# Smart system for worker safety: scenarios and risk

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The introduction of IoT (Internet of Things) in work environments has the potential to revolutionise the industrial scenario. Among others, IoT technologies have the capability to innovate the customer experience, to improve the effectiveness and accuracy of the process, to identify in the early stages possible problems and/or defects, to enhance the efficiency and the sustainability of the activities. Moreover, IoT can dramatically improve the safety of workers, allowing to assess the psycho-physical state of the workers, the effectiveness and the correct use of the safety devices and the status of the environment, with the capability to provide on-line and in the field assessment in order to improve the situational awareness. In this paper, we will illustrate the main uses of such technologies in the OSH framework providing a taxonomy in terms of purpose and typology of sensors (either worn or environmental), type of measurements collected and information processing. A specific attention will be posed on the privacy, since the risk of potential remote control of the worker is an aspect that can negatively impact on the adoption of these solutions. Moreover, we will carry out an analysis of the problems related to the use of smart systems at large in the safety framework. Specifically, the paper will analyse the negative consequences that can be induced in the consequence of the employee de-responsibilities and due to the systemic fragility introduced by the cyber security aspects. Finally, using a specific case study, we will provide some recommendations to design an effective and "safe" smart safety environment. In this way the paper provides an overview on the technological solutions that enable cutting-edge applications in the OSH framework.

*Keywords*: smart environment, privacy, OSH, cyber risk, IIoT, wearable devices.

## 1. Introduction

Over the last decades, awareness has been raised about the importance of managing safety and health in working environments in order to prevent occupational accidents and work-related diseases. Where occupational accident is defined by the World Health Organization (WHO) as an unexpected occurrence, arising out of or in connection with work, which results in an *occupational injury* for one or more workers (Verbeek 2007). The European Agency for Safety and Health at Work (EU OSHA) estimated that in 2013 in the European Union there were 3,674 fatal accidents and approximately 3.1 million non-fatal accidents, causing at least 4 days of absence from work (Heuvel et al. 2017); estimating that about 3.3% of European Gross Domestic Product (GDP) is lost because of work-related accidents and diseases and the European economic loss is about 476 billion EUR per year (Elsler, Takala, and Remes 2017).
Nowadays the large availability of low-energy, low-cost and high-performance IoT technologies can be exploited to enhance Situational Awareness (SA) and threat prediction. Indeed, IoT sensors enable to monitor environmental parameters such as temperature, humidity and pressure. These sensors also allow accurate measurements of the concentration and state of aggregation of dangerous chemical substances, when present, and provide essential elements for the classification of plants into groups with different hazard potentials. On the other hand, recent progresses in the field of wearable devices have led to the development of robust wearable-based activity recognition systems for real life situations that enable a constant monitoring and localization of workers. Moreover, the adoption of wearable technologies in the occupational work context provides continuous information on several physiological parameters (e.g., respiratory rate, heart rate, blood pressure), allowing a timely intervention in case of any worsening symptom of the worker's health status.

## 2. Smart systems for worker safety

The aforementioned technologies represent powerful tools to enhance Health, Safety and Environment (HSE) management, but pose crucial security and privacy issues

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that may represent a serious obstacle for their approval and adoption in workplaces. Here we will present a brief resume of the main ambient intelligence solutions and wearable technologies that have been tested so far in real working scenarios and we will discuss the necessary privacy and security requirements for the so achieved smart environments.

Specifically, the diffusion of mobile and IoT devices can contribute to improve HSE in several categories, partially overlapping:

- Human Activity Recognition (HAR): the capability to understand the activity performed by the worker in order to assess its safety and correctness
- Worker's health status: in order to identify anomalous situations which can compromise the capability of the worker to operate safely, so as to identify in early stage pathological situations.
- Environmental monitoring: this is the capability to monitor the environment to identify anomalous or dangerous conditions.
- Localization: this is the capability to track the worker's location when the employee is working away from a fixed base. Data on positioning give an overview of where the workers are located within the facility, enabling, for instance, a better management of emergency situations.

Such functionalities are summarized in the following section, while section 3 is devoted to illustrate the most adopted technologies.

### 2.1. Human Activity Recognition

Indoor localization and Human Activity Recognition (HAR) are relevant tasks for HSE management. For what concerns HAR applications, the various types of activities that can be recognized, like walking, running or activities that require interactions, may vary greatly depending on the services carried out in the working environment and on the objects that characterize the industrial scenario. Indeed, in large-sized enterprises, production processes are more structured and less variable over time, compared with small and medium-sized enterprises (SME). Therefore, the first step towards an automatic assessment is the identification of the different activities that build up the industrial tasks. In SME a higher level of flexibility for the HAR system will be required.

HAR techniques can be divided into three main areas: action-based, motion-based and interaction-based (Hussain, Sheng, and Zhang 2019). Motion-based activities are distinguished into motion detection, tracking, and people counting; interaction-based activities can be grouped in a single category, namely human-object interaction; while action-based activities can be further divided into 6 sub-categories: gesture recognition, posture recognition, fall detection, activities of daily living, behavior recognition, and ambient assisted living (Hussain, Sheng, and Zhang 2019).

The typical approach for HAR applications is made of three main steps: (i) data collection from the sensors; (ii) data pre-processing and features extraction; (iii) using specific algorithm to recognize or infer activities. Usually, spatial and temporal features, extracted from sensory data of human operators performing tasks, are used as inputs for a machine learning tools, that classifies discrete time frames using either supervised classification techniques (i.e., k-Nearest Neighbor (k-NN), Support Vector Machines (SVM), Gaussian Mixture Models (GMM), and Random Forest (RF)) or unsupervised classification techniques (i.e., k-Means, Gaussian mixture models (GMM) and Hidden Markov Model (HMM)). These approaches aim at recognizing different activities on the basis of a series of observations on the actions carried out by human operators. To this end, lots of activities datasets must be collected in order to train the machine learning-based classifier. However, in certain cases, the events of interest may have a low occurrence rate, making it difficult to collect sufficient training data to develop models for such events. To address the difficulty of unusual events detection, clustering algorithms may be used to divide data into different groups depending on a similarity measure (Zelnik-Manor and Irani 2001). Even so, due the limited training data, clusters may not be archetypal enough to build up a prediction model for rare events.

A different approach is based on the use of threshold-based strategies, where. unsafe conditions, e.g. running, too long stay, etc., are recognized because sensor data overcome prescribed level of intensity or duration.

The most common sensing modalities exploited for HAR applications are surveillance cameras, depth cameras, inertial sensors (e.g., accelerometers, magnetometers, gyroscopes), motion sensors and proximity sensors.

#### 2.1.1 Fall and anomalous situation

A fall is a rare abnormal event, whose identification represents a major challenge in the workplace domain. Failing in the detection of such abnormal events can induce serious safety risks for the worker. Indeed, falls, together with overexertion and contact with objects or equipment, were found to be the top three leading causes for work-related injuries, which can lead the victim to a temporary or permanent incapacity for work. Thus, an effective fall detection system is needed to provide a timely first aid and to identify the risk factors in order to build up powerful prevention strategies. This process would lead to a significant reduction in the healthcare costs associated with fall-related injuries and to the avoidance of a loss in productivity caused by the victim's absence from work.

Fall detection approaches can be categorized into three main groups: wearable devices based, environmental sensors based and camera based (Mubashir, Shao, and Seed 2013). Since falls are diverse, unexpected and rare events it may be difficult to construct a proper model to predict them (Khan and Hoey 2017).

Usually, artificially simulated falls are used as input data to train classifiers. However, when replicating real fall

scenarios, data may still not be sufficient for the recognition task.
Hence, being real falls unusual events, typical supervised machine learning techniques may not be efficient enough to detect them and other classification methods, based on semi-supervised learning, cost-sensitive learning, and threshold-based approaches could be used. Being generally the fall characterized by high linear or angular acceleration, it can be detected using threshold based solution (De Cillis et al. 2015).

#### 2.1.2 Correct use of Personal protective equipment (PPE)

To reduce specific risks, workers must wear adequate Personal Protective Equipment (PPE) as a defense against occupational hazards. Unfortunately, the effectiveness of protective equipment is drastically reduced if it is not worn correctly.
In this framework, the presence of smart PPE, i.e. protective devices enhanced with smart materials and wearable electronics, may contribute to improve the safety of workers. Indeed, the availability of wearable electronics, merged with traditional passive protective devices, allows the implementation of new functionalities, such as alerting in the case of inadequate or absent PPE, when PPE malfunctions or when the workers is not adequately informed about the use of a specific PPE and so on. Moreover smart PPE can displaying warnings to the worker in case of emergency situations; monitoring health-associated parameters; activating protective systems after exceeding a danger-related threshold, and assessing the PPE's protection performance level (Podgórski et al. 2017).

### 2.2. Worker's health status

A strict health surveillance of workers is crucial to prevent occupational and work-related diseases. Recent technological advances have enabled the acquisition of relevant information about the worker's health status. For instance, the development of miniaturized and unobtrusive wearable sensors has enabled a continuous monitoring of the workers' physiological signals (e.g., heart rate (HR), respiration rate, skin temperature, skin conductivity, electrocardiogram, etc.). Moreover, wearable sensors for vital signs estimation paved the way for the assessment of work-related stress that affects individuals as a consequence of excessive workloads (Carneiro et al. 2019), (Sedighi Maman et al. 2017). The monitoring of workers' health status can emphasize in early stage the presence of pathological but also physiological conditions that can induce human error or inability to perform specific tasks.

#### 2.2.1 Emergency request & communication

Employers are obliged to set up effective safety and health management systems, train workers to cope with emergencies and designate an emergency coordinator that has to put in place the necessary measures and call external aid. As emphasized by the Refire project (Pascucci et al., 2012) the capability to communicate, especially during emergency situations, is considered the most relevant aspect to correctly manage anomaly conditions.
In recent years, the adoption of communication networks of distributed sensor nodes has largely increased. A wireless sensor network (WSN) is composed of a large number of intelligent sensors (i.e., nodes) distributed across a geographical area and equipped with transceivers. Each device can communicate with other devices within a defined range. Recent implementations allow a continuous monitoring of critical factors, such as the pollution level or the structural integrity of industrial sheds. These networks allow a real-time delivery of critical data and communication between the peripheral sensory elements and the control center. These goals are achieved not only by the implementation of efficient communication protocols but also by the use of advanced IoT technologies as peripheral nodes (Khalil et al. 2014). Indeed, latest advances in hardware and wireless technologies have enabled the monitoring of an always wider range of parameters and a real-time processing of data. Sensor networks are an essential prerequisite for emerging smart environments, but pose relevant privacy and security issues to take into consideration (Chan and Perrig 2003).

### 2.3. Environmental monitoring

Differently from base sensors, that detect changes in physical quantities and produce an electrical output that is sent to a transmitter in the control loop, IoT sensors sense physical properties, convert data, performs digital pre-processing and can communicate with other devices in the cloud. For these reasons IoT sensors are referred to as "smart sensors" and are often composed of a base sensor, a microprocessor, a communication module and on-board self-diagnostic tools to detect, for instance, sensor contamination or switch failures. IoT includes many different areas, some of which are addressed in the article, such as mobile devices, sensors, cloud and Radio Frequency Identification (RFID).
Even if the monitoring of an industrial plant is a usual task of any automated control, the availability of IoT and wearable devices allows to enlarge such capability in order to acquire more elements and data. In this line such sensors can contribute to monitor the concentration of pollutants or toxic gases in the air, to ensure thermal comfort to workers, to detect fires by temperature, gases and humidity measures, to monitor people's behaviour using for instance fall detectors or smoke detectors..
According to (Sehrawat and Gill 2019), the main IoT sensors, that can be found in the manufacturing industry, can be classified as:

- Proximity sensors: detect nearby objects without any physical contact, by emitting electromagnetic radiation (i.e., infrared).
- Position sensor: senses the motion of a person or object within a circumscribed area.

- Occupancy sensors: detect the presence of a person or object by measuring parameters like temperature, humidity light and air.
- Motion sensors: sense all the kinetic and physical movements in the environment.
- Chemical sensors: measure the chemical composition of the environment.
- Physical sensors: measure of temperature, pressure, humidity, vibration, ecc.

  The availability of information about the status and the environment can significantly contribute to improve situation awareness and, consequently, prevent failure in plant and potential dangerous conditions for the workers.

### 2.4. Localization

Information about the location of workers is a mandatory requirement to adequately manage emergency situations. While Global Navigation Satellite System (GNSS), e.g GPS, represents the actual gold-standard for outdoor localization, it has limited effective in indoor scenarios and also in the presence of structure, as industrial plant, where large (mechanical) structure create canyon phenomena and extensive shadow area. Alternative .

A possible solution to overcome GNSS limits is represented by indoor positioning systems (IPS) often based on fingerprinting technique or on different types of wireless sensor network (WSN). A WSN is a net of fixed physical devices where neighbor nodes can directly communicate. In certain applications, like object tracking, mobile nodes calculate their position in relation to fixed nodes (Franceschini et al. 2009).

IPS allow a continuous tracking of the worker's position, which is a useful information to provide a prompt aid, for instance, in the event of a dangerous situation (e.g., fire) or when an occupational accident occurs. However, IPS can also be exploited to locate objects, like PPE, products and means of production in fields like remote machinery control or mobile maintenance (Heck and Frey 2004). In this perspective, location data can be used to control and optimize production processes (De Cillis et al., 2014).

Important requirements for IPS in industrial environments are reliability, scalability, robustness (i.e., life cycle cost), accuracy and precision. There are several approaches for indoor localization (Brian Ray, n.d.). Some of them are listed below:

- Proximity-based systems: systems that allow to know the location of a worker at room level. They rely low range device as tags, beacons and Bluetooth Low Energy (BLE) protocol to transmit location-based messages up to some meters. Proximity-based systems can be reader based or reference point based systems. In the first case, the BLE beacon actively looks for BLE tags, which transmit their ID continually. The beacon reads the dumb tags in its proximity and communicates the tags' ID and the received signal strength indication (RSSI) to a server, which uses an algorithm to compute the distance of each tag from the reader. An estimation of the worker's location is given on the basis of the nearest tag. In the second case, beacons are used as reference points. The smart RFID tags scan the environment periodically looking for reference-points, calculate their distance from the found beacon and communicate the location data to a central access point which sends it to a server.
- Wi-fi based systems: tags are Wi-Fi transmitters that send simple packets to multiple Wi-Fi access points in the facility. These access points report the time and strength of a reading to a backend system, computes the position and sends the information to the cloud. Wi-Fi IPS need at least three access points to hear each tag transmission and time difference of arrival (TDOA) measures to reach a certain level of accuracy. Access points are spaced about every 100 feet in a facility.
- Ultra-Wide Band (UWB) systems: at least three UWB readers transmit a wide pulse over a GHz of spectrum. The reader listens for chirps from UWB tags which are activated by an exciter and generate a coded instantaneous burst. The readers send accurate time measurements from the tags to a central server. UWB systems are the most accurate ones for indoor positioning. However, installation costs are very high.

  Acoustic systems: they work like UWB systems but use sound in the ultrasonic range instead of radio.

## 3. Approaches

In this section we illustrate the most adopted solution to perform one or more of the functionalities illustrated in Section 2.

### 3.1. Video surveillance

Computer vision can be exploited to extract several types of information from the scene portrayed by videos or images, such as objects and workers' location or environmental condition.

Cameras can be worn by the worker which can show to control room the status of an equipment, emphasize a dangerous condition, etc. Such a camera can be used also to localize the worker: the images (i.e., query images) provided continually by the camera are compared to the images contained in a database to estimate the location. For instance, Jeelani et al. used a wearable camera to estimate the location of workers inside a construction site and to send a warning in case of proximity to a static or dynamic hazard (Jeelani et al. 2021).

Alternatively, surveillance cameras can be installed in the environment to detect objects or employees operating in the facility (Fritsch et al. 2000).

Few research studies applied vision-based approaches to address the improper use of PPE. Chen et al. developed a vision-based approach to monitor decommissioning workers of the Fukushima Daiichi nuclear power station (NPS). They created a dataset of images of helmets and face masks to train their model and used geometric relationships to identify workers that were not correctly wearing the equipment (Chen and Demachi 2020).
In addition, vision-based monitoring can be used to develop HAR. Video clips collected by the cameras can be analyzed by a human operator or by automatic computer vision techniques. However, in many surveillance applications, events of interest may have a low occurrence rate, making it difficult to collect sufficient training data to develop models for such rare events. To address the difficulty of unusual events detection, Zelnik-Manor et al. (Zelnik-Manor and Irani 2001) proposed the use of a clustering algorithm that divides video clips into different groups depending on a similarity measure. However, due to limited training data, clusters may not be representative enough to build up a prediction model for rare events.
Interesting results can be achieved using Depth cameras, such as Kinect, which are able to reconstruct 3D virtual skeleton. However, high computational costs, short range of operation, and complexity are the main reasons why the use of depth cameras is discouraged for activity recognition tasks.
Unfortunately, video cameras need that the worker is every time in the line-of-sight (hence they are unable to manage the presence of obstacles) and it may be complex to follow a worker in the presence of large worker space and their effectiveness largely degrades in the presence of a large number of workers in the same environment. However, the main disadvantage of video surveillance systems is their invasiveness with respect to the privacy of workers (Rajpoot and Jensen 2016) and due to the constraint on their use imposed by several national legislations.

### 3.2 Wearable sensors

The large-scale diffusion and miniaturization of data-capturing sensors and data storage components, that came along with Digital Transformation, have enabled the integration of these elements into garments or their application directly on the skin to assess the performance, health status, motion or location of a given subject (Lara and Labrador 2013).
The predominant wearable sensors for posture or motion recognition are inertial sensors, namely accelerometers and gyroscopes (Olgu and Pentland 2006). For instance, Koskimäki et al. (Koskimäki et al. 2009) used a single inertial measurement unit (IMU) attached to the active wrist of a worker to acquire acceleration and angular speed information. This information was used to identify the activity performed at a certain time interval. The recorded activities could be recognized online every half second, using a windowing method to select data within a two-second interval and overlapping two adjacent windows by 1.5 s. The system was tested on a set of basic tasks (e.g., hammering, screwing) and on a null activity class, consisting of activities like moving around or changing tools. The method used for recognition was the k nearest neighbor method. Results showed an accuracy of almost 90%.
In the context of the wearIT@work project, Lukowicz et al. (Lukowicz 2007) tested the use of unobtrusive body-worn sensors for tracking the maintenance and production workers activities tested in four application areas: aircraft maintenance, car production, healthcare, and emergency response. In (Stiefmeier 2008) the author uses inertial sensors embedded into a jacket and a wearable computer running a real-time spotting method to track the worker's movements.
Wearable devices can also be exploited to discriminate fall activities from normal activities of daily living (ADL) and relay warning messages and/or emergency coordinator in the workplace. For instance, Yang et al. used wearable inertial measurement units (WIMUs) and a semi-supervised learning algorithm (i.e., on-class support vector machine) to detect near-miss falls exploiting kinematics data of ironworkers in the construction industry (Yang et al. 2016). The proposed approach was tested on 183 near-miss falls simulated on an indoor steel frame and 69 near-miss falls simulated outdoor. Near-miss falls were detected with an accuracy that varies across subjects from 71.9% to 77.6% in the laboratory settings and from 73% to 87.5% outdoor. Such a dependency of the accuracy on the individual vulnerability and across different experimental settings indicates that the frequency of detected near-miss falls could be used to predict the risk for each individual in the workplace.
The project SmartBench, co-founded by the Italian Workers Compensation Authority (INAIL), regarded the development of an architecture based on ambient and wearable sensors to provide the workers with data from industrial machines and environmental sensors in the field, (Faramondi et al. 2020). The project offered three different services: a *localization service* to know the position of the worker, an *indirect shared warning system* to manage the exchange of relevant information about human and environmental conditions, and a *state estimation tool* to detect hazardous situations. More in detail, the infrastructure comprehends several environmental nodes (EN) placed in strategic positions and a human node, i.e. a worker equipped with a personal tablet and a smart wrist-mounted platform, able to record acceleration and angular speed signals. The EN are used both to support dynamic locazation of the workers and realise a dynamic mesh where EN store relevant information, e.g. anomalous measurements collected by a worker, in order to share the information with any other workers which move close to the EN. Faramondi et al. found that the wearable device is feasible for a continuous activity recognition, to discover anomaly behavior and to share relevant information in a cost-effective manner.
Lee et al. (Lee et al. 2017) proved the reliability of wearable sensors for monitoring HR, energy expenditure, metabolic

equivalents, and sleep efficiency in roofing workers' in a period of three consecutive days. By means of a feature extraction process, vital signs can also be used to improve accuracy of activity recognition applications (Yurtman 2012). However, Tapia et al. (Tapia et al. 2007), combining five triaxial accelerometers with a heart rate monitor, found that the HR has little discriminatory power in HAR. Indeed, after physically demanding activities, HR stays high for a while, even if the individual lays in a resting position.

### 3.3. Sensors in the environment

IoT sensors are used in monitoring environmental parameters, energy consumption, peoples and objects' position, dangerous or toxic gas levels etc.
(Oikonomou et al. 2016) presented the implementation of a wireless sensing system to monitor particular volatile organic compounds (VOCs) in printed flexing packaging industries. Experimental results revealed a good sensing performance of the system, characterized by a high repeatability and long-term stability.

### 3.4. Mobile devices

Nowadays personal mobile devices are available and affordable on a large scale. In recent years these devices have been equipped with sensors that enable several advanced functionalities and services useful for the owner, without the need for extra sensors to perform specific tasks, e.g. accellerometers, gyroscope, etc.. For instance, recent mobile phones are able to recognize activities and actions of the user for several applications, thanks to inertial sensors embedded in their housing (Ayu et al. 2012).

Table 1. A 0 to 10 effectiveness score was assigned to each approach for the aforementioned applications.

| *Approaches* | HAR | Detect falls | PPE correct use | Health status | Environmental monitoring | Localization |
|---|---|---|---|---|---|---|
| *Video surveillance* | 7 | 7 | 3 | 5 | 2 | 8 |
| *Wearable sensors* | 9 | 9 | 10 | 10 | 4 | 10 |
| *Sensors in the environment* | 9 | 7 | 3 | 0 | 10 | 9 |
| *Mobile devices* | 9 | 9 | 6 | 4 | 0 | 0 |

## 4. Communication

As discovered by the RISING project (De Cillis et al. 2016) the capability to communicate among workers is considered the most important element for a smart safety system, especially in the case of an emergency situation. While in the office like-structure it is normal to use wi-fi connectivity (even if the reliability of such media is not guaranteed during emergency), the biggest challenge is the plant scenario. Indeed, in this case wi-fi generally does not cover the whole area. Someone suggested using Long Term Evolution (LTE) but it has several limitations especially for indoors and in the presence of significant metallic infrastructures. A different solution is to create ad-hoc network using short range communication protocols as BLE or RFID. In this case to extend the coverage area, it is necessary to consider, multi-hop strategies (Gnoni et al. 2020).
A different aspect is related to the methodology used to provide information to workers. Most of the solutions provided in the literature assume the use of smart devices, e.g., mobile phones, to provide information using a touch screen. In this way it is possible to provide a significant amount of information allowing workers to navigate through data to acquire details on specific aspects. Some solutions also provide context-oriented interface able to emphasize to workers more relevant elements in the specific scenario. Unfortunately, the use of touch screens might be unfeasible when the worker has to wear safety gloves or when he/she needs both hands to perform the tasks. In this case some authors suggest using acoustic or vibration signals which represent a useful compromise except in scenarios characterised by a high level of noise or vibration. A more advanced solution integrates safety information into the augmented reality (AR) device. This represents definitely the most innovative solution, unfortunately AR is still in its infancy and the actual devices are not rugged.
Surprisingly, the studies on how to create an efficient and effective user interface to be used by workers in the field, especially when handling dangerous situations, are very limited and this is an area on which research will have to focus on.

## 5. Side effects

As mentioned before, the introduction of IoT devices can concretely improve the workers' safety. However, the use of such solutions has several drawbacks which should be carefully considered. The main elements to be taken into account are:

- Privacy: to avoid getting into dangerous situations, the safety 4.0 solutions use instrument to monitor the activities and status of the workers. Hence, they have impact on their privacy and might, at least theoretically, used also for remote control of the workers. Some approaches, e.g., video surveillance, are more invasive but almost all the proposed solutions have this drawback. Notice that remote control of worker is prohibited in several countries and the use of devices to monitor workers activities is in general strongly opposed by trade union organizations. To overcome such drawbacks, it is mandatory to carefully consider issue of privacy. For example, in (Faramondi et al. 2020) a privacy by design paradigm is adopted. Data about workers' activities are collected and stored only in the mobile device carried by the workers. At the end of the task all data are automatically erased except when some anomalous event happens (in the latter case information is shared to speed up emergency activities and for forensic activities).

- Complexity & Fragility: the massive diffusion of IoT in plants, besides a large number of benefist, represents a systemic fragility as pointed out by (Perrow, 2011), because the complexity of a system is itself a source of fragility. The numerous protocols and applications used in IT platforms make the whole system prone to effects of software bugs and misconfigurations. Moreover, one has to consider the risk induced by cybersecurity, i.e. the malicious data manipulation. Such events should mask some anomalous situations or, on the contrary, emphasize danger conditions during normal scenarios. In both cases, workers could be tricked into performing wrong tasks with potential dramatical consequences for the safety. As pointed out in the literature for the Industrial Control System (ICS) the more a system is designed for safety, the less it is able to handle security issue. Consequently, cyber issue induced by the use of smart devices must be included in the risk assessment in order to correctly consider both the benefits and problems induced by these systems.
- Release of liability: the presence of automatic systems capable of alerting workers in case of violations of safety protocols could reduce the awareness of the workers. In other words, workers could reduce their attention to the safety issue being sure that the automatic system will alert him/her. This might expose workers to dangerous events in case of anomalous behaviour of the safety 4.0 elements. To reduce this distorting effect, it is mandatory to adapt the training activities. Anyway, it is not enough in order to compensate this problem. In reality, it ought to be necessary to associate a reliability level to these safety 4.0 elements so that it is possible to calculate the probability of failure, useful to estimate the residual risk for the worker. A similar way to deal with this situation for machinery application is represented by safety related sensors (SRS) and safety related sensor systems (SRSS) used for the protection of persons described in IEC TS 62998-1:2019.

## 6. Conclusions

This paper aims at providing an overview on the recent technological advances in several domains, such as ambient intelligence and IoT, that have enabled novel solutions for application in the OSH framework. For instance, a wide range of smart PPE, WSNs and wearable devices have been developed to improve the workers' safety and health in working environments. Here we decided to focus on the main ambient intelligence solutions and wearable technologies that have been tested in real working scenarios so far. However, the use of such solutions has several drawbacks, especially in terms of privacy and security issues. To conclude, the use of IoT could definitively improve the level of safety of workers but it needs further interdisciplinary research in order to manage the different side effects and to achieve an adequate level of users' acceptability.

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