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Review

Environmental Risk Assessment and Management in Industry 4.0: A Review of Technologies and Trends

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Abstract: In recent decades, concern with workers' health has become a priority in several countries, but statistics still show that it is urgent to perform more actions to prevent accidents and illnesses related to work. Industry 4.0 is a new production paradigm that has brought significant advances in the relationship between man and machine, driving a series of advances in the production process and new challenges in occupational safety and health (OSH). This paper addresses occupational risks, diseases, opportunities, and challenges in Industry 4.0. It also covers Internet-of-Things-related technologies that, by the real-time measurement and analysis of occupational conditions, can be used to create smart solutions to contribute to reducing the number of workplace accidents and for the promotion of healthier and safer workplaces. Proposals involving smart personal protective equipment (smart PPE) and monitoring systems are analyzed, and aspects regarding the use of artificial intelligence and the data privacy concerns are also discussed.

Keywords: occupational risk assessment; Industry 4.0; internet of things; smart PPE

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1. Introduction

According to the International Labour Organization [1], occupational injury is a personal injury, disease, or death that results from an occupational accident. Occupational accidents, in turn, are unexpected occurrences, including acts of violence, arising out of or in connection with work and resulting in one or more workers incurring personal injury, disease, or death. Occupational diseases are acquired through personal exposure to environmental risks, such as physical, chemical, and biological agents in situations above the tolerance limits imposed by legislation or applicable standards. These diseases are caused or aggravated by specific activities, and are characterized when the causal link is established. between damage to the worker's health and exposure to certain work-related risks. Occupational diseases occur after various years of exposure, and in some cases, they can arise even after the worker is no longer in contact with the causative agent [2].

Many countries have prioritized concerns about workers' health in recent decades, but statistics show an urgent need to take further action to prevent accidents and illnesses related to work. Worldwide, about two million people die every year because of work-related illnesses or work-related accidents. Many work-related accidents and diseases are not reported, because in several countries there are no adequate data collection systems. Even in countries that adopt sufficient methods for this purpose the number of reported accidents often does not reflect reality, due to the presence of informal workers [3,4].

In addition, the incidence of fatalities in the workplace varies considerably between developed and developing countries. Insufficient OSH services contribute to the occurrence of accidents and deaths in low- and middle-income countries [5]. In terms of economic sectors, agriculture, forestry, mining, and construction have the highest death rates. Companies with fewer than 50 employees have a higher incidence of serious and fatal injuries [6]. In general, migrant workers are more susceptible to informal, abusive, and dangerous work, because the types of work they accept is often affected by lower levels of education [7].

With respect to methods and systems to prevent occupational diseases and accidents, as new technologies are added to workplaces, new risks are identified as well as new opportunities. Especially in the last decade, the term Industry 4.0 became more popular, referring to a new paradigm that has revolutionized factories by inserting and integrating several different technologies. Industry 4.0 technologies have impacted OSH by providing new possibilities in environmental risk monitoring and preventing accidents. Workers' health conditions can also be monitored in real-time. However, aside from new opportunities, new concerns have emerged, especially related to the types of activity commonly performed in Industry 4.0 workplaces. For example, the availability of jobs characterized by sedentary postures or interactions with robots has grown. In this scenario, illnesses related to a sedentary lifestyle and accidents because of interactions with robots are likely to become more and more common. In view of developments to date, it has become necessary for companies to adapt their OSH policies and seek appropriate solutions to this new reality [8,9].

This paper addresses occupational risks and diseases reported in Industry 4.0, as well as opportunities and challenges. Technologies and devices for use in risk assessment in Industry 4.0 are described, and studies that have successfully applied these technologies are analyzed, especially regarding the use of artificial intelligence and data privacy concerns. In addition, this work indicates some directions for addressing data privacy in IoT and Industry 4.0, and comments on issues within this new context.

2. Occupational Risks and Diseases in Industry 4.0

An occupational risk factor is an agent that can cause damage to a worker's health. The potential risk factor is called hazard. Occupational risk is the combination of the probability of an adverse effect (damage) on the worker's health and the severity of this damage, assuming that there is exposure within the work environment [10].

Examples of common occupational diseases include occupational asthma [10,11], vibration-related diseases [12–14], noise related diseases [15], pulmonary fibrosis [16], bronchopulmonary pleural fibrosis and damage caused by the inhalation of asbestos dust [17], and occupational cancer [18].

As mentioned above, in Industry 4.0 workplaces the presence of new technologies brings new opportunities and new risks. In addition to common occupational diseases, the nature of work in Industry 4.0 has the potential to contribute to the increasing frequency of other diseases, including mental disorders and diseases related to sedentary behavior. In Industry 4.0, several workers can often be involved in creative value-added tasks, while routine activities, as well as certain dangerous tasks, are often performed by robots. This scenario, along with early and continuous risk analysis and management based on various technologies, could make workplaces safer. On the other hand, semi-skilled employees could lose workplace opportunities because of potential difficulties in performing more complex tasks. At the same time, the use of digital tools to continuously monitor the performance of employees may become common, which could result in privacy invasion and psychological pressure [19,20].

In addition, the risks related to interactions between humans and machines have increased and greater connectivity makes it possible to work anywhere at any time. This scenario brings benefits such as flexibility, but also has the potential to impact individuals' work–life balance, which may in turn be harmful to mental health [21]. According to [20], depression is very common in workplaces compared to other mental disorders, and affects workers by reducing productivity, diminishing job retention, and increasing the risk of accidents at work. Another issue related to Industry 4.0 is the existence of many sedentary jobs, such as computer-based work. High levels of sedentary posture are associated with an increased risk of cardiovascular disease and type 2 diabetes, several cancers including lung and breast, and mental disorders such as depression. In addition, poor lighting conditions in workplaces (for example, store warehouses, since online commerce has been growing) can cause severe headaches and discomfort. Insufficient lighting makes it difficult to perceive the depth, shape, speed, and proximity of objects, and related accidents may often occur [22].

3. Organizational Culture as a Key Factor in OSH

According to [23], the occurrence of occupational diseases and accidents causes significant losses in companies' reputation and decreases their productivity. For example, a worker who becomes aware of a colleague's illness may become discouraged and start to produce less or may look for another job opportunity with better OSH conditions. To combat or significantly minimize these problems, it is necessary to perform preventive actions. The management of a company has an obligation to foresee, organize, and coordinate the organization of work, providing methods for preventing incidents and accidents in the workplace, through the effective management of occupational risks [24].

Risk perception depends on a variety of factors, including values and educational level [25,26]. Environments where workers feel pressured and overworked are in general quite prone to accidents. In addition, unqualified workers are generally more susceptible to accidents, because they often perform dangerous tasks. The low education of these workers tends to affect perception of risks present in the work environment and may make it difficult to understand the issues addressed in the health and safety training provided by companies. This issue demands special attention from professionals who plan and train these workers, to make sure that the topics covered are really understood [27].

Aiming to ensure the effectiveness of measures to prevent illnesses and accidents in the work environment, it is necessary that managers remain continuously engaged with the objective of promoting actions focused on the safety and well-being of workers. Improvements within a company should not happen only after an unwanted event has occurred, because this type of approach often means workers fail to take proper precautions after a time and even forget about them completely [23].

In this context, the ISO 45001:2018—Occupational health and safety management systems–Requirements with guidance for use—is a standard that aims to provide guidelines to assist organizations in improving OSH performance and preventing work-related injuries and illnesses. This standard is applicable to any organization, regardless of its size or type [28].

4. Technologies and Trends in OSH

This section covers concepts related to smart PPE, IoT, and Industry 4.0, describing works that have successfully applied these technologies in the construction of equipment and systems. Later in this section, devices and communication protocols for IoT and possibilities involving machine learning are addressed, representing alternatives for building systems similar to those described here.

4.1. Smart Personal Protective Equipment

According to [29], if an activity carried out by a worker involves a risk that cannot be reduced or eliminated by collective, technical, or organizational means, the use of personal protective equipment (PPE) allows that person to perform their activities without risk or with reduced risk of suffering injuries. In recent years the term 'smart PPE' has become more common. Every piece of smart PPE can interact with the environment and/or react to environmental conditions. This type of equipment combines traditional PPE with an electronic aspect, such as sensors, data transfer modules, or batteries. Sensors are used to monitor real-time hazardous factors for workers. In addition, the use of computer-based systems can facilitate OSH functions related to risk identification and management [30].

Aiming to assure that no new risks are added by the inclusion of electronic devices, tests must be performed designed for traditional PPE and related to electrical safety, such as surface temperature and battery safety. However, there are still no standards available for smart PPE, and standardization bodies must formulate requirements and procedures for testing this type of equipment. In Europe, there are some initial standardization projects in progress. Some of the challenges for the development of smart personal protective equipment are reliability, privacy, security, ergonomics, acceptance by users, applicable certifications, market surveillance, recycling, and the avoidance of additional risks [30].

4.2. Industry 4.0 Related Technologies and the Internet of Things (IoT) in OSH

Industry 4.0 can be defined as the Fourth Industrial Revolution, and encompasses a broad system of advanced technologies that are changing production and business models around the world. Industry 4.0 is related to the integration of the manufacturing process, aiming at continuous improvement, and avoiding waste [8,9].

The term Internet of Things (IoT), in turn, was introduced in the late 1990s by Kevin Ashton, a researcher at the Massachusetts Institute of Technology (MIT), referring to the connection of different objects to exchange data with other devices and systems over the Internet. IoT aims to supply a network infrastructure with interoperable communication protocols and software to connect this variety of devices. The term industrial IoT (IIoT) is related to the application of IoT technology in industrial environments [31].

IoT has been used in many OSH applications, including monitoring physiological variables of workers engaged in dangerous activities, as well as for sensors and alarm systems to prevent a variety of accidents. For example, Li and Kara [32] presented a methodology for monitoring factory conditions including temperature and air quality, by using wireless sensor networks and IoT. According to Awolusi et al. [33], wearable systems have been employed in construction sites to collect data to detect environmental conditions, and for determining whether people are close to danger. The authors described how gyroscopes can verify the rotation of different parts of the body, while ultrasonic sensors can monitor muscle contractions. Described below are proposals for OSH that use Industry 4.0 and/or IoT-related technologies.

Aqueveque et al. [34] proposed a device to measure physiological variables including the electrocardiogram and respiratory activity of miners working at high altitudes. The proposed system's noninvasive sensors are embedded in a T-shirt. The device can monitor heart rate and respiration rate, and exchanges data with a central monitoring station.

Yu et al. [35] presented a wearable system involving physiological sensors embedded into firefighters' garments, assessing their physiological state by evaluating data collected from the sensors. The data was sent to the command center and the system evaluated the gravity of the risk scenario, sending messages, for example, to instruct that the action should be canceled because it is too dangerous. All collected data and messages were sent to the cloud.

Wu et al. [36] presented a hybrid wearable sensor network system for IoT-connected safety and health monitoring applications for outdoor workplaces. A local server processed raw sensor signals, displaying the environmental and physiological data, and triggered an alert if any emergency circumstance was detected. Temperature, humidity, Ultraviolet (UV) radiation, CO_2, heart rate, and body temperature were measured by the wearable sensors. The gateway pre-processed the sensor signals, displayed the data, and triggered alerts when emergency occurred. An IoT cloud server was used for data storage, web monitoring, and mobile applications.

Marques and Pitarma [37] proposed a real-time indoor quality monitoring system using a sensor to measure particulate matter (PM), temperature, humidity, and formaldehyde. The system included a mobile application for data consultation and notifications, and served a dataset to plan changes for improving indoor quality. The dataset can also support clinical diagnostics and correlate health problems with living environment conditions.

Balakreshnan et al. [38] proposed a system to check the safety of workers in the vicinity of machines. The solution used artificial intelligence and machine vision to identify use of safety glasses in areas where there are risks to the eyes, and can also detect the lack of other equipment. The system can initiate different control actions when safety violations occur.

Sanchez et al. [39] proposed a smart PPE using a sensor network located on a helmet and a belt, to monitor the worker and their environment. The system monitored biometrics risks and can detect external impact, shock, luminosity, gases, and environmental temperature, and provided real-time recommendations. Data were observable by the user on a tablet or a mobile phone. The device incorporated a flashlight that activated automatically if the worker was in poorly lighted areas, and a loudspeaker to assist the detection of audible alarms.

Márquez-Sánchez et al. [40] presented a system for the detecting anomalies in workplaces using a helmet, a belt, and a bracelet. Intelligent algorithms are applied to collected data through edge computing, in which processing takes place closer to the data source, providing faster services. The system early predicts and notifies anomalies detected in working environment. Then, data is sent to the cloud, where deep learning models verify possible anomalies because of the training of the set of data inserted previously.

Shakerian et al. [41] the authors proposed and examined an assessment process to evaluate workers' bodily responses to heat strain, to continuously and non-intrusively collect and evaluate workers' physiological signals acquired from a wristband-type biosensor. The proposed process assesses heat strain exposure through the collective analysis of electrodermal activity, photoplethysmography, and skin temperature biosignals. The physiological signals are uploaded to a cloud server, decontaminated from noise, and the measurable metrics are extracted from the signals and interpreted as distinct states of workers' heat strain by employing supervised learning algorithms.

Kim et al. [42] proposed an IoT-based system to monitor construction workers' physiological data using an off-the-shelf wearable smart band. The platform was designed for construction workers performing at high temperatures, to collect a worker's physiological data through a wearable armband that consists of three sensors—photoplethysmography (for heart rate monitoring), a temperature sensor, and an accelerometer, which provides the current position of a worker. The acquired data reflect a worker's current physiological status, sent to the web and to a smartphone application for visualization.

Yang et al. [43] conducted a study to monitor the level of physical load during construction tasks, to assess ergonomic risk to an individual construction worker. By using an ankle-worn wearable inertial measurement unit to monitor a worker's bodily movements, the study investigated the feasibility of identifying various physical loading conditions by analyzing a worker's lower body movements. In the experiment, the workers performed a load-carrying task by moving concrete bricks. This study developed and evaluated a classification model to detect different physical load levels, using Bidirectional long short-term memory (Bi-LSTM).

Marques and Pitarma [44] presented a real-time acoustic comfort monitoring solution suitable for occupational usage. The system was designed to be easy to install and use, incorporating a device for ambient data collection called iSoundIoT, and including Web/mobile data access based on Wi-Fi communication. The solution includes a notification feature to alert people when poor acoustic comfort scenarios are verified, and continuous real-time data collection enabling the generation of reports containing sound level values and alerts.

Mumtaz et al. [45], motivated by the COVID-19 outbreak, proposed an IoT-based system for monitoring and reporting air conditions in real time with the data sent to a web portal and mobile app. The solution can monitor multiple air pollutants, including carbon dioxide (CO2), particulate matter (PM) 2.5, nitrogen dioxide (NO2), carbon monoxide (CO), and methane (CH4), as well as temperature and humidity. The system generates alerts after detecting anomalies in the air quality. Various machine learning algorithms were employed to classify indoor air quality, and long short-term memory (LSTM) was applied for predicting the concentration of each air pollutant and predicting the overall air quality of an indoor environment.

Zhou and Ding [46] presented an IoT-based system to generate early warnings and alarms as dynamical safety barriers for different types of hazards on underground construction sites. Their solution was able to collect, analyze, and manage multisource information, automate monitoring and warning, and minimize the hazard energy coupling by using IoT. The data-sensing layer included an IoT reader, IoT tag with warning device, ultrasonic detector, and infrared access device, achieving about 1.5 m locating accuracy in underground workspaces. The portable warning device, designed with RFID-based positioning technology, was installed on the safety helmet. Each IoT tag consisted of a RFID chip and a wireless antenna, and stored information about the worker wearing it. In case of accident, the proposed system can be used also for investigation purposes.

Zhan et al. [47] proposed a monitoring system for cold storage based on Industrial IoT, to identify abnormal stationary and acquire the spatial-temporal information of workers in real time. In these workplaces, an abnormal stationary position is a sign of danger, such as falling or fainting. A deep neural network was applied to learn specific features involving location and vibration for anomaly detection. The Bluetooth low energy (BLE) and a log-distance path loss model were used to fulfill indoor localization to allow rapid responses to an incident on site. In addition, digital twin technology that mirrors physical objects in cyberspace can be used to enhance spatial-temporal traceability and cyber-physical visibility to enforce safety monitoring by managers. Cloud and edge computing can be used to improve overall computational efficiency and system responsiveness.

Campero-Jurado et al. [48] proposed a smart helmet prototype that monitored the conditions in the workers' environment and performed a near real-time evaluation of risks. The data collected by the sensors was sent to an AI-driven platform for analysis, where different intelligent models were evaluated by the authors. The design is intended to protect the operator from possible impacts, while monitoring the light, humidity, temperature, atmospheric pressure, presence of gases, and air quality. Alerts can be transmitted to the operator by means of sound beeps. For visualization of environmental data, through color codes an LED strip deployed on the helmet can notify the worker of anomalies in the environment.

A comparison between the proposals mentioned above can be found in Section 5, along with further discussion.

For the design of IoT systems and devices for OSH, such as those described above, various low-cost devices and free software allow the implementation and use of IoT-based systems by small and medium-sized companies. Some of these technologies are described below.

4.3. IoT Devices

According to Lacamera [49], embedded systems consist of a class of systems that run on an architecture based on microcontrollers, that offer constrained resources. A microcontroller or microcontroller unit (MCU) is a device made of a dedicated processor for the purpose of running a specific application, unlike general purpose computers. These devices are often designed to be inexpensive, low-resource, and low-energy consuming. These devices can be used in factories and for several IoT applications. They are often used as sensors, actuators, or smart devices and may form networks. Below, the Arduino and ESP32 platforms are described, which are each widely used in IoT applications.

Arduino is an open platform for prototyping, based on free software and low-cost hardware, where the programs are written in the simplified C++ language. Arduino Integrated Development Environment (IDE) is used to write code and upload it to the board. The hardware consists of an open hardware design with a microcontroller manufactured by the Atmel Microchip company. The boards are sold preassembled, but hardware design information is available for people who want to build or modify them [50]. There are various types of Arduino boards supporting different features, such as Wi-Fi [51], Bluetooth, Bluetooth Low Energy (BLE) [52] and Global System for Mobile Communication (GSM) [53].

ESP32 is a series of low-cost and low-power microcontrollers and is a system-on-a-chip (SoC) with integrated microcontroller, Wi-Fi, and Bluetooth. ESP32 is a dual-core system and be used as a standalone system or can serve as a slave device to a host microcontroller. ESP32 is commonly used for academic and industrial purposes, especially in IoT. It can be programmed by ESP-IDF, which is a framework developed by ESPRESSIF, or by the Arduino Integrated Development Environment (IDE), which is the easiest way to start writing code for this platform [54].

4.4. Protocols for IoT

Below are described two protocols widely used in IoT, the Constrained Application Protocol (CoAP) and the Message Queue Telemetry Transport (MQTT). According to Shelby et al. [55], Constrained Application Protocol (CoAP) is suitable for resource-constrained environments, including those with power-constrained devices, low-bandwidth links, and lossy networks. In this protocol, the network nodes interact through a request–response model and support the built-in discovery of services. CoAP is very similar to the client–server model of Hypertext Transfer Protocol (HTTP), the widely used protocol that allows contents to be requested and transmitted between browsers and web servers via the Internet. However, CoAP implementations can often act in client and server roles. A client sends a request using a method code on a resource (identified by a URI—Universal Resource Identifier) on a server. The server, in turn, sends a response with a response code. CoAP executes these interchanges asynchronously using User Datagram Protocol (UDP). The messages support optional reliability, and CoAP supports secure messages using Datagram Transport Layer Security (DTLS), described in [56].

By other hand, MQTT provides asynchronous communication between devices [57]. This protocol uses a message publishing and signature model, and was invented by the IBM company in the late 1990s. MQTT was originally designed to link oil pipeline sensors to satellites. It is a lightweight protocol that can be implemented on devices with many restrictions, such as low computational power, and in networks with limited bandwidth and high latency. These features make MQTT suitable for several applications in IoT; publish–subscribe is the standard model for exchanging messages in MQTT. MQTT comprises two entities: a broker and the clients, where the message broker is a server receiving messages from clients and then sending these messages to other clients, that can subscribe to any message topic. Clients must publish their messages on a topic and send the topic and the message to the broker. The broker then forwards the message to all clients who subscribe to that topic. Clients can connect to the broker through simple TCP/IP connections or encrypted TLS connections.

4.5. Machine Learning

As described by Abiodun et al. [58], machine learning (ML) is a branch of artificial intelligence (AI) that uses computers to simulate human learning. In ML, computers can autonomously modify their behavior based on their own experience (training). ML algorithms are classified based on the approach used in the learning process.

In supervised learning, the learning algorithm aims to predict how a given set of inputs conducts to the output. The algorithm receives labeled data and learns from this data. In unsupervised learning the algorithm does not receive labels. This type of algorithm is mainly focused on finding hidden patterns in data. Semi-supervised learning algorithms have an incomplete training set, often with many target outputs missing, from which they must learn. Finally, the algorithm used in reinforcement learning learns from the external feedback received in terms of punishments and rewards [59].

Below are described recommender systems [59–62], anomaly detection, [63,64] and long short-term memory (LSTM) [65–69], which have each been applied in a variety of systems, and more recently have been suggested for use in IoT, healthcare, and OSH solutions.

4.5.1. Recommender Systems

Recommender systems use artificial intelligence (AI) methods to serve users with item recommendations (filtered content). These systems try to predict a user's preference for an item, based on available information about items, users, and the interactions between them. These systems aim to retrieve only the most relevant information services from a large volume of data [59,60].

Traditional applications for recommender systems include movies, music, tourism, e-learning, and more recently, healthcare (Health Recommender Systems—HRS) [53]. In addition, using data obtained from IoT devices, such as smart wearable and smart PPE, recommender systems can extract information to be used in OSH, for example, to predict risks and try to predict the emergence of occupational diseases.

4.5.2. Anomaly Detection

During IoT data analysis, it is in general necessary to identify uncommon states within the systems being monitored by sensors. Defining maximum and minimum limits for sensor readings to identify problems may increase the number of false alarms and missed dangerous conditions. In this context, anomaly detection methods that have been largely applied in cybersecurity, financial surveillance, risk management, and healthcare, among other areas, can be useful in IoT applications, including OSH systems [63,64].

Anomalies can be defined as measurements or observations that do not reflect expected behavior. Considering the context of the IoT, an anomaly is related to the measurable consequences of an unexpected modification in a system which is outside its standard. Anomaly detection is the process of detecting measurements with relevant deviations from other data. Anomaly detection methods consider the combination of two or more variables to identify problems. Obstacles to the development of anomaly detection, especially for IoT/OSH, include the lack of datasets with real-world anomalies, and sensor readings that are often affected by significant noise [63,64].

4.5.3. Long Short-Term Memory (LSTM)

As described in [65], recurrent neural networks (RNNs) are artificial neural networks which handle sequential or time-series data. RNNs have "memory" since they use information from past inputs to induce current input and output. LSTM is an RNN, suitable for classifying, processing, and predicting time series with intervals of unknown length. The fact that LSTM is relatively insensitive to gap length is an advantage compared to traditional RNNs.

Traditional examples of applications for this type of deep learning algorithm include language translation and speech recognition. In addition, LSTMs have been used in a variety of solutions [66–69], such as machine health monitoring and air-pollution forecasting [70,71].

5. Discussion

It is important to develop solutions that allow daily monitoring of the health conditions of workers, and their exposure to occupational risks, for the reasons explained earlier in this work and because the data obtained can support studies by companies to identify problems and guide OSH policies.

The studies described above were compared regarding the use of artificial intelligence and the use of techniques to ensure data privacy. The comparison is presented in Table 1.

The data obtained from continuous monitoring of occupational health, risks, and environmental conditions can also support academic research. Such research may allow new relationships to be established in the long term between occupational hazards and the occurrence of certain diseases. Keeping an updated record of changes in the health conditions of each worker is also a fundamental part of the process, so that the technologies mentioned above can help companies more significantly in making long-term decisions. Reliable data obtained by companies can also guide changes in legislation [45,47,48].

In this context, the use of artificial intelligence and machine learning is essential to obtaining better results, by identifying within work environments which settings or conditions may be safer or more harmful to workers' health. This type of approach has the potential to reduce workers' long-term absences, as well as their early retirement. AI/ML can be used to identify dangerous conditions that could result in accidents and/or diseases; by training with large datasets obtained over long periods of time, AI/ML may identify trends and suggest changes in workplaces to make them safer. Various AI/ML techniques have been used in recent studies [38–41,43,45,47,48]. Despite the various approaches involving AI/ML, none of the works mentioned take into account the health history of workers, to generate personalized alerts for example. This is a point that can be explored in future research.

Table 1. Study comparison.

Title	Data Privacy	AI
Monitoring Physiological Variables of Mining Workers at High Altitude [34]	NO	NO
A wearable intelligent system for real time monitoring firefighter's physiological state and predicting dangers [35]	NO	NO
An Internet-of-Things (IoT) Network System for Connected Safety and Health Monitoring Applications [36]	YES	NO
mHealth: Indoor Environmental Quality Measuring System for Enhanced Health and Well-Being Based on Internet of Things [37]	NO *	NO
PPE Compliance Detection using Artificial Intelligence in Learning Factories [38]	YES	YES
Smart Protective Protection Equipment for an accessible work environment and occupational hazard prevention [39]	NO	YES
Intelligent Platform Based on Smart PPE for Safety in Workplaces [40]	NO	YES
Assessing occupational risk of heat stress at construction: A worker-centric wearable sensor-based approach [41]	NO	YES
Development of an IoT-Based Construction Worker Physiological Data Monitoring Platform at High Temperatures [42]	NO	NO
Deep learning-based classification of work-related physical load levels in construction [43]	NO	YES
A Real-Time Noise Monitoring System Based on Internet of Things for Enhanced Acoustic Comfort and Occupational Health [44]	NO	NO
Internet of Things (IoT) Based Indoor Air Quality Sensing and Predictive Analytic—A COVID-19 Perspective [45]	NO *	YES
Safety barrier warning system for underground construction sites using Internet-of-Things technologies [46]	NO	NO
Industrial internet of things and unsupervised deep learning enabled real-time occupational safety monitoring in cold storage warehouse [47]	NO	YES
Smart Helmet 5.0 for Industrial Internet of Things Using Artificial Intelligence [49]	NO	YES

* This is a solution for monitoring the environment, not a wearable item or PPE.

It is important to highlight that the challenges involved in implementing new technologies can vary significantly according to the activity. For example, construction sites are very dangerous places because workers are exposed to hazards that can be very hard to measure due to the way tasks are executed in this type of workplace [33].

With respect to data privacy, according to [72], data collected from wearable devices are transferred to a receiver through wireless networks, making data privacy a very critical issue for this type of device and making workers unwilling to use them. For example, workers may be very uncomfortable in sharing with employers their location information during rest periods. In the study conducted by Häikiö et al. [73] an anonymous online questionnaire was applied to construction workers to collect their opinions regarding IoT-based work safety. 4385 workers responded to the questionnaire. 49.7% were very (18.2%) or rather interested (31.5%) in using activity wristbands or other devices for monitoring their movement or physical activities in the workplace. Experienced professionals were less interested in using wearables than younger ones. In general, workers were more interested in sharing their data when they were sure it could help to preserve their health.

Systems for OSH often need to handle workers' personal data, which according to the General Data Protection Regulation (GDPR) must be anonymized [74]. Anonymized personal data is has gone through stages that ensure its disconnection from the person, for example, a document number may have some digits suppressed. In such a case, it would not be possible through technical or other means to find out who the data subject was. Anonymized data is no longer subject to the GDPR and is essential for expanding the use of IoT and artificial intelligence. However, in some applications anonymization is not feasible. For this purpose, pseudo-anonymized data that is subject to GDPR may be used. Pseudo-anonymization is treatment through which a data loses the possibility of association, directly or indirectly, with a person. Additional information may be kept separately in a controlled and safe environment, for example, under the responsibility of the company that develops and provides the application. If a system does not handle personal data, GDPR is not applicable. Data privacy was addressed only in [36,38]. However, it is important to note that not all solutions deal with personal information, as some are intended for monitoring environments. In these cases, it is understood that secure communication, despite being desirable, is not a priority.

According to Zamfir et al. [75], in respect to the IoT protocols described earlier in this paper, CoAP and MQTT communication can be secured by Transport Layer Security with digital certificates, as widely used in Internet applications. However, this approach may be costly for a large number of devices, and is often too heavy for IoT devices. In a simpler way, a pre-shared key (TLS-PSK) is an alternative. In this case, the messages are encrypted and signed using the shared key between the parties involved in communication. The same key is used for decryption and authentication of messages at the destination. It is recommended that the pre-shared key (PSK) is configured between each device and the server. Both approaches can be used to provide data privacy, especially when the applications handle sensitive information such as physiological data and location.

According to Maltseva [76], wearable devices' characteristics create multiple opportunities and can help to improve organizational performance. Wearable wristbands are very popular devices, which can continuously collect data such as heart-rate variability and can continue collecting data after working hours. These devices bring benefits and can help to identify health risks. However, extending the use of wearables after working hours causes confusion distinguishing work and rest. It is important to note that training individuals in a clearly and sufficient way is a key factor for success regarding the use of any technologies in the workplace. In addition, workers need to be aware that their data is being used to protect them from work-related diseases and that enough means are being used to keep that data safe.

When it comes to costs and people, the technical and organizational complexity of manufacturing processes have increased in Industry 4.0, and related technologies have imposed great challenges especially on small- and medium-sized enterprises (SMEs). Even with several options for free software and low-cost hardware, as mentioned before, more complex monitoring systems tend to be expensive because they demand continuous updating and maintenance service from the manufacturer. However, in Industry 4.0 the use of these technologies is likely to become increasingly common and, with the emergence of more manufacturers, prices will possibly become more affordable. Companies of all sizes are impacted by the availability of sufficiently qualified people to work within complex production systems. In this context, workers will need to spend some time in continuing education [77].

In addition to the great need to monitor physiological variables and environmental risks, as revealed in all the studies mentioned in this work, new occupational risks have emerged along with complexity in working environments, such as ergonomic and psychosocial risks, and those associated with the use of collaborative robots (cobots) [78]. Monitoring the use of PPE with the aid of computer vision, as implemented in [38], especially in high-risk activities such as operating machines and working with robots, is very important, mainly because unsafe actions can cause serious injury, amputation, or death.

Regarding psychosocial risks, the study by Verra et al. [79] presented a comparison of policies and practices in Europe for promoting health at work. It was identified that more than 70% of establishments in the European Union adopt preventive measures against direct physical damage, and more than 30% implement measures to avoid psychosocial risks. Psychosocial risks are often addressed in national policy, but they have not been addressed by most institutions. In the context of Industry 4.0, psychosocial risks deserve special attention because workers tend to be pressured towards greater productivity, and need to be constantly updated on new technologies, concepts, and tools. In addition, many workers feel obliged to respond to text messages and even solve problems outside work hours, jeopardizing their leisure and rest. Another point that deserves attention is that Industry 4.0 workplaces usually offer a variety of sedentary jobs, for example, information technology positions. As highly documented in the literature, a sedentary lifestyle is often associated with obesity and cardiovascular diseases. Certainly, monitoring psychosocial risks, risks related to sedentary working conditions, and the health conditions of workers in sedentary jobs without intruding on their personal lives are big issues, and bring significant challenges for the OSH sector in the context of Industry 4.0.

Finally, we identified the following points to be explored in future research:

- Use of AI to monitor the use of PPE, especially in dangerous activities.
- Monitoring psychosocial risks and risks related to sedentary working conditions.
- Consideration of workers' health history, together with data obtained from monitoring the work environment, to generate personalized alerts.
- Data privacy issues.

6. Conclusions

As mentioned above, Industry 4.0 has brought significant advances in the production process as well as several challenges for OSH. Various benefits arising from the integration of IoT-related technologies in OSH within this new context have been presented in this work. It is important to develop of solutions that allow daily monitoring of exposure to occupational risks and the health conditions of workers, because the data obtained can support more focused studies by companies and more assertively guide OSH policies. For example, artificial intelligence can contribute to building solutions that map existing problems and predict future problems.

Regarding privacy concerns, several studies have shown that data privacy is a critical issue in wearable technology development and that uncertainties around this topic can make workers especially reluctant to use wearable devices. In this context, it is important to highlight that training people in a clear and sufficient way is a key factor for success in the use of any workplace technology. In addition, workers need to be aware that the use of their health-related data may be important to protect them from work-related diseases, and that enough means will be used to keep that data safe. In this case, the agreement of workers is necessary and applicable laws and standards shall be adopted.

For future work, the authors are developing a system for individual environmental risk assessment based on IoT-related technologies. The device is intended to have sufficient energy autonomy to allow monitoring and communication for at least one working day. Issues related to the device's ergonomics and data privacy must be considered in the project, as well as durability and the viability of cost for industries of all sizes. The main goal is to contribute in the long run to reducing the incidence of occupational diseases resulting from exposure to harmful agents, by facilitating the visualization of data by organizations.

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