

Perspective

An Overview of Tools and Challenges for Safety Evaluation and Exposure Assessment in Industry 4.0

Spyridon Damilos , Stratos Saliakas , Dimitris Karasavvas and Elias P. Koumoulos * 

Innovation in Research & Engineering Solutions (IRES), 1030 Schaerbeek, Belgium; sdamilos@innovation-res.eu (S.D.); esaliakas@innovation-res.eu (S.S.); dkarasavvas@innovation-res.eu (D.K.)
* Correspondence: epk@innovation-res.eu

Abstract: Airborne pollutants pose a significant threat in the occupational workplace resulting in adverse health effects. Within the Industry 4.0 environment, new systems and technologies have been investigated for risk management and as health and safety smart tools. The use of predictive algorithms via artificial intelligence (AI) and machine learning (ML) tools, real-time data exchange via the Internet of Things (IoT), cloud computing, and digital twin (DT) simulation provide innovative solutions for accident prevention and risk mitigation. Additionally, the use of smart sensors, wearable devices and virtual (VR) and augmented reality (AR) platforms can support the training of employees in safety practices and signal the alarming concentrations of airborne hazards, providing support in designing safety strategies and hazard control options. Current reviews outline the drawbacks and challenges of these technologies, including the elevated stress levels of employees, cyber-security, data handling, and privacy concerns, while highlighting limitations. Future research should focus on the ethics, policies, and regulatory aspects of these technologies. This perspective puts together the advances and challenges of Industry 4.0 innovations in terms of occupational safety and exposure assessment, aiding in understanding the full potential of these technologies and supporting their application in industrial manufacturing environments.

Keywords: Industry 4.0; exposure assessment; safety; air quality; occupational health and safety



Citation: Damilos, S.; Saliakas, S.; Karasavvas, D.; Koumoulos, E.P. An Overview of Tools and Challenges for Safety Evaluation and Exposure Assessment in Industry 4.0. *Appl. Sci.* **2024**, *14*, 4207. <https://doi.org/10.3390/app14104207>

Academic Editors: Jaskó Szilárd and Tamás Ruppert

Received: 10 April 2024

Revised: 10 May 2024

Accepted: 13 May 2024

Published: 15 May 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Based on reported data from the International Labour Organization (ILO) [1], approximately 1 billion workers and operators every year are exposed to hazardous chemicals, including dust, fumes, and vapours, in their working environments, leading to illnesses or even fatal diseases. Workers are susceptible to exposure to a series of different airborne hazards depending on the processing materials and manufacturing procedures. Workplace airborne contaminants include the release of particulate matter (PM), volatile organic compounds (VOC) and semi-volatile organic compounds (SVOC) from equipment and operating machines, which could cause skin and eye irritation and respiratory inflammation [2]. PM is also associated with harmful effects on the respiratory tract, while their effect on human health is related to their size, since the smaller the size, the more prone to navigate through bronchioles and deposit in the alveoli [3]. Work practices such as polymer thermal processes [4], grinding [5], welding [6], as well as agricultural and wood-related dust, gases, vapours, fumes, and crystalline silica could lead to respiratory diseases such as pneumoconiosis and silicosis, while exposure to asbestos could lead to asbestosis and other fatal disorders [7,8].

The shift of manufacturing processes towards digitalisation and the use of the automation and interconnection of different devices and equipment is described as “Industry 4.0” or “4th industrial revolution”, signifying the development of smart factories and systems generating and analysing data for process optimisation [9]. The smart factory market is considered to be worth approximately USD 100.6 billion in 2024 and it is projected to reach

USD 164 billion by 2029 with a significant compound annual growth rate of 10.3% [10]. In the Industry 4.0 concept, the use of smart and autonomous systems exploits the technological advances of artificial intelligence (AI) and machine learning (ML) analytics, advanced manufacturing procedures, such as 3D printing and real-time connection and communication between computers and machines through the concept of Internet of Things (IoT). These technologies lead to the demand of novel and dynamic health and safety systems to support employees in their tasks [9].

The use of automated technologies is considered to promote workplace safety, especially through the replacement of humans by robotic systems, continuous data analytics to monitoring employees' well-being, and the development of ergonomic and comfortable workplaces and smart personal protective equipment (PPE) [11]. Zorzenon et al. [12] reviewed the positive and negative impacts of Industry 4.0 technologies on occupational safety, signifying the potential improvements in occupational environments and the health of employees, while there are alarming concerns on increased stress, fatigue, and psychosocial risks. Musarat et al. [13] analysed the used of advanced technologies and wireless monitoring and sensors as tools for improving health and safety in the construction industry of Malaysia. Similarly, the use of wearable technology has been investigated as part of health and safety monitoring on site, providing input on physiological data, environmental sensing, and proximity detection and tracking [14,15].

In this study, the various tools of the Industry 4.0 concept are reviewed, while comparing their characteristics with occupational health and safety assessments. This perspective highlights the applicability of the technologies in monitoring and evaluating airborne hazards and supporting exposure assessments conducted onsite by safety professionals, promoting a safer occupational environment. Finally, the potential challenges of the exposure assessments to airborne hazards in Industry 4.0 are summarised, addressing the needs and areas of further research and refinement on innovative exposure assessment tools.

2. Airborne Hazards in the Workplace

Exposure to particulate matter is a major concern in both occupational and residential settings [16]. Particulate matter is commonly grouped as inhalable or coarse particles with a diameter smaller than 10 μm (PM₁₀), respirable particles with a diameter under 4 μm (PM₄), and fine particles with a diameter under 2.5 μm (PM_{2.5}). According to their size, particles are differentiated based on their aerodynamic equivalent diameter; the smaller the particle size, the larger the surface per unit mass, increasing the potency of the particles that can reach the soft tissue, leading to adverse health effects [17,18]. In recent years, interest in ultrafine particles or nanoparticles smaller than 100 nm has increased [19]. Nanoparticles include particles that are either (i) natural (independent from any specific process), (ii) incidental (produced unintentionally during a process), (iii) engineered (purposefully manufactured). During inhalation, particles present different deposition patterns depending on their size [3]. A large portion of particles smaller than 10 μm can enter the respiratory system while a substantial portion of PM₄ can pass through the head airways and reach the alveoli. Particles between 100 nm and 1 μm enter the respiratory tract but are mostly removed through exhalation. Ultrafine particles (UFPs) pose the highest risk since they are mainly deposited in the alveolar region [3]. They can be absorbed by blood circulation and translocate to other organs of the body or cause adverse brain effects by depositing in the olfactory pathway. Previous studies have shown that UFPs have the ability to penetrate the cellular membrane causing the generation of reactive oxygen species (ROS), leading to oxidating stress and subsequently mitochondrial damage [20] and apoptosis [21] (Figure 1).

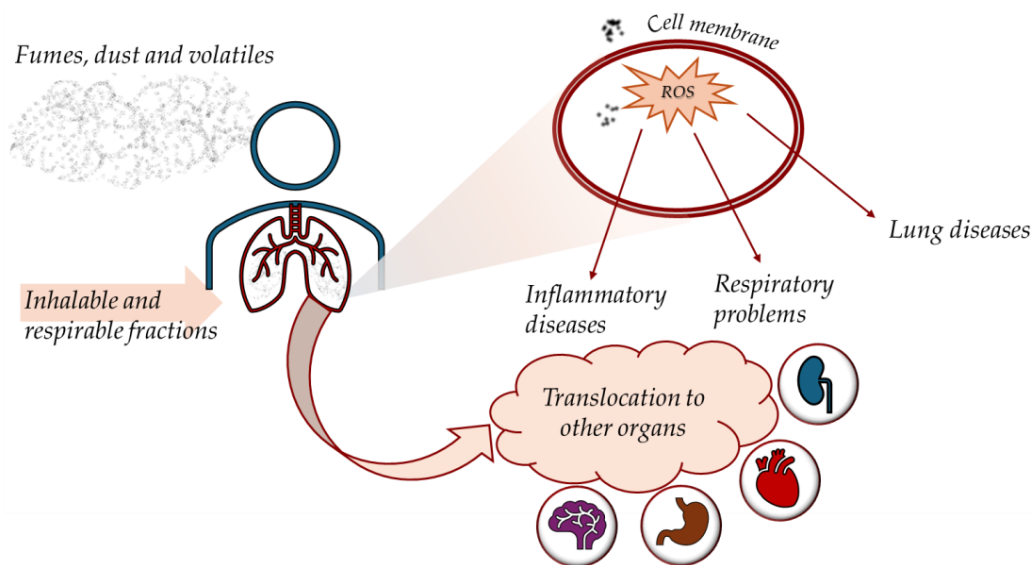


Figure 1. Illustration of inhalation exposure to airborne hazardous substances and particulate matter.

A detailed framework for occupational assessments of exposure to nanoparticles was developed by the Organisation for Economic Co-operation and Development (OECD) and published in 2015 [22]. This framework includes three tiers of increasing detail aimed at providing a cost-effective evaluation by moving to higher tiers only when substantial exposure cannot be excluded through lower assessment tiers. Following this approach, assessment begins with a detailed gathering of information related to materials, process, and workplace characteristics that may significantly impact exposure. At higher tiers, on-site real-time measurements of airborne particles are performed followed by the off-site analysis of air samples. The principles of the framework have been expanded to apply to the exposure assessment for larger particles [23].

Bioaerosols constitute a complicated and serious hazard in the workplace, which can lead to mucous membrane irritation, hypersensitivity pneumonitis, and benign organic dust toxic syndrome [24]. Known as “organic dust”, bioaerosols contain biological agents, such as bacteria, fungi, viruses, or other allergens and microorganisms, from indoor or outdoor sources. Indoor sources can be linked to the occupational environment, leading to particles of cotton and wood dust, flour, and skin scales, or associated with human activity (e.g., breathing, sneezing, coughing) [25]. Exposure to bioaerosols is similar to airborne particulate matter, since the penetration of bioaerosol particles in the respiratory tract depends on several physical and chemical properties, such as their shape, size, and chemical composition. An occupational exposure assessment includes the collection of air samples via cyclones and dust cassettes and subsequent chemical analysis or cultivation- and culture-based methods concerning airborne fungi and bacteria [24,26]. The great variety of biological agents hinders the analysis and evaluation of risks associated with bioaerosol exposure.

Exposure to fumes in the workplace constitutes a significant health hazard, occurring in various activities, such as metal welding, soldering, and spray painting [27,28]. During welding, the emitted fumes comprise gaseous and aerosol by-products, metal oxides and volatile chemical species that could cause respiratory damage, asthma, lung inflammation, and increased lung cancer risk. The adverse health effects are related to the specific metal used and the produced ions can lead to metal fume fever and severe irritation to the upper respiratory tract [29]. Vapours and gases are another type of airborne health hazard present in occupational environments. Exposure to gases can occur due to accidental release or leaks in gas containers. Vapours, like VOC and SVOC, can be released during the handling of liquids. The effects of exposure to VOC have been extensively studied with many species experiencing severe health effects, including carcinogenic, mutagenic, and reprotoxic

effects (CMR) [30]. Two technologies can be applied to VOC exposure assessments. Gas chromatography/mass spectrometry (GC/MS) is used for the identification of gases and vapours in collected air samples [31]. GC/MS can offer a specific list of the captured substances but does not offer results for time resolution, limiting the ability of evaluators to connect the release of hazardous substances to specific process steps. Photoionization detectors (PID) provide real-time readings of total volatile organic compounds (TVOC) [32]. PIDs are used as complimentary to GC/MS, as part of a medium tier assessment, or in cases where the mix of released VOC can be theoretically predicted.

3. Industry 4.0 Safety and Exposure Assessment Tools

3.1. Industry 4.0 Overview

The introduction of automation and digitisation in the manufacturing environment and the inter-connection of sensors and machines with the physical world is often described as the Fourth Industrial Revolution. The term “Industry 4.0” was first introduced by the German government as the “Industrie 4.0” initiative, signifying a new era with the evolution of “smart factories” and the establishment of digital technologies in the manufacturing sector [33]. The First Industrial Revolution involved the use of water and steam power in the manufacturing sector in the late 18th and mid-19th century. The Second Industrial Revolution in the late 19th century brought the evolution of electricity and electrical power to the assembly lines, while the Third Industrial Revolution began in the mid-20th century with the introduction of electronic devices (such as computers) and information technologies [11,33,34].

The concept of Industry 4.0 is based on the establishment of data generation and exchange between digital and physical systems using innovative technologies (such as cloud computing and data analytics) and advanced manufacturing platforms (such as autonomous robots and 3D printing). Figure 2 depicts the technologies and manufacturing systems developed as part of the Industry 4.0 and “smart manufacturing” concept. Internet of Things (IoT) refers to the connection of different devices and the data exchange between sensors and electronic devices [35], allowing for the control of dynamic systems and real-time optimisation, benefiting economic and industrial growth. At the same time, cloud computing architecture provides a platform for data storage and sharing, as well as resources for data analytics and on-demand services, supporting data management within the scope of IoT [36]. Smart factories require the use of descriptive and predictive data analytics to analyse past historic patterns as well as investigate through AI and ML techniques future trends and possibilities [37]. Based on the data structure and the complexity of the real-world problems, different machine learning techniques are used either individually or connected by employing multiple machine learning approaches for data analysis and the development of decision-making processes [38,39].

Digital twin (DT) technology describes the connection between the physical and digital world by developing a digital replica of the physical system, allowing the simulation, prediction, control, and optimisation of the system [40,41].

Real-time sensor data and AI algorithms have been utilised to explore the development of dynamic systems and predictive DT platforms [42]. Additionally, virtual reality (VR) platforms have become widespread as training and simulation tools for education, qualification, and product design and development [43]. However, recent advances in the industrial sector have shifted towards the research and development of augmented reality (AR) tools that project a “hologram” of virtual elements onto a device. Such solutions allow for the simultaneous observation of the real and virtual world and support the user in a variety of services, such as repair, maintenance, and training, maximising employees’ efficiency and minimising risk [44,45]. Wearable devices have also been developed to support time-consuming processes or the optimisation of manufacturing organisation via the use of data exchange through Cloud, IoT, and sensors, as well as a real-time connection between employees and desired industrial sectors [46]. Finally, the development of autonomous robots and 3D printing as part of an intelligent production network—part of

the IoT—minimises risk by transforming the manufacturing landscape to operate without human presence and control, while offering a low-waste economic solution [47,48].

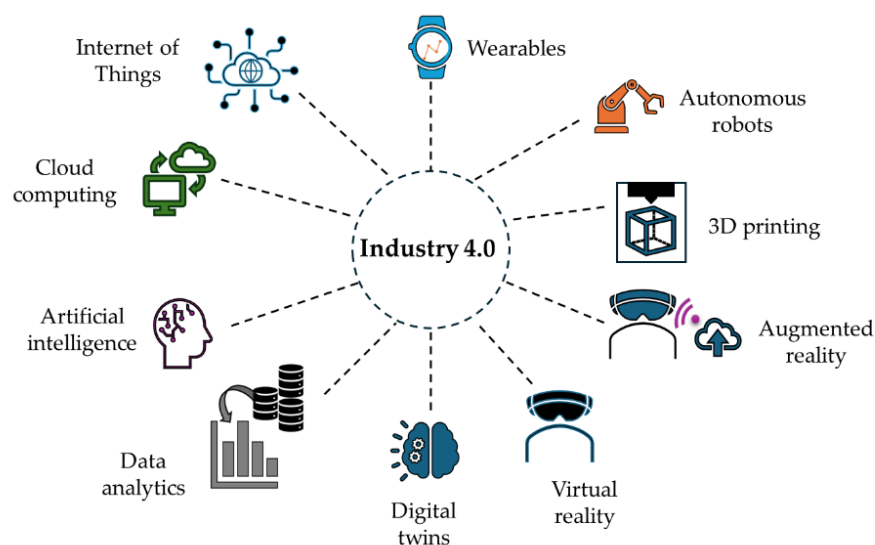


Figure 2. Technologies and manufacturing systems described within Industry 4.0.

3.2. Occupational Safety Technologies

In recent years, the concepts and technologies developed within the Industry 4.0 framework have been employed in health and safety sectors via predictive modelling and the development of innovative solutions focusing on employee safety in an occupational environment. Figure 3 depicts the increasing number of research publications (original articles, reviews, and conference proceedings) over the last decade obtained by using “Industry 4.0” as a keyword in the Web of Science platform. These numbers reflect the attention of Industry 4.0 solutions and technologies and ongoing research for the optimisation of existing solutions and development of innovative systems. At the same time, studies on the application of Industry 4.0 technologies as health and safety solutions, obtained by using both “Industry 4.0” and “Safety” as keywords in the Web of Science platform, projects at an increasing pace but at a lower magnitude; approximately 7% of the published papers on the Industry 4.0 subject over the last 5 years refer to the development of safety solutions and devices. Although the described analysis was based solely on a single academic journal search engine, it highlights the limited research on the exploitation of innovative and digitisation technologies for risk minimisation and safety improvements in the occupational workplace.

Emerging technologies developed and employed as part of “smart factories” have been investigated in the literature to mitigate and prevent occupational risks. The use of virtual simulation via DT and autonomous robotic systems and advanced manufacturing technologies can reduce the human presence in dangerous occupational environments [49,50]. The use of smart sensors and IoT applications allows for the continuous monitoring of the indoor environment quality (dust, humidity, noise, temperature, etc.) [12,51,52]. The use of wearable devices and data analytics of several well-being factors—such as fatigue, heart rate, etc.—through ML algorithms can lead to predictive modelling and instigate the development of smart personal protective equipment to prevent accidents in the workplace [53–55]. Proper implementation planning has been investigated to enhance the adoption of technologies in the workforce, increase safety in the occupational environment and minimise any negative effects arising from potential stress due to the increased complexity of manufacturing tasks and discomfort [56]. In particular, VR/AR systems have been investigated as training platforms for new employees that can highlight ergonomic issues and reduce accidents [57,58]. At the same time, AR technologies coupled with AI

solutions and real-time data analytics can lead to rapid data exchange and prevent actions, minimising occupational risks during operation, maintenance, and complex tasks [59].

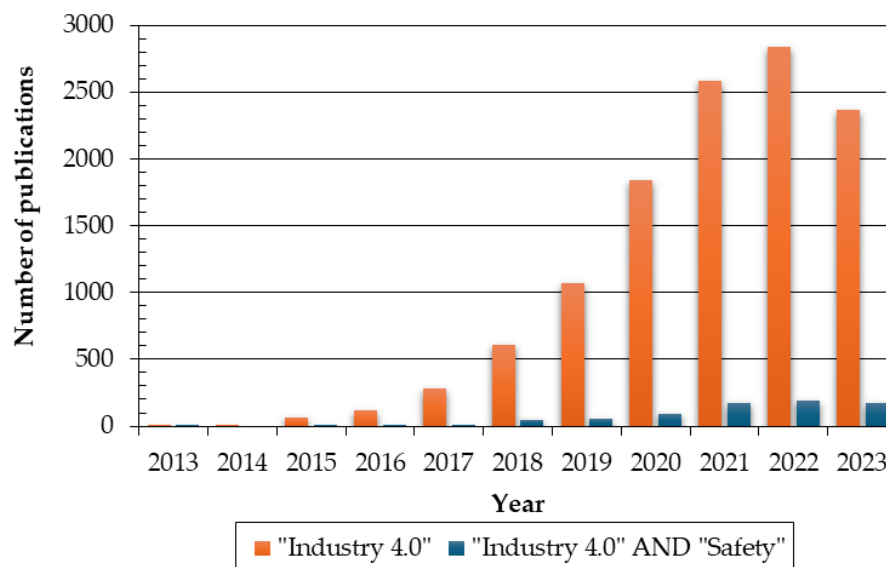


Figure 3. Trend of number of publications between 2013 and 2023 referring to the keywords, “Industry 4.0” and “Industry 4.0” AND “Safety” (based on Web of Science platform).

Following the guidelines of a hierarchical hazard control—as also outlined in the ISO 45001 for the design of a health and safety management system—the tools of Industry 4.0 can be adopted in almost all aspects of hazard control and risk prevention. In detail, the hierarchy of control schemes presents a series of measures from the most to the least effective, namely elimination of hazard (removing the hazard), substitution (replacement with less hazardous options), engineering controls (isolation from the hazard), administrative controls (training and risk awareness), and PPE [60]. DT systems can be expressed as an engineering control system since they provide an exemplary tool for process isolation, where operators are not present in the physical environment and simulations and controls can be performed, checked, and optimised in the virtual domain. Similarly, the use of AR technologies coupled with AI analytics can be described as real-time automated engineering controls. On the other hand, smart sensors and detection systems, as well as the wearable devices, are administrative controls offering risk awareness to the operators. Coupled with ML algorithms and being part of the IoT, they can be used as surveillance tools to monitor work patterns and give instructions [61]. Additional training tools are the VR/AR for safety coordination, induction training and providing instructions in the workplace. Smart PPE has been developed in the literature, whereas equipment, as both as a safety tool and a monitoring device for environmental, proximity, and biometrics data, enhances workers’ safety and health [62].

Within the concept of transforming the manufacturing and workplace environments within the Industry 4.0 and Industry 5.0 concepts, as well as the transformation of occupational and operational routines in the COVID-19 post-pandemic era, digital transformation technologies and the analyzed safety assessment tool can be utilized in a variety of sectors [63]. Felkner et al. outlined the main driving influences for human-centric occupational health and safety assessments, including the virtual workplace and non-standard employment, thus minimizing potential exposure to hazards [64]. Additionally, climate change and the use of advanced technologies present new challenges in the safety assessment, while the use of intelligent systems presents a novel human–machine dynamic for further examination [64]. Summarizing the application of digital technologies in occupation health and safety in general, Arana-Landín et al. categorized different risks in the occupational workspace, such as physical, chemical, mechanical, biological, ergonomic and psychologi-

cal, explaining how the use of automated processes and tools could support minimizing their impact [63]. For example, in their analysis, the use of digital tools could aid in minimizing the potential chemical exposure, as well as providing a training platform for the optimization of an organization's ergonomics. Furthermore, accidents due to mechanical risks can be prevented by developing tailored AI algorithms and designing safety zones to improve company safety and sustainability systems. In this way, the digital transformation of safety systems in general can revolutionize multi-faceted occupational health and safety foundations and support accident and risk prevention systems [65].

3.3. Tools for Exposure Assessment and Control

Real-time data analytics and IoT can provide significant improvements in the case of airborne hazards and mitigation of risks from occupational exposure. The use of smart sensors in the workplace and their installation in areas of high concern can provide live feedback on the operation control room and engineering equipment for emergency shutdown and the operators, as well as the employees via information exchange with their smart devices and wearables [66]. These areas are thermal treatment and processing facilities with high risks of releasing particulate matter or VOC. Additionally, the use of descriptive statistics for trend analyses between hazardous events and unfortunate or catastrophic outcomes provide guidance for health and safety professionals to conduct a risk assessment and design and implement adequate control systems [51,67]. Predictive AI algorithms have been found to correlate chemical and physical data from installed sensors and provide information on the occupation environment in terms of airborne particles and bioaerosol material [68].

More specifically, a real-time fluorescence-based aerosol cytometer was used to identify bioaerosols based on the light-scattering and fluorescence spectra of airborne particles, classifying them as either bacteria-, fungi- or pollen-like by analysing their fluorescence and optical size. The physical and chemical properties of indoor air (temperature; relative humidity; and the concentrations of carbon dioxide, TVOC, PM2.5, and PM10 particulate matter) were monitored using a commercial-grade indoor air quality (IAQ) sensor. AI models were developed to predict real-time or near-future concentrations of five target features: bacteria-, fungi-, and pollen-like particles (in a number of concentrations), as well as PM2.5 and PM10 (in mass concentrations). To assess the predictive accuracy of each model, the disparities between the measured values and the predictions generated by each model were evaluated. This evaluation was conducted using metrics such as mean squared error (MSE), root-mean-square error (RMSE), and/or a revised version of Willmott's index (WI) for prediction errors between models and actual values. Of course, such predictive algorithms are susceptible to human mobility, temporal variations, and activities in the workplace. These parameters could hinder data quality, highlighting the importance of sensor validation and the dataset provided for the AI training [68,69].

On-site measurements are limited by the spatiotemporal distribution of hazardous substances in the workplace. The use of virtual simulations and real-time information exchange from wearable devices on the operators' safety gear, could support decision making for movement and—in the worst case—emergency evacuation when the concentrations of chemicals exceed the permitted exposure limits. Digital twins have the ability to simulate the airflow patterns in the workplace and the concentration of particulate matter and chemical species released during manufacturing [69]. These simulations allow the optimisation of the hazard control systems (ventilation, PPE, etc.) [49,70]. Simulation accuracy and model validation should be taken into careful consideration, comparing the simulated values against real-time data from sensors, ensuring the predictability of models [70]. VR systems (and to a lesser extent, AR devices) have been investigated for employee training during risk assessment and safety procedures in the workplace, taking into account the emissions of airborne hazardous substances [71,72]. The drawbacks of this technology is the stress induced in the employees by the continuous information reception, discomfort, and visual fatigue [12]. Finally, wearable sensors—such as wristband devices—have been showcased

to continuously monitor air quality and can provide real-time information exchange with control equipment via the cloud network [73,74].

Currently, there is limited research on the use of smart technologies for the exposure assessment of airborne pollutants in the workplace. Lee et al. investigated the use of AI algorithms for the correlation of physical and chemical data on airborne particulate matter (PM_{2.5} and PM₁₀) with approximately 90% accuracy, compared with on-site gathered data [68]. However, according to their findings, data set training is vital to maintain a model's accuracy, since changes in workplace activities and variations in indoor environments could hinder its prediction abilities. Kim et al. implemented the use of computational fluid dynamic (CFD) modelling for airflow pattern simulations coupled with on-site measurements for data set training of AI prediction algorithms for sufficient removal of airborne hazardous materials [69]. The developed predictive models allowed the design of airflow control, particle removal and residual particle concentrations, while offering further input on the estimation of energy consumption, and thus sustainable development strategies. The use of deep learning techniques is gaining increasing attention in an effort to correlate low-cost sensors and real-time data with airborne pollutant concentrations and flow patterns [75,76]. A recent study by Imani utilized deep learning to estimate PM_{2.5} and PM₁₀ concentrations by analysing moderate resolution imaging spectroradiometer (MODIS) satellite images. The neural network was trained on publicly available ground scenes captured by MODIS. It linked the intensity values of the satellite image bands with particulate matter measurements at various spatial locations, offering a straightforward and cost-effective mapping of PM_{2.5} and PM₁₀ across large areas [77].

3.4. Limitations and Challenges

In the digital era, there are several aspects of cyber-security, data handling and privacy aspects. Mashaly reviewed the challenges of using virtual models via DT, showcasing the need for a safe and secure infrastructure of data encryption, authentication protocols, and the optimisation of the blockchain for storing data records [41]. AR can further support peoples' health and mobility in the workplace via the visualisation of the indoor environment and real-time information exchange via IoT architecture. However, VR/AR system could negatively impact workers' performance due to loss of control over their tasks and difficulty to distinguish between the virtual and real world [78,79].

Despite the technological challenges, ethical aspects of VR/AR systems and wearable technologies focus on the breach of privacy of subjected employees and the adaptation of the technology by older workers [54]. Ethical issues in the Industry 4.0 environment can be generalised into two major categories, namely the source of complexity and the risks for the humans and operators involved [80]. The increasing complexity of systems derives from the involvement and evolution of AI systems at work, the environment they evolve in, and the diversity of the systems and the humans involved (e.g., operators, users, agencies, as well as people's characteristics such as age, gender, disabilities, etc). Future developments instigate the joint operation of humans and autonomous systems (such as cobots), which increases the unpredictability of the situation and the potential risks of operators' harm. Several ethical concerns should be taken into account in the implementation of Industry 4.0 technologies in the occupational environment, including the ability of machines to prevent harm to operators, avoid data storage and potential spying on humans, and provide support to humans and operators in need or when injured in the manufacturing environment [80,81].

Corporate ethics fall within the Company Social Responsibility (CSR) and Global Data Protection Regulation (GDPR) frameworks that address compliance with fair and equitable financial policies, data collection, and usage [82]. Berrah et al. proposed the incorporation of ethics in industrial performance evaluations, illustrated as a tetrahedron covering efficiency–effectiveness–relevance–ethics dimensions [82]. Rahanu et al. listed a number of heuristics that can be followed for the ethical implementation of Industry 4.0 technologies [83], such as the definition of a new regulatory body, training of professionals, conducting operational

feasibility studies and risk analysis, protection of intellectual property rights, formulation of ethical policies on employee surveillance, and development towards general data protection and (cyber-)security.

At the same time, policies and regulations are still undergoing development and refinement to ensure that the implementation of these technologies is needed [54]. A regulatory guide published by the World Economic Forum (WEF) in 2020 highlighted the issues of developing regulatory frameworks due to the struggle of regulatory bodies to keep pace with innovations and risks in disruptive technologies. Additionally, the WEF report outlined the foundations of good regulatory practice [84]. These founding principles include openness and trust of the regulatory policies, proportionality between cost and benefit, and fairness without conflicts of interest, bias, and improper influence. “Agile regulation” provides flexibility in technology development and adaptation by organisations [84].

Kuo et al. aggregated policy instruments into three categories, namely supply side, environmental side and demand side, and each category has four different policy tools, for example, scientific and technical development, education, taxation and political system, procurement, public services, and commercial services [85]. Comparing the current policy development towards Industry 4.0 technologies and initiatives between United States of America (USA), China, and Germany, it was shown that each country differed to a certain degree on policy orientation, depending on the countries’ dynamics and industrial development [85]. A study at a European level showed that new policies and regulations on Industry 4.0 should focus on the development of digital manufacturing—including education, migration, and research—support small and medium enterprises (SME) on adapting the new technologies, and improve access to finance, supporting regional clusters and partnerships, and safeguarding data protection and (cyber-)security [86].

4. Conclusions and Future Perspectives

Industry 4.0 technologies are gaining attention in the manufacturing sector, providing vital tools for process monitoring, optimization, and sustainability. These technologies have been investigated as means of risk assessment and safety tools. However, there is limited research on the subject of how to ensure better indoor environment quality via the monitoring and estimation of trajectories of airborne pollutants and risk minimization at the workplace via predictive algorithms, simulations and real-data analytics from sensors or wearable devices. Several aspects of cyber-security, data management, and ethical and policy aspects should be taken into account to ensure the adaptation of these technologies in the workplace, while maintaining the privacy of the employees.

As technology progresses, additional technological innovations have been investigated for use in risk management and safety inspections. The use of unmanned aerial vehicles (UAV) such as drones can be implemented for monitoring high-risk areas, disasters, and jobsite supervision, as they can fly rapidly over different areas [87]. At the same time, the development of smart PPE could signal the proximity of employees to hazardous areas or locations with high potential exposure to airborne hazardous substances [11]. In the dawn of Industry 5.0, the technological objectives are the adaption to human-centered approaches, sustainability, and social responsibility to ensure and promote the cooperation between humans and machines (such as cobots) [88]. Cognitive cyber-physical systems, cognitive AI, and extender reality (XR) platforms offer the development of disruptive technologies characterized by interoperability, modularity, and integration in various aspects of the value chain.

Author Contributions: Conceptualization, S.D.; methodology, S.D. and S.S.; investigation, S.D. and S.S.; resources, E.P.K.; writing—original draft preparation, S.D. and S.S.; writing—review and editing, S.S. and D.K.; supervision, E.P.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. International Labour Office. *Exposure to Hazardous Chemicals at Work and Resulting Health Impacts: A Global Review*; International Labour Office: Geneva, Switzerland, 2021.
2. Nezis, I.; Biskos, G.; Eleftheriadis, K.; Kalantzi, O.-I. Particulate Matter and Health Effects in Offices—A Review. *Build. Environ.* **2019**, *156*, 62–73. [[CrossRef](#)]
3. Oberdörster, G.; Oberdörster, E.; Oberdörster, J. Nanotoxicology: An Emerging Discipline Evolving from Studies of Ultrafine Particles. *Environ. Health Perspect.* **2005**, *113*, 823–839. [[CrossRef](#)] [[PubMed](#)]
4. Damilos, S.; Saliakas, S.; Kokkinopoulos, I.; Karayannis, P.; Karamitrou, M.; Trompeta, A.-F.; Charitidis, C.; Koumoulos, E.P. Occupational Safety Analysis for COVID-Instigated Repurposed Manufacturing Lines: Use of Nanomaterials in Injection Moulding. *Polymers* **2022**, *14*, 2418. [[CrossRef](#)] [[PubMed](#)]
5. Paoli, L.; Guttová, A.; Grassi, A.; Lackovičová, A.; Senko, D.; Loppi, S. Biological Effects of Airborne Pollutants Released during Cement Production Assessed with Lichens (SW Slovakia). *Ecol. Indic.* **2014**, *40*, 127–135. [[CrossRef](#)]
6. Lee, M.; Jung, S.; Do, G.; Yang, Y.; Kim, J.; Yoon, C. Measurement of Airborne Particles and Volatile Organic Compounds Produced during the Heat Treatment Process in Manufacturing Welding Materials. *Saf. Health Work* **2023**, *14*, 215–221. [[CrossRef](#)] [[PubMed](#)]
7. Barnes, H.; Glaspole, I. Occupational Interstitial Lung Diseases. *Immunol. Allergy Clin. North Am.* **2023**, *43*, 323–339. [[CrossRef](#)] [[PubMed](#)]
8. Seaman, D.M.; Meyer, C.A.; Kanne, J.P. Occupational and Environmental Lung Disease. *Clin. Chest Med.* **2015**, *36*, 249–268. [[CrossRef](#)] [[PubMed](#)]
9. Aoun, A.; Ilinca, A.; Ghandour, M.; Ibrahim, H. A Review of Industry 4.0 Characteristics and Challenges, with Potential Improvements Using Blockchain Technology. *Comput. Ind. Eng.* **2021**, *162*, 107746. [[CrossRef](#)]
10. MarketsandMarkets. Smart Factory Market Size, Share, Industry Report, Revenue Trends and Growth Drivers. Available online: <https://www.marketsandmarkets.com/Market-Reports/smart-factory-market-1227.html> (accessed on 8 April 2024).
11. Leso, V.; Fontana, L.; Iavicoli, I. The Occupational Health and Safety Dimension of Industry 4.0. *Med. Lav.* **2018**, *110*, 327–338. [[CrossRef](#)]
12. Zorzenon, R.; Lizarelli, F.L.; Moura, D.B.A.d.A. What Is the Potential Impact of Industry 4.0 on Health and Safety at Work? *Saf. Sci.* **2022**, *153*, 105802. [[CrossRef](#)]
13. Musarat, M.A.; Alaloul, W.S.; Irfan, M.; Sreenivasan, P.; Rabbani, M.B.A. Health and Safety Improvement through Industrial Revolution 4.0: Malaysian Construction Industry Case. *Sustainability* **2023**, *15*, 201. [[CrossRef](#)]
14. Hajifar, S.; Sun, H.; Megahed, F.M.; Jones-Farmer, L.A.; Rashedi, E.; Cavuoto, L.A. A Forecasting Framework for Predicting Perceived Fatigue: Using Time Series Methods to Forecast Ratings of Perceived Exertion with Features from Wearable Sensors. *Appl. Ergon.* **2021**, *90*, 103262. [[CrossRef](#)]
15. Awolusi, I.; Nnaji, C.; Marks, E.; Hallowell, M. Enhancing Construction Safety Monitoring through the Application of Internet of Things and Wearable Sensing Devices: A Review. In *Computing in Civil Engineering 2019*; American Society of Civil Engineers: Reston, VA, USA, 2019; pp. 530–538. [[CrossRef](#)]
16. US EPA. Particulate Matter (PM) Basics. Available online: <https://www.epa.gov/pm-pollution/particulate-matter-pm-basics> (accessed on 8 April 2024).
17. Saleh, Y.; Antherieu, S.; Dusautoir, R.; Alleman, L.Y.; Sotty, J.; De Sousa, C.; Platel, A.; Perdrix, E.; Riffault, V.; Fronval, I.; et al. Exposure to Atmospheric Ultrafine Particles Induces Severe Lung Inflammatory Response and Tissue Remodeling in Mice. *Int. J. Environ. Res. Public Health* **2019**, *16*, 1210. [[CrossRef](#)]
18. Marval, J.; Tronville, P. Ultrafine Particles: A Review about Their Health Effects, Presence, Generation, and Measurement in Indoor Environments. *Build. Environ.* **2022**, *216*, 108992. [[CrossRef](#)]
19. European Commission. *Commission Recommendation of 10 June 2022 on the Definition of Nanomaterial (Text with EEA Relevance) 2022/C 229/01*; European Commission: Brussels, Belgium, 2022.
20. Li, N.; Sioutas, C.; Cho, A.; Schmitz, D.; Misra, C.; Sempf, J.; Wang, M.; Oberley, T.; Froines, J.; Nel, A. Ultrafine Particulate Pollutants Induce Oxidative Stress and Mitochondrial Damage. *Environ. Health Perspect.* **2003**, *111*, 455–460. [[CrossRef](#)] [[PubMed](#)]
21. Kim, J.Y.; Kim, J.-H.; Kim, Y.-D.; Seo, J.H. Ultrafine Diesel Exhaust Particles Induce Apoptosis of Oligodendrocytes by Increasing Intracellular Reactive Oxygen Species through NADPH Oxidase Activation. *Antioxidants* **2022**, *11*, 1031. [[CrossRef](#)]
22. Organisation for Economic Co-operation and Development. *ENV/JM/MONO(2015)19 Harmonized Tiered Approach to Measure and Assess the Potential Exposure to Airborne Emissions of Engineered Nano-Objects and Their Agglomerates and Aggregates at Workplaces*; Organisation for Economic Co-Operation and Development: Paris, France, 2015.
23. Saliakas, S.; Damilos, S.; Karamitrou, M.; Trompeta, A.-F.; Milickovic, T.K.; Charitidis, C.; Koumoulos, E.P. Integrating Exposure Assessment and Process Hazard Analysis: The Nano-Enabled 3D Printing Filament Extrusion Case. *Polymers* **2023**, *15*, 2836. [[CrossRef](#)]

24. Eduard, W.; Heederik, D.; Duchaine, C.; Green, B.J. Bioaerosol Exposure Assessment in the Workplace: The Past, Present and Recent Advances. *J. Environ. Monit.* **2012**, *14*, 334–339. [[CrossRef](#)] [[PubMed](#)]
25. Jabeen, R.; Kizhisseri, M.I.; Mayanaik, S.N.; Mohamed, M.M. Bioaerosol Assessment in Indoor and Outdoor Environments: A Case Study from India. *Sci. Rep.* **2023**, *13*, 18066. [[CrossRef](#)]
26. Eduarda, W.; Heederik, D. Methods for Quantitative Assessment of Airborne Levels of Noninfectious Microorganisms in Highly Contaminated Work Environments. *Am. Ind. Hyg. Assoc. J.* **1998**, *59*, 113–127. [[CrossRef](#)]
27. Loomis, D.; Dzhambov, A.M.; Momen, N.C.; Chartres, N.; Descatha, A.; Guha, N.; Kang, S.-K.; Modenese, A.; Morgan, R.L.; Ahn, S.; et al. The Effect of Occupational Exposure to Welding Fumes on Trachea, Bronchus and Lung Cancer: A Systematic Review and Meta-Analysis from the WHO/ILO Joint Estimates of the Work-Related Burden of Disease and Injury. *Environ. Int.* **2022**, *170*, 107565. [[CrossRef](#)] [[PubMed](#)]
28. De Oliveira, H.M.; Dagostim, G.P.; da Silva, A.M.; Tavares, P.; da Rosa, L.A.Z.C.; de Andrade, V.M. Occupational Risk Assessment of Paint Industry Workers. *Indian J. Occup. Environ. Med.* **2011**, *15*, 52–58. [[CrossRef](#)] [[PubMed](#)]
29. Wang, Y.-F.; Kuo, Y.-C.; Wang, L.-C. Long-Term Metal Fume Exposure Assessment of Workers in a Shipbuilding Factory. *Sci. Rep.* **2022**, *12*, 790. [[CrossRef](#)] [[PubMed](#)]
30. Li, A.J.; Pal, V.K.; Kannan, K. A Review of Environmental Occurrence, Toxicity, Biotransformation and Biomonitoring of Volatile Organic Compounds. *Environ. Chem. Ecotoxicol.* **2021**, *3*, 91–116. [[CrossRef](#)]
31. Davis, A.Y.; Zhang, Q.; Wong, J.P.S.; Weber, R.J.; Black, M.S. Characterization of Volatile Organic Compound Emissions from Consumer Level Material Extrusion 3D Printers. *Build. Environ.* **2019**, *160*, 106209. [[CrossRef](#)]
32. Stefaniak, A.B.; Bowers, L.N.; Knepp, A.K.; Luxton, T.P.; Peloquin, D.M.; Baumann, E.J.; Ham, J.E.; Wells, J.R.; Johnson, A.R.; LeBouf, R.F.; et al. Particle and Vapor Emissions from Vat Polymerization Desktop-Scale 3-Dimensional Printers. *J. Occup. Environ. Hyg.* **2019**, *16*, 519–531. [[CrossRef](#)] [[PubMed](#)]
33. Davies, R. *Industry 4.0: Digitalisation for Productivity and Growth*; Think Tank; European Parliament: Brussels, Belgium, 2015.
34. Sharma, A.; Singh, D. Evolution of Industrial Revolutions: A Review. *Int. J. Innov. Technol. Explor. Eng.* **2020**, *9*, 66–73. [[CrossRef](#)]
35. Kumar, S.; Tiwari, P.; Zymbler, M. Internet of Things Is a Revolutionary Approach for Future Technology Enhancement: A Review. *J. Big Data* **2019**, *6*, 111. [[CrossRef](#)]
36. Aravinth, S.S.; Krishnan, A.S.R.; Ranganathan, R.; Sasikala, M.; Kumar, M.S.; Thiyagarajan, R. Cloud Computing—Everything as a Cloud Service in Industry 4.0. In *Digital Transformation: Industry 4.0 to Society 5.0*; Kumar, A., Sagar, S., Thangamuthu, P., Balamurugan, B., Eds.; Springer Nature: Singapore, 2024; pp. 103–121. ISBN 978-981-9981-18-2.
37. Gandomi, A.H.; Chen, F.; Abualigah, L. Big Data Analytics Using Artificial Intelligence. *Electronics* **2023**, *12*, 957. [[CrossRef](#)]
38. Brnabic, A.; Hess, L.M. Systematic Literature Review of Machine Learning Methods Used in the Analysis of Real-World Data for Patient-Provider Decision Making. *BMC Med. Inform. Decis. Mak.* **2021**, *21*, 54. [[CrossRef](#)]
39. Sarker, I.H. Machine Learning: Algorithms, Real-World Applications and Research Directions. *SN Comput. Sci.* **2021**, *2*, 160. [[CrossRef](#)] [[PubMed](#)]
40. Yao, J.-F.; Yang, Y.; Wang, X.-C.; Zhang, X.-P. Systematic Review of Digital Twin Technology and Applications. *Vis. Comput. Ind. Biomed. Art* **2023**, *6*, 10. [[CrossRef](#)] [[PubMed](#)]
41. Mashaly, M. Connecting the Twins: A Review on Digital Twin Technology & Its Networking Requirements. *Procedia Comput. Sci.* **2021**, *184*, 299–305. [[CrossRef](#)]
42. Guo, J.; Lv, Z. Application of Digital Twins in Multiple Fields. *Multimed. Tools Appl.* **2022**, *81*, 26941–26967. [[CrossRef](#)] [[PubMed](#)]
43. Bellalouna, F. New Approach for Industrial Training Using Virtual Reality Technology. *Procedia CIRP* **2020**, *93*, 262–267. [[CrossRef](#)]
44. Machała, S.; Chamier-Gliszczyński, N.; Królikowski, T. Application of AR/VR Technology in Industry 4.0. *Procedia Comput. Sci.* **2022**, *207*, 2990–2998. [[CrossRef](#)]
45. Damiani, L.; Demartini, M.; Guizzi, G.; Revetria, R.; Tonelli, F. Augmented and Virtual Reality Applications in Industrial Systems: A Qualitative Review towards the Industry 4.0 Era. *IFAC PapersOnLine* **2018**, *51*, 624–630. [[CrossRef](#)]
46. Periša, M.; Sente, R.E.; Cvitić, I.; Kolarovszki, P. Application of Innovative Smart Wearable Device in Industry 4.0. In Proceedings of the 3rd EAI International Conference on Management of Manufacturing Systems, Dubrovnik, Croatia, 6–8 November 2018.
47. Jandyal, A.; Chaturvedi, I.; Wazir, I.; Raina, A.; Ul Haq, M.I. 3D Printing—A Review of Processes, Materials and Applications in Industry 4.0. *Sustain. Oper. Comput.* **2022**, *3*, 33–42. [[CrossRef](#)]
48. Bahrin, M.A.K.; Othman, M.F.; Azli, N.H.N.; Talib, M.F. Industry 4.0: A Review on Industrial Automation and Robotic. *J. Teknol.* **2016**, *78*, 137–143. [[CrossRef](#)]
49. Zio, E.; Miqueles, L. Digital Twins in Safety Analysis, Risk Assessment and Emergency Management. *Reliab. Eng. Syst. Saf.* **2024**, *246*, 110040. [[CrossRef](#)]
50. Li, M.; Milojević, A.; Handroos, H. Robotics in Manufacturing—The Past and the Present. In *Technical, Economic and Societal Effects of Manufacturing 4.0: Automation, Adaption and Manufacturing in Finland and Beyond*; Collan, M., Michelsen, K.-E., Eds.; Springer: Cham, Switzerland, 2020; pp. 85–95. ISBN 978-3-030-46103-4.
51. Sun, S.; Zheng, X.; Villalba-Díez, J.; Ordieres-Meré, J. Indoor Air-Quality Data-Monitoring System: Long-Term Monitoring Benefits. *Sensors* **2019**, *19*, 4157. [[CrossRef](#)] [[PubMed](#)]
52. Albert Raj, A.; Vijila, J. Design of Indoor Air Quality Monitoring System to Ensure a Healthy Universe. In Proceedings of the 2020 International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 10–12 September 2020; pp. 1123–1127.

53. Erol, M. Occupational Health and Work Safety Systems in Compliance with Industry 4.0: Research Directions. *IJEBEG* **2019**, *11*, 119–133. [[CrossRef](#)]
54. Pasquale, V.D.; De Simone, V.; Radano, M.; Miranda, S. Wearable Devices for Health and Safety in Production Systems: A Literature Review. *IFAC PapersOnLine* **2022**, *55*, 341–346. [[CrossRef](#)]
55. Shajari, S.; Kuruvinashetti, K.; Komeili, A.; Sundararaj, U. The Emergence of AI-Based Wearable Sensors for Digital Health Technology: A Review. *Sensors* **2023**, *23*, 9498. [[CrossRef](#)] [[PubMed](#)]
56. Wixted, F.; Shevlin, M.; O’Sullivan, L.W. Distress and Worry as Mediators in the Relationship between Psychosocial Risks and Upper Body Musculoskeletal Complaints in Highly Automated Manufacturing. *Ergonomics* **2018**, *61*, 1079–1093. [[CrossRef](#)] [[PubMed](#)]
57. Scorgie, D.; Feng, Z.; Paes, D.; Parisi, F.; Yiu, T.W.; Lovreglio, R. Virtual Reality for Safety Training: A Systematic Literature Review and Meta-Analysis. *Saf. Sci.* **2024**, *171*, 106372. [[CrossRef](#)]
58. Erten, B.; Oral, B.; Yakut, M.Z. The Role of Virtual and Augmented Reality in Occupational Health and Safety Training of Employees in PV Power Systems and Evaluation with a Sustainability Perspective. *J. Clean. Prod.* **2022**, *379*, 134499. [[CrossRef](#)]
59. Sabeti, S.; Shoghli, O.; Baharani, M.; Tabkhi, H. Toward AI-Enabled Augmented Reality to Enhance the Safety of Highway Work Zones: Feasibility, Requirements, and Challenges. *Adv. Eng. Inform.* **2021**, *50*, 101429. [[CrossRef](#)]
60. *ISO 45001:2018*; Occupational Health and Safety Management Systems—Requirements with Guidance for Use. International Organization for Standardization: Geneva, Switzerland, 2018.
61. Bourou, S.; Maniatis, A.; Kontopoulos, D.; Karkazis, P.A. Smart Detection System of Safety Hazards in Industry 5.0. *Telecom* **2024**, *5*, 1–20. [[CrossRef](#)]
62. Rasouli, S.; Alipouri, Y.; Chamanzad, S. Smart Personal Protective Equipment (PPE) for Construction Safety: A Literature Review. *Saf. Sci.* **2024**, *170*, 106368. [[CrossRef](#)]
63. Arana-Landín, G.; Laskurain-Iturbe, I.; Iturrate, M.; Landeta-Manzano, B. Assessing the Influence of Industry 4.0 Technologies on Occupational Health and Safety. *Heliyon* **2023**, *9*, e13720. [[CrossRef](#)] [[PubMed](#)]
64. Felknor, S.A.; Streit, J.M.K.; Edwards, N.T.; Howard, J. Four Futures for Occupational Safety and Health. *Int. J. Environ. Res. Public Health* **2023**, *20*, 4333. [[CrossRef](#)] [[PubMed](#)]
65. Ávila-Gutiérrez, M.J.; Suarez-Fernandez de Miranda, S.; Aguayo-González, F. Occupational Safety and Health 5.0—A Model for Multilevel Strategic Deployment Aligned with the Sustainable Development Goals of Agenda 2030. *Sustainability* **2022**, *14*, 6741. [[CrossRef](#)]
66. Fanti, G.; Spinazzè, A.; Borghi, F.; Rovelli, S.; Campagnolo, D.; Keller, M.; Borghi, A.; Cattaneo, A.; Cauda, E.; Cavallo, D.M. Evolution and Applications of Recent Sensing Technology for Occupational Risk Assessment: A Rapid Review of the Literature. *Sensors* **2022**, *22*, 4841. [[CrossRef](#)] [[PubMed](#)]
67. Núñez-Alonso, D.; Pérez-Arribas, L.V.; Manzoor, S.; Cáceres, J.O. Statistical Tools for Air Pollution Assessment: Multivariate and Spatial Analysis Studies in the Madrid Region. *J. Anal. Methods Chem.* **2019**, *2019*, e9753927. [[CrossRef](#)] [[PubMed](#)]
68. Lee, J.Y.Y.; Miao, Y.; Chau, R.L.T.; Hernandez, M.; Lee, P.K.H. Artificial Intelligence-Based Prediction of Indoor Bioaerosol Concentrations from Indoor Air Quality Sensor Data. *Environ. Int.* **2023**, *174*, 107900. [[CrossRef](#)] [[PubMed](#)]
69. Kim, N.K.; Kang, D.H.; Lee, W.; Kang, H.W. Airflow Pattern Control Using Artificial Intelligence for Effective Removal of Indoor Airborne Hazardous Materials. *Buuld. Environ.* **2021**, *204*, 108148. [[CrossRef](#)]
70. Topping, D.; Bannan, T.J.; Coe, H.; Evans, J.; Jay, C.; Murabito, E.; Robinson, N. Digital Twins of Urban Air Quality: Opportunities and Challenges. *Front. Sustain. Cities* **2021**, *3*, 786563. [[CrossRef](#)]
71. Pochwatko, G.; Jędrzejewski, Z.; Kopeć, W.; Skorupska, K.; Masłyk, R.; Jaskulska, A.; Świdrak, J. Representation of Air Pollution in Augmented Reality: Tools for Population-Wide Behavioral Change. In *Digital Interaction and Machine Intelligence*; Biele, C., Kacprzyk, J., Kopeć, W., Owsiniński, J.W., Romanowski, A., Sikorski, M., Eds.; Springer Nature: Cham, Switzerland, 2023; pp. 150–158.
72. Kačerová, I.; Kubr, J.; Hořejší, P.; Kleinová, J. Ergonomic Design of a Workplace Using Virtual Reality and a Motion Capture Suit. *Appl. Sci.* **2022**, *12*, 2150. [[CrossRef](#)]
73. Patel, V.; Chesmore, A.; Legner, C.M.; Pandey, S. Trends in Workplace Wearable Technologies and Connected-Worker Solutions for Next-Generation Occupational Safety, Health, and Productivity. *Adv. Intell. Syst.* **2022**, *4*, 2100099. [[CrossRef](#)]
74. Ye, S.; Ziemann, M.; Wenig, M. Personal Air Pollution Exposure Assessment Using Wearable Sensors. In Proceedings of the EGU General Assembly 2023, Vienna, Austria, 24–28 April 2023.
75. Popescu, S.M.; Mansoor, S.; Wani, O.A.; Kumar, S.S.; Sharma, V.; Sharma, A.; Arya, V.M.; Kirkham, M.B.; Hou, D.; Bolan, N.; et al. Artificial Intelligence and IoT Driven Technologies for Environmental Pollution Monitoring and Management. *Front. Environ. Sci.* **2024**, *12*, 1336088. [[CrossRef](#)]
76. Grant-Jacob, J.A.; Mills, B. Deep Learning in Airborne Particulate Matter Sensing: A Review. *J. Phys. Commun.* **2022**, *6*, 122001. [[CrossRef](#)]
77. Imani, M. Particulate Matter (PM_{2.5} and PM₁₀) Generation Map Using MODIS Level-1 Satellite Images and Deep Neural Network. *J. Environ. Manag.* **2021**, *281*, 111888. [[CrossRef](#)] [[PubMed](#)]
78. Missala, T. Paradigms and Safety Requirements for a New Generation of Workplace Equipment. *Int. J. Occup. Saf. Ergon.* **2014**, *20*, 249–256. [[CrossRef](#)] [[PubMed](#)]

79. Lundin, R.M.; Yeap, Y.; Menkes, D.B. Adverse Effects of Virtual and Augmented Reality Interventions in Psychiatry: Systematic Review. *JMIR Ment. Health* **2023**, *10*, e43240. [[CrossRef](#)] [[PubMed](#)]
80. Trentesaux, D.; Caillaud, E. Ethical Stakes of Industry 4.0. *IFAC PapersOnLine* **2020**, *53*, 17002–17007. [[CrossRef](#)]
81. Peckham, J.B. The Ethical Implications of 4IR. *J. Ethics Entrep. Technol.* **2021**, *1*, 30–42. [[CrossRef](#)]
82. Berrah, L.; Cliville, V.; Trentesaux, D.; Chapel, C. Industrial Performance: An Evolution Incorporating Ethics in the Context of Industry 4.0. *Sustainability* **2021**, *13*, 9209. [[CrossRef](#)]
83. Rahanu, H.; Georgiadou, E.; Siakas, K.; Ross, M.; Berki, E. Ethical Issues Invoked by Industry 4.0. In *Systems, Software and Services Process Improvement*; Yilmaz, M., Clarke, P., Messnarz, R., Reiner, M., Eds.; Springer: Cham, Switzerland, 2021; pp. 589–606.
84. World Economic Forum. Agile Regulation for the Fourth Industrial Revolution: A Toolkit for Regulators. Available online: <https://www.weforum.org/about/agile-regulation-for-the-fourth-industrial-revolution-a-toolkit-for-regulators/> (accessed on 1 May 2024).
85. Kuo, C.-C.; Shyu, J.Z.; Ding, K. Industrial Revitalization via Industry 4.0—A Comparative Policy Analysis among China, Germany and the USA. *Glob. Transit.* **2019**, *1*, 3–14. [[CrossRef](#)]
86. Directorate-General for Internal Policies of the Union (European Parliament); Carlberg, M.; Kreutzer, S.; Smit, J.; Moeller, C. *Industry 4.0*; Publications Office of the European Union: Luxembourg, 2016; ISBN 978-92-823-8815-0.
87. Umar, T. Applications of Drones for Safety Inspection in the Gulf Cooperation Council Construction. *Eng. Constr. Arch. Manag.* **2020**, *28*, 2337–2360. [[CrossRef](#)]
88. Ghobakhloo, M.; Iranmanesh, M.; Tseng, M.-L.; Grybauskas, A.; Stefanini, A.; Amran, A. Behind the Definition of Industry 5.0: A Systematic Review of Technologies, Principles, Components, and Values. *J. Ind. Prod. Eng.* **2023**, *40*, 432–447. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.