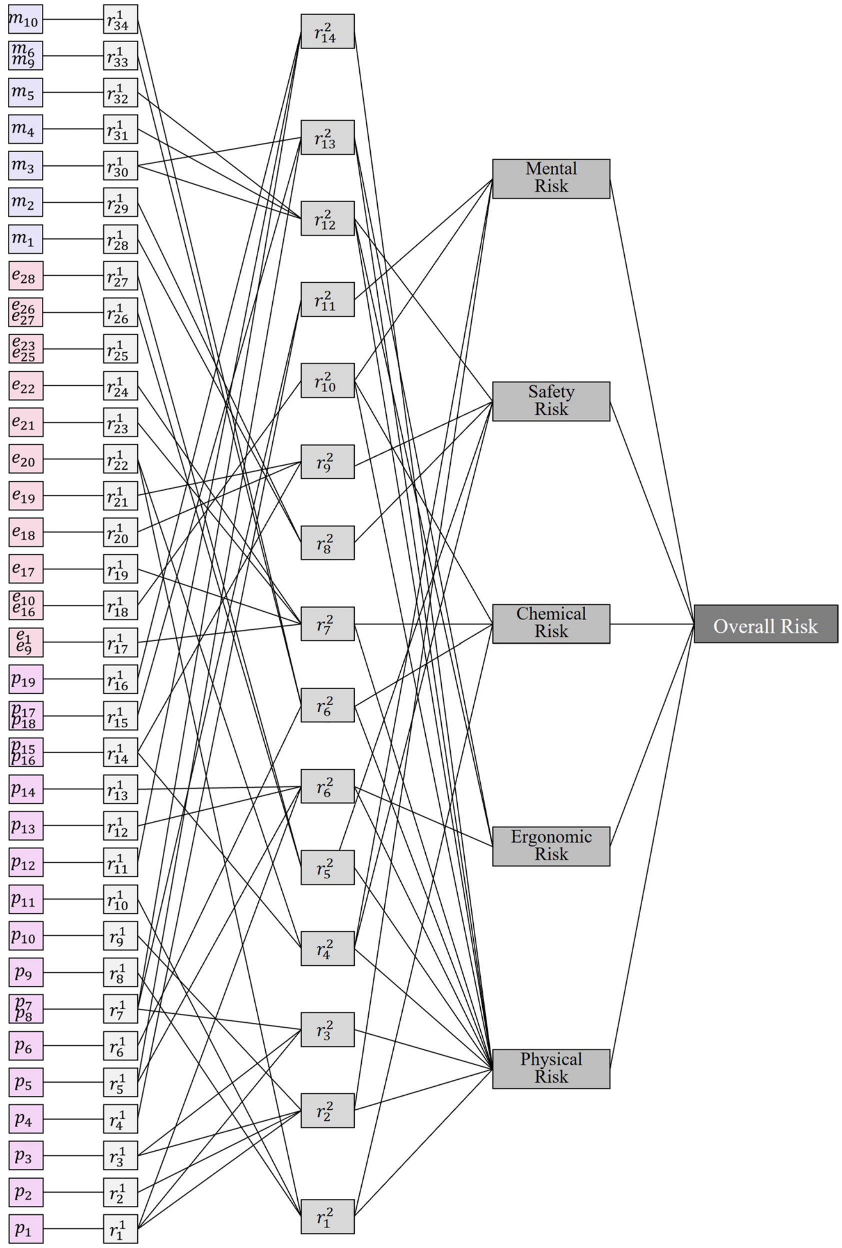


Fig. 6 Data fusion tree for the case study

5 Results and discussion

5.1 Scenario 1

In scenario # 1, an operator/process-related risk was simulated. Specifically, the hypothesis is that the current working configuration includes the young and fit operator on the semi-automatic process, while the elderly operator is allocated to the manual process because of his experience and skills. The system detected that these working conditions are not suitable for the elderly operator. To address this issue, one possible solution is to swap the operators. By implementing this swap, the elderly operator would be assigned to the semi-automatic process, while the young operator would take over the manual process.

Figures 7–10 present the results for both operators, i.e. young and elderly for both processes, i.e. manual and semi-automatic. The charts are obtained by plotting each type of risk (physical, ergonomic, chemical, safety, mental, and overall) against the time. The charts report also the warning and critical thresholds, in order to be able to quantify the time exposure (in minutes) to risks within or above such thresholds.

The results of the manual processes performed by elderly operator reveal higher levels of risk, as shown in Fig. 7. As regards the physical risk (Fig. 7a), a warning level for approximately 74.08 min and a critical level for 75.92 min were reported, indicating a relatively high risk of physical strain or hazards for the operator. Ergonomic risk (Fig. 7b) exhibited a significantly higher warning level for approximately 106.68 min, with a short exposure to critical level for 1.93 min at the end of the shift, indicating considerable posture concerns amplified by the higher BMI. Chemical risk (Fig. 7c) displayed a duration in the warning level of 51.15 min and a negligible duration in the critical level of 0.27 min.

For the semi-automatic processes performed by young workers, Fig. 8 shows no significant warning or critical levels for any of the factors or the overall process. It is possible to appreciate the variations of the various risk factors throughout the shift, with small peaks of physical, safety and mental risks in correspondence of the grinding phase (Fig. 8a, d, e) along some peaks in ergonomic risks during the inspection (Fig. 8b). It is also possible to appreciate the increasing risk trend during each assembly task due to the fatigue. The charts indicate a relatively low level of risk associated with the semi-automatic process for the young operator.

In order to mitigate the risk for the elderly operator, an operator swap is considered. In this way, the elderly operator will be allocated to the semi-automatic welding, while the young operator will be allocated to the manual welding.

Following the operator swap, the results for semi-automatic processes performed by the elderly operator (Fig. 9) indicate a generally low level of risk. While ergonomic risk reach warning level for 2 min (Fig. 9b), no significant warning or critical levels were reported for other factors or the overall process, suggesting minor corrective measures in terms of ergonomic risk mitigation.

When examining the results for manual processes performed by young workers (Fig. 10), it can be observed that the ergonomic risk (Fig. 10b) reaches the warning level for approximately 14.47 min, indicating the need for attention to posture considerations during the welding and inspection processes. The chemical risk reaches the warning level for a total of 41.3 min. Similarly, the safety risk (Fig 10d) reaches warning level for approximately 9.77 min during the welding process phase, suggesting to improve the safety-related conditions (such as PPE). Moreover, the overall risk within the warning level for the

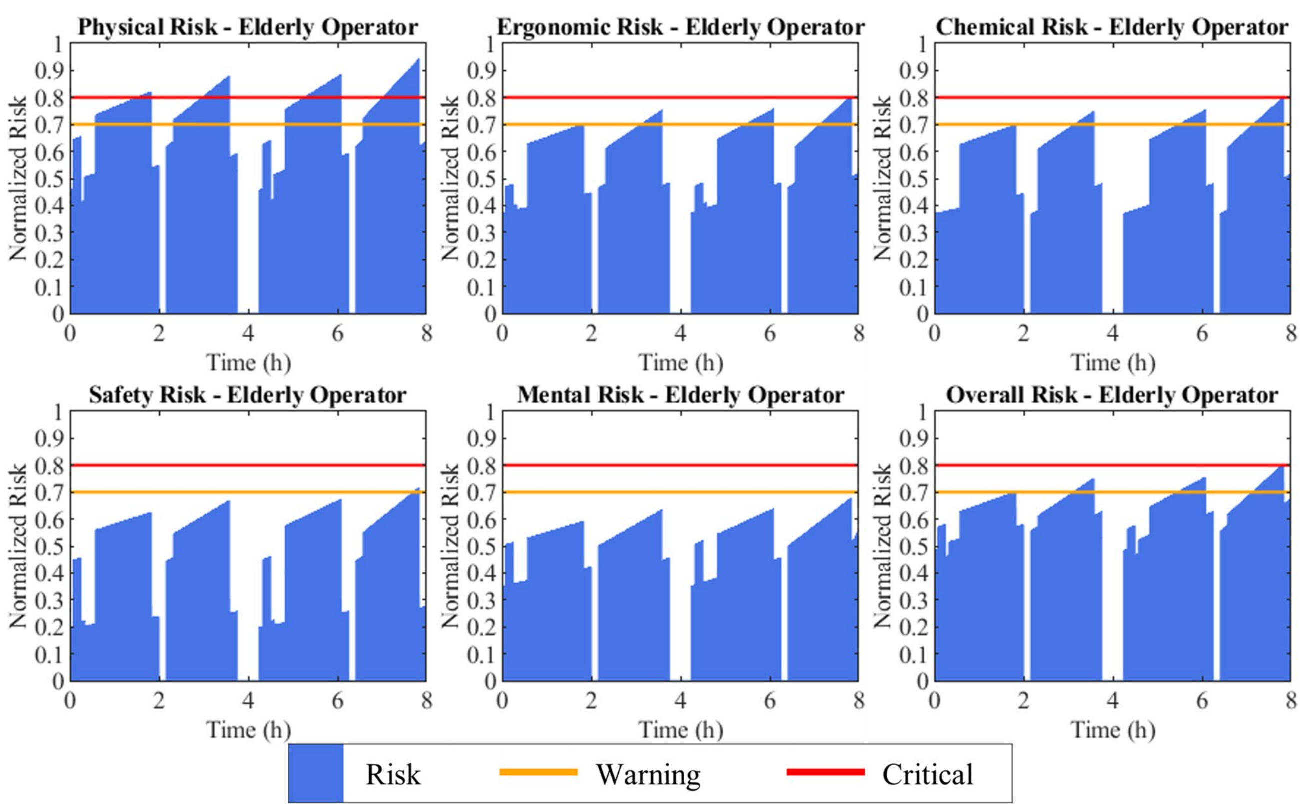


Fig. 7 Manual welding — elderly operator, risk breakdown: **a** physical risk, **b** ergonomic risk, **c** chemical risk, **d** safety risk, **e** mental risk, and **f** overall risk

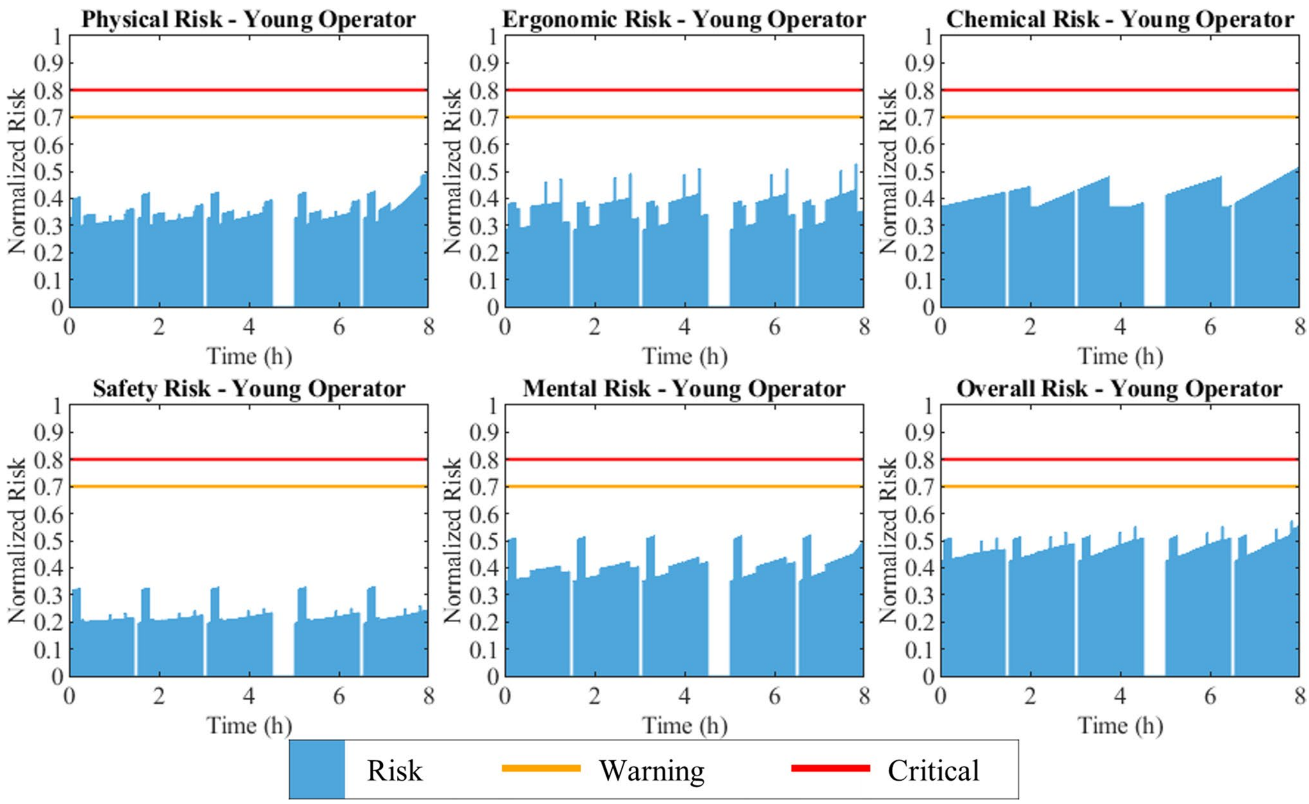


Fig. 8 Semi-automatic welding — young and fit operator, risk breakdown: **a** physical risk, **b** ergonomic risk, **c** chemical risk, **d** safety risk, **e** mental risk, and **f** overall risk

duration of 6 min (Fig. 10f) indicates a moderate level of concern across all factors combined, limited to the end of the shift, when the fatigue will increase to its maximum extent, remaining however below the critical level.

5.2 Scenario 2

In scenario # 2, a workshop equipment–related risk was simulated. The hypothesis is that a failure of the ventilation system occurred during the first break, specifically during the manual process with the young operator. In this way, the equipment fault-related hazards will begin to appear starting from the second welding assembly. This scenario has been simulated by setting significant changes to the dataset in terms of ambient ventilation, oxygen deficiency, and noise, keeping however such values within the legal ranges.

Fig. 11 compares the equipment fault scenario to the no-fault scenario with the same operator (young and fit operator referred to the manual welding). It is possible to see how, for the first assembly task, all the risks are perfectly overlapped. As the second assembly task begins, the physical risk (Fig. 11a) has a rapid and high rise, reaching warning levels for 154.16 min, and critical levels for a total duration of 86.75 min. This is due to the worsening of critical respiration–related factors in the physical risk, such as the air quality and the breathing difficulties, due to the ventilation system fault. The ergonomic, safety, and mental risks show no change, while chemical risk (Fig. 11c) reaches the warning level for about 51 min. The overall risk (Fig. 11f) reaches the warning level for 109.55 min, and it never reaches the critical level. On average, the overall risk results to be higher than the no-fault case by 14% from the fault occurrence to the end of the working shift.

Among the various scenarios that could be simulated, two specific scenarios, namely, operator-related risk and workshop equipment–related risk have been selected as case study. These scenarios, which are described in detail in Section 4, offer clear and effective demonstrations of the feasibility of the proposed method.

The same approach can be applied to more complex scenarios involving multiple risk sources, e.g. related to the operator, the process/machine and the working environment together. In this case, the system allows to characterize the risk breakdown by performing a backward root cause analysis enabled by the intermediate fusion layers (as shown in Figs. 3 and 6) and prompt customized courses of actions.

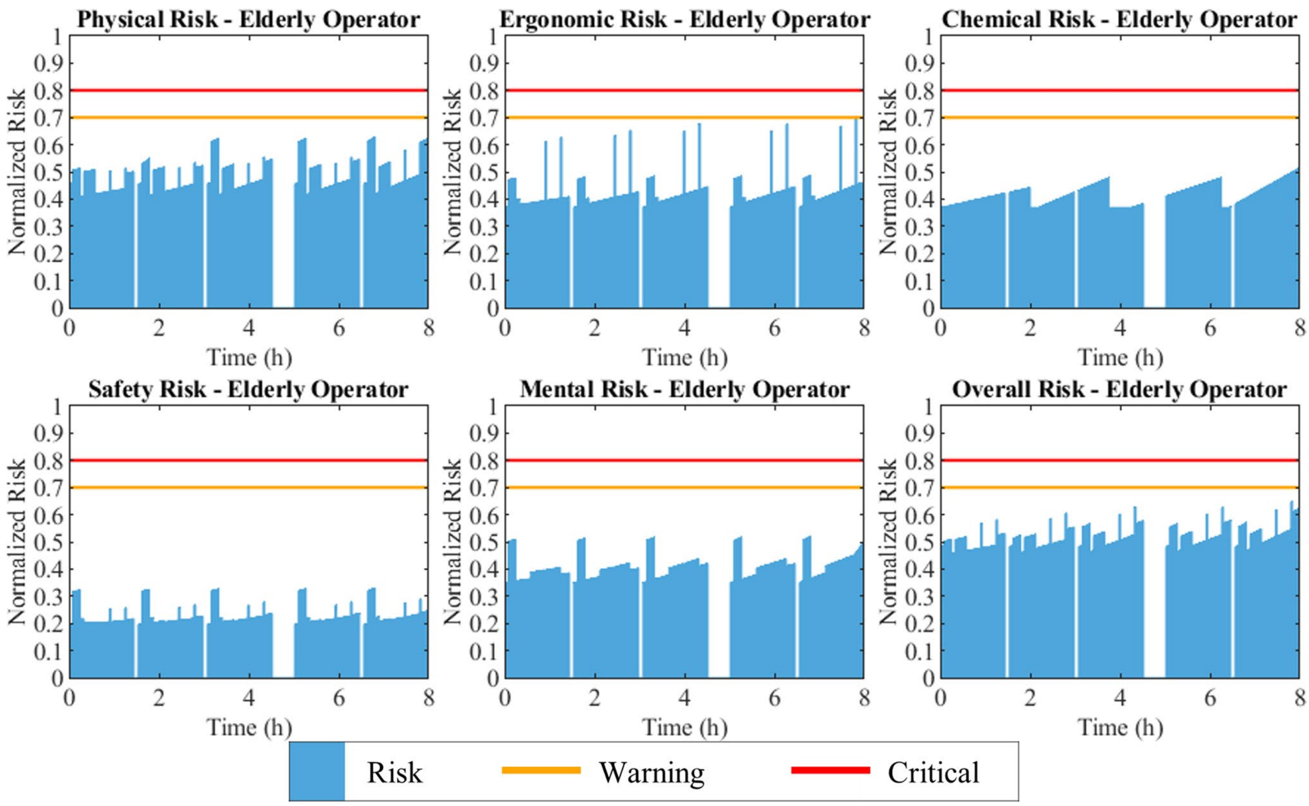


Fig. 9 Semi-automatic welding — elderly operator, risk breakdown: **a** physical risk, **b** ergonomic risk, **c** chemical risk, **d** safety risk, **e** mental risk, and **f** overall risk

6 Conclusions

The HCPS developed in this paper provides a valuable tool for understanding and managing operator risks in manufacturing environments by leveraging the power of data fusion and advanced analytics. It highlights safety hotspots, supports decision-making processes, and assists the work processes optimization to ensure the well-being and productivity of operators. The potential of such HCPS lies in the adaptability, reconfigurability, and scalability over a number of processes, environments, and operators. The contribution beyond the state of the art provided by this research work is represented by the development of the HCPS, based on Industry 4.0 key enabling technologies, that collects a variety of diverse data related to the operator, the process/machine, and the working environment and dynamically estimates the risk for the operator during the work shift. This methodological approach can serve as online health and risk monitoring tool with the possibility of being implemented as ex-ante risk assessment during the design phase of the production system, scheduling definition, and scenario construction as well as during daily manufacturing system operation. The data simulation utilized in the case study for proof-of-concept purpose includes two likely scenarios occurring in a common manufacturing system, which were selected as clearly identifiable and effective to demonstrate the application feasibility of the proposed method.

The sensing variables to be selected in the HCPS are process specific; therefore, a thorough preliminary study is required for their identification. The variables are identified and normalized into three risk classes: low, medium, and high. A challenging task is represented by the modelling of relationships among variables for data fusion, which requires building an updatable knowledge base from relevant literature and specialized practices. The main contribution of this research is the development of a methodology for deploying these relationships via layer-wise data fusion, using an operational fuzzy inference procedure to categorize a large number of sensing variables into a defined number of risk categories, considering their complex interactions.

The fuzzy inference fine-tuning relies, by definition, on the expertise. Alternatives can be found in neuro-fuzzy or other intelligent regression paradigms, taking into account the computational complexity and load.

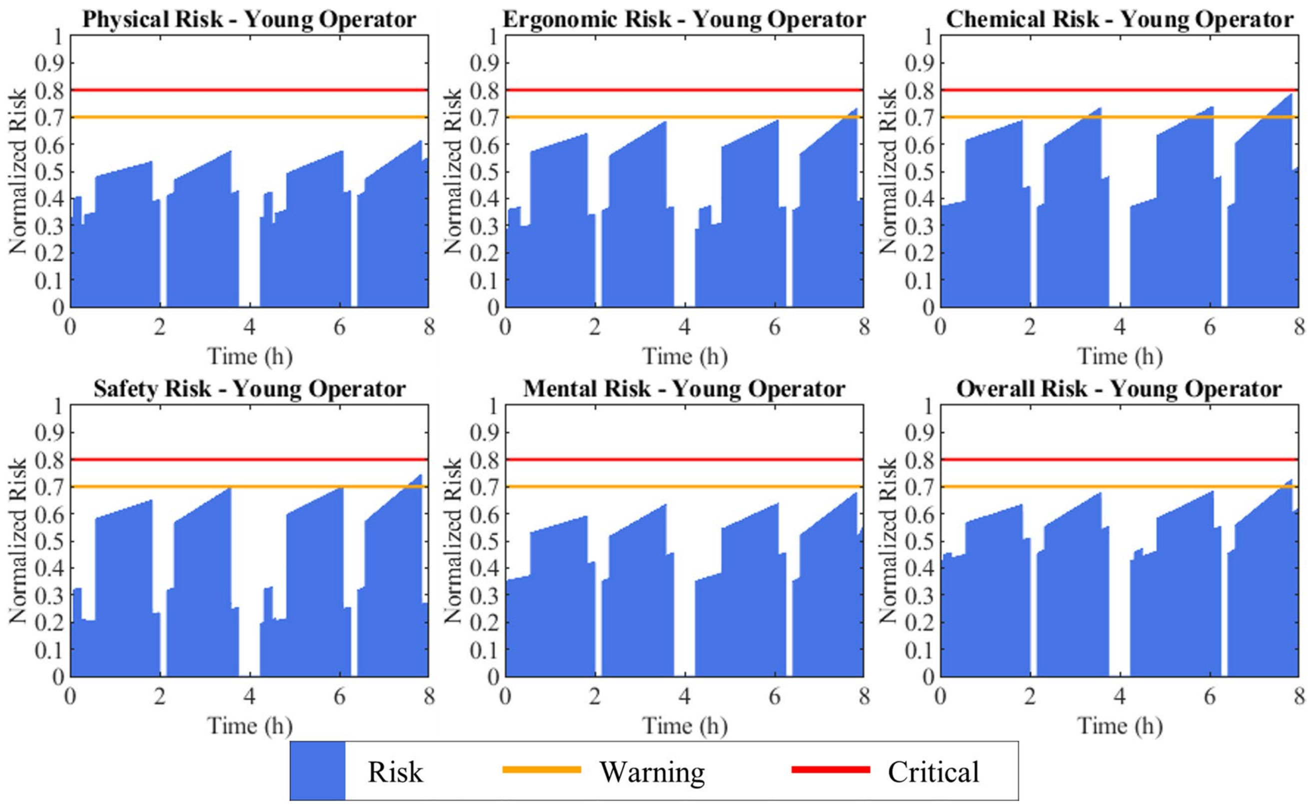


Fig. 10 Manual welding — young and fit operator, risk breakdown: **a** physical risk, **b** ergonomic risk, **c** chemical risk, **d** safety risk, **e** mental risk, and **f** overall risk

In case the operator swap still indicates non-tolerable levels of risk, it can be assumed that the problem lies in the operator personal health only. Such scenario has not been included in the case study as considered redundant, whereas the case study shows the system ability to detect risks related to both equipment and human physiology.

From a hardware perspective, the proposed methodology requires the acquisition and setup of the physical layer sensing units, which must undergo a feasibility assessment to minimize the number and invasiveness of the required sensors. Similar considerations apply to the network infrastructure setup and configuration. From a soft computing perspective, the main challenge is the construction and the calibration of the knowledge base, including the fuzzy-based inference fine-tuning. In terms of decision-making, the system administrator, along with the management team, should identify suitable risk thresholds which properly fit the company scope and requirements based on the specific characteristics of the manufacturing system including processes, equipment, operators, environment, etc.

Further developments of this research work involve the implementation of a machine learning–based classification system within the application layer for an enhanced risk cause diagnosis. A possible approach consists in inputting the risk-related features generated by the HCPS presented in this work into a machine learning–based pattern classifier such as neural networks, support vector machines, and decision trees, to be trained with available historical data. This approach can enable the automatic identification of risk reduction strategies. The exploration of such mitigating actions is beyond the scope of this paper and is currently being investigated by the authors in terms of development of procedures for automatic action identification. It is worth mentioning that other commercially available simulation software tools, such as NX®/Tecnomatix® Process, simulate software or more recent motion capture systems, typically perform specific risk assessments in silos, with possibility to produce a body loading report and show areas of stress across the body for ergonomic improvement. As simulation modelling for the human-in-the-loop is becoming far more common and increasing in accuracy and representation, it is also raising the need to include other risk factor considerations from other elements of the system beyond the human (interactions, equipment, environment, etc.).

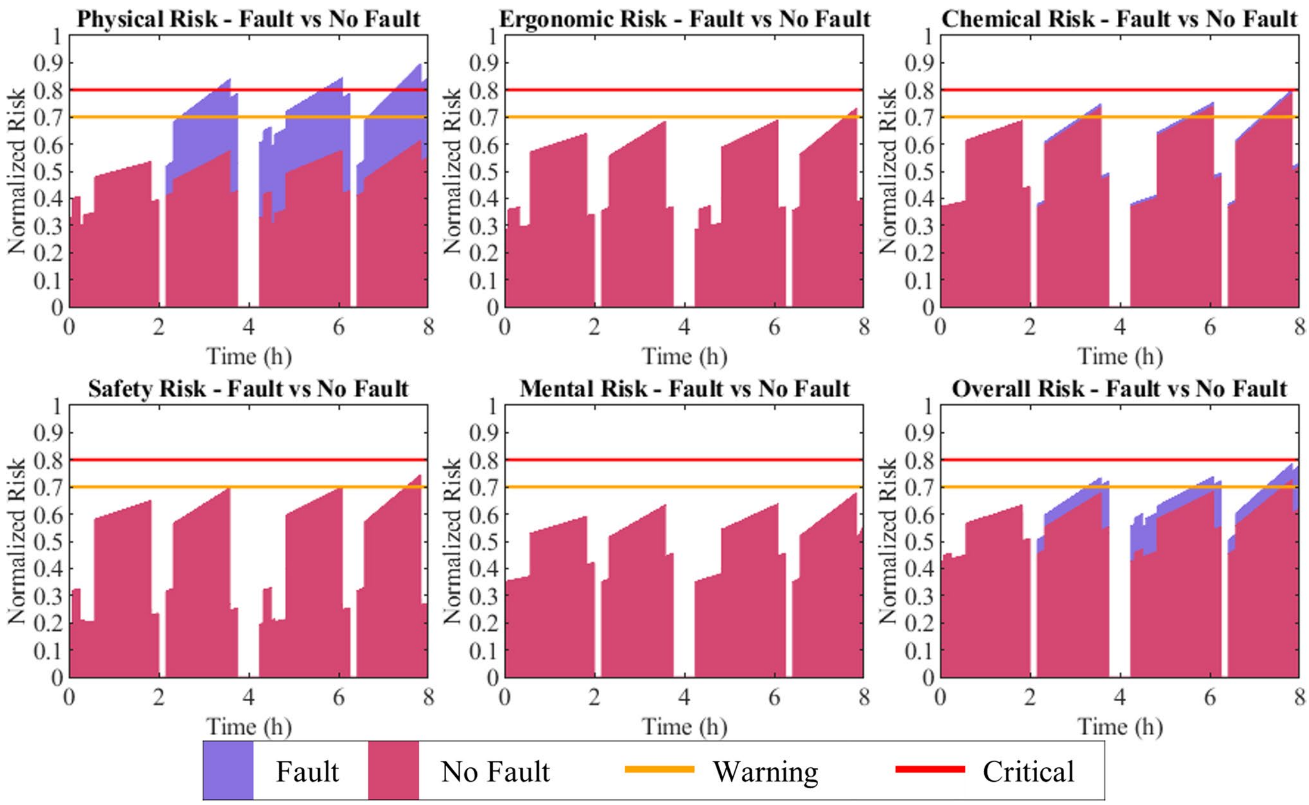


Fig. 11 Manual welding — young operator — faulty equipment vs non-faulty equipment risk breakdown: **a** physical risk, **b** ergonomic risk, **c** chemical risk, **d** safety risk, **e** mental risk, and **f** overall risk

Moreover, the development of digital twins, i.e. computable virtual abstractions of manufacturing personnel, objects, processes, and phenomena, will be investigated in view of their implementation with the aim to simulate behaviours, monitor real-world status and operating conditions, reveal abnormal patterns, and predict future trends.

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Author contribution All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Alessandro Simeone and Alessandra Caggiano. The first draft of the manuscript was written by Alessandro Simeone and Alessandra Caggiano, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Declarations

Competing interests The authors declare no competing interests.

References

1. Romero D, Stahre J (2021) Towards the resilient Operator 5.0: the future of work in smart resilient manufacturing systems. Procedia CIRP 104:1089–1094. https://doi.org/10.1016/j.procir.2021.11.183
2. Panagiotis Stavropoulos P, Alexios Papacharalampopoulos D, Konstantinos Tzimanis M, Andreas Lianos M (2020) Manufacturing resilience during the coronavirus pandemic: on the

investigation manufacturing processes agility. Eur J Soc Impact Circ Econ 1(3):28–57. https://doi.org/10.13135/2704-9906/5073
3. Longo F, Padovano A, Umbrello S (2020) Value-oriented and ethical technology engineering in Industry 5.0: a human-centric perspective for the design of the factory of the future. Appl Sci 10/12:4182. https://doi.org/10.3390/app10124182
4. Akundi A, Euresti D, Luna S, Ankobiah W, Lopes A et al (2022) State of Industry 5.0—analysis and identification of current research trends. Appl System Innov 5/1:27. https://doi.org/10.3390/asi5010027
5. Kothamasu R, Huang SH, VerDuin WH (2006) System health monitoring and prognostics — a review of current paradigms and practices. Int J Adv Manuf Technol 28(9–10):1012–1024. https://doi.org/10.1007/s00170-004-2131-6
6. Utne IB, Brurok T, Rødseth H (2012) A structured approach to improved condition monitoring. J Loss Prev Process Ind 25(3):478–488. https://doi.org/10.1016/j.jlp.2011.12.004
7. Wang B, Zheng P, Yin Y, Shih A, Wang L (2022) Toward human-centric smart manufacturing: a human-cyber-physical systems (HCPS) perspective. J Manuf Syst 63:471–490. https://doi.org/10.1016/j.jmsy.2022.05.005
8. Romero D, Stahre J, Taisch M (2020) The Operator 4.0: towards socially sustainable factories of the future. Comput Ind Eng 139:106128. https://doi.org/10.1016/j.cie.2019.106128
9. Sun S, Zheng X, Gong B, García Paredes J, Ordieres-Meré J (2020) Healthy Operator 4.0: a human cyber–physical system architecture for smart workplaces, Sensors, 20/7:2011. https://doi.org/10.3390/s20072011
10. Simeone A, Caggiano A, Boun L, Grant R (2021) Cloud-based platform for intelligent healthcare monitoring and risk prevention in hazardous manufacturing contexts. Procedia CIRP 99:50–56. https://doi.org/10.1016/j.procir.2021.03.009
11. Monostori L, Kádár B, Bauernhansl T, Kondoh S, Kumara S et al (2016) Cyber-physical systems in manufacturing. CIRP Ann 65(2):621–641. https://doi.org/10.1016/J.CIRP.2016.06.005
12. Gao RX, Wang L, Helu M, Teti R (2020) Big data analytics for smart factories of the future. CIRP Ann 69(2):668–692. https://doi.org/10.1016/j.cirp.2020.05.002
13. Simeone, A., Grant, R., Ye, W., Caggiano, A., 2023, Operator 4.0 intelligent health monitoring: a cyber-physical approach, in Procedia CIRP, pp. 1033–1038.
14. Annaswamy AM, Yildiz Y (2020) Cyber-physical-human systems. In: *Encyclopedia of Systems and Control*. Springer London, London, pp 1–12
15. Ye W, Li C, Zheng C, Sanchez NP, Gluszek AK et al (2016) Mid-infrared dual-gas sensor for simultaneous detection of methane and ethane using a single continuous-wave interband cascade laser. Opt Express 24(15):16973. https://doi.org/10.1364/OE.24.016973
16. Angelucci A, Cavicchioli M, Cintorrino I, Lauricella G, Rossi C et al (2021) Smart textiles and sensorized garments for physiological monitoring: a review of available solutions and techniques. Sensors 21(3):814. https://doi.org/10.3390/s21030814
17. Argyle EM, Marinescu A, Wilson ML, Lawson G, Sharples S (2021) Physiological indicators of task demand, fatigue, and cognition in future digital manufacturing environments. Int J Human-Comp Stud 145:102522. https://doi.org/10.1016/j.ijhcs.2020.102522
18. Ward S, Hu S, Zecca M (2023) Effect of equipment on the accuracy of accelerometer-based human activity recognition in extreme environments. Sensors 23(3):1416. https://doi.org/10.3390/s23031416
19. Cheng Y, Wang K, Xu H, Li T, Jin Q et al (2021) Recent developments in sensors for wearable device applications. Anal Bioanal Chem 413(24):6037–6057. https://doi.org/10.1007/s00216-021-03602-2
20. Shen Z, Zhu X, Majidi C, Gu G (2021) Cutaneous ionogel mechanoreceptors for soft machines, physiological sensing, and amputee prostheses. Adv Mater 33(38):2102069. https://doi.org/10.1002/adma.202102069
21. Yin R, Wang D, Zhao S, Lou Z, Shen G (2021) Wearable sensors-enabled human–machine interaction systems: from design to application. Adv Funct Mater 31(11):2008936. https://doi.org/10.1002/adfm.202008936
22. Sers R, Forrester S, Moss E, Ward S, Ma J et al (2020) Validity of the perception neuron inertial motion capture system for upper body motion analysis. Measurement 149:107024. https://doi.org/10.1016/j.measurement.2019.107024
23. Sers R, Forrester S, Zecca M, Ward S, Moss E (2021) The ergonomic impact of patient body mass index on surgeon posture during simulated laparoscopy. Appl Ergon 97:103501. https://doi.org/10.1016/j.apergo.2021.103501
24. Manghisi VM, Uva AE, Fiorentino M, Gattullo M, Boccaccio A et al (2020) Automatic ergonomic postural risk monitoring on the factory shopfloor – the ErgoSentinel tool. Proc Manuf 42:97–103. https://doi.org/10.1016/j.promfg.2020.02.091
25. Ciccarelli M, Corradini F, Germani M, Menchi G, Mostarda L et al (2022) SPECTRE: a deep learning network for posture recognition in manufacturing. J Intell Manuf. https://doi.org/10.1007/s10845-022-02014-y
26. Reid CR, Schall MC, Amick RZ, Schiffman JM, Lu M-L et al (2017) Wearable technologies: how will we overcome barriers to enhance worker performance, health, and safety? Proc Human Factors Ergon Soc Ann Meeting 61(1):1026–1030. https://doi.org/10.1177/1541931213601740
27. Liang L (2021) Calibrating low-cost sensors for ambient air monitoring: techniques, trends, and challenges. Environ Res 197:111163. https://doi.org/10.1016/j.envres.2021.111163
28. Teti R, Mourtzis D, D'Addona DM, Caggiano A (2022) Process monitoring of machining. CIRP Ann Manuf Technol 71(2):529–552
29. Ye W, He L, Xia Z, Liu W, Huang Y et al (2023) Miniaturized methane detection system based on photoacoustic spectroscopy. Microw Opt Technol Lett. https://doi.org/10.1002/mop.33611
30. Guadalupe-Fernandez V, De Sario M, Vecchi S, Bauleo L, Michelozzi P et al (2021) Industrial odour pollution and human health: a systematic review and meta-analysis. Environ Health 20(1):108. https://doi.org/10.1186/s12940-021-00774-3
31. Wegener K, Bleicher F, Heisel U, Hoffmeister HW, Möhring HC (2021) Noise and vibrations in machine tools. CIRP Ann 70(2):611–633. https://doi.org/10.1016/j.cirp.2021.05.010
32. Lacava A, Zottola V, Bonaldo A, Cuomo F, Basagni S (2022) Securing Bluetooth low energy networking: an overview of security procedures and threats. Comput Netw 211:108953. https://doi.org/10.1016/j.comnet.2022.108953
33. Mozaffariahrar E, Theoleyre F, Menth M (2022) A survey of Wi-Fi 6: technologies, advances, and challenges. Future Internet 14(10):293. https://doi.org/10.3390/fi14100293
34. Mocanu, S., Geampalia, G., Chenaru, O., Dobrescu, R., 2018, Fog-based solution for real-time monitoring and data processing in manufacturing, 2018 22nd International Conference on System Theory, Control and Computing, ICSTCC 2018 - Proceedings, pp. 504–509. https://doi.org/10.1109/ICSTCC.2018.8540783.
35. Mouradian C, Naboulsi D, Yangui S, Glitho RH, Morrow MJ et al (2018) A comprehensive survey on fog computing: state-of-the-art and research challenges. IEEE Commun Surv Tutorials 20(1):416–464. https://doi.org/10.1109/COMST.2017.2771153
36. Atlam H, Walters R, Wills G (2018) Fog computing and the Internet of things: a review. Big Data and Cogn Comp 2(2):10. https://doi.org/10.3390/bdcc2020010
37. Mishra D, Roy RB, Dutta S, Pal SK, Chakravarty D (2018) A review on sensor based monitoring and control of friction stir

welding process and a roadmap to Industry 4.0. J Manuf Process 36:373–397. https://doi.org/10.1016/j.jmapro.2018.10.016
38. Rivera Domínguez C, Pozos Mares JI, Zambrano Hernández RG (2021) Hazard identification and analysis in work areas within the Manufacturing Sector through the HAZID methodology. Process Saf Environ Prot 145:23–38. https://doi.org/10.1016/j.psep.2020.07.049
39. Tepe S, Kaya İ (2020) A fuzzy-based risk assessment model for evaluations of hazards with a real-case study. Hum Ecol Risk Assess Int J 26(2):512–537. https://doi.org/10.1080/10807039.2018.1521262
40. Mahdavi A, Berger C, Bochukova V, Bourikas L, Hellwig RT et al (2020) Necessary conditions for multi-domain indoor environmental quality standards. Sustainability 12(20):8439. https://doi.org/10.3390/su12208439
41. Bienvenido-Huertas D, Sánchez-García D, Rubio-Bellido C, Oliveira MJ (2020) Influence of adaptive energy saving techniques on office buildings located in cities of the Iberian Peninsula. Sustain Cities Soc 53:101944. https://doi.org/10.1016/j.scs.2019.101944
42. Ji Z, Pons DJ, Pearse J (2020) Integrating occupational health and safety into plant simulation. Saf Sci 130:104898. https://doi.org/10.1016/j.ssci.2020.104898
43. Galizzi M, Tempesti T (2015) Workers' risk tolerance and occupational injuries. Risk Anal 35(10):1858–1875. https://doi.org/10.1111/risa.12364
44. Glock CH, Grosse EH, Kim T, Neumann WP, Sobhani A (2019) An integrated cost and worker fatigue evaluation model of a packaging process. Int J Prod Econ 207:107–124. https://doi.org/10.1016/j.ijpe.2018.09.022
45. Dawson D, Ian Noy Y, Härmä M, Åkerstedt T, Belenky G (2011) Modelling fatigue and the use of fatigue models in work settings. Accid Anal Prev 43(2):549–564. https://doi.org/10.1016/j.aap.2009.12.030
46. Williamson A, Lombardi DA, Folkard S, Stutts J, Courtney TK et al (2011) The link between fatigue and safety. Accid Anal Prev 43(2):498–515. https://doi.org/10.1016/j.aap.2009.11.011