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Predictive Assessment of Human Operators in Industry 5.0: A Conceptual Framework

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To my parents, my sister, my girlfriend, and my cat.

What's the most you ever lost on a coin toss?

Abstract

The advent of Industry 5.0 represents a paradigm shift towards a more human-centric approach in manufacturing, focusing on integrating human operators with advanced technological systems. Despite significant progress in predictive maintenance for machinery, there is a notable gap in predictive assessment technologies to safeguard human operators.

This thesis introduces a novel conceptual framework designed to fill this gap by leveraging predictive technologies and methodologies to monitor human operators in Industry 5.0 paradigm settings proactively. Our framework emphasizes the importance of human well-being and safety by integrating data collection, advanced analytics, and targeted intervention techniques.

Through a literature review of related works, a formulation of a taxonomy of the human factors to be considered, and a detailed exposition of our framework, we highlight its potential to enhance operational efficiency, environmental sustainability, and, most importantly, the overall welfare of the workforce. This research underlines the critical need for a balanced focus on both technological advancement and the well-being of human operators, proposing a preemptive approach that aligns with the pillars of Industry 5.0. We discuss the implications of our findings for future research, particularly the need for ethical data collection practices, real-time data processing techniques, and personalized interventions.

The proposed framework categorizes conceptual approaches and introduces recent innovations in predictive assessment technologies, outlining the way for more sustainable, efficient, and human-centric industrial environments.

Sommario

L'avvento dell'Industria 5.0 rappresenta un cambio di paradigma verso un approccio più umano-centrico nella produzione, incentrato sull'integrazione degli operatori industriali con sistemi tecnologici moderni ed avanzati. Nonostante i significativi progressi nella manutenzione predittiva dei macchinari, il panorama scientifico attuale mostra lacune nelle tecnologie di valutazione predittiva per la tutela e salvaguardia dei lavoratori nelle industrie.

Questa tesi introduce un nuovo quadro concettuale progettato per colmare questa deficienza nel contesto dell'Industria 5.0, sfruttando le tecnologie e metodologie predittive per monitorare in modo proattivo gli operatori. Il framework proposto enfatizza la centralità dell'uomo nei processi produttivi, sottolineando l'importanza del benessere e della sicurezza umana integrando la raccolta dei dati, l'analisi avanzata di questi ed apposite tecniche di intervento mirate e personalizzate.

La dettagliata revisione della letteratura svolta, assieme alla formulazione della tassonomia dei fattori umani da considerare e alla esposizione dettagliata del framework, evidenziano il potenziale di questo lavoro nel migliorare l'efficienza produttiva, la sostenibilità ambientale, ma soprattutto il benessere generale della forza lavoro. Questa ricerca sottolinea la necessità critica spinta dal paradigma dell'Industria 5.0 di concentrarsi in modo equilibrato sia sul progresso tecnologico che sul benessere degli operatori umani, proponendo un approccio preventivo che si allinea con i pilastri di questo approccio industriale. Vengono inoltre discusse le implicazioni dei risultati per le ricerche future, in particolare la necessità di pratiche etiche di raccolta e analisi dei dati, tecniche di elaborazione dei dati in tempo reale, e possibilità di aumentare il grado di personalizzazione delle tecniche di intervento.

Il framework proposto categorizza gli approcci concettuali presentati nella letteratura e introduce le reecenti innovazioni nelle tecnologie di monitoraggio e valutazione predittive, marcando la strada per contesti industriali più sostenibili, efficienti e incentrati sull'uomo.

Contents

Acronyms

ABM Agent-based Modelling. 89

AI Artificial Intelligence. 1, 8, 12, 19, 21–25, 27, 28, 30, 31, 35, 38, 74, 89, 90, 98

AR Augmented Reality. 25, 27, 36, 90, 94, 97

ASEP Accident Sequence Evaluation Program. 52

BRR Blink-rate Ratio. 46, 47

CERI Comprehensive Environmental Risk Index. 86–88

CNN Convolutional Neural Network. 79, 89

CoBot Collaborative Robot. 16, 22, 23, 25, 36–38, 43, 68

CPS Cyber-physical System. 13, 14

DES Discrete Event Simulation. 89

DT Digital Twin. 24, 27, 28, 36, 73, 88–90, 96

EAR Eye-aspect Ratio. 46, 47, 68, 81

EAWS Ergonomic Assessment Worksheet. 57

ECG Electrocardiogram. 66, 75

EEG Electroencephalography. 46, 47, 50, 67, 75, 76, 89, 93

EMG Electromyography. 46, 67

FFT Fast Fourier Transform. 77

FOM Frequency of Mouth. 80

HEP Human Error Probability. 50

HR Heart Rate. 77–79

HRA Human Reliability Assessment. 52

HRP Human Reliability Probability. 50

HRV Hearth Rate Variability. 78, 92

I4.0 Industry 4.0. 1, 2, 4, 8, 12–16, 20–22, 24, 32, 41–44, 47, 101

I5.0 Industry 5.0. 1, 2, 4, 8, 15, 16, 19–28, 30–32, 35–39, 41–43, 47, 48, 50, 57, 63, 65, 68, 69, 71, 88, 90, 94–98, 101, 103

IIoT Industrial Internet of Things. 23

IMU Inertial Measurement Unit. 66, 67, 76

IoT Internet of Things. 12, 13, 17, 19, 21–24, 27, 37, 38, 95

IR Industrial Revolution. 1, 2, 4, 7, 8, 10, 11, 101

MAR Mouth-aspect Ratio. 46, 68, 80

ML Machine Learning. 8, 74, 75, 79, 86, 89, 98

MMH Manual Material Handling. 48–50, 56, 57

MR Mixed Reality. 25, 94

MWL Mental Workload. 58

NASA-TLX Nasa Task Load Index. 58, 61

NLP Natural Language Processing. 89

OWAS Ovako Working Posture Analyzing System. 45

PERCLOS Eye-opening Frequency. 46, 47, 68, 83

PPE Personal Protective Equipment. 65, 68, 95

PRE Perceived Rating Exertion. 45

RAMP Risk Assessment and Management tool for manual handling Proactively. 56

REBA Rapid Entire Body Assessment. 45, 53, 55

RNN Recurrent Neural Network. 79, 86, 89

ROM Range of Movement. 46

RSME Rating Scale Mental Effort. 58, 59, 61

RULA Rapid Upper Limb Assessment. 45, 53, 54

SHARP Systematic Human Action Reliability Procedure. 52

SOFI Swedish Occupational Fatigue Industry. 45

SWAT Subjective Workload Assessment Techniques. 59, 62

THERP Technique for Human Error Rate Prediction. 52

UX User Experience. 58

VR Virtual Reality. 25, 27, 36, 89, 90, 94, 97

WHO World Health Organization. 46

Chapter 1

Introduction

Throughout history, human progress and societal evolution have been intrinsically linked with technological progress. The shift from one industrial approach to another, primarily driven by advancements in technology, is defined as an Industrial Revolution (IR). Recently, the advent of the Industry 4.0 (I4.0) paradigm has pointed out a significant move towards a data-driven industry strengthened by digitalization and Artificial Intelligence (AI) technologies. However, this model has been increasingly discussed as it does not adequately address the current socioeconomic and political challenges. These criticalities include environmental emergencies due to the excessive exploitation of natural resources, various crises such as the COVID-19 pandemic, and escalating political tensions worldwide, as in the Russo-Ukrainian war. Additionally, the rapid adoption of AI technologies, while enhancing efficiency, has originated significant social issues, leading companies to reduce the number of operators, causing unemployment problems and deep social tensions.

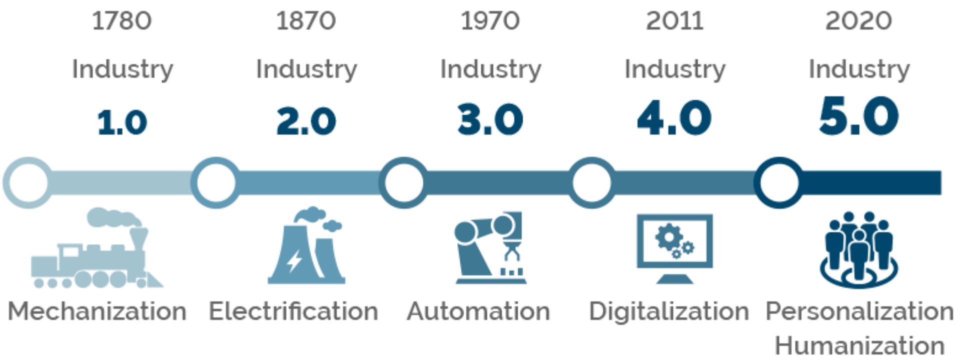


Figure 1.1: Timeline of Industrial Revolutions from Industry 1.0 to Industry 5.0 [1].

In response to these new societal and technical challenges, a new paradigm, Industry 5.0 (I5.0), was proposed by Michael Rada in 2016 [2]. This model emphasizes a balanced approach to industrial development, focusing on the three core pillars shown in Figure 1.2:

1. **Human-centricity**;

2. **Resilience**;

3. **Sustainability**.

However, it is more appropriate to consider I5.0 not as a standalone industrial paradigm but rather as a logical continuation of I4.0 since they share the same enabling technologies. Indeed, while previous Industrial Revolutions had significant technological advancements, with I5.0 the changes are in perspective: instead of focusing on technologies, it is proposing a shift where people are at the core, the collaboration between humans and machines is enhanced, and there is a critical interest in social and environmental issues [3].

This paradigm transition marks a change towards re-centering human factors in manufacturing, emphasizing operators' overall welfare and well-being [4]. That introduces a pressing need for formulating and implementing systems that can monitor, assess, and enhance all those human factors critical to maintaining a satisfied and motivated workforce. However, given the early stages of I5.0, this domain is still under-covered, and the related works are mainly developed in the context of I4.0, showing an interest in the human workers as a mere productivity factor. To fit within the human-centric principles of I5.0, such a system should not only enhance operational efficiency but also safeguard and improve workers' mental and physical health and address critical workplace challenges such as stress, fatigue, and demotivation.

This work aims to propose a novel conceptual framework for assessing the condition of human operators in industrial environments by leveraging the technological foundations of I4.0 and embracing the pillars of I5.0. The technologies employed in our framework follow the same approach as the key enabling technologies of I5.0: merging various I4.0 technologies into components specifically designed, in our case, to assess and support the conditions of human operators proactively.

The outcome is a system able to identify potential health and safety risks before they occur, optimize working conditions, and promote a balanced focus on productivity, environmental sustainability, and social well-being.

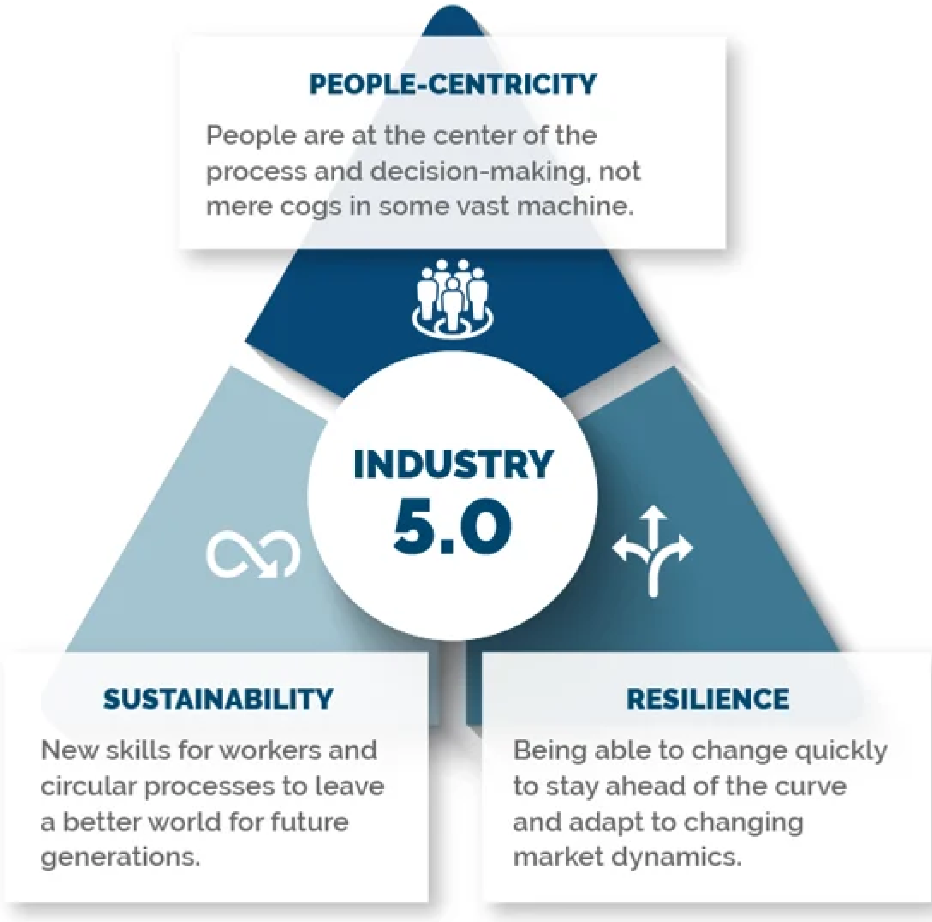


Figure 1.2: Diagram of the three core pillars of Industry 5.0 [1].

Consider the last time you heard about a workplace accident: how often do we attribute these incidents to a lack of technological intervention tailored to human needs? This thesis aims to bridge this gap, presenting a paradigm where technology serves not just the machines but the core of any industry: the human operators. Can we overlook the potential of integrating human-centric predictive technologies to safeguard our most valuable resource? [5].

Specifically, the objectives of this work can be summarized into four Milestones (MSs):

- **MS1**: Define a taxonomy of the human factors impacting operators in the industry, outlining the critical elements the framework needs to address.

- **MS2**: Evaluate current methodologies for assessing these human factors to identify best practices and areas needing innovation.

- **MS3**: Explore technologies for automating data collection and the assessment methodologies linked to these human factors.

- **MS4**: Develop a comprehensive framework incorporating human factors and technologies into a structured three-stage approach: data collection, data analysis, and intervention module.

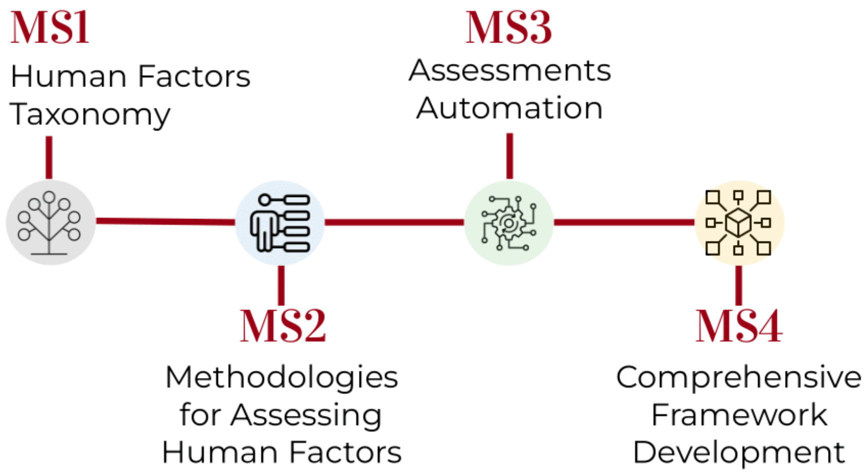


Figure 1.3: Flowchart outlining the four main milestones of the thesis research.

The first step to achieving these goals has been to review the literature, using previous works on the topic as a starting point to formulate the taxonomy of human factors (MS1) and determine the assessment methodologies (MS2). By doing that, we were able to understand the metrics of interest and, therefore, the data needed to be collected.

The second phase involved the determination of the I4.0 technologies that can be used to collect all those data linked to the human factors defined within the second milestone to automate the assessments (MS3).

Finally, the selected technologies have been merged into components, enabling the collection of data, their analysis, and the triggering of appropriate interventions when needed (MS4).

1.1 Contributions

The author conducted most of his thesis work during his period abroad in Viana do Castelo, Portugal, where he was hosted at the AditLab [6] of the Instituto Politécnico de Viana do Castelo (IPVC) under the onsite supervision of Professor Sérgio Ivan Lopes. The author has received funding from the European Union under the Erasmus+ Program.

This work has been done in the context of the Agenda Drivolution – Transition to the factory of the future, Ref. 02/C05-i01.02/2022.PC644913740-00000022, funded by the Portuguese Resilience and Recovery Plan (PRR).

The research efforts led to two accepted publications: one at the *SASYR 4^{th} National Conference*, held in Bragança, Portugal, on July 3rd, 2024 [7, 8], and the second at the *IEEE 29^{th} ETFA international conference*, which will take place in Padua from September 10th to 13th, 2024 [5, 9]. The expenses related to these publications and conference participations were covered by the Drivolution project.

1.2 Document Structure

The thesis is organized into four main chapters.

Chapter 2 introduces the historical context and evolution of Industrial Revolutions, discussing the first three revolutions and then focusing on the contemporary paradigms of I4.0 and I5.0.

Chapter 3 explores the predictive approaches for human operator assessment, starting with the taxonomy of the human factors that the framework needs to cover, considering four main domains: Safety, Health, Well-being, and Human Errors. Following that, it presents a review of various qualitative and quantitative assessment methodologies that have been discussed in the literature.

Chapter 4 details the developed conceptual framework, divided into three primary and interconnected modules: Data Collection, Data Analytics and Predictive Modeling, and Intervention Techniques.

Finally, Chapter 5 summarizes the thesis findings, outlines future research directions, and concludes with some closing thoughts and considerations.

Chapter 2

Industrial Revolutions and the New Paradigms

An Industrial Revolution (IR) represents a profound transition from one manufacturing process to another, typically pushed by technological advancements and societal progresses [10]. The series of IRs, illustrated in Figure 2.1, have drastically changed production processes since the 18th century. Before this time, the production of essentials such as food, clothing, and housing primarily relied on manual labor or, at most, was aided by animal power [11].

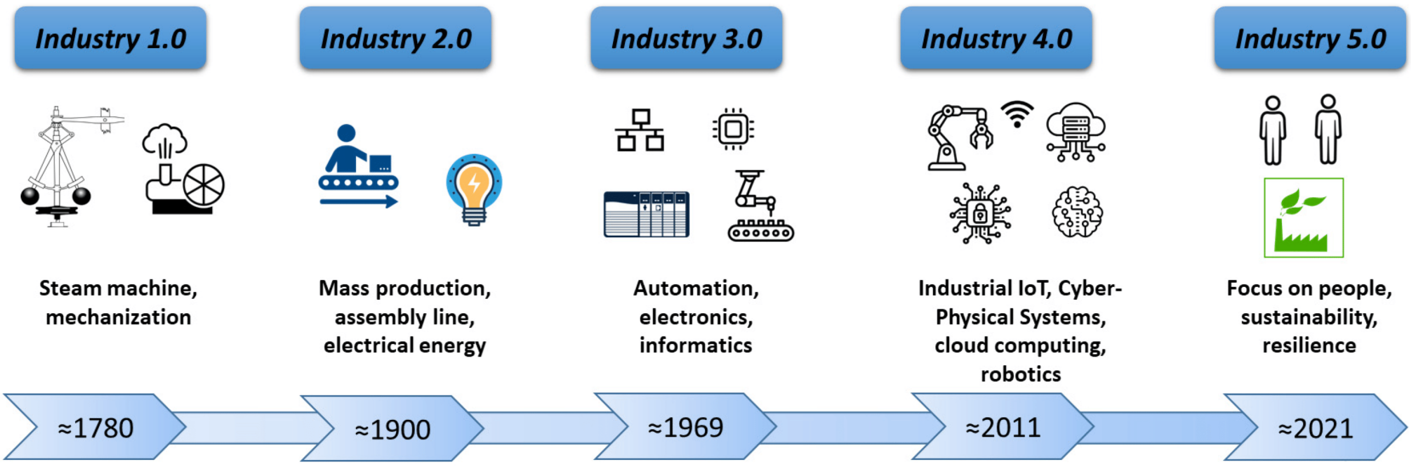


Figure 2.1: Industrial Revolutions' evolution [12].

Spanning the 18th and 19th centuries, the Industrial Revolutions transformed largely rural and agricultural societies in Europe and America into industrialized and urbanized landscapes. This shift introduced machines, factories, and mass production techniques, significantly impacting industries like steel and textiles, along with the development of the steam engine. These advancements improved transportation, communication, and banking systems and critically increased the volume and variety of manufactured goods. However, while some enjoyed the improved living conditions originating from these transitions, they also introduced harsh working and living conditions for the working class and impoverished populations [13].

The most recent paradigms, namely Industry 4.0 (I4.0) and Industry 5.0 (I5.0), are characterized by their potential to be recognized as true Industrial Revolutions if their impacts prove to be sufficiently profound and transformative. These revolutions are driven by a combination of emerging cutting-edge technologies, such as Machine Learning (ML) and Artificial Intelligence (AI), rapid evolutionary pace, and global scale [13]. Furthermore, by integrating internet technology with operational technology, these paradigms enhance automation and optimization across industries, resulting in more autonomous decision-making, evolving workforce roles, new organizational structures, and the development of intelligent systems.

In this Chapter, we will explore the historical development and impacts of Industries 1.0, 2.0, and 3.0, and delve into the details of the emerging paradigms of I4.0 and I5.0.

2.1 History of Industrial Revolutions

2.1.1 The First Industrial Revolution: Mechanical Production

The First Industrial Revolution, starting in the 1780s in Great Britain, was marked by the mechanization of production powered by steam or water [3]. This era was characterized by a drastic increase in production capabilities, where machinery boosted productivity more than eightfold compared to manual manufacturing, in which processes were highly dependent on the workers' personal schedules and physical capabilities [11, 14].

This revolution brought a vast number of benefits. Steam power found applications beyond machinery, including electricity generation and locomotive operation, thus enhancing production efficiency, speeding up travel, and improving communication [15].

From the onset of the 1800s, Industry 1.0 concentrated on developing water and steam-powered machines that assisted in labor processes. These innovations not only advanced production capabilities but also fostered business growth by expanding the scope and efficiency of manufacturing and, for some, improved living standards by reducing the difficulty and enhancing the comfort of production tasks [13].

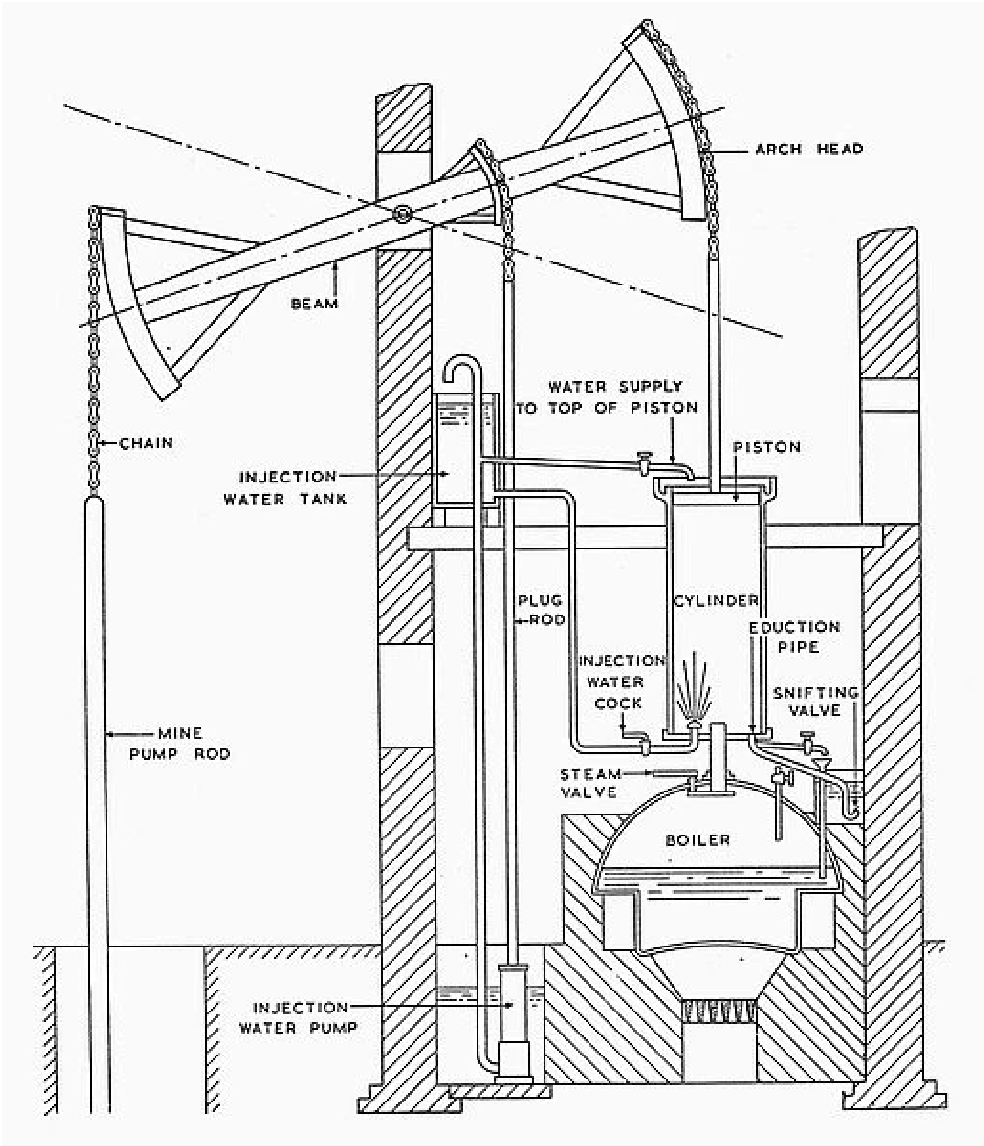


Figure 2.2: An illustration of early steam-powered machinery used during the First Industrial Revolution [16].

The impact of the First Industrial Revolution extended across multiple industries, including glass, coal mining, steam navigation, agriculture, and textiles. Pivotal inventions like the mechanical loom and the spinning machine revolutionized the textile industry. The increased need for capital investment led to the growth of banking institutions, crucial in providing loans to escalating entrepreneurs [14]. In transportation, steam locomotives facilitated the movement of goods over greater distances at reduced costs, significantly boosting the economy by increasing production capacities [17].

However, these technological and economic advancements also originated significant sociocultural changes. They aggravated poverty among workers and exposed them to insecure working conditions, absent protections, and non-existent workplace regulations. Moreover, the revolution imposed disruptive pressures on the working class, with an acute demand for labor. The lack of regulatory frameworks for factory operations often led to the inappropriate use of hazardous equipment and machinery, resulting in frequent and severe injuries. Extended working hours, often extending into the night, further exacerbated these dangers.

The most negative feature of this industrial age was the widespread employment of children, leading to the emanation of the *Factory Act* in 1833. This legislation aimed to limit the working hours of children and introduced measures to safeguard workers.

2.1.2 The Second Industrial Revolution: Mass Production

The Second Industrial Revolution, or Industry 2.0, began in the 19th century and was characterized by the adoption of electricity as the primary power source. Electricity was easier to use than water and steam, and it concentrated power on specific machines, making production more efficient. During this period, technological innovations such as portable machinery, each with its power source, further enhanced production systems and facilities [11].

By the early 20th century, electrical technology became the predominant power source, revolutionizing factory environments and enabling businesses to operate individual machines more effectively [13]. Moreover, in the 1870s, factories started to transform into modern production lines, introducing a revolutionized mass production that allowed the optimization of work processes and methods while maintaining high-quality standards in output. [15, 18].

One of the significant milestones of this period was the development of the assembly line by Ransom E. Olds in 1901, first implemented in the production of Oldsmobile cars. By employing that approach, his company was able to increase the output from a few units to 20 per day, obtaining a 500% increase in the production rate in just one year, all of that while significantly reducing manufacture costs [19]. Henry Ford further refined this method, making the assembly line a pivotal component of his automotive manufacturing process. Ford's system utilized a conveyor belt to support a step-by-step assembly procedure, enabling the rapid production of high-quality products at lower costs [14].

To further enhance production quality and management, Industry 2.0 in-

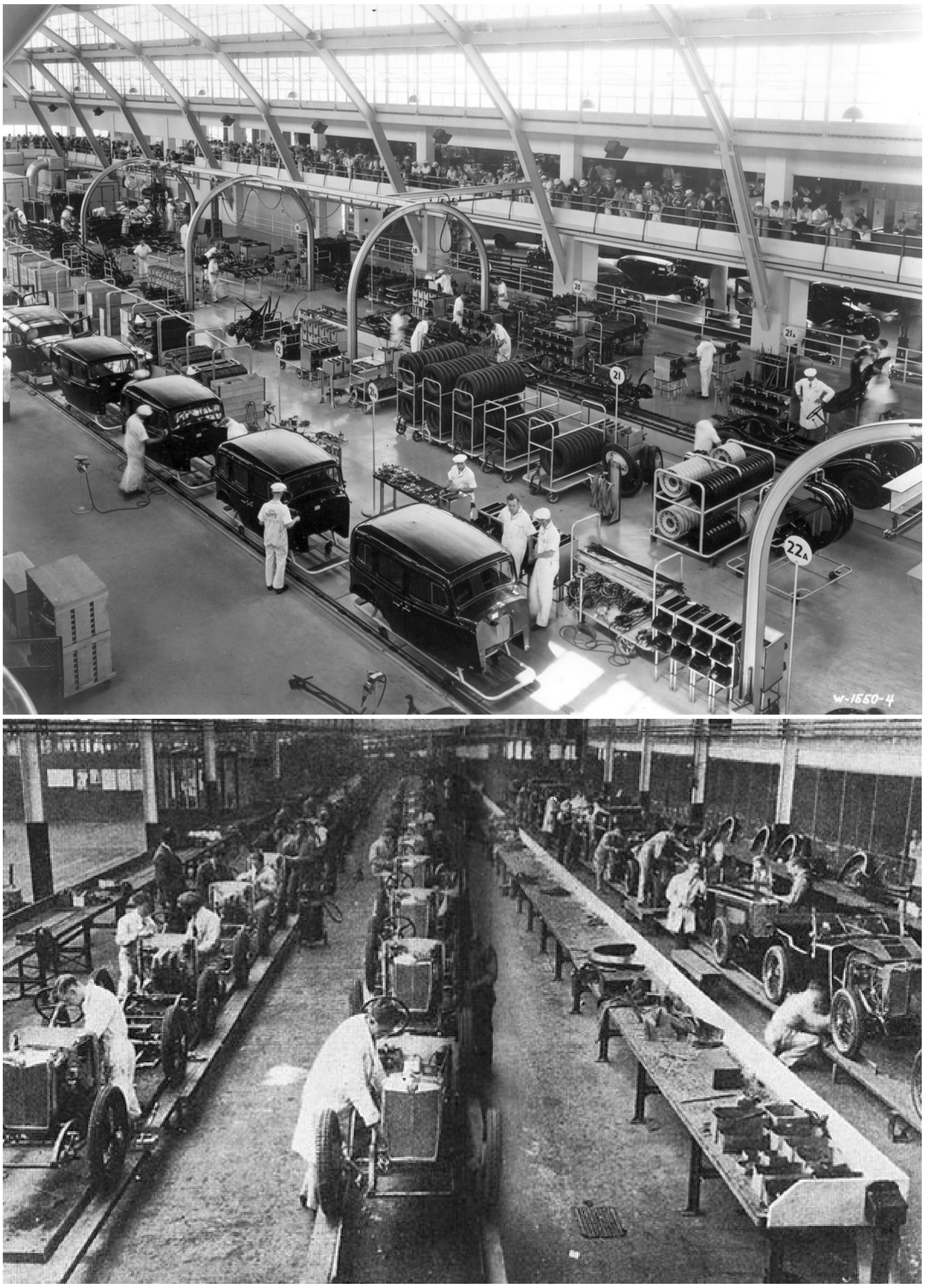


Figure 2.3: Early 20th-century Henry Ford's assembly line setup for the mass production of automobiles [20].

troduced more sophisticated strategies, including improved labor division and resource allocation, and leveraged advancements in telecommunication, such as the use of calls and telegrams, to accelerate business operations and information transfer [19]. All of that led to a rapid increase in urbanization, as large numbers of migrants moved from rural areas to cities, exacerbating environmental pollution [3].

2.1.3 The Third Industrial Revolution: Automated Production

The Third Industrial Revolution, also known as Industry 3.0 or Automation Revolution, began around half of the 20th century with the introduction of digital computers and electronic technologies. This period marked a significant shift towards manufacturing automation in factories, where machinery increasingly took over complex tasks previously performed by humans. Furthermore, the transition from analog to digital technologies enabled the creation of precise duplicates of original items, enhancing production accuracy and efficiency [11].

The Internet was a crucial invention during this era. It allowed computers to connect and communicate with a central device, revolutionizing information and communication technologies. This technological evolution contributed to the emergence of a "new economy", originating some concepts that are still modern nowadays, such as globalization and outsourcing.

Moreover, the Automation Revolution radically changed how individuals and companies interact, enabling small businesses to access larger markets and significantly reducing technology costs while boosting productivity and business performance [15].

Another innovation worth mentioning was the introduction of Programmable Logic Controllers (PLCs), which automated tasks that had traditionally required human intervention, although some level of human input and intervention was still necessary [13].

Industry 3.0 evolved significantly again in 1969 with the use of robots, electronic devices, and communication technologies in the production process, leading to more sophisticated automated production systems [3, 19, 21].

The mass production and widespread adoption of digital logic chips, MOS2 transistors, integrated circuits, and various ICT technologies transformed traditional production and commercial practices by converting analog to digital formats. Pioneers like Charles Babbage and Ada Lovelace laid the foundations for programmable computers in the 1820s with their Analytical Engines. However, the first operational device appeared much later. During this period, Konrad Enrst Otto Zuse developed the Z3, a fully autonomous, freely programmable, and program-controlled computer, which later evolved into the Z4, recognized as the first commercially used computer by ETH Zurich [15].

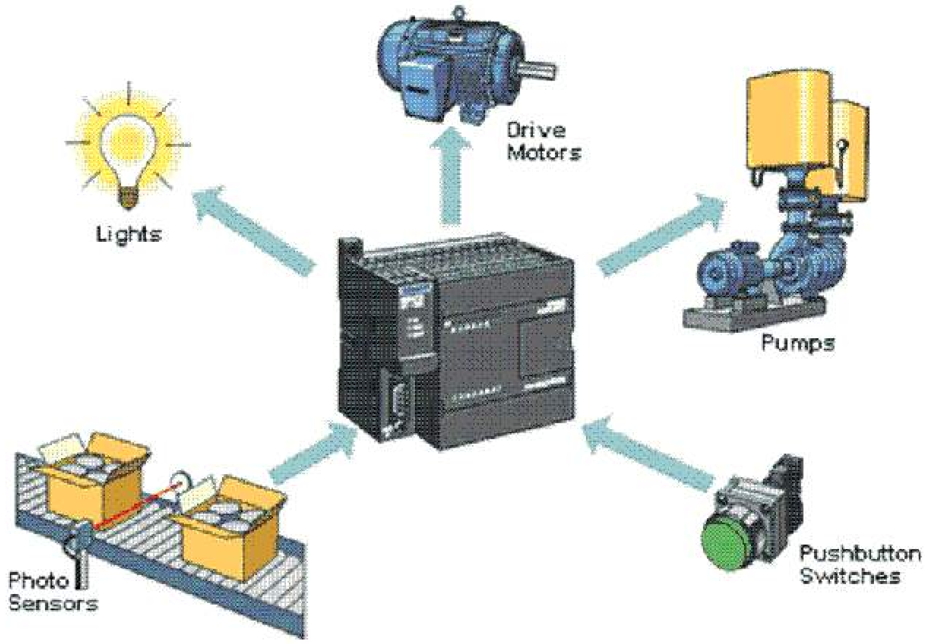


Figure 2.4: Example of hardware PLC control used in automated production during Industry 3.0 [22].

The accelerated development pace of these technologies in the early 1980s led to the dominance of fully automated Personal Computers (PCs) in offices and household markets, replacing the typewriters of Industry 2.0. At the same time, this era witnessed the emergence of some contemporary major IT companies such as Apple and Microsoft. The software systems developed during this period facilitated various management procedures, such as inventory management, product tracking, enterprise resource planning, product flow scheduling, and shipping logistics. These software tools effectively replaced manual operations previously performed by humans, improving efficiency and accuracy but, at the same time, leading to widespread human unemployment, a challenge that will be enforced by Industry 4.0 [14].

2.2 Industry 4.0

Industry 4.0 (I4.0) represents a significant paradigm shift rather than a conventional industrial revolution. Emerging in the 2010s, this transformation extends the digital integration of Industry 3.0 through the incorporation of advanced technologies such as Artificial Intelligence (AI), Cloud Computing, the Internet of Things (IoT), and Robotics [11].

The term "Industry 4.0" was first popularized by the German government in 2011 as a strategic initiative to drive manufacturing industries towards greater efficiency and automation using these cutting-edge technologies [23]. Although I4.0 has substantially influenced modern industrial practices, its classification as a historic revolution remains to be determined as its long-term societal and economic impacts continue to unfold.

The foundational technologies of I4.0 include [17]:

- **Cyber-physical Systems (CPSs)**, integrating physical operations with computer-based algorithms.
- **Internet of Things (IoT)** and **Cloud Computing**, facilitating a highly interconnected environment that enables seamless machine-to-machine and machine-to-human interactions.
- **Cognitive Computing** and **Big Data Analytics**, enhancing decision-making and operational efficiency.

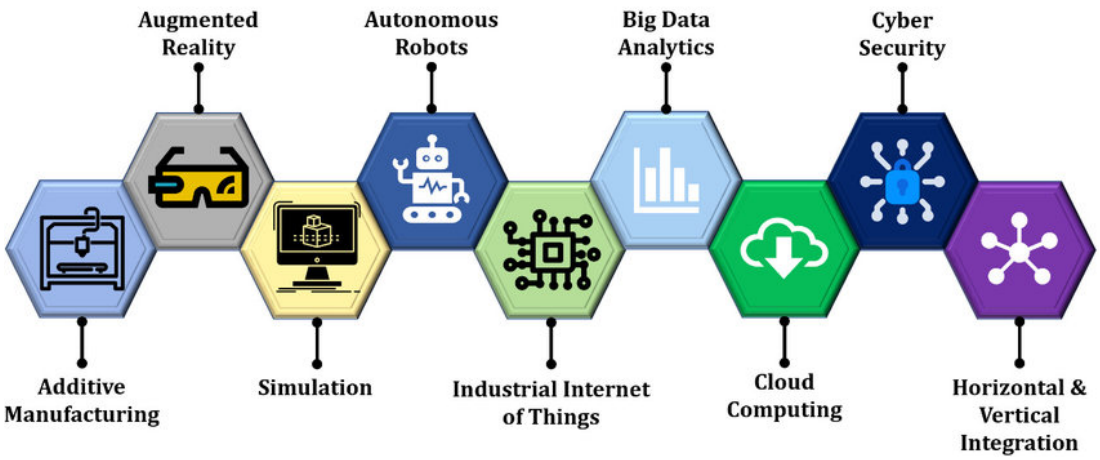


Figure 2.5: Industry 4.0 key enabling technologies [24].

These technologies enable a smart factory landscape characterized by significant autonomy and efficiency, where machines operate independently and interact seamlessly with one another, enabling functionalities like [13]:

- **Interoperability** through IoT and the Internet of People, allowing extensive communications among machines, devices, and humans.
- **Virtualization**, where CPS create accurate virtual copies of the physical world to simulate processes.

- **Decentralization**, facilitating autonomous decision-making by CPS in managing complex tasks and malfunctions.
- **Real-time Capability**, enabling the processing and analysis of data instantaneously to respond promptly to changes and challenges within the industrial environment.
- **Service Orientation and Modularity**, supporting flexible and rapidly adaptable manufacturing systems that can respond quickly to consumer demands and market changes.

The technologies integrated by Industry 4.0 enhance manufacturing flexibility and efficiency, reduce costs, and improve the quality of outputs and services, enabling the creation of smart products and services that can be customized in real-time to meet increasingly specific customer demands [25]. Furthermore, automation and intelligent systems promote scalability and more efficient resource utilization, contributing to sustainability in production processes [21].

However, despite its potential, the transition to Industry 4.0 introduces several challenges [21, 26]:

- **Security Risks**: As industries become more connected, at the same time, they become more vulnerable to cyberattacks, which can lead to significant financial and reputational damages.
- **High Costs of implementation**: The financial effort required for upgrading to smart factory systems can be prohibitive, especially for small and medium enterprises, potentially widening the technology gap.
- **Workforce Displacement**: Automation may reduce the need for human workforce in specific sectors, creating job displacement and requiring significant workforce retraining.

Furthermore, the pervasive use of advanced technologies in I4.0 raises crucial ethical and social questions, particularly concerning privacy, data security, and the societal role of automation in the workforce. There is an essential need for policies that protect individuals' rights while fostering innovation [27]. As these technologies advance, they should be leveraged not only for economic growth but also to enhance societal welfare and address environmental challenges [10].

In response to these considerations, a growing shift towards Industry 5.0 (I5.0) is emerging, emphasizing the reintegration of the human element into the industrial framework. This new paradigm focuses on balancing technological efficiency with social equity, promoting sustainable practices that respect both human operators and the environment [10, 28]. I5.0 seeks to enhance the synergy between humans and machines, thus creating a more resilient and adaptable industrial environment [3].

2.3 The New Industrial Paradigm: Industry 5.0

Industry 5.0 (I5.0) represents a pivotal paradigm shift from Industry 4.0, proposing a more human-centric approach in manufacturing. Unlike its predecessor, which emphasized improving productivity through automation and, in some cases, replacing human operators, I5.0 seeks to reintegrate the human element at the core of industrial processes. This new paradigm marks a significant transition towards a more balanced approach, where technology serves to augment human capabilities rather than replace them [29, 30].

Following the limitations and societal impacts highlighted by I4.0 discussed in Section 2.2, the European Commission formally introduced I5.0 in July 2020 through a series of discussions and workshops, defining it as [31]:

> *"A movement towards a sustainable, resilient, and human-centric industrial model."*

This approach aims to evolve traditional industrial processes by prioritizing the overall well-being of workers and respecting the environment, trying to improve the socio-environmental impact of the industrial sector [10, 31].

The motivation for evolving to I5.0 arises from critical reflections on the current and future directions set by I4.0, which continued to emphasize the push on automation and digital integration while overlooking the human aspects and societal repercussions. Industry 5.0 addresses these open challenges by focusing on both technological advancements and social and environmental responsibilities, seeking to find a balance among these.

At its core, I5.0 confronts the "*dehumanization*" that was implicitly and inadvertently fostered by I4.0. The three core pillars of this new paradigm are:

1. **Human-centricity**;
2. **Resilience**;
3. **Sustainability**.

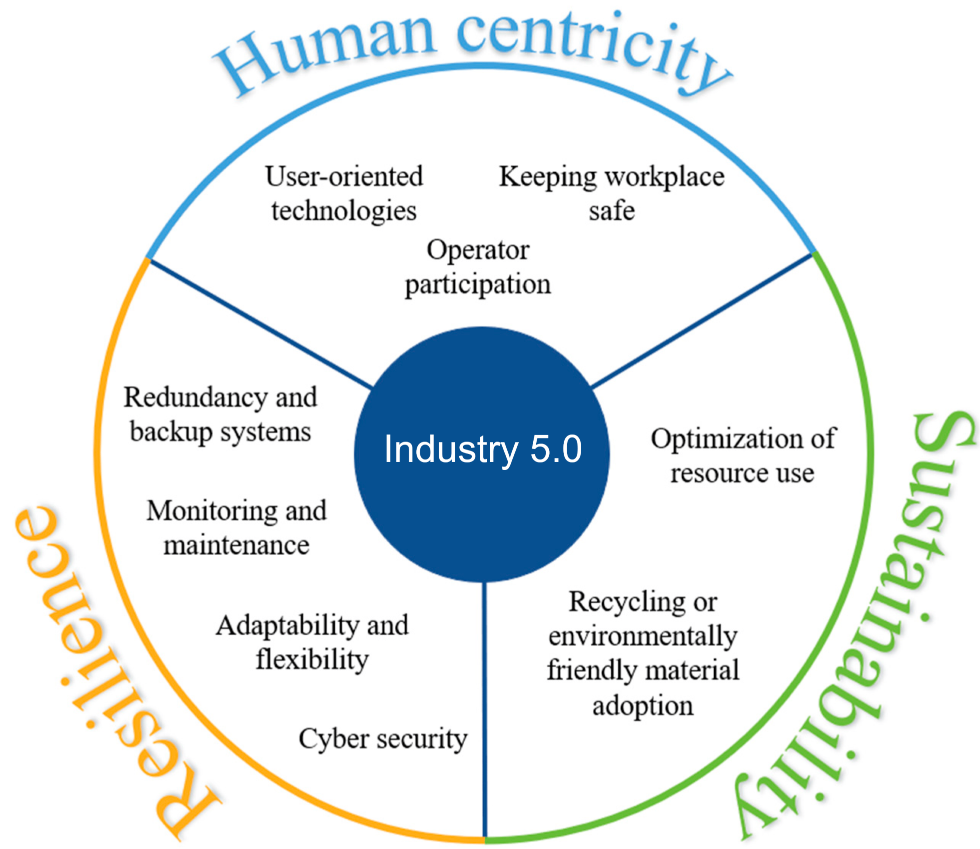


Figure 2.6: The three foundational pillars of Industry 5.0 [32].

Human-centricity emphasizes enhancing the capabilities of industrial operators, recognizing the importance of creativity, personal skills, reasoning, critical thinking, and adaptability. In this context, machines are seen not as replacements for humans but as aids that support their daily tasks, thus reducing physical and mental workloads and providing continuous on-site support [11, 33]. A prime example of this approach is the development of Collaborative Robots (CoBots), designed to work alongside humans rather than independently, demonstrating that shifting from pure automation to collaboration can enhance process efficiency and product quality while ensuring safety and adding a personal touch [18].

The pillar of **Resilience** underscores the industry's ability to adapt and respond to challenges of various severity types. Especially in recent times, this emerged as a critical requirement, considering the COVID-19 pandemic and the various geopolitical tensions disseminated around the globe [10].

Lastly, **Sustainability** underscores the need for industrial strategies that not only minimize negative impacts but actively and positively contribute to the environment. This concept, formalized as "*Net Positive*", suggests that industries should aim to leave the environment better than they found.

Overall, I5.0 promotes the *Triple Bottom Line (TBL)* principle, which puts on the same level Profits, People, and the Planet, integrating these into the core of industrial strategies [34, 35].

2.3.1 Japan Society 5.0 Manifest

Japan's Society 5.0 is the foundational concept of I5.0, and it started being implemented in 2016 in order to leverage digital advancements to push societal progress [28]. This idea was introduced by Japan's most potent industrial association, Keindanren (Japan Business Federation), and later adopted by the Japanese government as part of a national strategy to use technological innovations to advance society overall.

Society 5.0 was formally defined in Japan's Fifth Science and Technology Basic Plan by the Japanese government, proposing technology as a pivotal tool to address demographic and economic challenges, culminating in the so-called "*super-smart society*". On this occasion, it has been stated that [28]:

> *"Society 5.0 has decided to put technological innovation in the spotlight based on the fact that it can be fully considered as a tool for social innovation and not just a factor leading to changes in firms and business processes"*

and Society 5.0 has been described as:

> *"A process that must be carried out together with citizens who are required to actively participate and, therefore, not just top-down; recognizes and underlines the importance of creating less formal relationships between people, businesses, universities and the Public Administration; highlights the need to develop a more intense collaboration with foreign people and firms, which bring in technological knowledge of the frontier"*

Keindanren identified five barriers, referred to as *walls*, that Japan must overcome to succeed in evolving to Society 5.0 [11]:

1. **The wall of the Ministries and Agencies**, underscoring :

> *"the need for the formulation of national strategies and construction of promotion system by a unified effort of government departments"*

Consequently, it is imperative that the government formulates national strategies in an integrated manner, collaborates with academia and industry, and builds IoT platforms meant to serve as a framework for government support.

Society 5.0 technologies have the potential to establish a link between key decision-makers and the general public, thereby enhancing stakeholder engagement and potentially influencing sustainability decisions. Furthermore, ministries and agencies have to require private sector participation to leverage appropriate actions that align with "*the image of the future economy and society*" [11, 36].

2. **The wall of the legal system**, promoting:

> *"regulations, system reforms, and administrative digitization to exploit Industry 5.0 technologies for implementing advanced techniques by considering citizens' voices for the development of further reforms"*

Moreover, guidelines for encouraging data uses and applications need to be created with both easy access to the general public's life and the development of competitive advantages for governments and corporations in mind [37].

3. **The wall of technologies**, requiring the employment of all available technologies, from the most developed and well-established to the newest and most promising. This calls for significant funding for research and development initiatives, changes to national innovation systems, and robust social policies that promote inclusion, equality, and good working conditions [37].

4. **The wall of human resources**, demanding the specialization of human resources in advanced digital skills by providing educational opportunities that promote creativity and training in information technology. By doing that, citizens will be able to [36]:

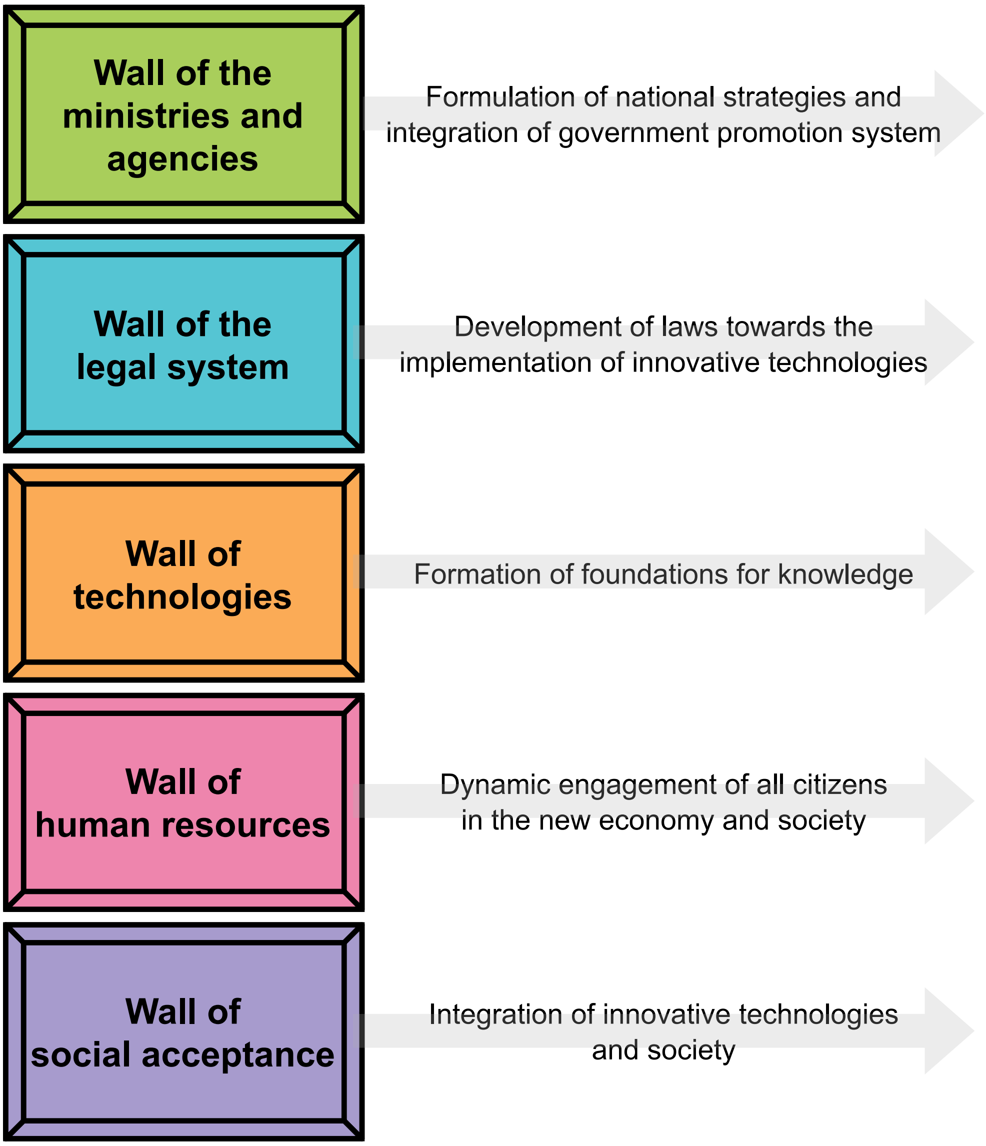


Figure 2.7: Society 5.0's five walls [11].

> *"think independently and create new values by combining various items while working with others and leveraging new key technological innovations"*

5. **The wall of social acceptance**, including the significance of achieving social consensus, looking into the ethical and moral issues raised by man-machine interactions and defining what constitutes personal happiness and humanity [36].

Society 5.0 aims to harmonize several dimensions of human life, including economic, social, and environmental dimensions, by integrating technologies like Artificial Intelligence, Internet of Things, and robotics into everyday life, enhancing comfort, safety, and sustainability. These technologies transform societal challenges into opportunities for growth, promoting a balance between economic progress and social problem-solving [11].

Applications of Society 5.0 include healthcare, disaster response, and environmental management, showing its practical impact on real-world problems. Furthermore, the strategy emphasizes the importance of data and connectivity in creating interconnected systems that enhance both industrial and social processes. By integrating IoT and AI across various sectors, Japan aims to establish a more responsive and efficient societal model that better anticipates and reacts to human needs.

However, Society 5.0 is not merely about technological enhancements but also about fostering a cultural shift towards sustainable practices and inclusive policies, ensuring that the benefits of innovation are broadly distributed across society [28].

Ultimately, Japan's Society 5.0 serves as a blueprint for the following stages of industrial and societal evolution within the I5.0 paradigm, signifying a shift from viewing technology solely as a tool for industrial efficiency to an enabler for a better, more integrated, and sustainable society.

Actually, Industry 5.0 and Society 5.0 are similar since they both speak of a fundamental shift in our economy and society towards a new paradigm that underscores human dignity, privacy, autonomy, and universal worker rights. They also emphasize the significance of innovation and research in assisting Industry in providing long-term services to humanity within planetary bounds [10].

In practice, organizations and stakeholders, including the public, governments, and academic institutions, will play a significant role in Society 5.0.

2.3.2 European Commission on Industry 5.0

The European Commission's vision for Industry 5.0 marks a significant evolution from the technology-centric approach of Industry 4.0, focusing on a new paradigm of industrial development that overextends digital advancements to redefine the relationship between technology and society fundamentally. As a result, Industry 5.0 expands and enhances the main components of Industry 4.0, coexisting with the currently in-use technologies [3, 31].

Formally introduced by the European Commission in 2020, Industry 5.0 represents a crucial step towards integrating deeper societal goals within industrial practices, enforcing the need for a system where technology empowers humans, enhancing their capabilities rather than replacing them [31]. The Commission's definition highlights the role of Industry in achieving broader societal objectives, stating that:

> *"Industry 5.0 recognizes the power of industry to achieve societal goals beyond jobs and growth to become a provider of prosperity, by making production respect the boundaries of our planet and placing the well-being of the industry worker at the center of the production process"*

Figure 2.8: The European Commission view of Industry 5.0 [38].

The European Commission has defined three core pillars for I5.0, designed to drive European industries towards more adaptive, responsible, and inclusive economic models:

1. **Human-centricity**: This pillar emphasizes enhancing human work and creativity within the industrial context, ensuring that technological advancements contribute to worker well-being and job satisfaction. It proposes a shift from viewing workers merely as part of the workforce to recognizing them as central figures whose talents and diversity drive innovation [11].

2. **Resilience**: Highlighting the need for industries that are not only technologically advanced but also robust enough to withstand and adapt to various crises. Recent global challenges, such as the COVID-19 pandemic and geopolitical tensions disseminated worldwide, underscore the importance of prioritizing long-term stability and adaptability over short-term gains [10].

3. **Sustainability**: Focusing on sustainable practices that respect ecological limits and prioritize long-term environmental health. Aligned with the

Sustainable Development Goals (SDGs), this strategy seeks to balance economic activities with environmental preservation, enabling industries to become part of the solution to environmental challenges [10, 34].

According to the European Commission, I5.0 involves leveraging advanced technologies to not only achieve economic benefits but also enhance the quality of life and societal well-being. This vision positions I5.0 as a means to revolutionize industries by including human creativity and personalization in production processes. Such a transformation should improve customer satisfaction through customized products and foster a deeper connection between workers and their work, leading to more fulfilling and satisfying industrial employment.

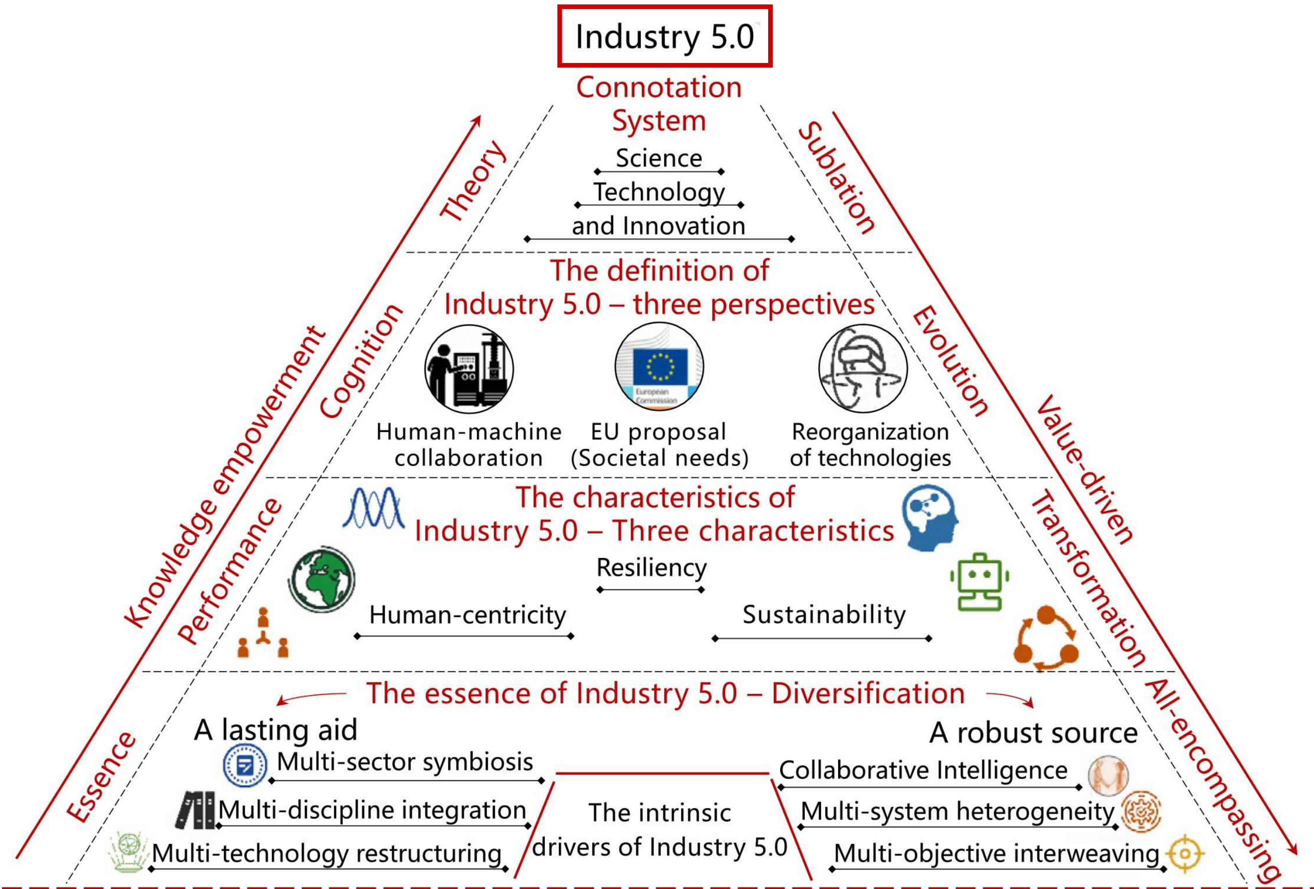


Figure 2.9: The comprehensive framework of Industry 5.0 as defined by the European Commission [18].

2.3.3 Industry 5.0 Enabling Technologies

As highlighted in recent statistics by *Statista* [39] and *Reputiva* [40], cutting-edge technologies are projected to influence global businesses strongly. These advancements, particularly the ones originating from Industry 4.0, are depicted in Figure 2.10 and include the Internet of Things, Artificial Intelligence, Cloud Infrastructures, and Big Data Processing, collectively referred to as "*the big-four technologies*". Notably, IoT positions as a critical technology, with 72% of the surveyed organizations acknowledging its pivotal role in current and future technological landscapes [39]. The second technology that highly impacted organizations worldwide is AI, used in many fields to increase efficiency and complement human skills [39].

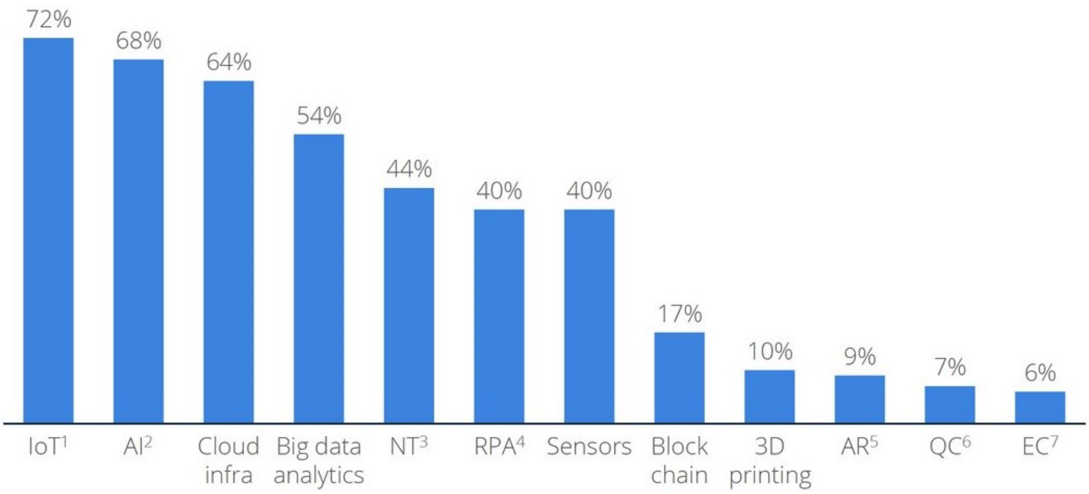


Figure 2.10: Industry 4.0 technologies with the greatest impact on organizations worldwide in 2020 [40].

While the core technologies of I5.0 largely overlap with those of I4.0, I5.0 shifts the focus towards enhancing human-machine collaboration rather than merely improving automation and efficiency, leading to the implementation of more intelligent systems. This evolution from I4.0 reflects a broader, more integrative approach where technology serves to augment human capabilities and is designed around societal needs rather than shaping society to fit technological capabilities.

For this reason, I5.0 should not be understood as a replacement or an alternative to I4.0 but rather as an evolution and logical continuation of the existing I4.0 paradigm. This paradigm shift underscores the importance of viewing technologies as tools for societal and ecological empowerment, not just as drivers of industrial productivity. In I5.0, technology is intended to enhance workers' abilities and create safer and more satisfying working environments rather than replacing human workers on the shop floor. The synergy of human intellect and industrial automation offers long-term benefits, merging industrial efficiency with cognitive and critical human capacities [41]. To support this shift, new skills and training for operators are essential, as discussed in Section 2.3.4.

Moreover, the need for personalized products in modern markets requires human creativity and critical thinking to understand and meet consumer demands deeply, a need that I5.0 aims to fulfill by integrating problem-solving skills and creative value-addition proper of humans [42].

The commitment to the principles has led to increased investments in CoBots, AI, and IoT technologies, reflecting a growing recognition of the benefits that I5.0 can offer. For instance, [31] stated that:

> *"Industrial Collaborative Robots are a unique technology that has the potential to improve both the economy and society while embracing Europe's values if conducted by proper management."*

Additionally, revenues from AI and robotics are projected to grow at an annual rate of 41% from 2019 to 2025, as shown in Figure 2.11 [39].

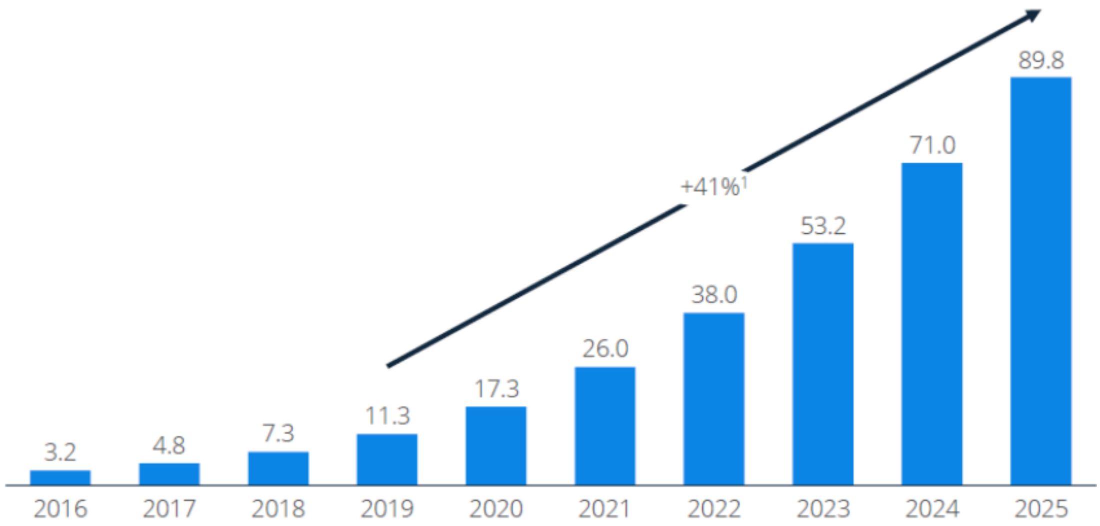


Figure 2.11: Potential impact of AI and Robotics in the Global Revenue Projections (in Billions US$) [40].

Furthermore, the proliferation of IoT, while not a new technology, has seen a growth in popularity due to decreased costs, enhanced computing capabilities, and improvements in cloud connectivity and machine-to-machine communication. These advancements have set the stage for the subsequent industrial development termed "Industrial Internet of Things (IIoT)", which enhances device connectivity and data exchange across the value chain for more comprehensive integration [43].

A 2020 survey by *Plataine*, an American provider of optimization solutions based on IIoT and AI, exposed a tripling in IoT adoption in manufacturing since 2018, with 66% of respondents identifying IIoT as critical to their company's future success and profitability [44]. Furthermore, the World Economic Forum (WEF) stated that IoT investments in production have doubled from US$35 billion in 2016 to US$71 billion by 2020, driven primarily by asset tracking, condition-based maintenance, and robotics processing [45].

More specifically, in the current manufacturing landscape, IoT systems are utilized for:

1. **Smart enterprise control**, enabling the linking of intelligent, networked machinery and interconnected manufacturing parts to a central processing unit, leading to more cost-effective and efficient productions.

2. **Asset performance management**, combining data analytics, cloud computing, and wireless sensors to allow for a more effective real-time information flow on the operation of linked machines, improving predictive maintenance and allowing for more accurate forecasts of machine breakdowns.

3. **Augmented operators**, leveraging the capabilities of IoT technologies to assist operators in taking on specialized roles, thereby shifting the focus of manufacturing environments from machines to users.

This user-led approach ensures that, while technology handles repetitive and error-prone tasks, strategic oversights and innovations are driven by human insights, reinforcing the principle that "*technology enables, people lead*" [43].

For that reason, the defining features of I5.0 include a series of "*Enabling Technologies*" that combine various aspects of I4.0 technologies within a comprehensive framework to enhance ecological and societal values. The European Commission has identified six key categories of these technologies, each interdependent and crucial in realizing the full potential of I5.0 [10]:

1. **Individualized Human-Machine Interaction** that links and integrates the strengths of both machines and humans;

2. **Bio-inspired Technologies and Smart Materials** that enable environmentally friendly materials with integrated sensors and enhanced features;

3. **Digital Twins and Simulations** to model entire systems;

4. **Data Transmission, Storage, and Analysis** technologies;

5. **Artificial Intelligence**;

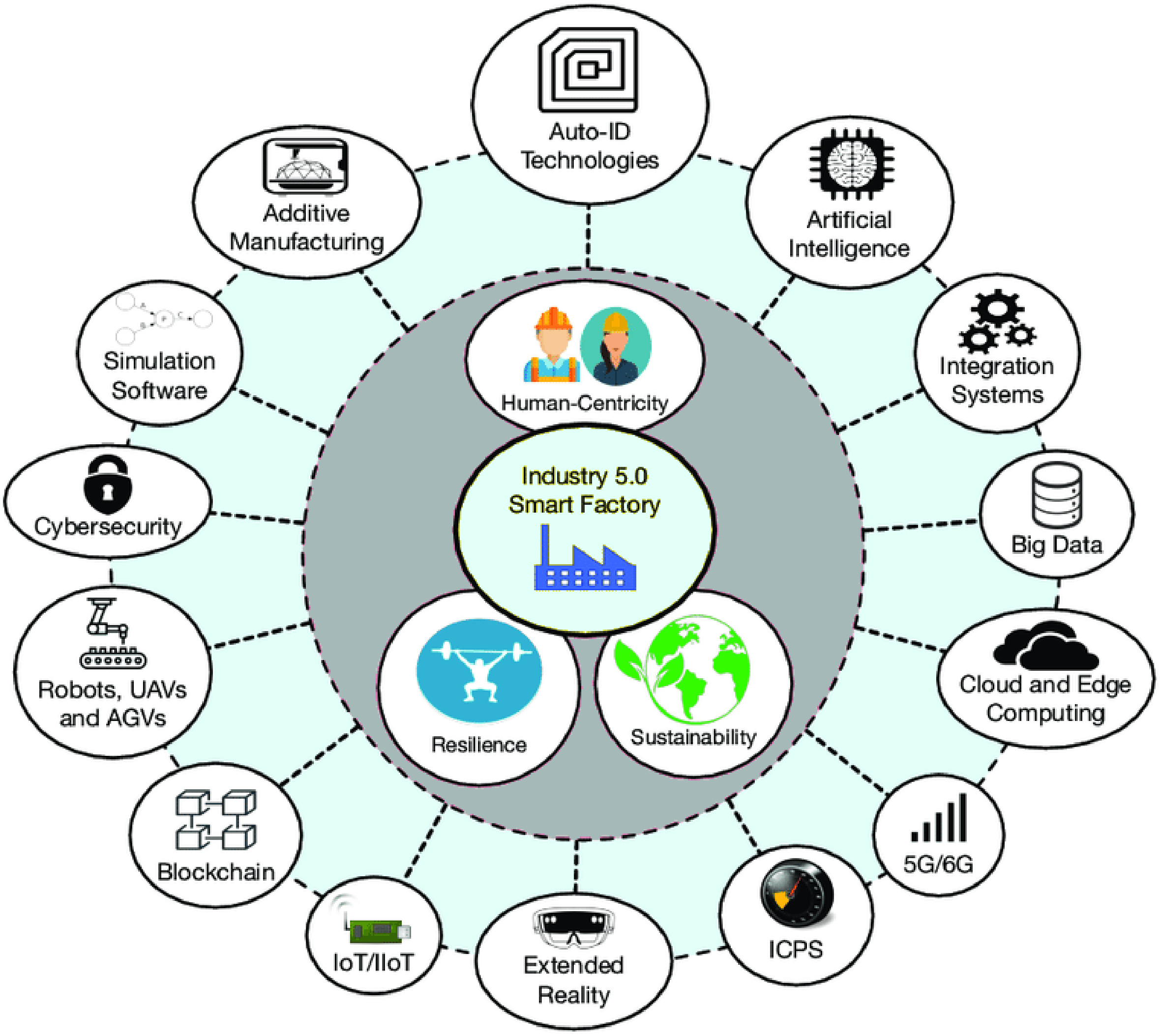


Figure 2.12: Industry 5.0 enabling technologies [46].

6. **Technologies for Energy Efficiency, Renewables, Storage, and Autonomy**.

Figure 2.12 shows a more comprehensive representation of these enabling technologies.

Individualized Human-Machine Interaction

Individualized human-machine interaction encompasses a range of technologies designed to augment human physical and cognitive tasks by integrating human innovation with machine capabilities. These technologies facilitate closer collaboration between humans and machines, enhancing the workplace by supporting daily activities and decision-making processes.

This category includes [43]:

- **Multi-lingual speech and gesture recognition and human intention prediction**, which facilitate intuitive interactions between humans and machines, making technology more accessible and responsive to individual worker needs.
- **Tracking technologies** for monitoring employees' mental and physical strain and stress, aiming to create healthier and more productive work environments.
- **CoBots**, designed to cooperate with humans, assisting and easing their daily tasks, enhancing worker efficiency and safety.
- **Technologies of Augmented Reality (AR), Virtual Reality (VR), and Mixed Reality (MR)**, enhancing training protocols and providing real-time on-site assistance. These immersive technologies also foster inclusiveness by adapting workspaces to diverse needs.
- **Exoskeletons and bio-inspired working gear**, which physically enhance human capabilities while promoting health and safety in industrial settings.
- **Technologies merging the potential of the human brain with Artificial Intelligence**, improving decision support systems by integrating human reasoning and creativity with the analytical capabilities of machines.

Bio-inspired Technologies and Smart Materials

Bio-inspired technologies and smart materials represent a significant segment of I5.0, aligning closely with the sustainability pillar of this industrial evolution. These technologies and materials seek to emulate biological processes and systems, embodying properties that enhance sustainability and functionality [10]:

- **Self-healing or self-repairing materials**, increasing the longevity and durability of products.
- **Lightweight materials**, reducing energy consumption in transport and manufacturing processes.
- **Recyclable materials**, supporting circular economy principles.

- **Raw material generation from waste**, turning industrial by-products into valuable resources.

- **Embedded sensor technologies and biosensors**, monitoring and adjusting processes in real-time.

- **Adaptive/responsive ergonomics and surface properties**, enhancing user interaction and product adaptability.

- **Materials with intrinsic traceability**, ensuring transparency and accountability throughout the supply chain.

In particular, the deployment of sensors has proven to significantly enhance operational efficiency across labor, logistics, and quality control. Sensors improve inventory management, material sorting, and automation, thereby increasing overall productivity. They are also crucial in identifying manufacturing errors and facilitating better product designs. By continuously monitoring assembly lines, engineers can detect manufacturing issues in real-time, preventing them from escalating into major failures, thus saving time and resources while improving safety [47].

Mitsubishi, for instance, has been investing in smart sensors since 2008, recognizing their potential to revolutionize automation systems and enhance manufacturing processes at every stage. Smart sensors contribute to [47]:

- **Improving operational efficiency**: Applied in labor monitoring to optimize task assignments and quality inspections on assembly lines.

- **Enhancing asset management**: Potential issues can be proactively managed by connecting and monitoring critical equipment.

- **Real-time inventory tracking**: Sensors facilitate touch-free item identification and monitoring, minimizing inventory shrinkage and automating reorder processes.

- **Innovative product design**: Connected products provide insights into customer behaviors and preferences, supporting responsive product development.

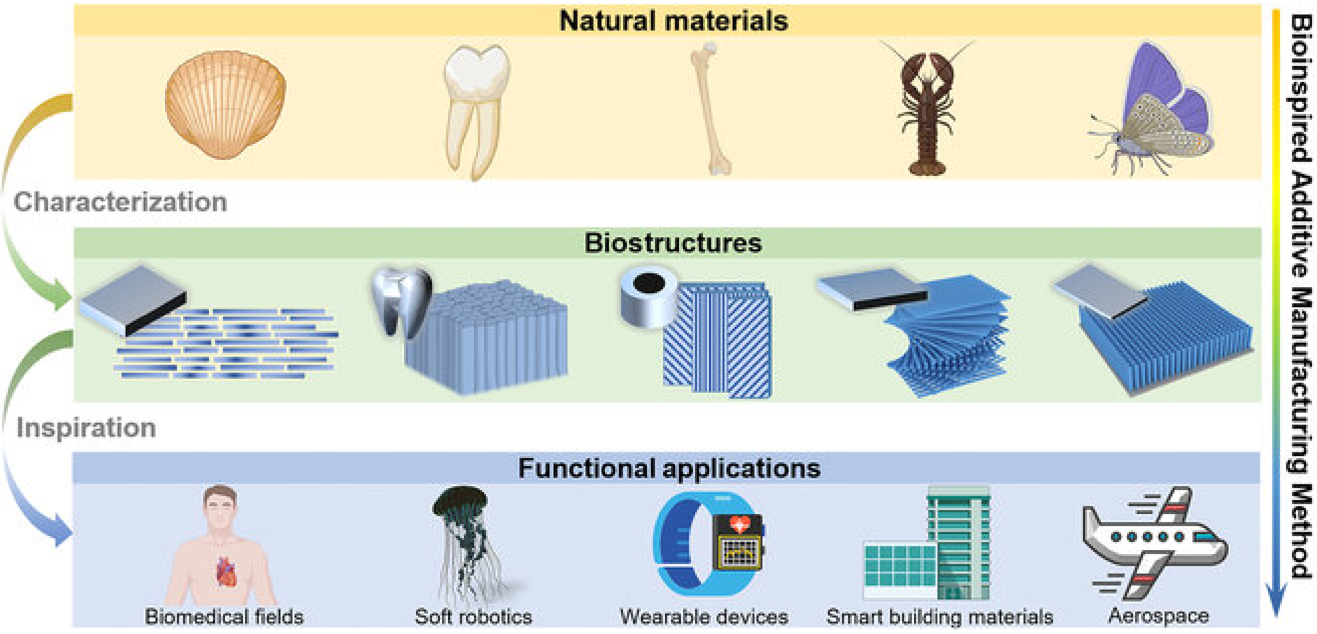


Figure 2.13: Applications of bio-inspired technologies in Industry 5.0 [48].

Digital Twins and Simulations

Digital Twins (DTs) and simulation technologies incorporate a suite of advanced technologies, including Artificial Intelligence, the Internet of Things, the Metaverse, Virtual Reality, and Augmented Reality, to create digital copies of physical objects, systems, or processes. These technologies play a critical role in modeling and understanding real-world scenarios and their potential variations. Simulations are used to predict future conditions, while DTs provide a mechanism to compare anticipated outcomes with current realities, enhancing decision-making and operational efficiency [43].

Key applications of these technologies include [43]:

- **Virtual simulation and testing of products and processes**, allowing for the refinement and optimization of designs before physical prototypes are built.
- **Multi-scale dynamic modeling and simulation**, providing insights across different product or system operations levels.
- **Simulation and assessment of environmental and social impacts**, facilitating more sustainable and responsible decision-making.
- **Planned maintenance based on predictive analyses**, reducing downtime and extending the lifespan of the equipment.

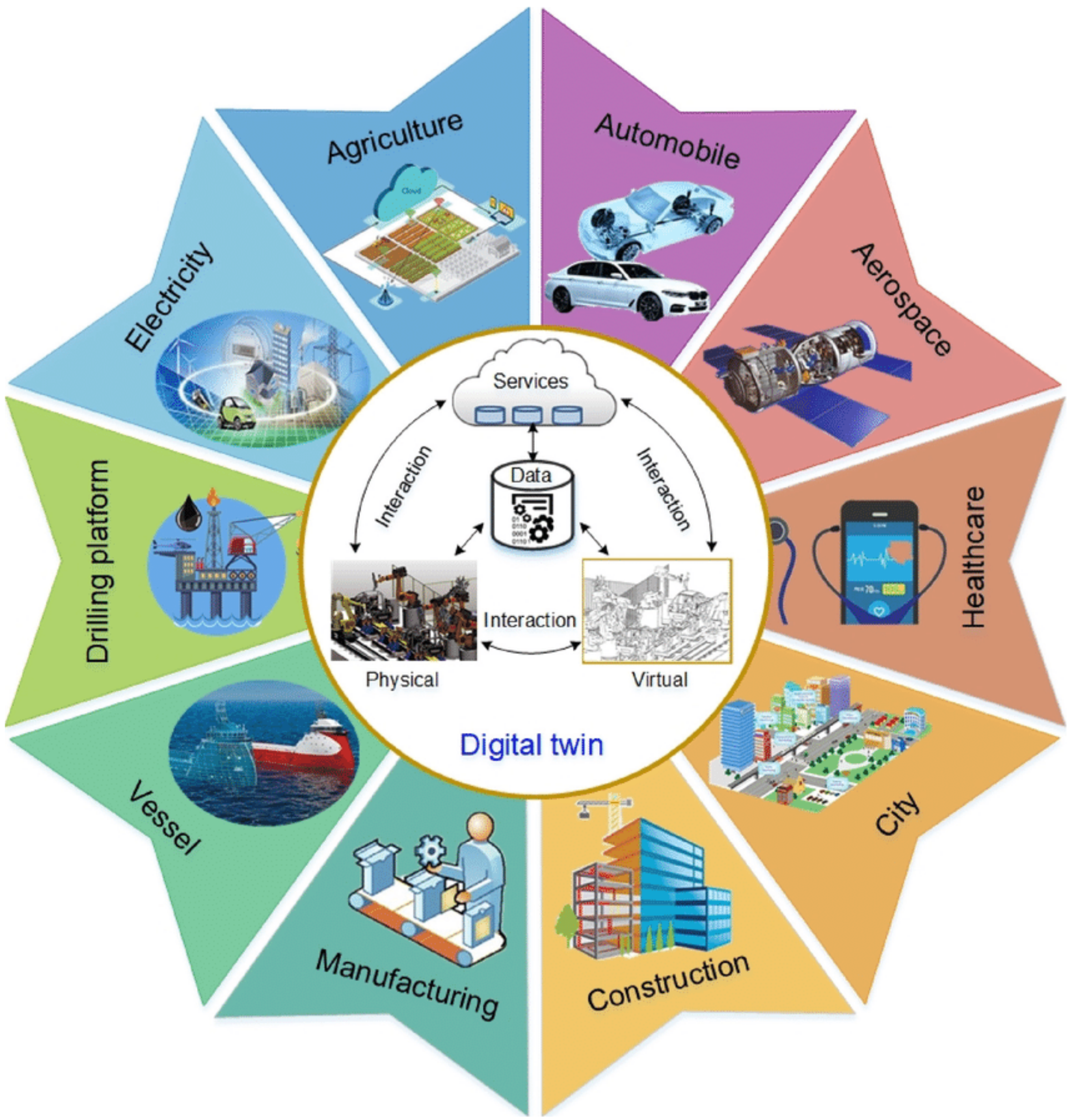


Figure 2.14: The different application fields of Digital Twins in Industry 5.0 [49].

One fundamental difference between simulations and DTs is their scope of analysis. While advanced simulations can consider thousands of variables to predict potential outcomes, DTs can assess entire lifecycles of products or systems, providing a comprehensive view from inception through disposal. This capacity makes DTs especially valuable for high-stakes applications in sectors like industrial facility management and power plant operations, where the complexity and cost of errors are potentially disruptive.

Globally, industries are increasingly adopting DTs across various domains, from engineering complex equipment to precision medicine and digital agriculture. However, the high costs of implementing these technologies often limit their use to high-value applications [50].

Tesla provides a notable example of practical DTs usage in that scope. By collecting data from sensors on its vehicles and uploading it to the cloud, Tesla has been able to create detailed digital simulations of its cars. Utilizing proprietary AI algorithms, they can predict where faults and breakdowns are most likely to occur, thereby minimizing maintenance needs. This proactive approach has significantly reduced warranty-related costs and enhanced customer satisfaction by improving reliability and service quality.

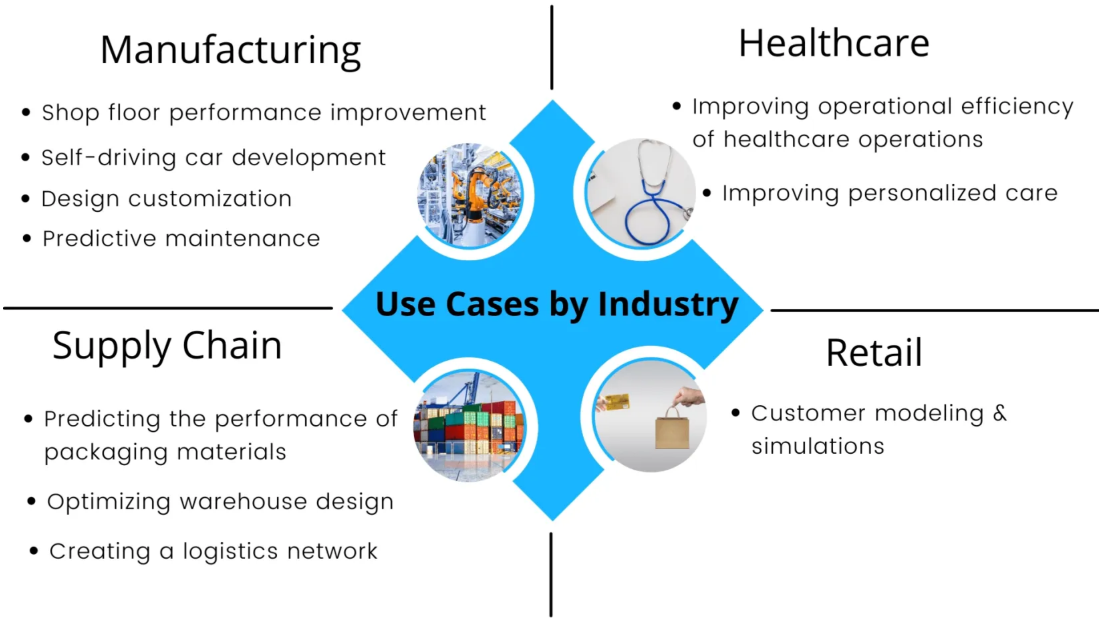


Figure 2.15: Digital Twins use cases by Industry in 2024 [51].

Data Transmission, Storage, and Analysis Technologies

In the context of I5.0, the technologies that ensure secure, reliable, and energy-efficient transmission, storage, and data analysis are of critical importance. These technologies form the foundation of intelligent industrial systems, enabling enhanced decision-making and operational efficiency.

The key properties of these technologies include:

- **Networked sensors**, facilitating real-time data collection across various points in the industrial environment.

- **Data and system interoperability**, ensuring seamless communication and integration across different platforms and devices.

- **Scalability** to accommodate growing amounts of data and expanding system requirements.
- **Multi-level cybersecurity** measures to protect against potential breaches and ensure data integrity.
- **Safe cloud infrastructure**, providing robust and secure data storage solutions.
- **Big data transmission and management** capabilities to handle vast volumes of data efficiently.
- **Data processing for learning processes** to extract actionable insights from complex datasets.
- **Edge computing** to process data closer to the source of data generation, reducing latency and bandwidth use.

The disseminated deployment of sensors across the industrial environment allows for substantial data volumes to be collected, which can be leveraged to extract patterns, trends, and insights. This wide range of data enables companies to make informed decisions promptly, thus responding to customer needs faster.

Two notable examples highlighting the strategic use of these technologies are [52]:

- **Amazon**: This e-commerce giant accurately stores every customer interaction to analyze spending behaviors. Insights gained from this data are utilized to enhance social media advertising, in-platform recommendation systems, and overall customer experience. For instance, when a product is added to a wishlist or purchased, Amazon suggests related items or products frequently bought together, enhancing the shopping experience.
- **Apple**: By collecting data on how consumers use its devices and services, Apple gains insights into real-life usage patterns. This information is crucial for making design changes that align with customer preferences and improving user satisfaction and product functionality.

Artificial Intelligence

In the evolving landscape of I5.0 Artificial Intelligence (AI) plays a pivotal role, applied across an ever-expanding set of domains and use cases. Within I5.0, AI

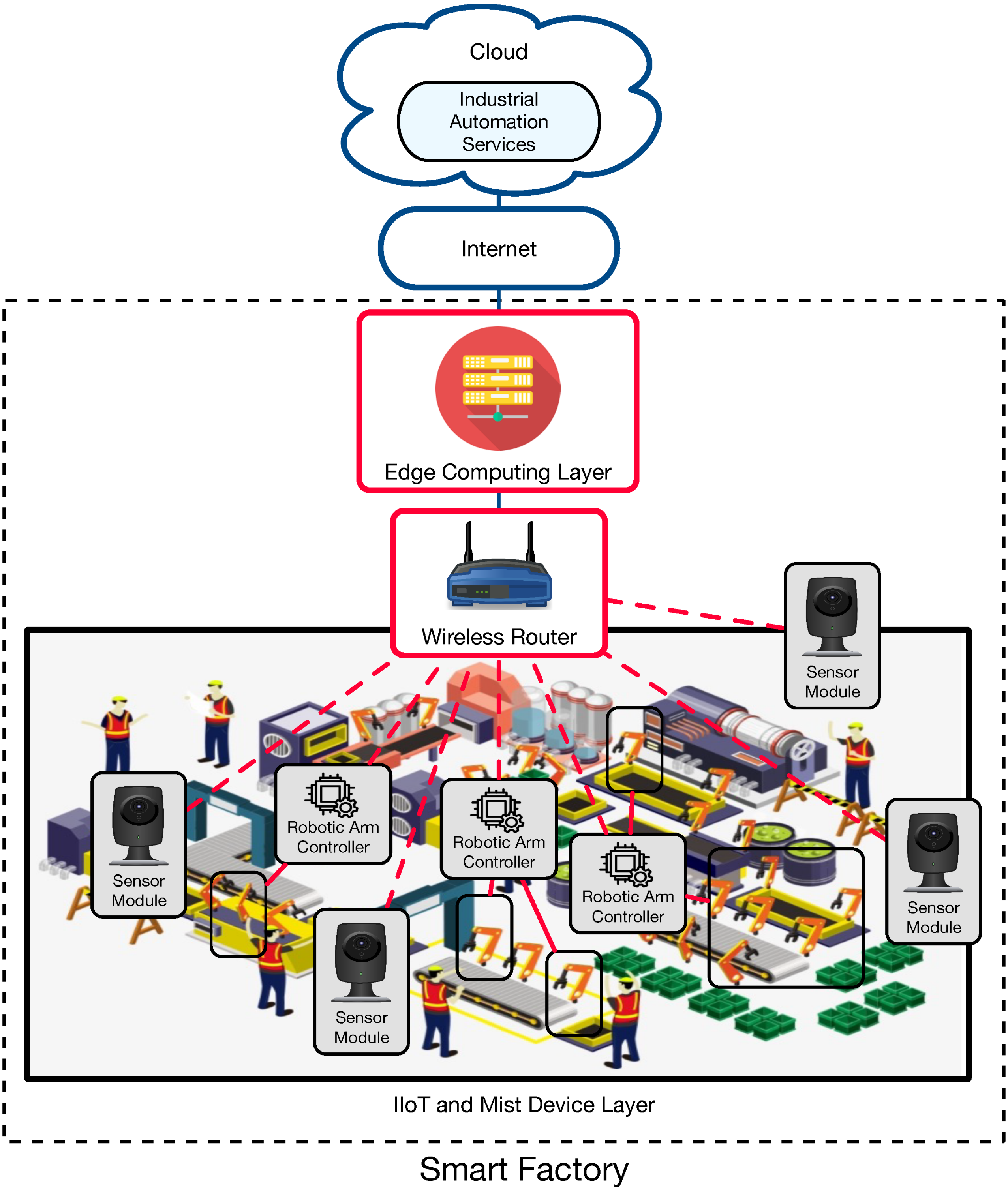


Figure 2.16: Diagram of a smart factory layout within Industry 5.0, showcasing the data flow between the cloud, edge computing layers, and IIoT devices [53].

technologies primarily function as advanced correlation analysis tools, given that their capabilities extend far beyond traditional computational methods [43].

Key properties of AI technologies include [43]:

- **Correlation-based and causality-based information extraction** to uncover meaningful patterns and causal relationships within data.
- **Revealing relations and network effects** extending beyond simple correlations, offering more profound insights into complex systems.
- **Autonomous response to new or unexpected conditions** without human intervention, enhancing system adaptability.
- **Brain-machine interfaces** integrating human cognitive functions with computer processes.
- **Informed deep learning**, which combines expert knowledge with AI capabilities to refine learning processes.
- **Skill matching of humans and tasks**, optimizing workforce allocation based on capabilities and system needs.
- **Identifying correlations among complex, interrelated data** from diverse origins to support comprehensive decision-making.
- **Scalability in dynamic systems** and within systems of systems, ensuring AI applications grow with organizational needs.

In today's data-rich landscape, there is a vast amount of information available that, if properly utilized, can significantly enhance work processes and outcomes. However, delivering this information effectively and at the right time is crucial, considering that it is impractical for operators to constantly switch between workstations and applications to access the needed insights. AI can automate the retrieval and synthesis of this information, allowing workers to spend less time searching for data and more time applying it to deliver value. This improves efficiency and enhances job satisfaction by reducing monotonous tasks and enabling more focused and satisfactory work.

Technologies for Energy Efficiency, Renewables, Storage, and Autonomy

Achieving the ambitious zero-emission goal of I5.0 necessitates a significant focus on energy efficiency and the integration of sustainable energy sources. This involves leveraging a wide range of advanced technologies designed to minimize energy consumption and maximize the use of renewable resources.

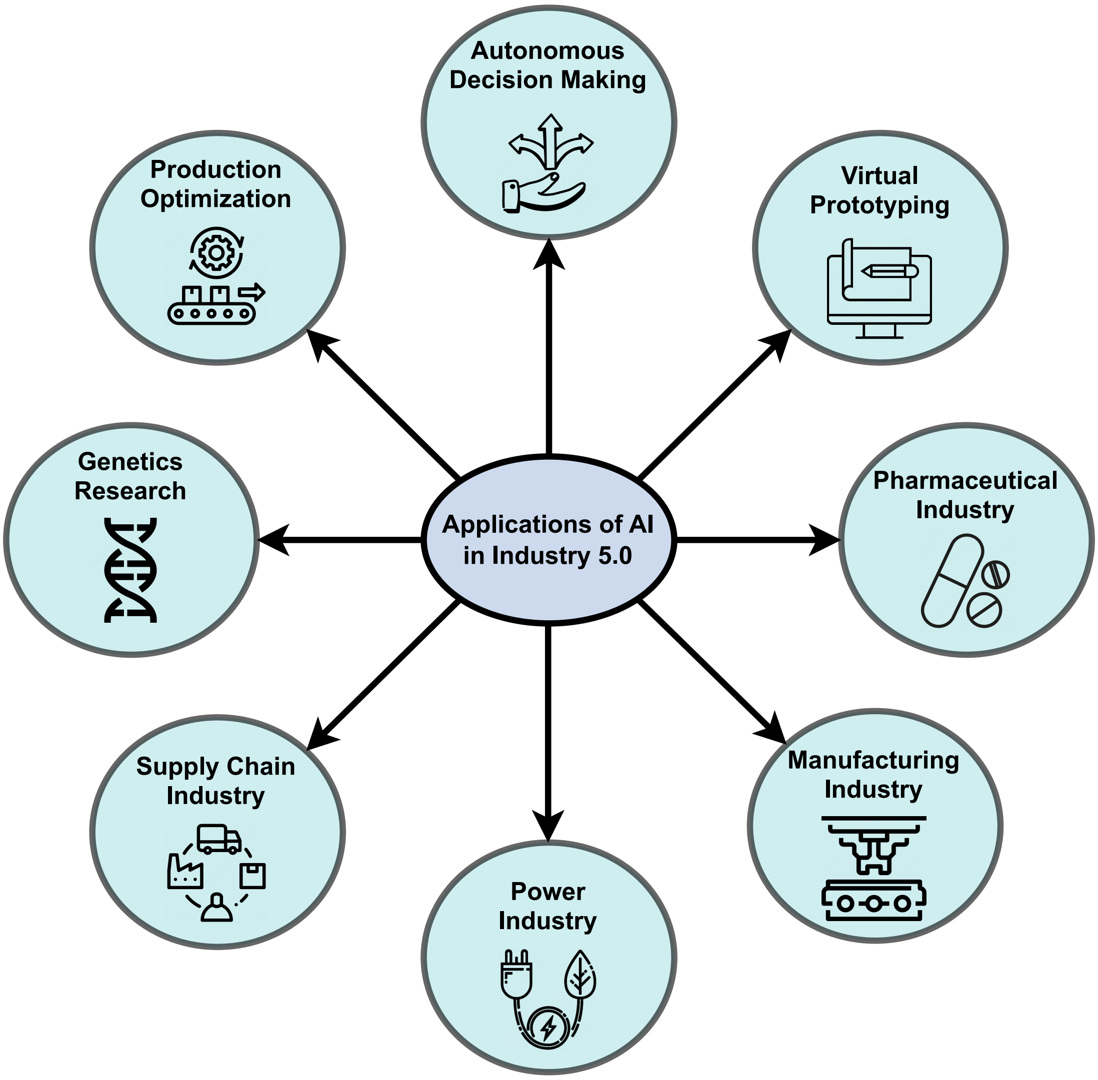


Figure 2.17: Domains of application of AI in Industry 5.0 [54].

Key technologies and strategies include:

- **Integration of renewable energy sources**, such as solar, wind, and hydroelectric power, into industrial operations.
- **Support for Hydrogen and Power-to-X technologies**, which convert electricity into other forms of energy, chemicals, or fuels, providing flexible energy solutions and enhancing storage capabilities.
- **Smart dust and energy-autonomous sensors**, namely micro-electromechanical systems that can collect and transmit data powered by small energy-harvesting devices, reducing the dependency on traditional power sources.
- **Low-energy data transmission and data analysis**, optimizing the en-

ergy efficiency of the vast data operations in industrial settings.

A notable innovation in this field is the development of "motion-sensitive smart lightning" by the Italian start-up Greenled Industry. This system minimizes lighting power consumption by integrating innovative zoning technologies, occupancy sensors, and performance monitoring algorithms. The system automatically adjusts the brightness of rooms based on occupancy, activity levels, ongoing operations, and time of day, significantly reducing energy usage [55].

2.3.4 The Role of Operators in Industry 5.0

The previous discussions on digital, data-driven, and interconnected industries originating with Industry 4.0 and evolving with Industry 5.0 underscore a transformative effect on society, particularly for industry workers. As jobs have become increasingly service-focused, demanding, and cognitively complex, there have been notable benefits in production efficiency and quality. However, this transition also introduces significant challenges, including stress and work-related diseases.

Despite advancements in technology fostering human-machine collaboration under the I5.0 paradigm, the industry is still struggling to fully realize the European Commission's vision of [31]:

> *"Choose technologies based on an ethical rationale of how those support human values and needs, and not only based on what they can achieve from a purely technical or economic perspective."*

While these technologies aim to create safer, more satisfying, and more ergonomic working environments where humans can utilize their creativity and adopt new roles, empirical evidence suggests that around 60-70% of the attempted implementations failed in quality, flexibility, or reliability, often due to an inadequate integration of human factors.

The transition to I5.0 requires profound changes in traditional career life cycles, including training, work, and retirement. The shift in roles and reliance on complex technologies demands novel educational and training programs to prevent the potential adverse effects of technology-driven frustration, neglect, and overwhelm [56]. Moreover, how technology impacts workplace mental health largely depends on its implementation, organizational norms around its use, and employee perceptions of its effect on their roles. Negative attitudes towards technology can hinder its acceptance and effectiveness despite its potential benefits [57].

Occupational safety and health experts are increasingly concerned by the potential adverse effects of new procedures, roles, and digital tools on workers' physical and mental health. Historical studies on automation's impact over the past decade revealed that rapid technological advancements can obstruct informal learning, motivation, and interdisciplinary cooperation among workers, potentially leading to increased uncertainty, decreased situational awareness, and resistance to automation [58, 59, 60, 61].

Furthermore, the relational impact of technology is considerable, as more abstract activities and digital-mediated relationships can increase misunderstandings and reduce physical interactions at work. Episodes of "*technostress*" are particularly concerning, as they arise from an always-connected technological environment that can cause feelings of detachment from reality. Factors influencing technostress include [43]:

- **Cognitive overload** due to excessive information quantity and pace;
- **Organizational issues** related to inadequate training and support for proper technology use;
- **Cultural challenges** linked to an insufficient focus on health and safety in new industrial contexts.

As jobs become more cognitively demanding, workers increasingly face distress related to insufficient training and job insecurity, fearing the automation of tasks they were previously handling [62, 63]. Such stress can originate anxiety, mental fatigue, and excessive cognitive workload, leading to decreased attention, physical exhaustion, and reduced mental capabilities.

However, rapid technological changes are unlikely to leave millions of workers unemployed. Instead, they pose a greater risk of job displacement without substantial investments in training and job transition programs. Education, reskilling, and upskilling are critical to aligning workforce capabilities with new roles, safeguarding them against the psychological impacts of job insecurity, and ensuring sustainable production and workforce welfare even in challenging or unexpected situations [10].

The future of work requires a total shift in the work model, necessitating two types of workforce changes:

1. **Upskilling**, where operators gain new skills to aid in their current roles;

2. **Reskilling**, where operators acquire capabilities for different or entirely new roles.

This shift is crucial as companies will need people with the right skills to develop, manage, and maintain automated equipment and digital processes while performing tasks that machines cannot [43]. For instance, the demand for physical and manual skills is expected to reduce by 30% over the next decade in Europe and the United States, while the demand for technological skills will likely increase by over 50% Furthermore, the need for high-level social and emotional skills, such as critical thinking, leadership, and entrepreneurship, is also expected to rise by more than 30% [64].

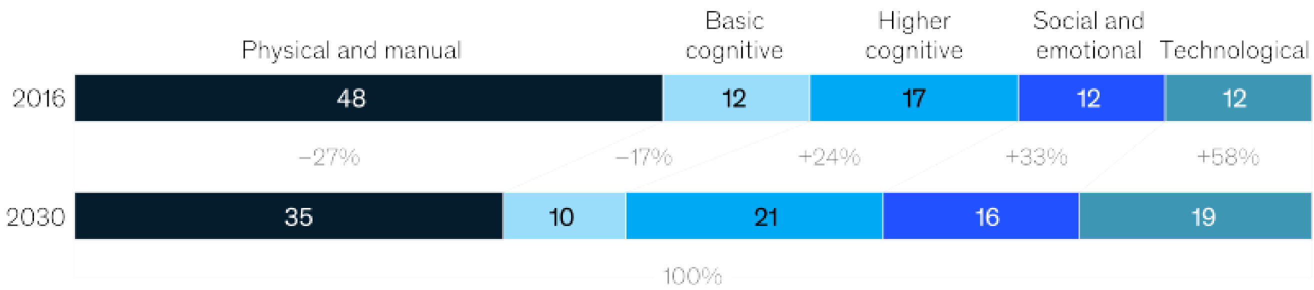


Figure 2.18: Skill shift in US and Western Europe by category (% of time spent) [64].

It is essential for companies to understand which skills their operators lack, leveraging direct access to the best technologies to anticipate future needs and adapt their educational and training programs accordingly. Figure 2.19 illustrates the critical barriers that large-scale reskilling efforts should aim to overcome [43].

Ultimately, Operator 5.0 should incorporate resilience, intelligence, and creativity, effectively applying the available technologies to overcome obstacles and innovate within the sustainable production paradigm of I5.0. This dual-aspect vision involves both "*auto-resilience*", rooted in physical, cognitive, and psychological health, and "*system resilience*", which refers to the adaptive autonomy and collaborative capacity of new industrial environments [65].

To achieve both these goals, [66] defined 12 key abilities that Operator 5.0 should have:

1. Creative problem solving;

2. Digital literacy, which is the ability to find, evaluate, and communicate information leveraging digital platforms;

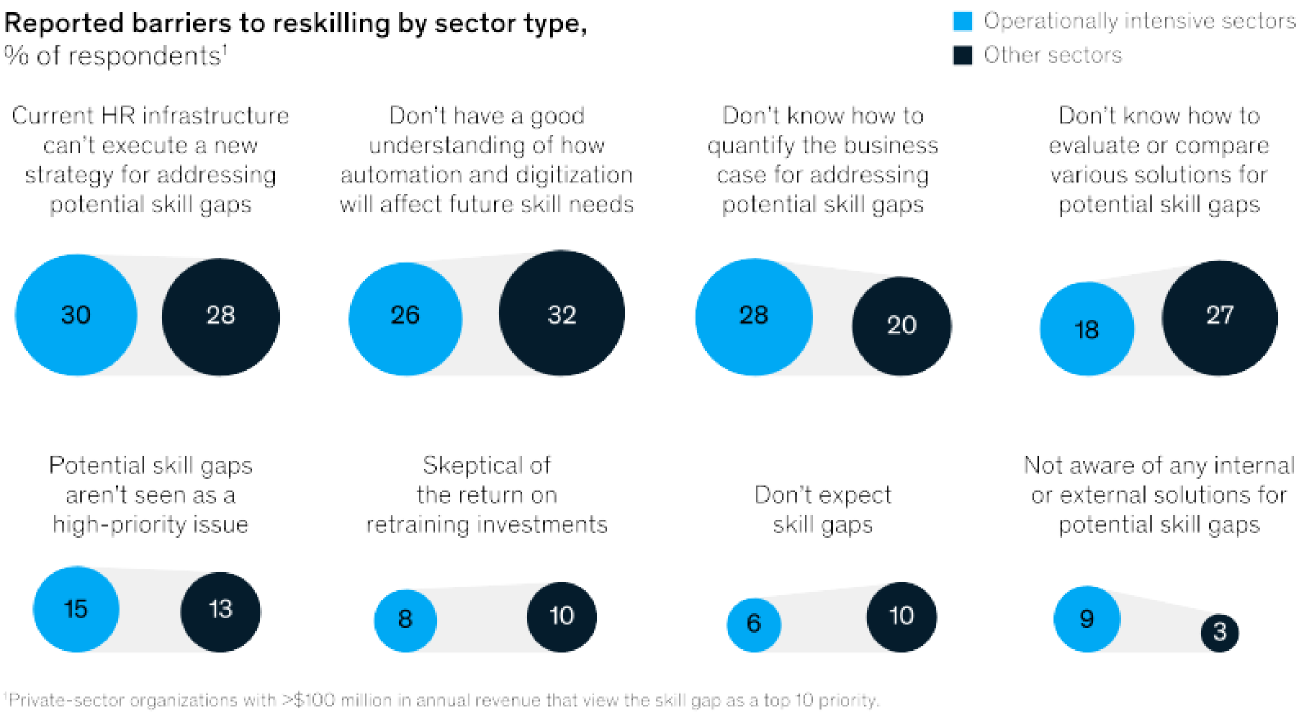


Figure 2.19: The most critical barriers that large-scale reskilling efforts should aim to overcome [64].

3. Proficiency in the use of AI and data analytics;
4. Critical interpretation of the results;
5. Strong entrepreneurship;
6. Working safely and efficiently with the new technologies;
7. Cross-cultural and disciplinary, inclusive and diversity-oriented mindset;
8. Cybersecurity and privacy;
9. Managing the increased complexity of many requirements and tasks simultaneously,
10. Communicate with human operators and AI systems via different interfaces and platforms;
11. Open mindset towards continuous changes;
12. Propensity for retraining and continuing education.

In the context of I5.0, technologies should present practical and positive impacts in facing the complex threats they are introducing to the operators. [67]

studied the most widely implemented I5.0's enabling technologies in the manufacturing field to understand their impact on organizations and operators. The results are divided into six technological categories:

1. **Smart Wearables** enhance operational safety by monitoring environmental conditions and workers' health metrics. However, the reliance on such technology must be balanced with concerns over privacy, physical comfort, and potential over-trust that may reduce human vigilance in safety practices [68, 69].

2. **Robots and CoBots** reduce physical strain and improve access to work for people with disabilities. Yet, these systems also alter work dynamics, potentially leading to psychological stress from reduced human interaction and increased demands to keep up with automated processes [70, 71].

3. **Augmented and Virtual Reality (AR and VR)** are fundamental in training and operational guidance. Still, they can lead to sensory overload, disorientation, and a potential decrease in the learning curve for job skills if overly relied upon [31, 72].

4. **Exoskeletons** support physical tasks and reduce the risk of injuries. Yet, they can introduce new risks such as restricted mobility, discomfort, or even new types of injuries due to improper use or poor ergonomic design [73].

5. **Digital Twins (DTs)** offer strategic insights through simulation and real-time data analysis but require careful implementation to avoid inefficiencies that could lead to decision-making errors or increased operational costs [74].

6. **Wireless Communication Technologies** facilitate real-time health and safety monitoring but depend heavily on reliable data transmission. Failures in the system can lead to significant safety risks, while continuous monitoring raises concerns about privacy and psychological impact [68].

These examinations underscore the necessity of a balanced approach to technology adoption in I5.0 that enhances operator capabilities while safeguarding against new risks. The focus must remain on developing resilience, enhancing skills, and ensuring that technology augments human work rather than replaces it.

Figure 2.20: The new skills needed to transition to Operator 5.0, underscoring the evolution from Operator 4.0 attributes to the advanced capabilities required in Industry 5.0 [66].

2.3.5 Industry 5.0 Applications

Industry 5.0, characterized by its innovative integration of human-centric technologies and intelligent systems, has begun to influence a variety of sectors with its advanced applications. The literature and ongoing projects provide insights into the practical implementation of I5.0 technologies and their transformative potential.

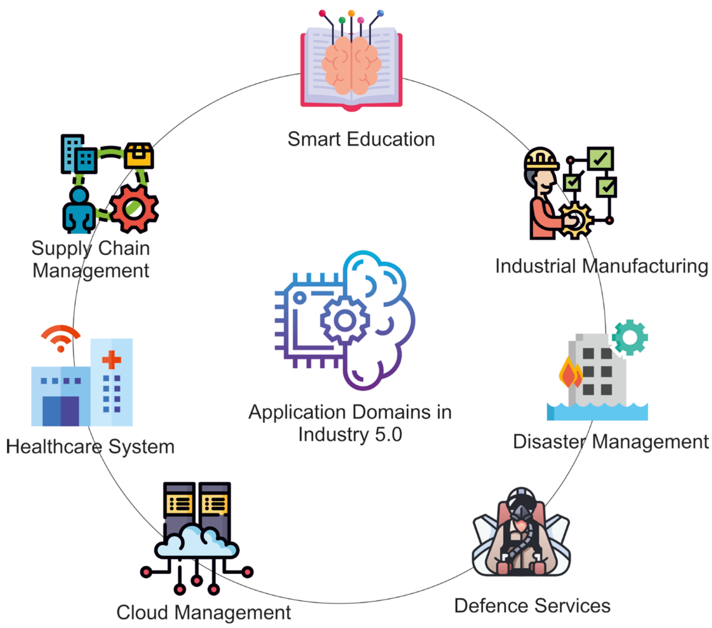


Figure 2.21: I5.0 applications across different domains [75].

Intelligent Healthcare

Intelligent healthcare systems in I5.0 utilize smart wearables and intelligent sensors to monitor patient health parameters continuously. These systems collaborate closely with medical personnel to provide personalized care and support routine medical tasks, enhancing the efficiency and personalization of healthcare services. Additionally, CoBots can support medical personnel in performing ordinary tasks like routine checkups, leaving more time to doctors for higher complexity tasks [17, 76].

Cloud Manufacturing

Cloud manufacturing uses advanced technologies like Edge Computing, IoT, Virtualization, and Simulations to innovate traditional manufacturing processes, providing reliability, excellent quality, cost-effectiveness, and on-demand capabilities. By leveraging the cloud infrastructure, it is possible to manage and optimize the production lifecycle, providing scalable solutions that take into account all the procedures related to the production, such as service composition, scheduling, and assembly [17].

Supply Chain Management

I5.0 enhances supply chain management by integrating IoT devices and CoBots with human intelligence to support industries in meeting demand and providing individualized and customized products more quickly. This integration facilitates mass customization, allowing companies to adapt quickly to market demands while reducing costs.

Manufacturing and Production

In manufacturing, I5.0 technologies delegate repetitive and physically demanding tasks to Robots and CoBots, freeing human workers to engage in more creative and fulfilling activities. This shift improves productivity and operational efficiency and enhances worker safety and job satisfaction by reducing workplace injuries, generating new job positions, and including AI and Robotics in training and scheduling processes. [3].

Disaster Management

In disaster management, Industry 5.0 technologies are critical in developing prevention and response strategies that mitigate the repercussions of catastrophic events. The integration of AI and IoT with human response teams enhances the effectiveness of these strategies, providing rapid and adaptive solutions to complex emergencies [17].

Horizon 2020 Case Studies

The EU's Horizon 2020 program highlights several impactful Industry 5.0 initiatives [31]:

- **FACT4WORKERS**: This project focuses on integrating user-friendly IT solutions into intelligent factories, enhancing worker experience and efficiency.

  A notable application is the one implemented at EMO Orodjarna, a Slovenian company that produces transfer and progressive tools for transforming sheet metal. By providing easier and faster access to context-specific information for workers across various manufacturing stages, they improved decision-making and response times, at the same time increasing participation and providing individual and collaborative problem-solving [77].

- **Thermolympic S.L.** is a company specialized in designing and producing the molds used in thermoplastic injection molding. This company utilized F4W (Factory for Work) tablets to foster a collaborative working environment, enabling real-time data analysis and knowledge sharing among operators. This technology helped troubleshoot and quickly resolve operational issues, significantly reducing downtime and promoting a proactive workplace culture [78].

  Examining a real-world scenario, how might one address the problem of being unable to pinpoint the source of machine-produced defective parts that could result in extended periods of downtime and affect output? In that use case, tablets are linked to a quality cloud, and the errors are examined instantly. As a result, the system can offer a potential fix for the error that has been identified, as well as instructions on how to restore the machine in accordance with the fix. By doing that, the user can prevent the machine from being interrupted and solve the issue on their own right away.

These devices also allow users to learn about machines and manufacturing processes at multiple levels of detail using textual descriptions, photos, and interactive videos. Additionally, the tablet can send alarm signals if a machine malfunction is identified, giving the operator complete control over the device. Another feature worth of mention lets operators inform management about potential optimization and improvement, enabling the manager to hear the operator's feedback at the end of the shift. This helps to increase the sense of responsibility and inclusion among the workforce.

These examples illustrate the broad scope and impact of Industry 5.0 applications, demonstrating how these technologies enhance operational efficiencies and significantly improve human-machine collaboration and workplace quality.

Chapter 3

Predictive Approaches for Human Operator Assessment

The transition from Industry 4.0 (I4.0) to Industry 5.0 (I5.0), as discussed in Section 2.3, signifies a pivotal shift towards re-emphasizing human factors in manufacturing. Since the advent of the first Industrial Revolution, human involvement has been integral to manufacturing systems, and no degree of automation or digitalization can function totally independently of human oversight.

While current literature underscores significant progress in efficiency and productivity, especially within the area of predictive maintenance of machinery and equipment, a notable gap persists in addressing operators' health and well-being. The majority of the studies often regard operators primarily from a productivity point of view, with the perspective that a fatigued operator diminishes productivity or that injuries on the shop floor can disrupt production and escalate company costs.

However, the focus should expand beyond merely mitigating negative impacts on production. Proper adherence to the pillars of I5.0 demands a paradigm shift towards a more human-centric approach. This involves considering all factors that influence not only the safety but also the overall welfare of operators, encompassing both short and long-term health implications and, more in general, well-being. It is common to hear of long-term or former industrial workers suffering from joint or musculoskeletal issues or expressing dissatisfaction, stress, or feelings of alienation at work. Therefore, there is an emerging and pressing need to formulate a comprehensive strategy that addresses all these aspects to enable a more effective integration of operators in the advanced manufacturing environments of I5.0.

The initial step towards that direction involves a comprehensive analysis of all elements within an industrial setting directly affecting operators to identify the various factors impacting them. Alongside this, it is crucial to establish metrics, approaches, and methodologies that can be utilized to monitor and evaluate these factors effectively.

These efforts are foundational for understanding the technologies that can be leveraged to collect the data needed to understand the interactions between operators and their environment. This creates the basis for the pioneering framework for the predictive assessment of human operators presented in Chapter 4.

In this Chapter, we will first detail the stages that led to the formulation of the taxonomy of human factors impacting operators in industrial environments. Then, we will discuss the methodologies that have historically and currently been employed to assess these aspects.

3.1 Human Factors Taxonomy

While often overlooked, the prioritization of human health and well-being within industrial settings has received attention in recent studies, particularly within the context of I4.0. Using those works as a starting point, we adapt their perspective to the pillars of I5.0 and propose a taxonomy of critical factors that influence operator health and well-being in industrial environments. Formulating this taxonomy is the first crucial step of our work, fundamental for integrating human welfare and technological advancements in a single path toward sustainable industrial progress.

To enhance working conditions for operators, we consider four primary domains:

1. **Safety**;
2. **Health**;
3. **Well-being and Satisfaction**;
4. **Human Errors**.

These domains cover both physical and psychological aspects of operator welfare, recognizing the interconnections of these factors in achieving optimal performance and satisfaction. It is essential to understand that these fields are not isolated but interconnected and mutually influence each other within the industrial environment.

By reviewing and analyzing the literature associated with these domains, they can be decomposed into various more specific sub-domains, detailed in the following Subsections.

3.1.1 Safety

Safety is probably the most critical domain concerning the welfare of operators in industrial settings. It covers a wide variety of risks associated with such environments, including manufacturing processes like cutting, welding, melting, and hammering, and potential dangers such as crushing, falling objects, collisions, fire, electrical shocks, explosions, and gas poisoning [79].

Historically, safety has gathered a lot of interest even within the domain of I4.0, as safety accidents can result in severe injuries or fatalities, disrupt production, and lead to legal and financial penalties for businesses.

The main factors contributing to accidents are [80]:

1. Collisions and falls due to human and equipment movements;

2. Fires, explosions, and gas poisoning, especially in narrow spaces;

3. Follow-up or secondary accidents, such as evacuation accidents, resulting from inadequate safety management.

To formalize these threats more precisely, safety can be categorized into three sub-domains:

1. Movement/Collision Situations

This sub-domain addresses risks associated with the physical movement of operators and machinery, including potential collisions, accidents caused by machinery movements, and falling objects.

In an industrial environment, the risk of being crushed or trapped between heavy objects is significant, as are slips and falls, which can result in severe trauma or even death if an adequate reaction is not available [81, 82]. The integration of CoBots and flexible manufacturing in I5.0 increased the need for enhanced human presence detection to mitigate those risks.

Therefore, monitoring the status of work areas and the workers' positions and movements can enable the gathering of information that can be used to detect potentially hazardous conditions and prevent accidents [80].

2. Environmental Dangers

Risks from the working environment, such as inadequate ventilation, ineffective dust removal, and exposure to toxins or chemicals, are critical [83].

Implementing environmental sensing technologies that can measure and manage these risks is crucial for maintaining a safe workplace that does not threaten the personal safety of the operators [84]. Monitoring various gases (flammable, explosive, toxic), as well as environmental factors like oxygen levels, carbon monoxide, carbon dioxide, hydrogen sulfide, methane, noise, temperature, dust, and smoke, enables the detection of deviations from safe thresholds and the triggering of appropriate safety measures [83, 84].

3. Operational Dangers

This sub-domain focuses on risks linked to specific tasks performed by operators, requiring robust monitoring of all those operations considered more prone to be hazardous [80].

Additionally, the potentially dangerous or hazardous components handled by operators, for instance, chemicals such as paints and sharp objects such as metal sheets, should be tracked and monitored [85].

3.1.2 Health

The domain of health, strictly connected to safety, is crucial for preserving both the short-term and long-term welfare of operators while ensuring the efficiency and productivity of manufacturing processes [86, 87]. Recognizing this critical interconnection, recent research within the context of I4.0 has begun to emphasize the health of industrial operators. However, the scope of such studies has often been limited.

Most of the literature has focused on physical health, addressing concerns like musculoskeletal disorders, exposure to hazardous conditions, and physical fatigue. While these are vital aspects of health management, they represent only a part of the overall health domain necessary for maintaining an effective, productive, and satisfied workforce.

Mental health is a crucial worker welfare component that has been neglected in industrial health studies. This aspect concerns the essential role that mental well-being plays in productivity, job satisfaction, and overall workplace safety. If unaddressed, mental health issues can lead to increased absenteeism, reduced job performance, and higher turnover rates, thus influencing industrial operations' operational efficiency and safety outcomes [88].

Therefore, physical and mental health are the two sub-domains composing the health domain in industrial settings. Each sub-domain has a fundamental role in protecting and enhancing operators' overall welfare.

1. Physical Health

Physical health in industrial environments includes risks related to musculoskeletal disorders, repetitive strain injuries, and other physical problems resulting from industrial activities.

The main factor to consider for managing these health issues is physical fatigue, which can significantly impair motor control, reduce strength, and decrease performance, increasing the rate of accidents and errors [89]. Furthermore, physical exhaustion can contribute to chronic fatigue, decreased immunological function, and even long-term health consequences such as increased illness, job disability, occupational accidents, diminished quality of life, and even mortality [88, 90].

Both subjective approaches and objective measurements can be employed to assess physical fatigue:

Subjective Assessments

Tools like the Swedish Occupational Fatigue Industry (SOFI), which uses as indicators the lack of energy, the bodily pain, and the Perceived Rating Exertion (PRE) can be used to gain insights about muscle fatigue [91, 92].

Posture-based assessment such as the Ovako Working Posture Analyzing System (OWAS) and the Rapid Upper Limb Assessment (RULA) enable the estimation of physical fatigue based on posture and musculoskeletal stress [93, 94]. Indeed, frequent changes in posture or a non-upright posture can signal physical fatigue due to prolonged static positions or repetitive actions [87]. The most employed metric in this scope is the Rapid Entire Body Assessment (REBA) [95].

Task duration is also a metric that can be used to assess rising fatigue levels. Indeed, if the time an operator is spending on performing the same task increases during time, it indicates the operator is probably accumulating fatigue [87].

Objective Measurement

Electromyography (EMG) is commonly applied to record the electrical activity produced by muscles and consequently determine the level of physical fatigue [86]. Additional metrics include brainwave power captured by Electroencephalography (EEG) and facial feature analysis such as Eye-opening Frequency (PERCLOS), Mouth-aspect Ratio (MAR), Blink-rate Ratio (BRR), and Eye-aspect Ratio (EAR) to detect signals of physical exhaustion [87, 96, 97, 98].

Furthermore, the analysis of body kinematics provides insights into physical fatigue. As fatigue accumulates, observable changes in joint kinematics such as Range of Movement (ROM), angular velocities, and angular accelerations can be detected, especially when performing repetitive tasks [99, 100, 101].

Nevertheless, variations in heart rate offer valuable information regarding the automatic regulation of the circulatory system and its response to fatigue, which is critical for assessing the overall physical condition of operators [102].

2. Mental Health

Mental health in industry concerns the psychological well-being of operators and covers all the workplace conditions that might affect their mental states.

The World Health Organization (WHO) defines mental health as [103]:

> *"a state of well-being in which every individual realizes his or her own potential, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to her or his community."*

This definition highlights that good mental health goes beyond the absence of mental disorders, concerning also the ability to handle stress, recognize individual potential, and contribute effectively in the workplace [104].

Therefore, promoting mental health in the workplace is crucial as it directly influences productivity, safety, and operators' satisfaction. Positive mental health induces a more satisfying work environment and enhances overall worker welfare [103].

To effectively monitor and enhance mental health in industrial settings, various metrics and indicators can be employed:

- **Physchological Indicators**: The metrics originating from the brain, such as EEG, enable the detection of stress and fatigue by analyzing brainwave patterns. EEG has proven effective in identifying changes in vigilance, sleep states, and stress [105, 106].
- **Facial and Eye Metrics**: The frequency and pattern of eyelid movements (PERCLOS, EAR, BRR) are significant indicators of mental fatigue and sleepiness, which are critical in assessing the tiredness and exhaustion level of operators [107, 108].
- **Behavioral Indicators**: Specific gestures, body movements, and behaviors of operators, such as sudden head nods (i.e., head falling suddenly and fighting it) or head shakes, can provide early signs of mental fatigue. The definition of a gesture dictionary can help in defining and interpreting these movements to assess risk levels associated with various mental states [109].

3.1.3 Well-being and Satisfaction

The domain of well-being and satisfaction is crucial in the taxonomy of factors affecting the welfare of operators within industrial settings. This domain intersects with the ones of health and safety, at the same time extending beyond those by addressing factors that are fundamental under the I5.0 paradigm but were often overlooked in I4.0. In the context of I5.0, as stated in Section 2.3.4, the perspective shifts from viewing operators as a matter of productivity and efficiency to recognizing them as central and core parts of the industrial ecosystem. Therefore, the well-being and satisfaction of operators are linked directly to their sense of creativity, realization, and value in their roles, which consequently can enhance overall productivity and innovation.

The sub-domains composing that domain, addressing specific aspects of it, are:

1. Repetitive Manual Material Handling (MMH);
2. Training and On-site Assistance;
3. Emotions and Mood States.

Repetitive manual tasks can affect physical health and decrease operators' sense of personal achievement. Training and on-site assistance ensure that operators feel confident and safe, reducing stress and anxiety associated with performing tasks, especially potentially hazardous ones. Finally, acknowledging and actively managing workers' emotional and mood states can lead to a more satisfactory and sustainable work environment.

These sub-domains, which will be further detailed in the following subsections, enable the creation of a workplace where operators are not only productive but also genuinely satisfied and engaged with their work, aligning with the human-centric pillar of I5.0.

Repetitive Manual Material Handling

Repetitive MMH includes tasks that require continuous physical effort, such as pushing, pulling, lifting, bending, and walking. These activities are physically demanding and often monotonous, adding to the bodily fatigue a component of mental fatigue. The physical aspects of these tasks can result in musculoskeletal disorders and discomfort, while the mental ones can diminish workers' sense of contribution and satisfaction [86].

Approaches for the assessment of MMH overlap with those used in assessing physical health (see Section 3.1.2), involving both direct measurements and observational techniques like standard questionnaires or body sensors [110]. Additionally, to enhance the overall understanding of the physical exertion caused by MMH, it is crucial to consider the weight and ergonomics of handled materials [111]. Nevertheless, integrating mental fatigue assessment techniques that leverage facial features provides a more comprehensive understanding of the operators' overall well-being.

By assessing the repetitive MMH, it is possible to implement changes in the industrial workflow, improving efficiency and productivity while diminishing the adverse effects of this task on operators.

Training and On-site Assistance

Proper training is crucial for operator confidence and efficacy, especially in performing complex tasks and handling dangerous equipment [112]. Comprehensive training programs can ensure operators are well-prepared for their roles, reducing anxiety and increasing job satisfaction. At the same time, on-site assistance enhances these aspects by providing real-time support and guidance, which is especially critical in high-stress or emergency situations [113, 114].

Traditional training methods, such as lecture-based or mentor-based approaches, face several limitations in reaching these requirements. While lecture-based training can be provided to many workers simultaneously, it lacks the hands-on experience that is critical for effective learning. Mentor-based training is more interactive but costly and can be inconsistent due to the variability in mentors' skills and experience [115].

The transition towards on-site assistance represents a change from conventional training to a more dynamic approach. This involves systems that provide real-time instructions and feedback to operators while performing their tasks, ensuring the correct execution of the latter without altering the workflow. Effective on-site assistance systems should be able to detect when operators require help and provide the necessary guidance in a fast and reliable way [115]. For instance, object detection technologies can identify the tools or components the operator is using and provide contextualized assistance based on the specific task being performed [116].

Furthermore, such a system should be able to understand operators' mental states, such as confidence or confusion levels, through behavioral and physiological indicators. These metrics can enhance the assistance system's responsiveness, enabling the provision of support when it is most needed.

Therefore, to provide adequate on-site assistance, the system should be able to understand when guidance is needed and offer it at the right time. The advice is associated with searching for parts or components and their information, recalling the assembly information, and being sure and confident about the task being performed.

Emotions and Mood States

Monitoring and actively managing the emotional well-being of operators is crucial to creating a satisfactory work environment. Here, we should merge all the components related to physical and mental health, as well as the ones related to safety. An operator can maintain a positive mood only if he is not under physical or mental stress and is confident that the workplace is safe and that appropriate measures to contain or counteract potential hazards are implemented.

When the operators' mood states are not positive, they are more prone to lapse in concentration, vigilance decline, sleepiness, and neglect of the risk, increasing the risk of injuries, especially when using machine tools [96].

Other factors severely impacting mood states are repeated working activities (e.g., repetitive MMH), noise levels, and shift changes [117].

Therefore, we can apply the vast array of assessment metrics mentioned in

Section 3.1.2, in particular the ones associated with EEG records [118, 119].

3.1.4 Human Errors

The last domain composing this taxonomy is the one of human errors. In the context of I5.0, human-machine interactions are frequent and complex; therefore, human errors are more significant regarding their influence on product quality and their potential impact on operators' safety and health. An error can have disruptive effects on safety, for instance, if the safety measures and protocols are not respected, or on mental health since a mistake can cause dissatisfaction or distress in the operator.

In this domain, "*Human Errors*" and "*Human Reliability*" describe two complementary aspects of human action. VDI 4006 defines human reliability as [120]:

> *"The capability of human beings to complete a task under given conditions, within a defined period of time, and within the acceptance limits."*

while a human error is defined as

> *"A human action that exceeds the defined acceptance limits."*

Accordingly, the Human Error Probability (HEP) and Human Reliability Probability (HRP) are metrics used to quantify the likelihood of errors over faultless actions. They are defined as:

$$HEP = \frac{number\ of\ observed\ errors}{number\ of\ the\ possibilities\ for\ an\ error} = \frac{n}{N} \tag{3.1}$$

$$HRP = 1 - HEP \tag{3.2}$$

These indicators can be used to gain valuable insights about the most frequent and impacting human errors in an industry, enabling the implementation of appropriate counteracting measures.

Regarding the classification of human errors, these can be divided into three categories [121, 122]:

1. **Memory Errors**: The first category involves those errors that occur when the worker does not remember the remaining steps of a process, including errors like:

    - Omissions;

    - Wrong amount of repetitions;
    - Inverted order;
    - Wrong point in time;
    - Task not assigned.

2. **Perception Errors**: These are errors arising from incorrect perception by the operator, and they can be divided into:
    - Perception of types and quantities, including incorrect selection and wrong counting;
    - Perception of states, comprising incorrect detection and errors in the perception of safety risks;
    - Perception of motions, including incorrect holding, positioning errors, and execution directions.

3. **Motion Errors**: This domain includes situations where the execution of a task is incorrect even though the operator correctly understood the task and perceived the situation accurately. Some typical errors belonging to this category include:
    - Wrong amount (when executing);
    - Unstable fixation;
    - Incorrect adjustments;
    - Insufficient prevention.

To address human errors effectively, Human Reliability Assessment (HRA) techniques enable the quantitative or qualitative evaluation of human reliability. The best approaches in the literature, in terms of usefulness, acceptability, and practicality, are [122]:

- the Systematic Human Action Reliability Procedure (SHARP);
- the Accident Sequence Evaluation Program (ASEP);
- the Technique for Human Error Rate Prediction (THERP).

THERP has been found to be, under the metrics mentioned above, the best HRA technique among those [123]. It estimates human errors and evaluates the related effects on the entire human-machine system. A probability tree is used as a primary tool to model decision steps, including wrong and correct choices. Additionally, a comprehensive set of tables links certain types of actions to a corresponding error probability [124].

One major issue with the quantitative evaluation of human error is the availability of reliable data. These can, for example, be determined via field study, experiment, statistics, estimation by experts, or interviews. Generally, data derived from measurements should be preferred over subjective estimations.

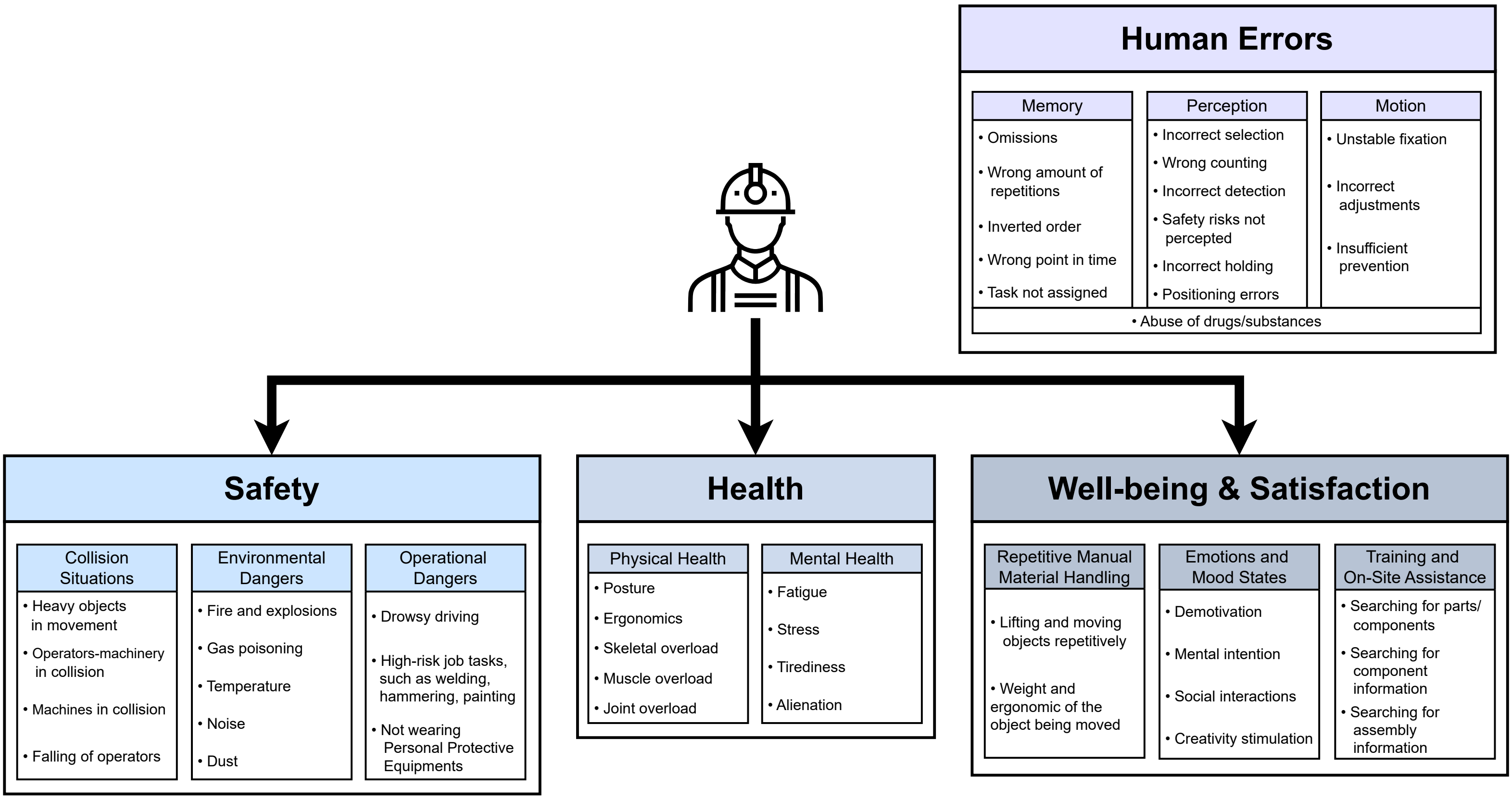


Figure 3.1: A visual representation of the formulated Human Factors Taxonomy.

3.2 Methods for Assessment

Over the years, several methods have been proposed to assess ergonomic risk factors, considering both physical (the study of mechanical and physical aspects of human interactions) and cognitive (the mental interactions of the operators with all the elements of the manufacturing system) aspects.

Traditional qualitative methods such as interviews and structured questionnaires are effective and reliable for reaching these objectives. However, the potential of these methods can be enhanced by integrating advanced technologies that enable dynamic and real-time data collection, leveraging the vast amount of information collected to establish quantitative evaluations.

By leveraging these survey approaches, we can identify the data of interest that needs to be collected to assess the workplace's physical and ergonomic conditions. Then, in the framework development detailed in Chapter 4, we will explore the technologies that can automate and improve the data collection process, ensuring that the data is continuously updated to reflect real-time conditions and changes in the workplace environment.

3.2.1 Posture-based Methods for Physical Ergonomics Evaluation

Posture-based methods are essential for identifying ergonomic risks associated with the physical positioning of workers during tasks. These methods provide systematic ways to observe and analyze body postures to ensure that workstations and tasks are designed according to ergonomic principles, thus preventing musculoskeletal disorders.

Rapid Upper Limb Assessment (RULA), developed by McAtamney and Nigel Corlett in 1993, serves as a foundational tool for assessing the ergonomic risks associated with upper limb disorders in various work environments. This method focuses on analyzing body postures, muscle function, and force exertion during task execution. Observers at the workplace record the posture of the worker's arms, wrists, neck, and trunk, alongside the muscle groups involved and the forces exerted. RULA employs a straightforward scoring system to evaluate each element, which cumulatively provides a risk score indicating the urgency for ergonomic intervention [94]. Although highly effective in identifying ergonomic risks, RULA primarily addresses the upper body and does not account for lower body postures or dynamic movements. The worksheet used for RULA assessment is illustrated in Figure 3.2

Expanding upon RULA, **Rapid Entire Body Assessment (REBA)** was designed to include the assessment of the entire body, thereby enhancing the method's applicability to a broader range of occupational tasks that involve complex movements and whole-body efforts. REBA analyzes the worker's body in segments, namely each arm, the neck, trunk, and legs are evaluated for posture with additional considerations for force, load, and activity level. The scores for each body segment are integrated using a detailed worksheet, as the one illustrated in Figure 3.2, enabling the computation of a comprehensive risk score that

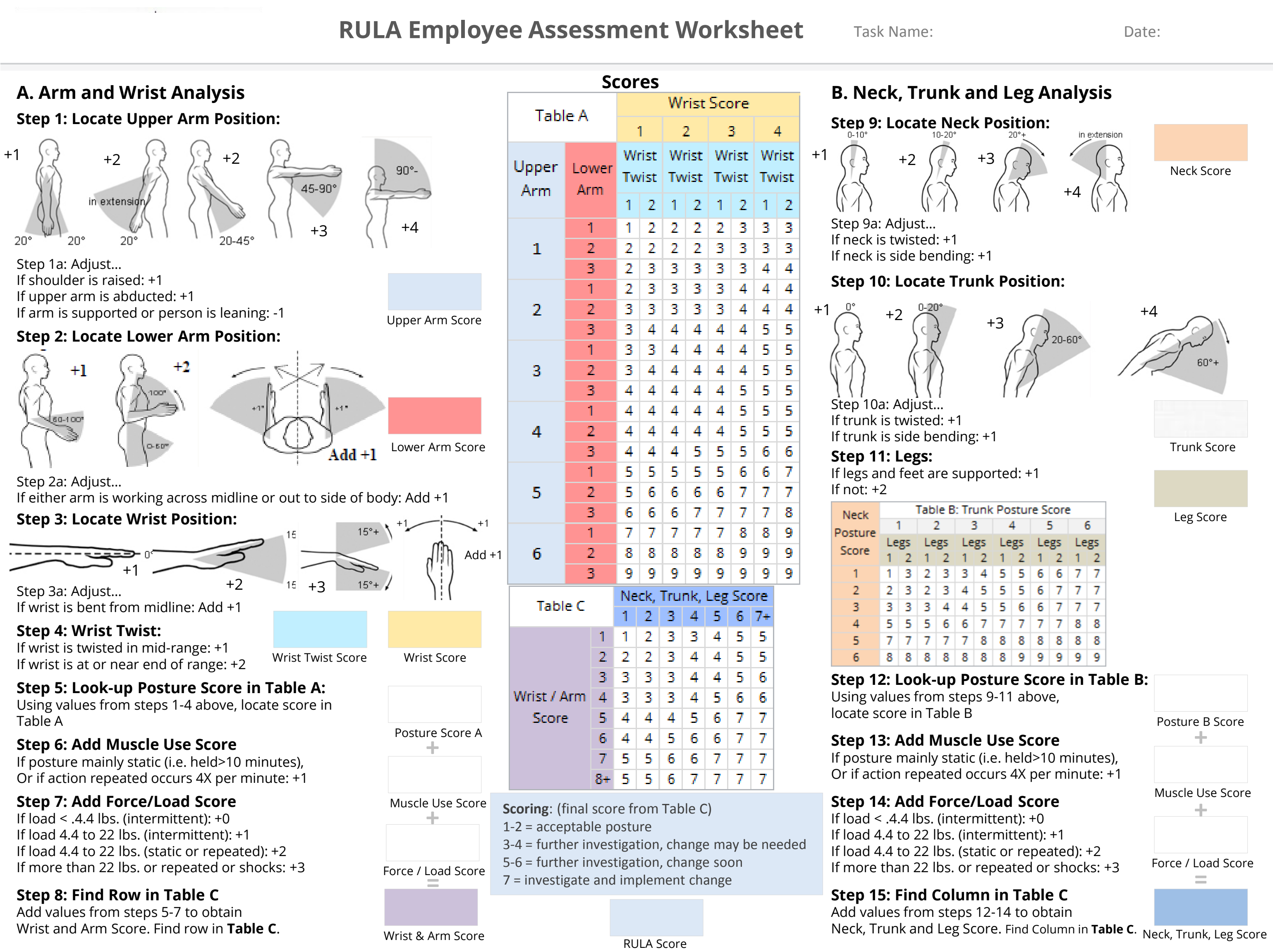


Table A		Wrist Score 1		2		3		4	
Upper Arm	Lower Arm	Wrist Twist 1	Wrist Twist 2	Wrist Twist 1	Wrist Twist 2	Wrist Twist 1	Wrist Twist 2	Wrist Twist 1	Wrist Twist 2
1	1	1	2	2	2	2	3	3	3
	2	2	2	2	2	3	3	3	3
	3	2	3	3	3	3	3	4	4
2	1	2	3	3	3	3	4	4	4
	2	3	3	3	3	3	4	4	4
	3	3	4	4	4	4	4	5	5
3	1	3	3	4	4	4	4	5	5
	2	3	4	4	4	4	4	5	5
	3	4	4	4	4	4	5	5	5
4	1	4	4	4	4	4	5	5	5
	2	4	4	4	4	4	5	5	5
	3	4	4	4	5	5	5	6	6
5	1	5	5	5	5	5	6	6	7
	2	5	6	6	6	6	7	7	7
	3	6	6	6	7	7	7	7	8
6	1	7	7	7	7	7	8	8	9
	2	8	8	8	8	8	9	9	9
	3	9	9	9	9	9	9	9	9

Table C	Neck, Trunk, Leg Score 1	2	3	4	5	6	7+
Wrist / Arm Score 1	1	2	3	3	4	5	5
2	2	2	3	4	4	5	5
3	3	3	3	4	4	5	6
4	3	3	3	4	5	6	6
5	4	4	4	5	6	7	7
6	4	4	5	6	6	7	7
7	5	5	6	6	7	7	7
8+	5	5	6	7	7	7	7

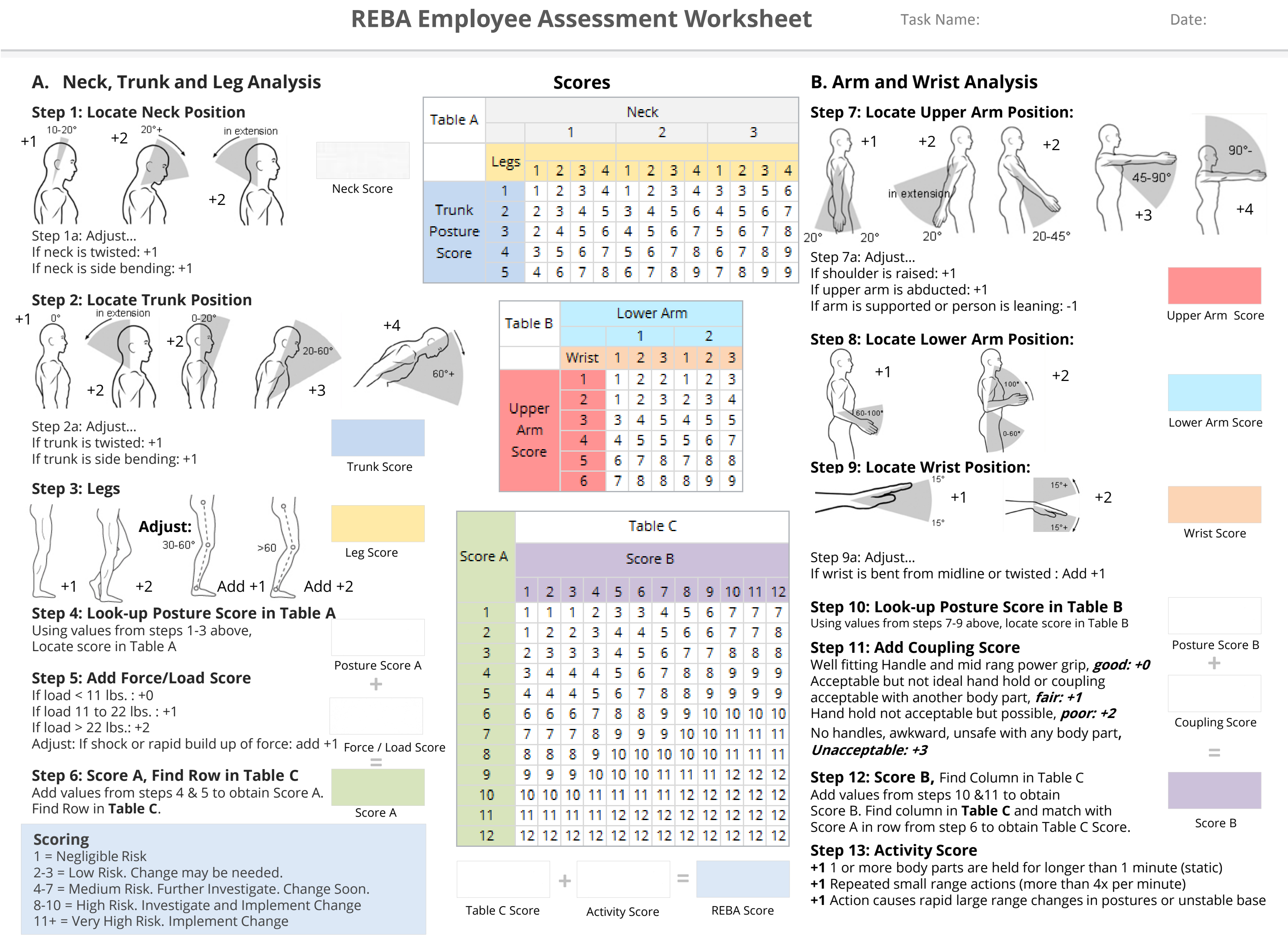
Neck Posture Score	Table B: Trunk Posture Score 1		2		3		4		5		6	
	Legs 1	Legs 2	Legs 1	Legs 2	Legs 1	Legs 2	Legs 1	Legs 2	Legs 1	Legs 2	Legs 1	Legs 2
1	1	3	2	3	3	4	5	5	6	6	7	7
2	2	3	2	3	4	5	5	5	6	7	7	7
3	3	3	3	4	4	5	5	6	6	7	7	7
4	5	5	5	6	6	7	7	7	7	7	8	8
5	7	7	7	7	7	8	8	8	8	8	8	8
6	8	8	8	8	8	8	8	9	9	9	9	9

Figure 3.2: RULA worksheet for operators assessment [125].

drives the prioritization of necessary ergonomic adjustments [95]. While REBA offers a more detailed evaluation, it requires a more intricate and time-consuming observation process, which may not be feasible in all work settings.

3.2.2 Biomechanic-based Methods for Physical Ergonomics Evaluation

Biomechanic-based methods offer a scientific approach to evaluating the physical demands on workers, focusing on the forces exerted and the mechanical loads sustained by the body during tasks. These methods are critical for assessing the



REBA Employee Assessment Worksheet Task Name: Date:

A. Neck, Trunk and Leg Analysis

Step 1: Locate Neck Position

+1 10-20° +2 20°+ in extension +2

Neck Score

Step 1a: Adjust...
If neck is twisted: +1
If neck is side bending: +1

Step 2: Locate Trunk Position

+1 0° in extension +2 +2 0-20° +3 20-60° +4 60°+

Step 2a: Adjust...
If trunk is twisted: +1
If trunk is side bending: +1

Trunk Score

Step 3: Legs

+1 +2 **Adjust:** 30-60° Add +1 >60 Add +2

Leg Score

Step 4: Look-up Posture Score in Table A
Using values from steps 1-3 above,
Locate score in Table A

Posture Score A

Step 5: Add Force/Load Score
If load < 11 lbs. : +0
If load 11 to 22 lbs. : +1
If load > 22 lbs.: +2
Adjust: If shock or rapid build up of force: add +1

Force / Load Score

Step 6: Score A, Find Row in Table C
Add values from steps 4 & 5 to obtain Score A.
Find Row in **Table C**.

Score A

Scoring
1 = Negligible Risk
2-3 = Low Risk. Change may be needed.
4-7 = Medium Risk. Further Investigate. Change Soon.
8-10 = High Risk. Investigate and Implement Change
11+ = Very High Risk. Implement Change

Scores

Table A		Neck 1				Neck 2				Neck 3			
	Legs	1	2	3	4	1	2	3	4	1	2	3	4
Trunk Posture Score	1	1	2	3	4	1	2	3	4	3	3	5	6
	2	2	3	4	5	3	4	5	6	4	5	6	7
	3	2	4	5	6	4	5	6	7	5	6	7	8
	4	3	5	6	7	5	6	7	8	6	7	8	9
	5	4	6	7	8	6	7	8	9	7	8	9	9

Table B		Lower Arm 1			Lower Arm 2		
	Wrist	1	2	3	1	2	3
Upper Arm Score	1	1	2	2	1	2	3
	2	1	2	3	2	3	4
	3	3	4	5	4	5	5
	4	4	5	5	5	6	7
	5	6	7	8	7	8	8
	6	7	8	8	8	9	9

Table C

Score A \ Score B	1	2	3	4	5	6	7	8	9	10	11	12
1	1	1	1	2	3	3	4	5	6	7	7	7
2	1	2	2	3	4	4	5	6	6	7	7	8
3	2	3	3	3	4	5	6	7	7	8	8	8
4	3	4	4	4	5	6	7	8	8	9	9	9
5	4	4	4	5	6	7	8	8	9	9	9	9
6	6	6	6	7	8	8	9	9	10	10	10	10
7	7	7	7	8	9	9	9	10	10	11	11	11
8	8	8	8	9	10	10	10	10	10	11	11	11
9	9	9	9	10	10	10	11	11	11	12	12	12
10	10	10	10	11	11	11	11	12	12	12	12	12
11	11	11	11	11	12	12	12	12	12	12	12	12
12	12	12	12	12	12	12	12	12	12	12	12	12

Table C Score + Activity Score = REBA Score

B. Arm and Wrist Analysis

Step 7: Locate Upper Arm Position:

+1 20° 20° +2 in extension 20° +2 20-45° 45-90° +3 90°- +4

Step 7a: Adjust...
If shoulder is raised: +1
If upper arm is abducted: +1
If arm is supported or person is leaning: -1

Upper Arm Score

Step 8: Locate Lower Arm Position:

+1 60-100° +2 100° 0-60°

Lower Arm Score

Step 9: Locate Wrist Position:

15° 15° +1 15°+ 15°+ +2

Wrist Score

Step 9a: Adjust...
If wrist is bent from midline or twisted : Add +1

Step 10: Look-up Posture Score in Table B
Using values from steps 7-9 above, locate score in Table B

Posture Score B

Step 11: Add Coupling Score
Well fitting Handle and mid rang power grip, ***good: +0***
Acceptable but not ideal hand hold or coupling
acceptable with another body part, ***fair: +1***
Hand hold not acceptable but possible, ***poor: +2***
No handles, awkward, unsafe with any body part,
Unacceptable: +3

Coupling Score

Step 12: Score B, Find Column in Table C
Add values from steps 10 &11 to obtain
Score B. Find column in **Table C** and match with
Score A in row from step 6 to obtain Table C Score.

Score B

Step 13: Activity Score
+1 1 or more body parts are held for longer than 1 minute (static)
+1 Repeated small range actions (more than 4x per minute)
+1 Action causes rapid large range changes in postures or unstable base

Figure 3.3: REBA worksheet for operators assessment [126].

potential for injury and designing interventions that enhance worker safety and health.

Revised NIOSH Lifting Equation offers a quantitative approach to evaluate the physical demands involved in lifting tasks. This method uses an equation to calculate a recommended weight limit, which helps prevent lower back injuries by ensuring lifting tasks are within safe limits. The parameters considered include the vertical and horizontal positioning of the object relative to the operator's body, the distance over which the object is moved, the frequency of lifting (i.e., number of lifts per minute), and the total duration of the lifting activity [127]. While highly effective in many settings, the Revised NIOSH Lifting Equation may not accurately reflect the risks associated with asymmetrical lifting tasks, variable load weights, or shifts in work routines. The assessment worksheet used in this method is detailed in Figure 3.4.

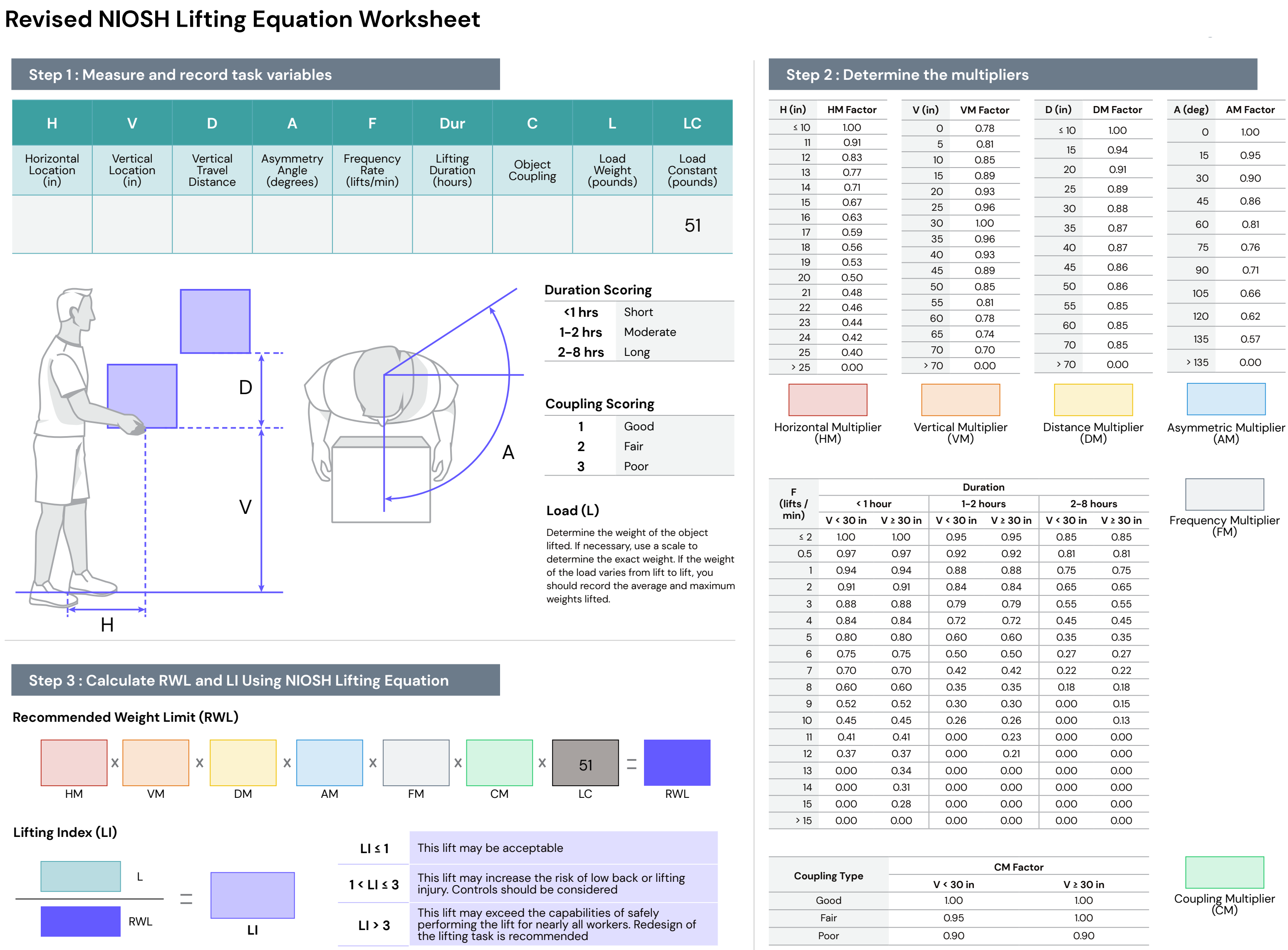


Figure 3.4: Worksheet for the Revised NIOSH assessment to evaluate the injury risks associated with Manual Material Handling tasks [128].

Another critical biomechanic-based assessment tool are the **SNOOK tables**. These tables use similar parameters to those in the NIOSH equation but are derived from extensive population studies. They provide guidelines for acceptable weights and forces for lifting, lowering, pushing, and pulling activities [129]. The SNOOK Tables, illustrated in Figure 3.5, offer a quick reference for ergonomic safety. Yet, they may lack the specificity needed to accommodate individual differences among workers or the unique conditions of specific job tasks [130].

Using the Snook Tables – Examples

Example 1: Above Shoulder Lift

Variables determined by the assessment:

- **Vertical Location - above shoulder lift (54"+)**
- **Frequency - average of 1 lift every 5 minutes**
- **Horizontal Distance – 10" (front of body to mid-line of hands)**
- **Distance of Lift – 30" (lifts from cart at 25" to rack height of 55")**

Above Shoulder
(above 54 in)

Frequency		Horizontal Distance (Front of Body to Hands) [in]: 7 – Distance of Lift [in]: 10	20	30	10 – Distance of Lift [in]: 10	20	30	15 – Distance of Lift [in]: 10	20	30
1 / 8 h	1 / 8 h	35	31	29	29	26	24	26	24	22
1 / 30 min	2 / 1 h	31	26	24	24	22	20	22	20	18
1 / 5 min	12 / 1 h	26	24	22	22	20	18	20	20	18
1 / 2 min	30 / 1 h	26	24	22	22	20	18	20	20	18
1 / 1 min	1 / 1 min	26	24	20	20	20	18	20	18	15
1 / 14 s	4.3 / 1 min	20	20	18	18	18	13	18	18	13
1 / 9 s	6.7 / 1 min	18	18	15	15	15	13	15	15	13
1 / 5 s	12 / 1 min	18	18	13	13	13	11	13	13	11

Design goal = **18 pounds**

Example 2: Floor to Knuckle Lift

Variables determined by the assessment:

- **Vertical Location – floor to knuckle lift (below 29")**
- **Frequency - average of 1 lift every 2 minutes**
- **Horizontal Distance – 10" (front of body to mid-line of hands)**
- **Distance of Lift – 20" (lowers from height of 32" to 4"= 28", rounded to value of 30)**

Floor to Knuckle
(below 29 in)

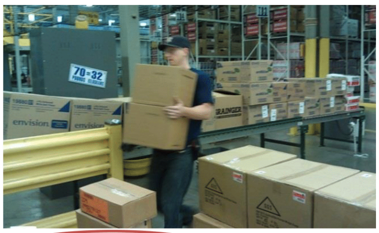
Frequency		Horizontal Distance (Front of Body to Hands) [in]: 7 – Distance of Lift [in]: 10	20	30	10 – Distance of Lift [in]: 10	20	30	15 – Distance of Lift [in]: 10	20	30
1 / 8 h	1 / 8 h	51	48	42	42	40	35	40	37	31
1 / 30 min	2 / 1 h	37	35	31	31	31	26	29	29	24
1 / 5 min	12 / 1 h	33	33	29	29	26	22	26	24	22
1 / 2 min	30 / 1 h	33	33	29	26	26	22	26	24	22
1 / 1 min	1 / 1 min	31	31	26	26	24	22	24	22	20
1 / 14 s	4.3 / 1 min	29	26	24	24	20	20	24	20	20
1 / 9 s	6.7 / 1 min	26	24	22	22	20	18	22	20	18
1 / 5 s	12 / 1 min	22	20	18	18	15	15	18	15	15

Design goal = **22 pounds**

Example 3: Carrying

Variables determined by the assessment:

- **Vertical Location – Carrying at about waist height with elbows bent**
- **Frequency - average of 1 carry every 2 minutes**
- **Distance of Carry – up to 40' (use highest value of 27')**



Carrying at about waist height
(elbows bent)

Frequency		Distance of Carry [ft]: 7	14	27
1 / 8 h	1 / 8 h	46	46	42
1 / 30 min	2 / 1 h	35	35	31
1 / 5 min	12 / 1 h	35	35	31
1 / 2 min	30 / 1 h	33	33	31
1 / 1 min	1 / 1 min	33	33	31
1 / 20 s	3 / 1 min	31	26	26
1 / 10 s	6 / 1 min	29	24	OR

Design goal = **31 pounds**

Example 4: Pulling

Variables determined by the assessment:

- **Vertical Location – Middle pull point**
- **Frequency – 1 pull every 10 minutes (round down to 1 /5 minutes)**
- **Distance of Pull – up to 75' (use value of 97')**

Middle Pull Point
(hands about 36 in)

Frequency		Pull Distance [ft]: 7 Initial	7 Sustained	24 Initial	24 Sustained	48 Initial	48 Sustained	97 Initial	97 Sustained	145 Initial	145 Sustained	194 Initial	194 Sustained
1 / 8 h	1 / 8 h	59	42	55	37	46	31	46	29	46	26	42	20
1 / 30 min	2 / 1 h	57	35	51	31	44	26	42	22	42	20	37	15
1 / 5 min	12 / 1 h	55	33	48	29	42	24	40	20	40	20	35	15
1 / 2 min	30 / 1 h	48	29	44	26	37	22	35	20	35	18	33	13
1 / 1 min	1 / 1 min	46	29	42	24	37	22	33	18	33	15	OR	OR
1 / 30 s	2 / 1 min	46	29	40	24	31	18	OR	OR	OR	OR	OR	OR
1 / 15 s	4 / 1 min	44	26	37	20	OR	OR	OR	OR	OR	OR	OR	OR
1 / 12 s	5 / 1 min	42	26	OR	OR	OR	OR	OR	OR	OR	OR	OR	OR
1 / 6 s	10 / 1 min	35	18	OR	OR	OR	OR	OR	OR	OR	OR	OR	OR

Design goal = **Initial 40 pounds, Sustained 20 pounds**

Figure 3.5: Applications of the SNOOK Tables for defining the acceptable weights and forces for various physical working activities [131].

3.2.3 Multi-aspect Methods for Physical Ergonomics Evaluation

Multi-aspect methods for physical ergonomics evaluation provide a holistic approach to assessing workplace risks. Considering various factors such as posture, force, repetition, and environmental conditions, these methods ensure a comprehensive ergonomic evaluation that addresses both workers' physical and cognitive demands.

Risk Assessment and Management tool for manual handling Proactively (RAMP) employs a comprehensive checklist to systematically identify and manage risks associated with Manual Material Handling (MMH). By evaluating task requirements, worker capabilities, and environmental conditions, RAMP facilitates a structured approach to mitigating potential ergonomic risks. Although RAMP is specifically developed to assess MMH risks, it is generally recommended to use it in conjunction with other tools to ensure a holistic ergonomic evaluation [132]. The RAMP assessment worksheet, which guides the evaluative process, is depicted in Figure 3.6.

Ergonomic Assessment Worksheet (EAWS), another multi-aspect evaluation tool, assesses ergonomic risks by considering various factors, including posture, force, task repetition, and environmental conditions within industrial settings. EAWS aggregates these risk factors into an overall risk score, aiding in the identification of areas needing ergonomic intervention. This method's comprehensive approach makes it highly effective but demands significant expertise for accurate application [134]. The EAWS worksheet, essential for conducting these assessments, is shown in Figure 3.7.

RAMP Worksheet

ACS Chemistry for Life®

Activity Name:	RAMP prepared by:	RAMP reviewed by:
	Date:	Date:

Safety Requirements

These requirements are based on the RAMP analysis documented on the following page(s) of the worksheet.

- Tie back long hair and secure loose clothing.
- Wear appropriate PPE as indicated in the chart to the right.
- Do not eat or drink food or liquids near this activity or demo.
- Clean up and dispose of materials properly when you have finished with this activity or demo.
- Thoroughly wash your hands after conducting this activity or performing this demo.
-
-
-
-
-

Activity facilitators, participants, demo presenters, and spectators must understand and exhibit the behaviors listed above during the preparation, presentation, and dismantling of this activity or demo.

Required PPE

The checked boxes indicate the form(s) of PPE that various people must wear when near this activity or demo.

	Hands-on Activity			Demo		
	Facilitator	Participant	Spectator	Presenter	Onstage volunteer	Spectator
Safety glasses	☐	☐	☐	☐	☐	☐
Splash goggles	☐	☐	☐	☐	☐	☐
Face shield	☐	☐	☐	☐	☐	☐
Food service gloves	☐	☐	☐	☐	☐	☐
Nitrile gloves	☐	☐	☐	☐	☐	☐
Thermal gloves (hot/cold)	☐	☐	☐	☐	☐	☐
Lab coat or apron	☐	☐	☐	☐	☐	☐
Hearing protection	☐	☐	☐	☐	☐	☐

☐ I recommend use of this activity or demo if the risk-lowering measures identified in this document are implemented.

☐ Do not use this activity or demo in an outreach setting.

Recognize the Hazards		Assess Risks	Minimize Risks		Prepare for Emergencies
What happens in each step of the procedure?	What types of hazard(s) does this step pose?	What is the risk level before making changes?	How can we lower risk to an acceptable level?	What is the risk level after implementing changes?	What action will we take if a mishap or injury occurs? (Write the type of emergency as a title, with the protocol for handling it directly beneath.)
		☐ Low ☐ Medium ☐ High		☐ Low ☐ Medium ☐ High	
		☐ Low ☐ Medium ☐ High		☐ Low ☐ Medium ☐ High	
		☐ Low ☐ Medium ☐ High		☐ Low ☐ Medium ☐ High	
		☐ Low ☐ Medium ☐ High		☐ Low ☐ Medium ☐ High	
		☐ Low ☐ Medium ☐ High		☐ Low ☐ Medium ☐ High	
		☐ Low ☐ Medium ☐ High		☐ Low ☐ Medium ☐ High	

Figure 3.6: RAMP worksheet for the assessment of MMH related risks [133].

In addition to physical ergonomics, within the scope of I5.0, it is crucial to address cognitive ergonomics. Cognitive ergonomics focuses on optimizing tasks' mental demands to align with operators' cognitive capabilities. This approach ensures that tasks are neither overly simplistic, leading to boredom, nor excessively complex, causing mental overload. It aims to improve efficiency, mental health, and job satisfaction by considering Mental Workload (MWL) and User Experience (UX). Assessments in cognitive ergonomics typically utilize both objective physiological measures, such as heart rate, brain activity, and eye movement, and subjective self-assessment methods to capture the MWL and UX effectively [136].

3.2.4 Subjective Methods for Assessing Mental Workload and User Experience

Subjective assessment tools are crucial in understanding the Mental Workload and User Experience in industrial settings. These tools allow operators to report their perceptions and experiences directly, providing insights into ergonomic design and task management.

Nasa Task Load Index (NASA-TLX), developed by Sandra Hart at NASA's Ames Research Center in the 1980s, is an effective tool in this domain. It utilizes a multi-dimensional rating system to derive an overall workload score from six distinct subscales:

1. Mental demand: The cognitive and mental demands placed on the operator;
2. Physical demand: The level of physical activity required to perform the task;
3. Temporal demand: The time pressure felt to complete the task;
4. Performance: The operator's perception of their overall performance;
5. Effort: The effort required to achieve the level of performance;
6. Frustration: The stress and annoyance experienced during the task.

Each of these aspects captures a different dimension of the task load, contributing to a comprehensive evaluation of the operator's workload. The factors are weighted according to their relevance to the specific task, allowing for targeted ergonomic interventions. Figure 3.8 displays the standardized worksheet used for this assessment.

Rating Scale Mental Effort (RSME), similar to NASA-TLX, provides a subjective evaluation of mental effort. It consists of a line scale from low to high effort with descriptive labels at each point, helping operators accurately evaluate their experienced MWL. RSME is preferred in settings where quick and simple tools are necessary for immediate feedback [138]. This tool focuses specifically on the mental effort component, as illustrated in Figure 3.9.

Subjective Workload Assessment Techniques (SWAT) evaluates workload by considering three factors:

1. Time load;
2. Mental effort;
3. Psychological stress.

Each factor is rated on a scale from 1 to 3 with descriptions for each level, facilitating a significant understanding of workload components [139]. The SWAT method's worksheet, shown in Figure 3.10, aids in this multi-dimensional assessment.

The **Bedford Workload Scale** offers a uni-dimensional rating system that measures the operator's mental capacity and satisfaction with their workload. Operators use a ten-point scale to rate how well they manage their workload without feeling overwhelmed [140]. This scale, depicted in Figure 3.11, is handy for determining the sustainability of task demands.

Ergonomic Assessment Worksheet v1.3.6 ESO

Plant	Gender of operator m ☐ f ☐		Body height
Line	MTM Analysis		Analyst
Task / Workplace	Task duration [s]	Observation ☐ Planning ☐	Date

Result of overall evaluation:

Calculate the total score of whole body and compare it to the UL score.The overall result is determined by the higher value and the appropriate traffic light is checked. Anyway, interpretation should take into account both values.

	Whole Body	=	Postures	+	Forces	+	Loads	+	Extra	Upper Limbs
☐ Green ☐ Yellow ☐ Red		=		+		+		+		

EAWS evaluation			
0-25 Points	Green	Low risk: recommended; no action is needed
>25-50 Points	Yellow	Possible risk: not recommended; redesign if possible, otherwise take other measures to control the risk
>50 Points	Red	High risk: to be avoided; action to lower the risk is necessary

	Extra points "Whole body" (per minute / shift)							Extra points
0a	Adverse effects by working on moving objects	0 none		3 middle	8 strong		15 very strong	Intensity
0b	Accessibility (e.g. entering motor or passenger compartment)	0 good		2 complicated	5 poor		10 very poor	Status
0c	Countershocks, impulses, vibrations 	0 light		1 visible	2 heavy		5 very heavy	Intensity × frequency
		0 [n]	1 1 - 2	2,5 4 - 5	4 8 - 10	6 18 - 20	8 > 20	
0d	Joint position (especially wrist) 	0 neutral		1 ~ 1/3 max	3 ~ 2/3 max		5 maximal	Intensity × duration or frequency
		0 [s] [n] [%]	2 3 1 5	2,5 10 8 17	4 20 11 33	6 40 16 67	8 60 20 100	
0e	Other physical work load (please describe in detail)	0 none		5 middle	10 strong		15 very strong	Intensity
	Extra = ∑ lines 0a – 0e	note: Max. score = 40 (line 0c, 0d); Max. score = 15 (line 0a, 0e); Max. score = 10 (line 0b)			note: correct evaluation, if duration of evaluation ≠ 60 s			=

Lines 0a-b mainly relate to the Automotive Industry, for other sectors additional elements may be necessary. For details see the EAWS manual.

Shift Duration and Tasks:		
Description	Formula	Result
Real shift duration [min]		
Lunch break [min]	-	
Other official pauses [min]	-	
Non repetitive tasks (i.e. cleaning, supplies, etc) [min]	-	
Net duration of repetitive task/s (a) [min]	=	
No. of real units (or cycles) (b)		
Net cycle time [s]	(a/b × 60) =	
Idle Time [s]		

Comments / proposals for improvements

Basic Postures / Postures and movements of trunk and arms — Postures

(incl. loads of <3 kg,
forces onto fingers of <30 N
and whole body forces of <40 N)

Static postures: ≥ 4 s

High frequency movements:
Trunk bendings (> 60°) ≥ 2/min
Kneeling/crouching ≥ 2/min
Arm liftings (> 60°) ≥ 10/min

Symmetric: Evaluation of static postures and/or high frequency movements of trunk/arms/legs

Duration [s/min] = duration of posture [s] × 60 / Task duration [s]

Asymmetric: Trunk Rotation 1) · Lateral Bending 1) · Far Reach 2)

No.			Posture											Sum of lines	Trunk Rotation 1) int (0-5)	Trunk Rotation 1) dur (0-3)	Lateral Bending 1) int (0-5)	Lateral Bending 1) dur (0-3)	Far Reach 2) int (0-5)	Far Reach 2) dur (0-2)
			[%]	5	7,5	10	15	20	27	33	50	67	≥ 83		Intensity × Duration		Intensity × Duration		Intensity × Duration	
			[s/min]	3	4,5	6	9	12	16	20	30	40	≥ 50							
			[min/8h]	24	36	48	72	96	130	160	240	320	≥400							
Standing (and walking)																				
1			Standing & walking in alteration, standing with support	0	0	0	0	0,5	1	1	1	1,5	2							
2			Standing, Confined space	0,7	1	1,5	2	3	4	6	8	11	13							
3	20° 0° 60°	a	Bent forward (20-60°)	2	3	5	7	9,5	12	18	23	32	40							
		b	with suitable support	1,3	2	3,5	5	6,5	8	12	15	20	25							
4		a	Strongly bent forward (>60°)	3,3	5	8,5	12	17	21	30	38	51	63							
		b	with suitable support	2	3	5	7	9,5	12	18	23	31	38							
5		a	Elbow at/above shoulder level	3,3	5	8,5	12	17	21	30	38	51	63							
		b	With S01 exoskeleton	2,5	3,8	6,4	9,0	13,1	16,2	23,1	29,0	39,0	48,0							
6		a	Hands above head level	5,3	8	14	19	26	33	47	60	80	100							
		b	With S01 exoskeleton	4,1	6,2	11,0	14,8	20,0	25,5	36,5	46,5	62,0	77,5							
Sitting																				
7			Upright with back support slightly bent forward or backward	0	0	0	0	0	0	0,5	1	1,5	2							
8			Upright no back support (for other restriction see Extra Points)	0	0	0,5	1	1,5	2	3	4	5,5	7							
9			Bent forward	0,7	1	1,5	2	3	4	6	8	11	13							
10		a	Elbow at / above shoulder level	2,7	4	7	10	13	16	23	30	40	50							
		b	With S01 exoskeleton	1,9	2,8	4,9	7,0	9,1	11,2	16,1	21,0	28,0	35,0							
11		a	Hands above head level	4	6	10	14	20	25	35	45	60	75							
		b	With S01 exoskeleton	2,8	4,2	7,0	9,8	14,0	17,5	24,5	31,5	42,0	52,5							
Kneeling or crouching																				
12			Upright	3,3	5	7	9	12	15	21	27	36	45							
13			Bent forward	4	6	10	14	20	25	35	45	60	75							
14		a	Elbow at / above shoulder level	6	9	16	23	33	43	62	80	108	135							
		b	With S01 exoskeleton	5,2	7,8	13,9	20,0	29,1	38,2	55,1	71,0	96,0	120,0							
Lying or climbing																				
15			Lying (on back, breast or side) w/ arms above head	6	9	15	21	29	37	53	68	91	113							
16			Climbing	6,7	10	22	33	50	66											
														∑ (a)	∑ (max.=15)		∑ (max.=15)		∑ (max.=10)	
															∑ (max. = 40) (b)					

1)

Trunk		0	1	3	5
int		slightly	medium	strongly	extreme
		≤10°	15°	25°	≥30°
dur		0	1,5	2,5	3
		never	4 s	10 s	≥ 13 s
		0%	6%	15%	≥ 20%

2)

Far Reach		0	1 (0,75)	3 (2,25)	5 (3,75)
int		close	60%	80%	arm stretched
dur		0	1	1,5	2
		never	4 s	10 s	≥ 13 s
		0%	6%	15%	≥ 20%

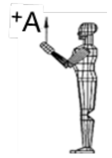
note: Max. duration of evaluation = duration of task or 100%!

note: correct evaluation, if task duration ≠ 60 s

Postures = ∑ lines 1 - 16	(a)	+	(b)	=	

Action forces (per minute) — Forces

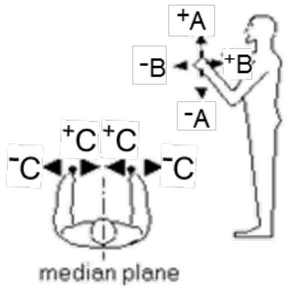
17	Forces onto fingers (e.g. clips, plugs)								Intensity × Duration
	Int		0	7	15	25	50		
			16,7% F_{max}	33,3% F_{max}	50,0% F_{max}	66,7% F_{max}	F_{max}		
	Duration stat	0	1	1	1,5	2	3,5	7	
		[s]	3	6	9	12	20	≥ 30	
		[%]	5	10	15	20	33	≥ 50	
	Duration dyn	0	1,5	2	2,5	3			
		[n]	4	10	15	≥ 20			



18	Forces onto arms / whole body forces								Intensity × Duration
	Int		0	6	15	25	50		
			16,7% F_{max}	33,3% F_{max}	50,0% F_{max}	66,7% F_{max}	F_{max}		
	Duration stat	0	1	1	1,5	2	4	8,5	
		[s]	3	6	9	12	20	≥ 30	
		[%]	5	10	15	20	33	≥ 50	
	Duration dyn	0	1	2	3	4,5	6,5	10	
		[n]	1	3	6	8	10	≥ 12	

Forces Fmax onto arms / whole body forces

M for males & F for females



Data based on the "Assembly specific force atlas" (Wakula, Berg, Schaub, Glitsch, Ellegast 2009)

	ST Upright M	F	ST Bent M	F	ST Above head M	F
+A	480	315	435	285	430	280
-A	500	325	370	240	495	320
+B	320	210	400	260	305	200
-B	485	315	605	390	480	310
+C	290	185	310	200	210	140
-C	255	165	205	135	210	140

	KN Upright M	F	KN Bent M	F	KN Above head M	F
+A	420	270	380	245	425	275
-A	430	280	345	225	495	320
+B	445	290	495	320	410	270
-B	495	325	445	290	425	275
+C	300	195	290	190	275	180
-C	245	160	205	135	280	180

	SI Upright M	F	SI Bent M	F	SI Above head M	F
+A	405	265	385	250	395	255
-A	440	285	375	245	455	295
+B	405	260	455	295	365	240
-B	380	250	425	275	370	240
+C	250	165	270	175	200	130
-C	235	155	205	135	210	135

Finger forces Fmax (F=Female M=Male)

Posture	F_{max} M	F_{max} F
Posture A1 (power grip, pliers)	315	205
Posture A2 (ball of the thumb)	235	155
Posture B1 (thumb or thumb to 4 fingers)	110	70
Posture B2 (index or wide pinch)	75	50
Posture C (hook, palmar, strong pinch)	85	55

Action forces = ∑ lines 17 - 18	note: correct evaluation, if task duration ≠ 60s	=	

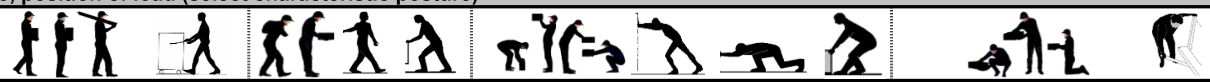
Manual Material Handling (per shift) — Loads

Weights of loads [kg] for repositioning (lifting / lowering), carrying and holding as well as pushing and pulling

+											
	Reposition, carrying & holding		Male (kg)	3	10	15	20	25	30	35	≥40
			Load points	1	1,5	2	3	4	10	17	25
			Female (kg)	2	5	7	10	12	15	20	≥25
			Load points	1	1,5	2	3	4	5,5	7	25

Pushing and pulling											
M1	Wheelbarrows and Dollies	Male (kg)	50	75	100	150	200	≥ 250			
		Female (kg)	40	60	80	115	155	≥ 195			
M2	Carriage, trolleys. No fixed rollers	Male (kg)	50	75	100	150	250	350	≥ 550		
		Female (kg)	40	60	80	115	195	270	≥ 425		
M3	Carts, roller conveyors, pallet truck	Male (kg)	50	75	150	250	350	500	600	800	≥ 1250
		Female (kg)	40	60	115	195	270	385	460	615	≥ 960
Load points	**Means of transport**		0,5	1	1,5	2	3	4	5	6	8

Posture, position of load (select characteristic posture)



+				
	trunk upright and / or not twisted load at the body	little trunk bending or twisting; load at or close to the body	bending trunk deep or far forward; little trunk bending forward and trunk twisting simultaneously; load far from body or above shoulder level	Asymmetric postures (bending trunk far forward and twisting; load far from the body; limited postural stability while standing or crouching) or kneeling
Posture points	1	2	4	8

Working Conditions (pushing and pulling only)

(+)	very low rolling resistance	trolley pushing / pulling on (very) slick floor	rough floor and above small gaps / edges	on structured sheet metal, into / out of a track	trolleys have to be teared off when starting, strongly damaged floor	very high rolling resistance
Conditions points	0	1	3	5	6	8

Frequency of load manipulations [frequecy/shift], holding time [min/shift] or travel distance [meter/shift]

×										
Frequency (#) of repositionings / pushing & pulling short	5	25	120	350	750	1000	1500	2000	2500	≥ 3000
Duration (holding time) [min]	2,5	10	37	90	180	≥ 240				
Distance (carrying, pushing & pulling long) [m]	300	650	2500	6000	12000	≥16000				
Duration points	1	2	4	6	8	10	11	13	14	15

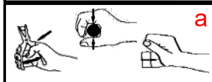
Manual Material Handling (result)

19	(Load + posture + (condition points)) × duration points	Repositioning 1)	(+) × =	Holding 1)	(+) × =	Carrying 1)	(+) × =	Pushing & Pulling short 1)	(+ +) × =	Pushing & Pulling long 1)	(+ +) × =

Handling = ∑ line 19	1) Maximal cumulative duration points for all tasks of repositioning, holding, carrying as well as pushing & pulling all together = 15	=	

Upper limb load in repetitive tasks	**Upper Limbs**

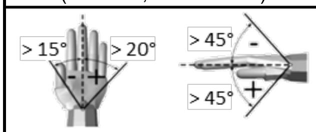
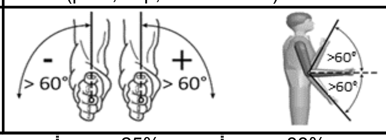
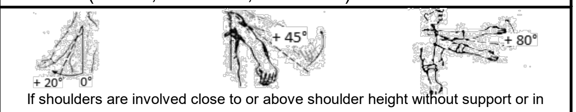
Force & Frequency & Grip (FFG)	Basis: number of real actions per minute or percent static actions (analyze only the most loaded limb)

Grip	Legend	
a  power grip/contact grip	%SA = Percentage of Static Actions	%DA = 100% - %SA
	FDS = Force-Duration Static	FFD = Force-Frequency Dynamic
b  finger or moderate pinch (thumb to >2 fingers, finger)	GS' = Modified Grip Points Static (Grip x %SA)	GD = Grip Points Dynamic
	%FLS = Percentage of Static Actions at force level	%FLD = Percentage of Dynamic Actions at force level
c  strong pinch (thumb to 1 or 2 fingers)	SC = Static Contribution	DC = Dynamic Contribution
	FDGS = Sum of Static Contributions	FFGD = Sum of Dynamic Contributions

Force [N]	Calc Stat				Static actions (s/min)						Grip			Dynamic actions (real actions/min)								Calc Dyn			
	FDS	GS'	%FLS	SC	≥45	30	20	10	5	3	0	2	4	2	10	15	20	25	30	35	≥40	FFD	GD	%FLD	DC
0 – 5					1	1	0	0	0	0	abc			0	0	0	1	2	3	4	7				
> 5 – 20					4	2	1	1	0	0	ab	bc		0	0	1	2	3	4	6	9				
> 20 – 35					7	5	3	2	1	1	ab	b	c	0	1	2	3	4	6	8	12				
> 35 – 90					11	8	5	3	2	1	a	b	b	1	2	3	5	7	9	12	18				
> 90 – 135					16	11	7	4	3	2	a	ab	b	2	3	5	7	9	12	15	***24***				
> 135 – 225					***21***	14	10	6	4	3	a	a	b	4	5	6	8	11	14	***20***	***32***				
> 225 – 300					***28***	18	12	8	5	4	a	a	b	5	6	7	9	12	16	***26***	***40***				

20a	FDGS = $\sum SC_i$	100%	**FFG** = FDGS + FFGD	FFG	%DA = ΣFLD_j	FFGD = $\sum DC_j$	%DA

Hand / arm / shoulder postures (use duration for worst case of wrist / elbow / shoulder)

20b	Wrist (deviaton, flex./extens.)	Elbow (pron, sup, flex./extens.)	Shoulder (flexion, extension, abduction)
			 If shoulders are involved close to or above shoulder height without support or in awkward postures, multiply score ×3

Posture points	10%	25%	33%	50%	65%	85%	PP
Wrist/Elbow	0	0,5	1	2	3	4	
Shoulder	0	1,5	3	6	9	12	
Shoulder w/exosk	0	1,1	2,3	4,5	6,8	9	

Additional factors

20c			
	Gloves inadequate (which interfere with the handling ability required) are used for over half the time	2	☐
	Working gestures required imply a countershock. Frequency of 2 time per minute or more (i.e.: hammering over hard surface)	2	☐
	Working gestures imply a countershock (using the hand as a tool) with freq. of 10 time per hour or more	2	☐
	Exposure to cold or refrigeration (less than 0 degree) for over half the time	2	☐
	Vibrating tools are used for 1/3 of the time or more	2	☐
	Tools with a very high level of vibrations	4	☐
	Tools employed cause compressions of the skin (rednesses, callosities, blebs, etc.)	2	☐
	Precision tasks are carried out for over half the time (tasks over areas smaller than 2-3 mm)	2	☐
	During almost the whole time one or more additional factor/s is/are present	3	☐
	Additional points (choose the highest value)	=	AF

Repetitive tasks duration

20d								
	Net Duration [min/shift]	60	90	180	300	420	480	+
	Shift Points (1 hour = 1 point)	1	1,5	3	5	7	8	

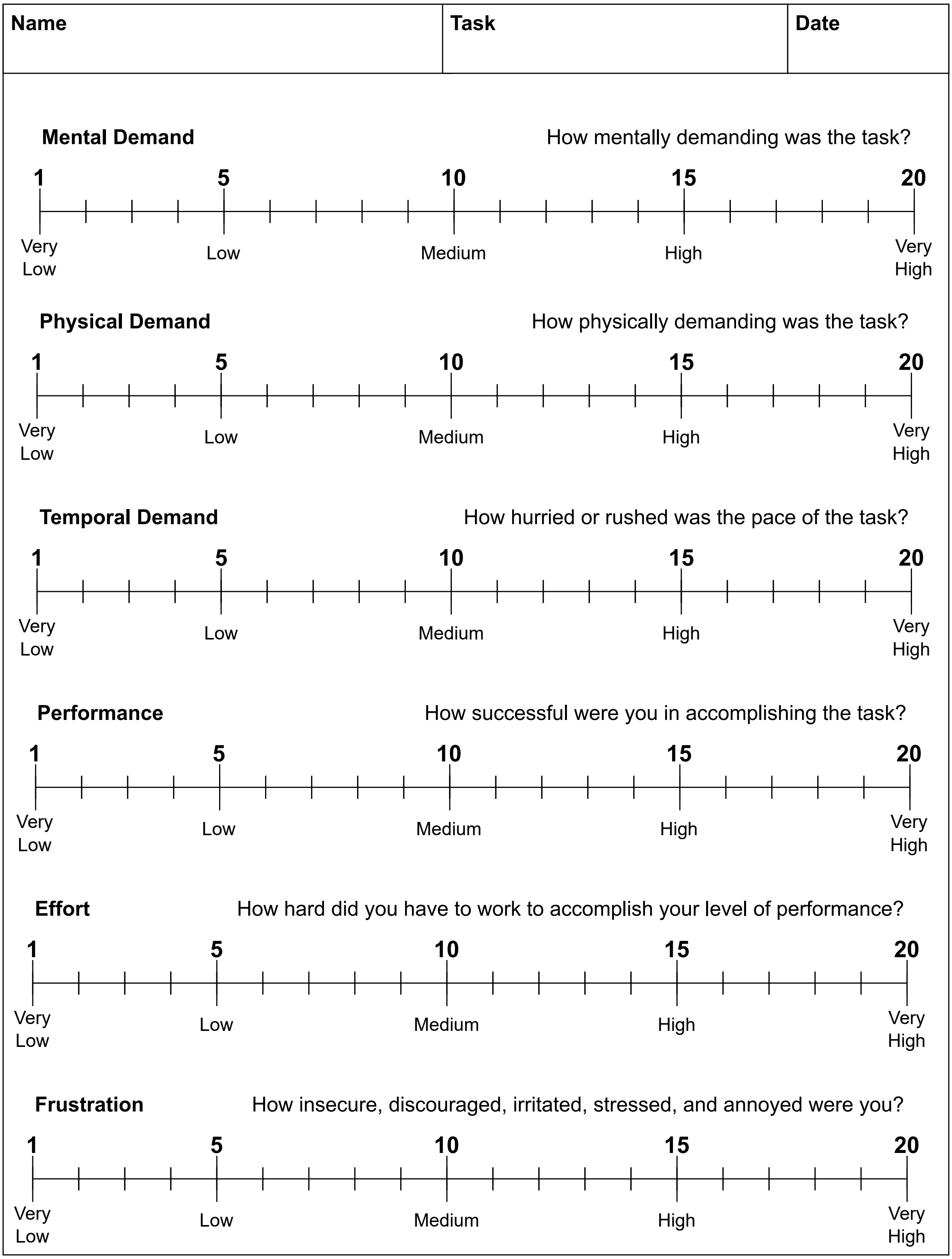
20d	Work Organization	Breaks are possible at every time (Cycle time longer than 10 minutes)	Breaks are possible at given conditions (Cycle time between 1 and 10 minutes)	Breaks lead to a stop of the process (Cycle time shorter than 1 minute)	+
	Work Organization Points	0	1	2	

20d	Breaks (≥ 8 min) [#/shift]	0	1	2	3	4	5	6	≥7	
	Break points *cycle time ≤ 30 s*	3	2	1	0	-1	-2	-3	-4	+
	cycle time > 30 s	0		-0,5		-1		-1,5	-2	
	Duration Points									= DP

Upper limb load in repetitive tasks

20	(a) Force & Frequency & Grip (FFG	+	(b) Postures PP	+	(c) Additional factors AF)	×	(d) Duration DP	=	Upper Limbs

Figure 3.7: EAWS worksheet [135].



Name	Task	Date

Mental Demand How mentally demanding was the task?

1 5 10 15 20

Very Low, Low, Medium, High, Very High

Physical Demand How physically demanding was the task?

1 5 10 15 20

Very Low, Low, Medium, High, Very High

Temporal Demand How hurried or rushed was the pace of the task?

1 5 10 15 20

Very Low, Low, Medium, High, Very High

Performance How successful were you in accomplishing the task?

1 5 10 15 20

Very Low, Low, Medium, High, Very High

Effort How hard did you have to work to accomplish your level of performance?

1 5 10 15 20

Very Low, Low, Medium, High, Very High

Frustration How insecure, discouraged, irritated, stressed, and annoyed were you?

1 5 10 15 20

Very Low, Low, Medium, High, Very High

Figure 3.8: NASA-TLX worksheet for workload assessment [137].

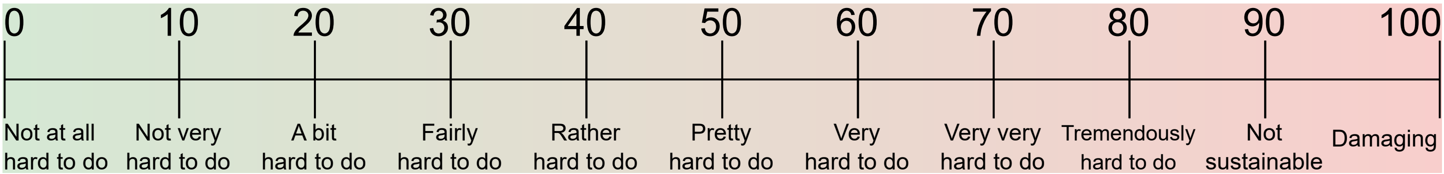
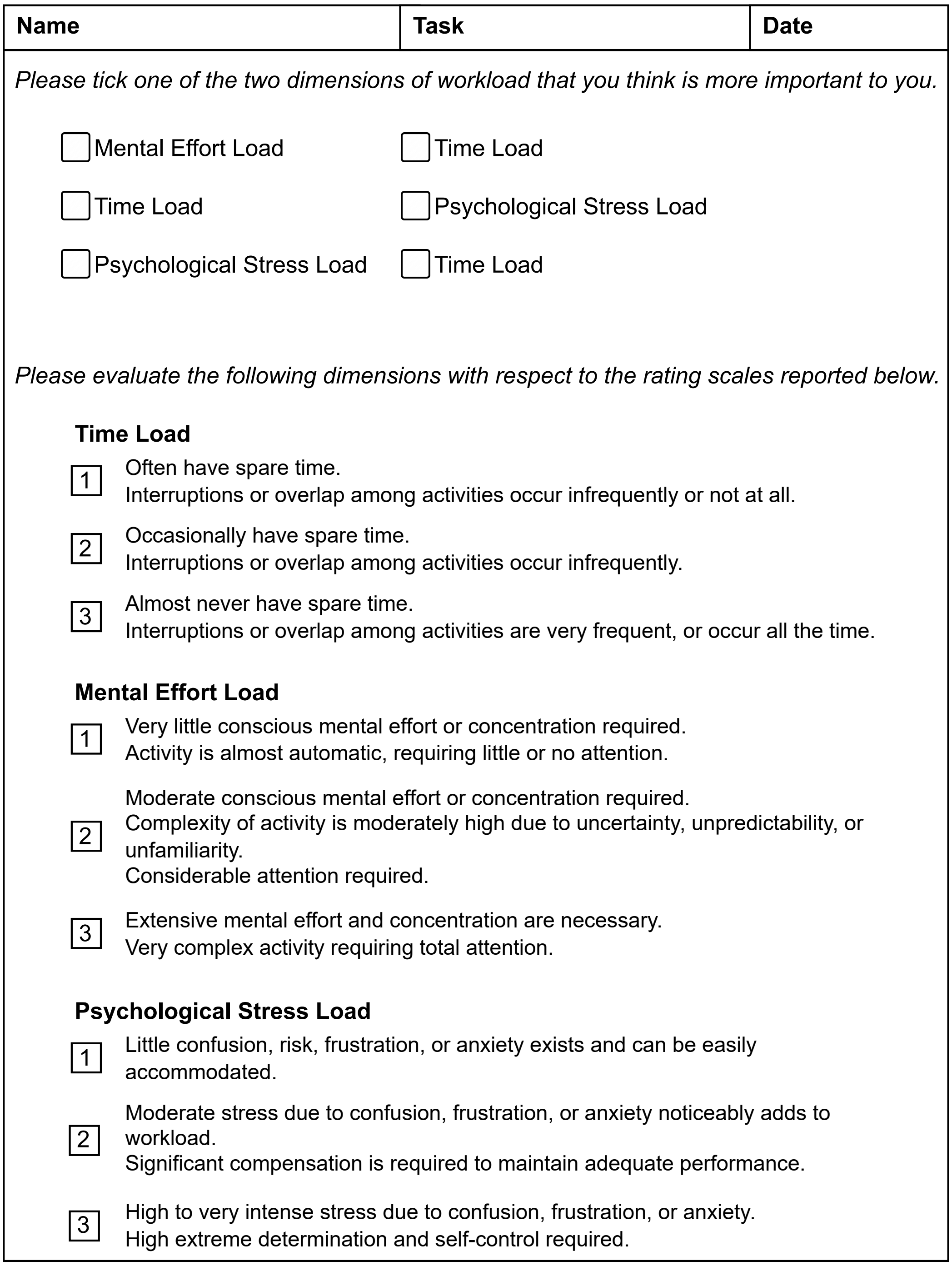


Figure 3.9: RSME worksheet for the subjective evaluation of mental effort [138].



Name	Task	Date

Please tick one of the two dimensions of workload that you think is more important to you.

☐ Mental Effort Load ☐ Time Load

☐ Time Load ☐ Psychological Stress Load

☐ Psychological Stress Load ☐ Time Load

Please evaluate the following dimensions with respect to the rating scales reported below.

Time Load

1 Often have spare time.
Interruptions or overlap among activities occur infrequently or not at all.

2 Occasionally have spare time.
Interruptions or overlap among activities occur infrequently.

3 Almost never have spare time.
Interruptions or overlap among activities are very frequent, or occur all the time.

Mental Effort Load

1 Very little conscious mental effort or concentration required.
Activity is almost automatic, requiring little or no attention.

2 Moderate conscious mental effort or concentration required.
Complexity of activity is moderately high due to uncertainty, unpredictability, or unfamiliarity.
Considerable attention required.

3 Extensive mental effort and concentration are necessary.
Very complex activity requiring total attention.

Psychological Stress Load

1 Little confusion, risk, frustration, or anxiety exists and can be easily accommodated.

2 Moderate stress due to confusion, frustration, or anxiety noticeably adds to workload.
Significant compensation is required to maintain adequate performance.

3 High to very intense stress due to confusion, frustration, or anxiety.
High extreme determination and self-control required.

Figure 3.10: SWAT worksheet for workload assessment [139].

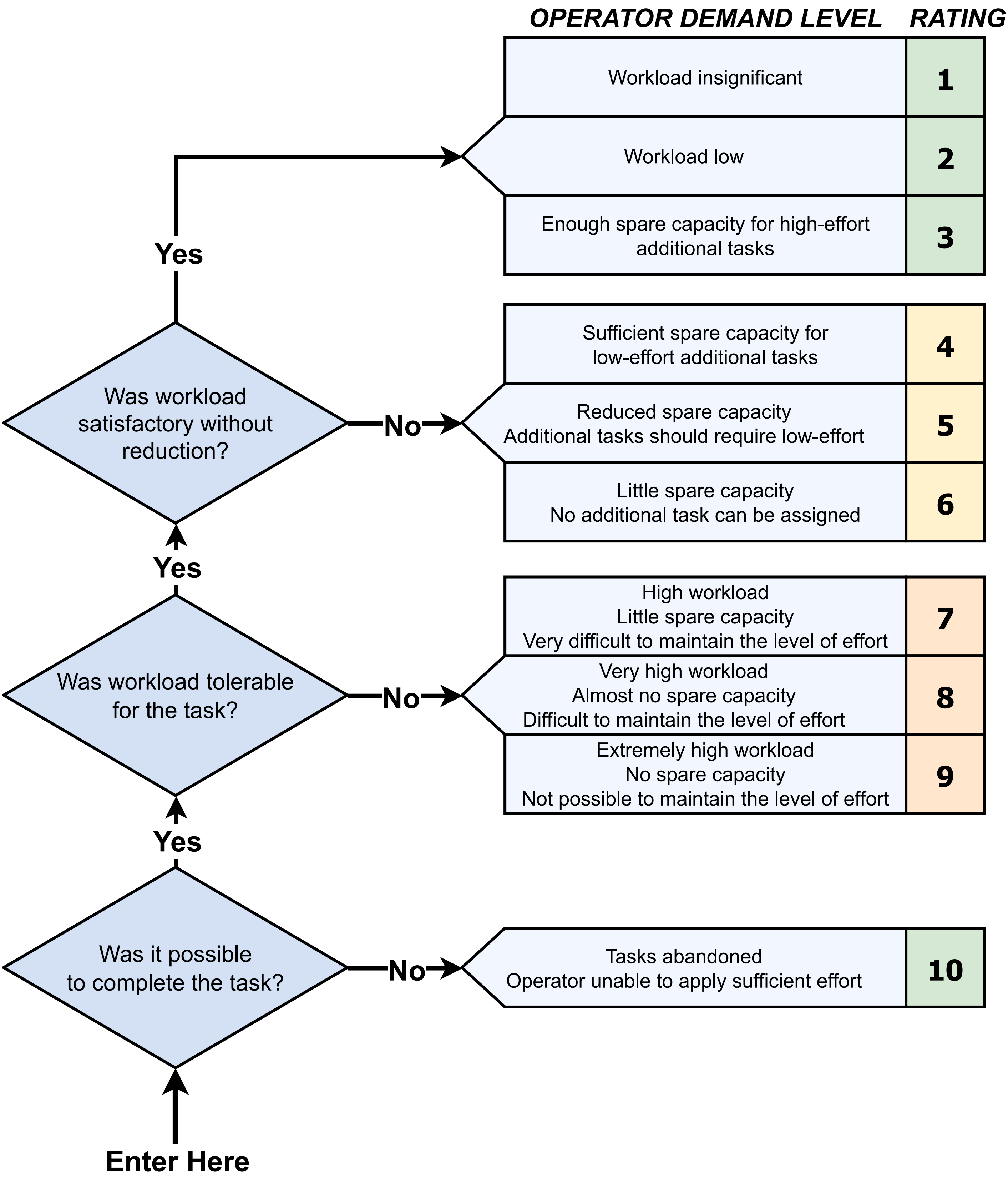


Figure 3.11: Bedford Workload Scale for the assessment of mental capacity and satisfaction of operators [140].

Chapter 4

Framework Development

The Industry 5.0 paradigm emphasizes the interplay between human capabilities and technological advancements, with a strong focus on enhancing operator welfare in industrial environments. Building on the definition of the human factors taxonomy discussed in Section 3.1 and the methodologies for their assessment explored in Section 3.2, the next step towards a more worker-centric industrial future lies in the development of a comprehensive approach that combines data collection, processing, analysis, and interventions strategies to address risks to operators welfare both reactively and proactively. This integration enables the establishment of a dynamic, closed-loop system capable of responding to current industrial conditions and anticipating future ones, setting a new standard for predictive assessment systems in industrial settings.

The proposed framework is structured into three distinct yet interconnected modules, each playing a critical role in implementing both reactive measures and proactive strategies:

1. **Data Collection Module**: Central to the framework, this module gathers a wide range of data, including workers' biometric parameters, environmental conditions within the industrial workspace, and machinery operational statuses. This broad spectrum of collected data is crucial for comprehensively analyzing the interactions between operators and their environments, setting the stage for effective predictive analysis.

2. **Data Analytics and Predictive Modelling Module**: Provided with extensive data, this module processes and analyzes the information to identify patterns and trends essential for predicting potential hazards and enhancing operator welfare. It facilitates reactive measures and preemptive

strategies by offering insights that help anticipate and mitigate risks before they occur.

3. **Intervention Techniques Module**: Informed by the analytics module, this component defines strategic responses designed to enhance workplace safety and improve the health and well-being of operators. The interventions, customized to individual and environmental needs, range from ergonomic adjustments to emergency responses, all aimed at fostering a safer and more supportive industrial workspace.

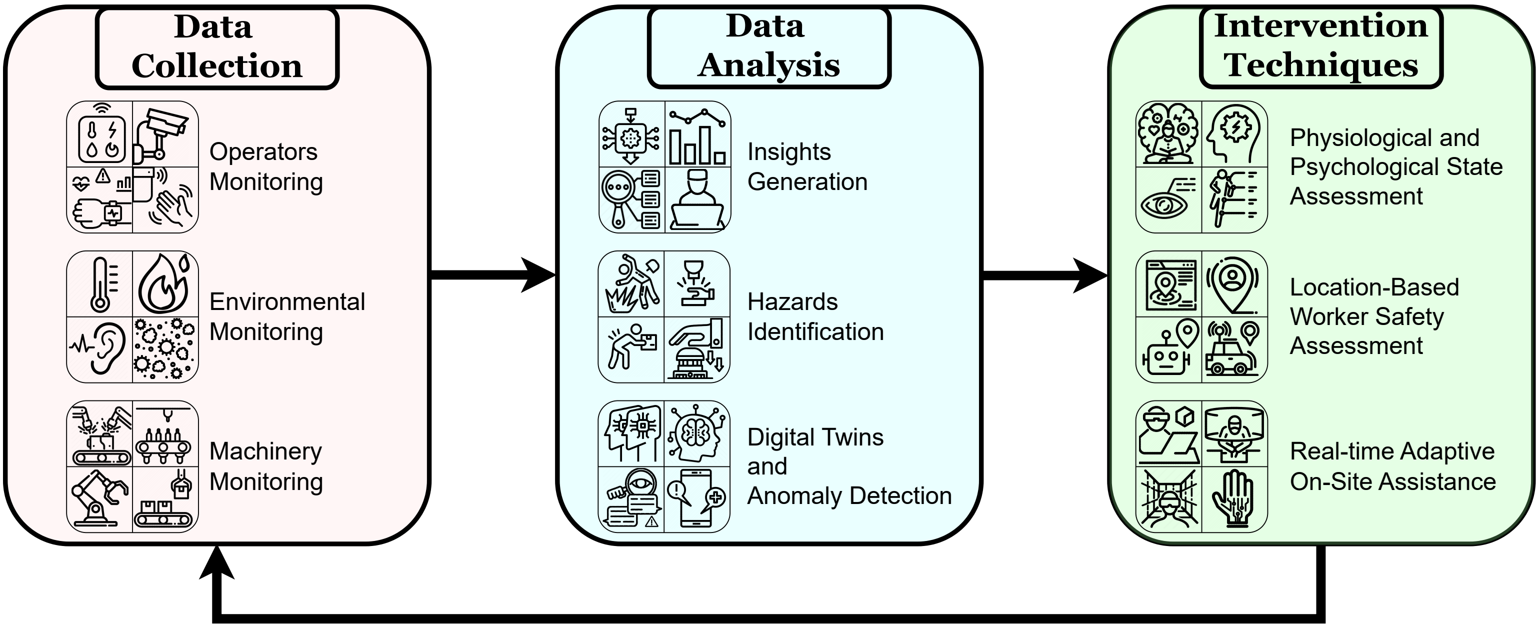


Figure 4.1: Flowchart illustrating the three modules of the framework and their main components.

This dynamic framework operates on a continuous feedback loop, allowing for constant refinement and adaptation based on evolving data insights. It facilitates an industrial environment that is both productive and supportive, evolving dynamically to meet the changing needs of human operators. Furthermore, it is a living system designed to maintain flexibility and responsiveness to ensure sustained operator welfare and system efficiency.

This Chapter begins with an in-depth exploration of the three core modules that compose the framework. Each module is specifically examined for its distinct functions, interactions, and contributions toward establishing a balanced and effective system that enhances operator welfare and productivity. The discussions presented in the last Section of this Chapter will evaluate the framework's overall impact, addressing its limitations, implementation challenges, and potential areas for future research and development.

4.1 Data Collection Module

The Data Collection Module is the foundational component of this framework, having the critical role of acquiring real-time data essential for the subsequent analysis processes. As outlined in Section 3.1, four key elements should be considered for enhancing the defined human factors: the operators, their working environment, the machinery in use, and the operational tasks performed. Accordingly, this module is strategically divided into four primary components:

1. **Operators Monitoring and Assessment**;
2. **Environment Monitoring**;
3. **Machinery Monitoring**;
4. **Operation Monitoring**.

Each component focuses on a specific aspect of the industrial setting, ensuring a comprehensive data-gathering approach that captures every critical variable. Subsequent subsections detail the technologies employed in this process, which enable the passive and continuous collection of data crucial to deriving actionable insights.

4.1.1 Operators Monitoring and Assessment

In the context of I5.0, data collection about human operators is fundamental to enhancing workplace ergonomics and optimizing the interactions between humans and machines. The collected data informs immediate safety measures and contributes to long-term health management and ergonomic interventions, which are essential for supporting an effective human-technology synergy.

Wearable Devices

Wearable devices are among the most effective technologies for monitoring operators. These devices are preferred for their direct contact with the user, non-intrusive nature, and easiness of integration into daily work routines through incorporation into clothing, accessories, and Personal Protective Equipments (PPEs) [96].

Heart monitoring is a critical function of wearable devices. Popular commercial products like *Apple Watch* and *Garmin Fenix*, along with specialized chest bands like *Polar H10* and *Garmin HRM Pro Plus*, offer robust accurateness for measuring heart rate, blood pressure, and oxygen saturation. These devices provide essential data for assessing cardiovascular health and stress levels in real-time, although they differ in accuracy and specific capabilities [102].

The mechanics of heath rate monitoring in smartwatches involve *photoplethysmography*, in which a green light emitted from the device is used to measure blood volume changes under the skin. Specifically, the rear of the smartwatch contains an optical sensor to detect the reflected light. The device measures the change in concentration of red blood cells as the blood vessels expand and contract: expanded blood vessels absorb more green light, and contracted blood vessels absorb less green light. The detector measures the reflected green light, and a software algorithm converts the changes in light intensity into pulse rate and blood pressure [141]. More recent devices can also detect complex cardiovascular conditions like atrial fibrillation (i.e., irregular heartbeat) with significant precision [142]. Despite their widespread usage, the accuracy of smartwatches can be affected by various variables, such as skin pigmentation and the physical separation between the light source and the sensor. Indeed, it is limited by the fact that the light source and the detector are positioned on the same side, making the detector entirely dependent on the amount of light reflected from the sample, i.e., the blood.

The approach used for measuring blood oxygen is similar. The smartwatch shines a red light to target hemoglobin, the protein particle in the blood responsible for carrying oxygen. Depending on how much oxygen it is transporting, it will absorb more or less wavelengths of light. Therefore, the reading of the reflected light will provide the percentage of oxygen in the blood [143].

On the other hand, chest bands provide measurements via Electrocardiogram (ECG), capturing electrical pulses from the heart to offer precise and rapid heart rate data, leading them to be more accurate and faster than smartwatches. Indeed, while a smartwatch can take around 10 to 30 seconds to provide a reliable measurement, chest bands like the *Polar H10* declare to have a frequency of 1000 Hz, which is 1 ms [144]. For what concerns accuracy, while smartwatches show an accuracy comprised between 80% and 88%, chest bands exhibit a precision of 99.6%. Therefore, the best approach for collecting data about the operators' cardiovascular and respiratory features is to use both simultaneously.

Additional monitoring technologies include Inertial Measurement Unit (IMU) sensors, which can capture detailed motion data across various body segments. Considering that any human motion can be divided into a series of displacements of the torso or the limbs, an IMU sensor is a device able to measure the moving object's acceleration, velocity, and orientation using a combination of accelerometers, gyroscopes, and magnetometers [96]. Consequently, the body-mounted IMU can measure body parts' movements, detecting accelerations, falls, abnormal postures, and changes in joints and articulations.

IMU sensors can also recognize hand and finger gestures and, if used as head-mounted displays, also measure head motions such as head nod, head shake, yawning, looking up, looking down, and some activities such as walking, turning, and crouching [145, 146, 147, 148].

Electroencephalography (EEG) sensors also play a pivotal role in collecting data about operators. They are sensors used for monitoring the power levels of brainwaves, enabling them to obtain information regarding mental states such as vigilance, sleep, and stress, and mental intentions, including feeling confident, confused, or stressed, in performing a task [105, 149]. In practice, monitoring the change of alpha (between 12 Hz to 30 Hz) and beta brainwaves (ranging between 8 Hz to 12 Hz) could determine if the mental state is changing from alert to non-alert, increasing the risk of accident [96].

Furthermore, it is possible to use pressure sensing mats to capture the standing states, and smart eye-wear containing cameras to perceive the surroundings from the first-person view of the operator as well as his facial features and eye movements, and Electromyography (EMG) sensors can be used to obtain the muscle activities [115].

Regarding the capturing of the operators' positions, the first approach is using smartphones since their built-in GPS, along with triangulations with Wi-Fi and accelerometers, enable the tracking of movements and locations [46]. Another possibility is to use RFID sensors or Bluetooth Low Energy (BLE) sensors, which, with properly disseminated actuators, can enable the detection of humans in certain areas of the factory. These technologies can also be applied as smart labels, allowing the tracking of parts, components, and equipment [85].

Finally, by integrating these sensors into bodysuits, we can collect data about joints, muscles, and other body metrics, along with heart and breathing rates,

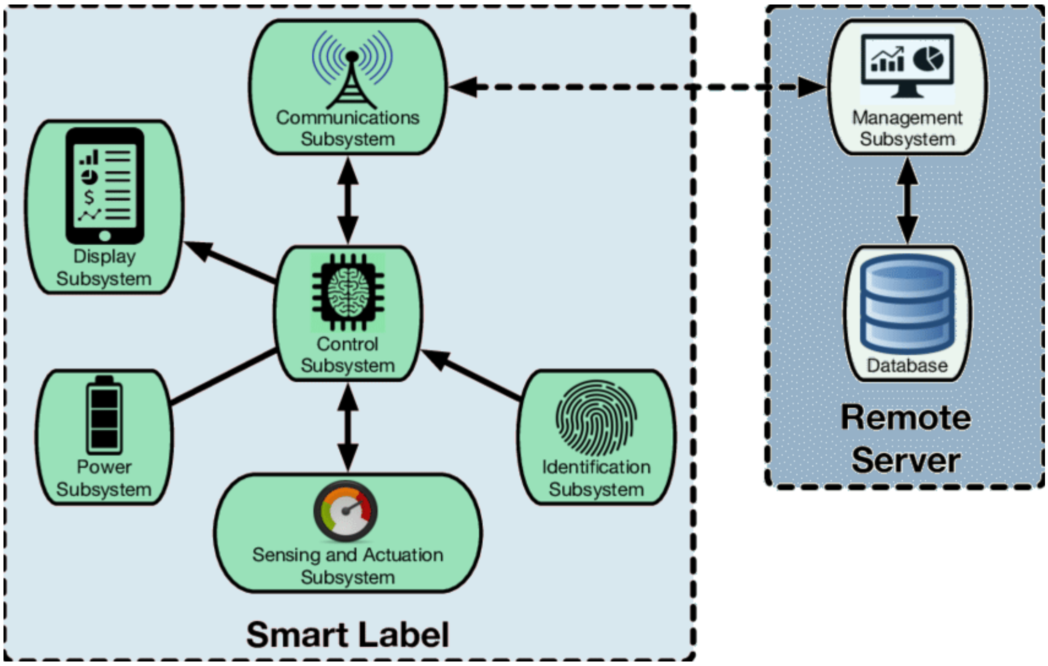


Figure 4.2: The basic architecture of smart labels [85].

to obtain even more details about musculoskeletal stress and posture in a less disturbing and all-in-one option. Bodysuits enable gathering all the sensors mentioned in that paragraph in a single comprehensive solution [111]. Another possibility for gathering all these sensors is to merge them in a safety helmet, which also enables the monitoring of operators wearing Personal Protective Equipments [96].

Imaging Systems

Imaging systems enhance operator assessment by providing real-time visual monitoring capabilities. The system can detect movements, count personnel, and monitor safety compliance across various zones within the industrial setting, thereby enforcing safety in I5.0 environments that may include CoBots and humans in the loop [150].

Depending on the needs and industrial environmental conditions, standard, thermal, infrared, or depth-sensing cameras can be employed to better capture the aspects of interest. In particular, the adoption of infrared and thermal cameras increases the probability of detecting humans in low-visibility conditions compared to conventional RGB cameras. Moreover, thermal cameras improve the system's sensitivity to non-medical-grade human-related activities since they focus on heat source detection. However, we should consider that thermal cameras are sensitive to temperature changes caused by their intrinsic variation during the day and other external factors. That must be taken into account by applying compensation mechanisms [151].

By deploying an imaging system in an industrial environment, it is feasible to implement a map that corresponds to the worksite. That map can be modified dynamically in response to detected alterations in the worksite, show each worker's location, and detect when an accident occurs [83].

Imaging systems can also be used to promptly trigger alarms in hazardous work areas, detect falling objects, and automatically register real-time job logs and operators' movement paths to reduce non-productive repetitive tasks and eliminate the errors caused by handwriting.

Cameras can also be positioned on the workstation. A top-camera view placed on the workbench can capture data to identify the actions carried out by operators during their work. A camera positioned at the side can serve for posture recognition, enabling the assessment and monitoring of posture changes throughout the workday. Moreover, by placing a camera in front of the operator on the worktable or mounted on the operator's helmet, we can recognize the face of the individual engaged in the activity, enabling the capturing of facial features associated with eyes and mouth to compute metrics such as Eye-opening Frequency (PERCLOS), Eye-aspect Ratio (EAR), and Mouth-aspect Ratio (MAR) [87].

4.1.2 Environment Monitoring

Environmental conditions within industrial settings critically influence both human performance and workplace safety. To effectively monitor these factors, fixed sensors within the workplace are the technology of choice since they can provide continuous and unobtrusive data collection.

The primary environmental risks in industrial environments include dust, chemicals, toxic gases, and potential fire hazards. To appropriately assess these, a comprehensive family of sensors is required, each designed to detect specific environmental pollutants and conditions:

- **Dust Sensors:** These sensors measure particulate matter levels such as *PM-1.0*, *PM-2.5*, and *PM-10*, providing data critical for assessing air quality and the presence of hazardous airborne particles.

- **Gas Sensors:** Various gases pose significant health risks in industrial settings. Sensors for *Oxygen* (O_2), *Carbon Monoxide (CO)*, *Hydrogen Sulfide*

(H_2S), *Methane (CH_4)*, and *Hydrogen (H_2)* can be deployed to monitor air quality and detect leakages or hazardous accumulations.

These sensors help maintain regulatory compliance and play a crucial role in ensuring workplace health and safety. Continuous monitoring allows for the timely detection of environmental anomalies, enabling immediate corrective actions to mitigate potential risks.

The types of environmental risks typically encountered in most industrial processes are outlined in Table 4.1, which provides a quick reference for identifying common hazards associated with specific manufacturing stages.

Table 4.1: Environmental risk factors [84].

Process	Factors
Machinery Receiving	Dust
Preprocessing	Dust
Part Fabrication	Dust
On-block Outfitting	Dust, fire, explosion
Part Assembly	Dust, fire, explosion, oxygen deficiency
Block Assembly	Dust, fire, explosion, gas choking
Painting	Dust, fire, explosion, gas choking
Pre-Election	Dust
Election	Dust, suffocation, fire, explosion
On-block Outfitting	Dust, fire, explosion

4.1.3 Machinery Monitoring

To advance workplace safety and operational efficiency, the developed I5.0 framework also demands accurate monitoring of both fixed and moving machinery. This monitoring is crucial not only for maintaining machinery performance but also for ensuring operator safety by preemptively identifying potential hazards. Both share the need to monitor potential threats, abnormal vibrations or sounds, and deviations from normal operating conditions.

Fixed Machinery Monitoring

In various manufacturing processes, stationary machinery requires constant vigilance to detect deviations from standard operating conditions that might indicate failures. The integration of the following sensors facilitates a comprehensive monitoring [112]:

- **Vibration Sensors:** These sensors detect unusual vibrations that could denote mechanical issues or misalignments within machinery.

- **Acoustic Sensors:** By capturing sound data, these sensors can identify abnormal noises or changes in operational sounds indicative of mechanical wear or failures.

- **Temperature Sensors:** Monitoring temperature variations can help detect overheating issues before they lead to machinery breakdowns.

- **Visual Inspection Cameras:** Cameras positioned around machinery provide real-time visual monitoring, enabling early detection of issues like leaks, breaks, or other visible signs of tears.

Machinery in Movement Monitoring

Machinery in motion presents additional challenges, particularly regarding operator safety and mechanical integrity. To address these obstacles, it is possible to employ [46, 112]:

- **Proximity Sensors:** These sensors are crucial for maintaining safe distances between mobile machinery and operators, helping to prevent accidents and collisions.

- **Speed Sensors:** Monitoring the machinery's speed helps ensure that all operations are performed within safe limits.

- **Current Sensors:** These sensors provide data on the electrical aspects of machinery, helping to predict potential electrical failures.

- **Load Monitoring:** For equipment that transports or handles heavy loads, it's vital to monitor the weight and stability to prevent overloads that could lead to equipment failure and pose risks to nearby operators.

4.1.4 Operation Monitoring

The last component of the Data Collection Module concerns operation monitoring, fundamental in the context of I5.0 to capture data related to potentially hazardous or stressful operations performed by operators. These operations might include dynamic activities such as hammering, welding, and lifting, as well as

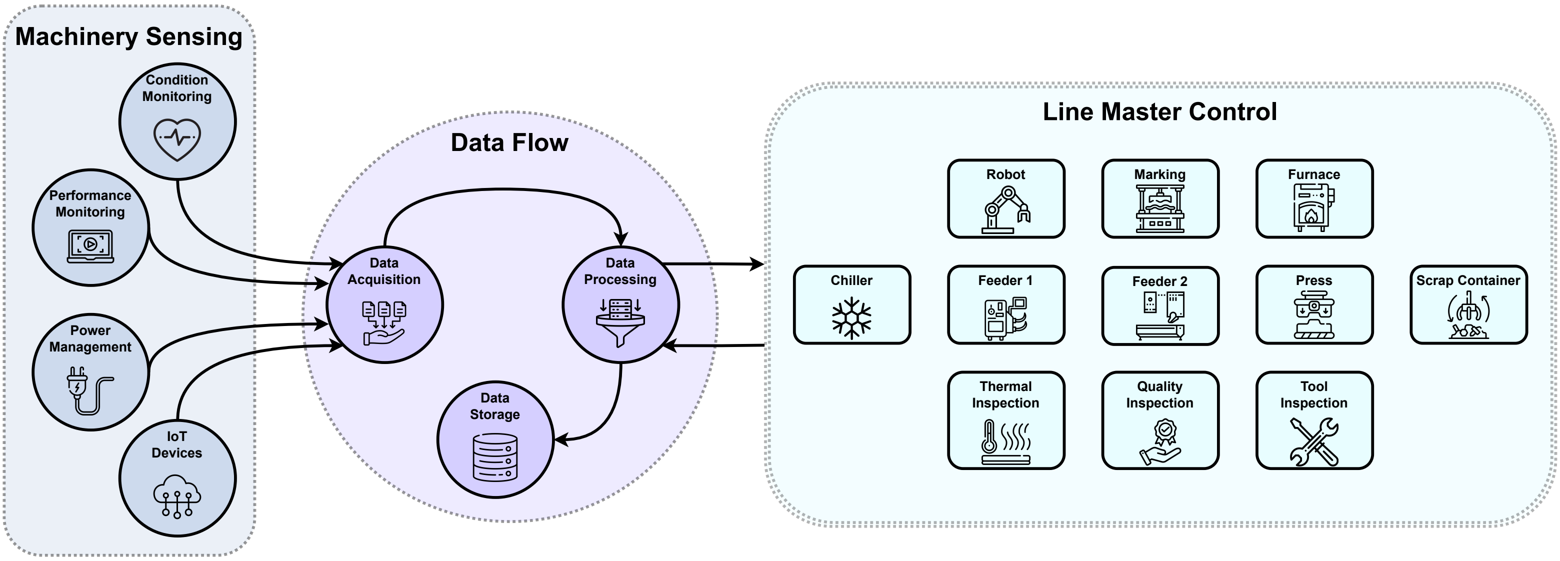


Figure 4.3: A possible setup for monitoring stationary and mobile machinery [152].

tasks requiring high precision or mental stress, such as assembly information recall or verification of task outcomes.

To effectively monitor these operations, the framework integrates a variety of technologies [66, 115]:

- **Close-look Imaging Systems:** Technologies such as smart glasses and workstation-mounted cameras play a crucial role in monitoring detailed task execution and ensuring adherence to safety protocols.
- **Disseminated Imaging Systems:** Cameras strategically placed around the work environment provide a comprehensive view, enabling the supervision of compliance with operational procedures and safety measures.
- **Wearable Devices:** Devices like smart gloves and wristbands are essential for tracking hand movements and muscle activity during tasks, providing insights into operators' ergonomic and physical demands.

The monitoring should also extend to operations involving potentially hazardous components, leveraging:

- **Sensor Deployment:** Existing sensor technologies can detect the presence of hazardous materials or conditions, such as toxic gases or extreme temperatures.
- **RFID and Camera Integration:** RFID tags and cameras facilitate the real-time identification and tracking of hazardous equipment, ensuring that any risks are immediately recognized and managed [85, 153].

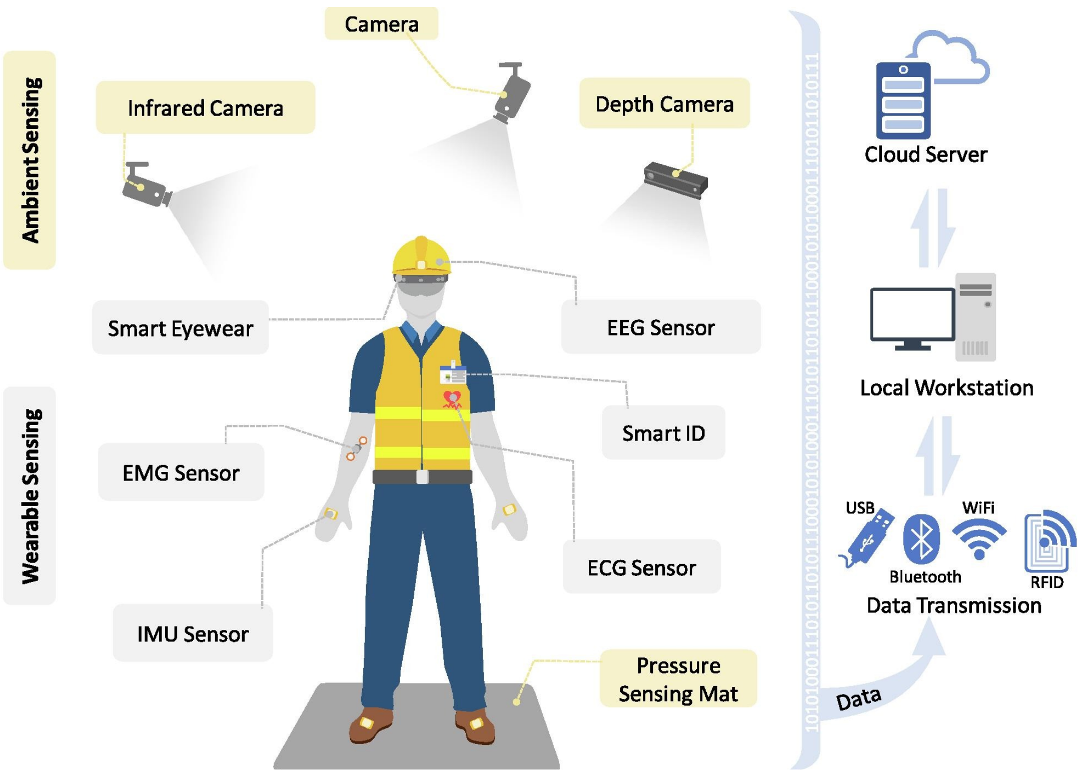


Figure 4.4: An example of an integrated setup illustrating the deployment of sensors, cameras, and wearable devices for operator monitoring [115].

4.2 Data Analytics and Predictive Modelling Module

The Data Analysis and Predictive Modelling Module serves as the analytical core of the framework, carefully analyzing the vast volume of collected data to identify patterns, trends, and imminent risks to human operators' safety, health, and well-being. This module processes the data using sophisticated algorithms and statistical techniques to extract actionable insights. These insights are fundamental to developing predictive models capable of anticipating and forecasting potential hazards for human operators.

This module is structured into four key components:

1. **Location-based Worker Safety Assessment**: Utilizing positional and motion data, this component focuses on monitoring and forecasting the movements, behaviors, and activities of operators within the workspace to enhance situational safety.

2. **Physiological and Psychological Operators Assessment**: This element deals with the analysis of data related to operators' physical and mental health, aiming to optimize their overall welfare and job satisfaction.

3. **Environmental Data Analysis**: Dedicated to examining environmental parameters, this component ensures that the conditions of the working ambient remain safe and facilitate productivity and comfort.

4. **Digital Twin Simulation**: Integrating data from all collection points, this part utilizes Digital Twins to simulate real-world scenarios, thus enhancing the predictive capabilities of the framework.

4.2.1 Location-based Worker Safety Assessment

This component utilizes position and movement data captured through wearable devices and imaging systems deployed on the shop floor to perform various analyses. It is crucial to detect operators within different zones, monitor their movements, ensure safe distances from machinery, and enforce virtual fences around restricted or hazardous areas [153].

To maximize safety, a redundant mechanism should be established using both imaging and position data to ensure accuracy and minimize false negatives. Two methods can be concurrently employed when using imaging systems: one to detect movements and the other to identify regions of interest within a frame. Both methods need to work simultaneously to determine if humans are present in an image. Indeed, a positive detection of human presence results from either method indicating activity: only when both agree on the absence of human presence a negative result is provided (i.e., no humans have been detected). Basically, it is like putting a logic OR between the two detection approaches [150].

The process employs direct subtraction of image matrices:

1. The first frame serves as the background reference. Subsequent frames are subtracted from this background, and if the resulting frame shows minimal pixel variation, it indicates the absence of new movement, and this frame becomes the new reference. The latter operation ensures the following comparison is performed with the most recent reference.

2. Significant changes, indicated by active pixel groups meeting a predefined threshold (e.g., 5% of total pixels), indicate movement. To better clarify, considering, for instance, an image having a resolution of 160 x 120 pixels,

its size will be 19200 pixels. A movement will be detected only when at least 5% of those pixels, i.e., 960 pixels, are considered active. Otherwise, the algorithm finds no significant movement, and no detection is signalized. The threshold can be adjusted for different conditions or to improve the algorithm sensitivity.

This approach allows for a good trade-off between performance and computing power because it does not rely on a compute-intense algorithm to identify humans in a frame, like most Machine Learning (ML) and Artificial Intelligence (AI) approaches available, enabling the reduction of the latency time, something crucial when dealing with location and movements data since a prompt response can stop machinery or alert operators before a dramatic incident happens. Additionally, no previous model training is required. Therefore, this approach can be easily implemented in an edge-like device with low energy consumption, computational power, and cost.

Building upon historical data on movements and positions, a predictive module can employ ML techniques, particularly those based on time-series analysis such as LSTM (Long Short-Term Memory), to forecast potential future operator locations and movements based on the current and past ones [154, 155].

These predictions enable proactive safety measures and operational efficiency by [156]:

- Analyzing and optimizing operators' movement paths relative to the workplace layout, suggesting more efficient routes and workflow improvements.
- Identifying patterns in operators' activities that may lead to physical strain or fatigue, proposing adjustments to mitigate health risks and enhance comfort.

4.2.2 Physiological and Psychological Operators Assessment

Analyzing physiological and psychological data collected from human operators is crucial for ensuring their overall welfare in industrial environments. Through the integration of multi-modal sensing techniques, such as EEG for brain activity, ECG for heart activity, and various sensors for musculoskeletal activity, this assessment helps ensure the well-being of operators by identifying potential issues in their physical and mental states.

Data from wearable and imaging technologies provide valuable information on operators' physical and mental health. By combining these data, we can

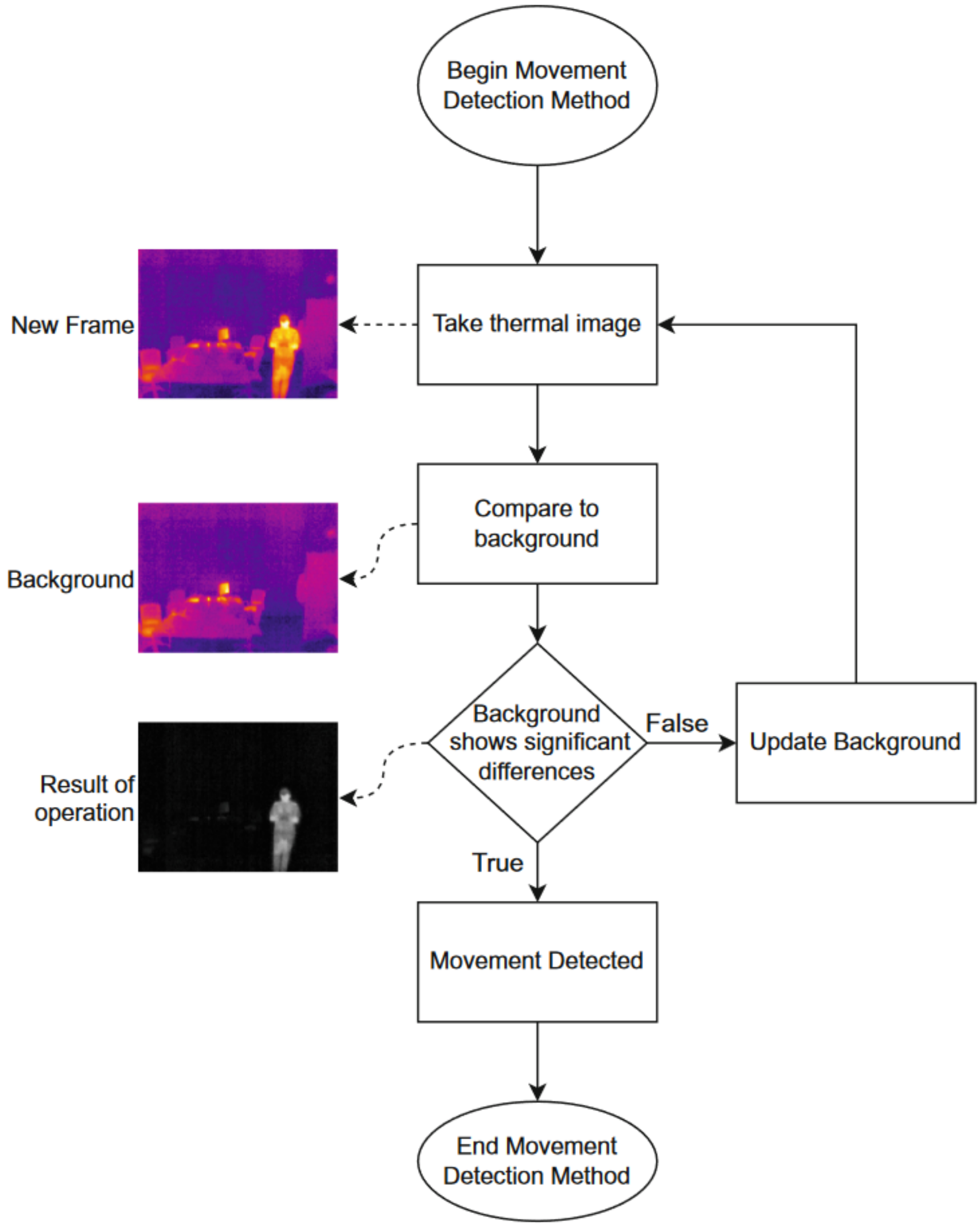


Figure 4.5: Workflow of the movement detection algorithm using image subtraction technique [150].

extract meaningful features that inform about the operators' current state. For example, head and torso movements recorded through sensors help identify and classify operator actions and motions. In that scope, it is possible to outline a dictionary of gestures, as the one illustrated in Figure 4.6, defining acceptable and non-acceptable motions in a workflow [96]. The head motions are sorted into two groups of basic actions corresponding to torso stillness and moving. The two bold axes in the images constitute the moving plane of corresponding head motion.

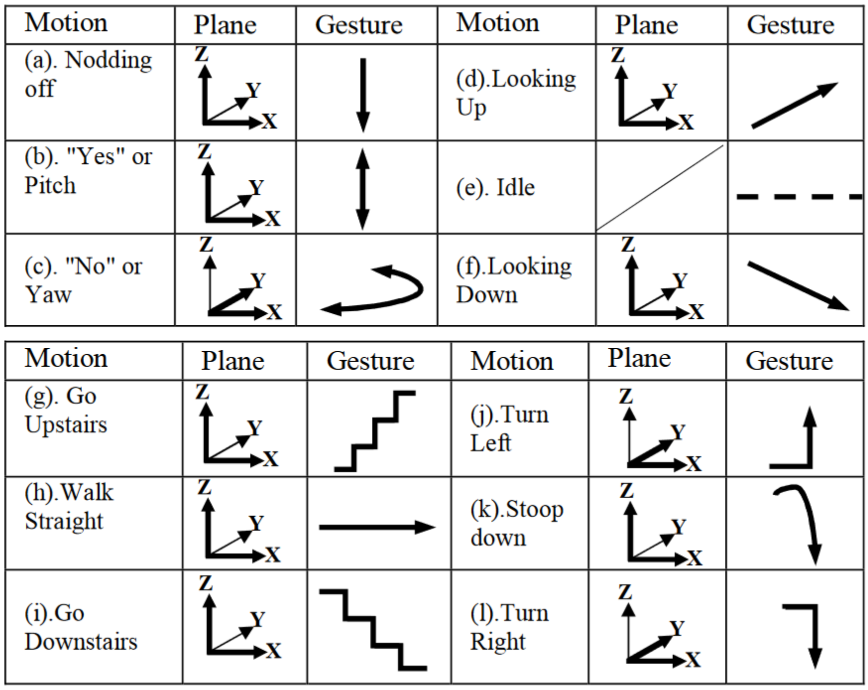


Figure 4.6: The dictionary of head motions at torso stillness (a-f) and at torso moving (g-l) [96].

We can supplement this gesture dictionary with the mental states extracted from EEG, which can be sorted into three groups, defined as:

1. **High-risk states**: fatigue or stress;

2. **Middle-risk states**: beginning of fatigue or stress;

3. **Low-risk states**: vigilant.

This categorization is based on the energy in specific frequency bands (Alpha and Beta) calculated using Fast Fourier Transform [96].

Furthermore, utilizing a matrix that combines physical actions with mental states, namely merging IMU and EEG data, it is possible to compute the accident severity level of potential risks. Each physical action, linked with corresponding mental stats, is scored and classified into risk levels ranging from 1 (low) to 3 (high), according to its underlying relationship with the accident or injury severity. Formally, the score multiplication of head motion and mental state determines the severity level. Table 4.2 shows some samples about how to evaluate the severity level. The results are categorized into three class levels: "*Low*", "*Middle*", and "*High*".

Table 4.2: Severity level determination sample [96].

	Vigilant (1)	Beginning of Fatigue or Stress (2)	Fatigue or Stress (3)
Torso Moving (1)	Low (1)	Low (2)	Middle (3)
Torso Stillness (2)	Low (2)	Middle (4)	High (6)
Nodding off (3)	Middle (3)	High (6)	High (9)

Subsequently, the accident risk level is determined by:

$$Risk = P \cdot O \cdot S \tag{4.1}$$

where O is the occurrence, S is the severity, and P the probability of accident. When a certain non-acceptable motion is repeated, the O value is increased in proportion. The severity S is determined from the data fusion of head gesture and mental states defined in Table 4.2. P is the probability of the accident, computed from the Energy weight of alpha and beta brainwaves using Fast Fourier Transform (FFT), as:

$$Weight_{\alpha} = \frac{\sum_{8}^{12} E_{freq}}{E_{total}} \tag{4.2}$$

$$Weight_{\beta} = \frac{\sum_{12}^{30} E_{freq}}{E_{total}} \tag{4.3}$$

Where E_{freq} is the energy inside the sub band frequency for each brainwave parameters and E_{total} is the total energy of all frequency spectrum.

According to Equations (4.1), (4.2), and (4.3), we can determine a severity score from 1 to 9, representing low, middle, and high-risk levels. As a result, a risk level determination and related actions can be defined as in Table 4.3

Table 4.3: Risk level determination and action.

Values	Risk Levels	Action
0 - 5	Low	Continue monitoring the status
6 - 10	Middle	Convey an alert to operator
> 10	High	Stop the machine tool or process

To complement this assessment, we can consider the data related to cardiovascular activity. Heart Rate is analyzed starting from *RR interval time series*, which is the series of time of occurrence of heartbeats [157]. It collects time intervals occurring between consecutive heartbeats, where the occurrence of a heartbeat is detected from R peaks [158]. Thus, the *RR series* is defined as:

$$RR = \{RR_k\,;\, k = 1, \ldots, N\} = \{R_{k+1} - R_k\,;\, k = 1, \ldots, N\} \tag{4.4}$$

where R_k is the instant of occurrence of the k-th beat and N is the number of beats occurring during a measurement session.

While Heart Rate undergoes normal physiological oscillations, the way it varies provides relevant information on the autonomic neural regulation of the heart and circulatory system, which, ultimately, is influenced by fatigue states [102]. To this end, assessment of Hearth Rate Variability (HRV) turns out to be helpful. HRV is typically analyzed considering a set of established metrics in the time and frequency domain [157, 158].

Time-domain metrics include statistical indices such as :

- the mean value of the RR series (*mean RR*):

$$\text{Mean RR} = \frac{1}{N}\sum_{k=1}^{N} RR_k \tag{4.5}$$

- the standard deviation of the RR series (*SDNN*):

$$\text{SDNN} = \sqrt{\frac{1}{N-1}\sum_{k=1}^{N}(RR_k - \text{Mean RR})^2} \tag{4.6}$$

- the root mean square of successive differences (*RMSSD*):

$$\text{RMSSD} = \sqrt{\frac{1}{N-1}\sum_{k=1}^{N-1}(RR_{k+1} - RR_k)^2} \tag{4.7}$$

- the percentage number of consecutive (normal) intervals differing by more than 50 ms in the entire recording (*pNN50*):

$$pNN50 = \frac{\#\text{ of intervals with}|RR_{k+1} - RR_k| > 50\text{ms}}{N} \times 100 \tag{4.8}$$

On the other hand, **frequency-domain metrics** account for:

- RR series power in the low frequency band (*LF*, 0.04-0.15 Hz):

$$LF = \sum_{f=0.04}^{0.15} P(f) \tag{4.9}$$

- RR series power in the high frequency band (*HF*, 0.15-0.40 Hz)

$$HF = \sum_{f=0.15}^{0.40} P(f) \tag{4.10}$$

- The ratio of low-frequency power to high-frequency power (*LF/HF ratio*):

$$\text{LF/HF ratio} = \frac{LF}{HF} \tag{4.11}$$

According to [102], there are significant statistical differences between rest and physical fatigue (*R-P*) and rest and mental-physical combined fatigue (*R-M&P*) for all of these performance measures. Interestingly, no significant differences were observed between the physical fatigue conditions and the joint physical and mental fatigue conditions. This suggests that physical fatigue causes a greater degree of variability in Heart Rate than mental fatigue, which hides this last when both sources of fatigue are present at the same time. Consequently, it is possible to conclude that it is challenging to identify mental exhaustion when other factors contribute to physical exhaustion.

Once these features are extracted, Machine Learning models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) can be employed to understand worker behavior and predict potential risks. The first comprises both spatial and temporal perspectives (e.g., walking towards a workstation, turning a screwdriver, etc.). At the same time, the latter includes mental activities related to specific tasks, such as having confidence in or feeling confused about a specific operation [115]. This helps in assessing worker performance and identifying the need for guidance or intervention. The operator's performance can be evaluated in comparison to the one exhibited by experienced workers, and a "*Demanding Score*" can be defined to represent the level of demand for support. Specifically, considering the time taken for each operational step, the *Demanding Score* is increased proportionally if a particular action takes more time than average. Then, if the *Demanding Score* is higher than a threshold, there should be the automatic triggering of assistance actions enabling the provision of guidance at the right time, which has to be timely enough but not disturb the ongoing operation.

By integrating the data on actions performed, blinking frequency, and posture changes, it is also possible to derive insights into the operator's fatigue level. By considering these key factors, the global level of fatigue experienced by operators during their work activities is defined using the following equation [87]:

$$fs = off \cdot \alpha + pff \cdot \beta + \frac{\sum_{1}^{nTask}(tts)}{nTask} \cdot \gamma + b \tag{4.12}$$

where

- fs = fatigue scoring
- α = fatigue scoring adjustment factor
- off = ocular fatigue factor
- β = ocular fatigue adjustment factor
- pff = positional fatigue factor
- $nTask$ = number of tasks
- tts = time task scoring
- γ = positional fatigue factor adjustment factor
- b = bias for personal adjustment of the operator

The equation consists of the following parts:

- **Ocular fatigue component**: Performed via imaging systems, either integrated on smart eye-wears or on the workstations. Although the face has many more features than eyes that can be used for fatigue assessment, such as Mouth-aspect Ratio (MAR), Frequency of Mouth (FOM), and yawning, the processing of all of these slows down the system performance, disrupting the ability to perform timely interventions [97, 159]. Therefore, reducing the focus on eyes detection is more convenient and appropriate. The computer vision workflow enabling that detection is illustrated in Figure 4.7, and it consists of the following steps [160]:

  1. Eyes detection on a new frame or after significant movement;
  2. Eyes tracking and Eye-aspect Ratio (EAR) evaluation;
  3. Eye closure detection and evaluation of the blinking rate.

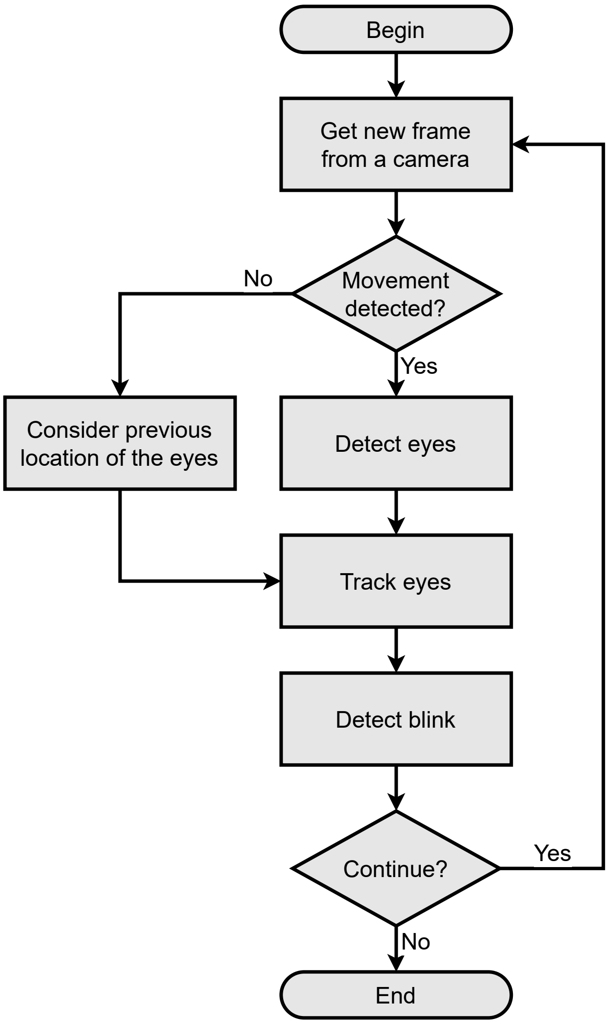


Figure 4.7: Workflow of the blink detection algorithm [150].

Eye detection can be done employing the Viola-Jones algorithm [161], commonly used for fast appearance-based detection of different kinds of objects. The Haar-like features are the input to the classifier and are specified by their shapes, positions within the region of interest, and scale, as shown in Figure 4.8 [162].

A classifier trained to detect both eyes can be used to improve the accuracy of blink detection. As a matter of fact, only involuntary blinks, in which both eyes close simultaneously, correlate with an individual's emotional-physical state [159]. As a result, if the system only records the closure of one eye while the other is open, it indicates that the blink is voluntary and should be ignored.

Given that the camera is fixed to a table, integrated into a laptop or

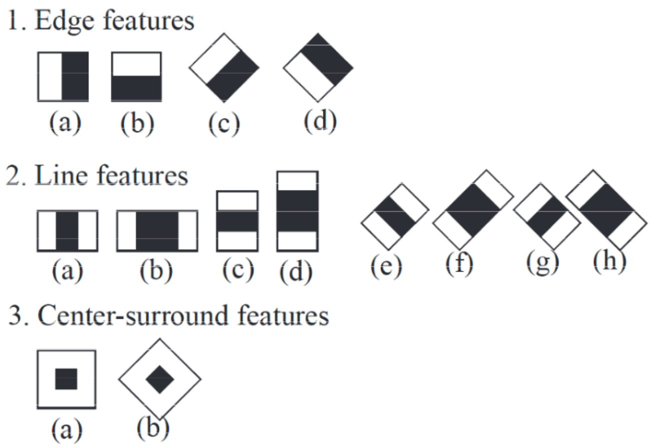


Figure 4.8: Example of Haar-like features for cascade training [162].

mounted on smart glasses, and that the average acquisition speed is approximately 30 frames per second, the difference between each subsequent frame is negligible, provided that the subject of the work does not move quickly or frequently and that the background is mainly static [160]. As a result, eye tracking can improve system performance by limiting the eye region's detection to moments when a notable frame change occurs.

Concerning blink detection, the first step is to compute the difference between each eye's current and previous frames separately. Then, the current frame is considered to contain a blink only if the number of different pixels exceeds the established threshold. Equation (4.13) defines the Boolean value *F(t)*, defining the detection of a blink in the frame t. Here, $mask_r(t)$ and $mask_l(t)$ are the difference masks between current and previous frames for right and left eyes, respectively. *CARD()* gives the cardinality of the input mask, and T is the predefined threshold, computed as a minimal number of pixels that should differ from classifying a blink.

$$F(t) = \begin{cases} 1, & \left(\frac{\sum mask_r(t)}{\text{CARD}(mask_r(t))} > T \text{ and } \frac{\sum mask_l(t)}{\text{CARD}(mask_l(t))} > \frac{1}{2}T \right) \\ \text{or} & \\ & \left(\frac{\sum mask_r(t)}{\text{CARD}(mask_r(t))} > \frac{1}{2}T \text{ and } \frac{\sum mask_l(t)}{\text{CARD}(mask_l(t))} > T \right) \\ 0, & otherwise \end{cases} \tag{4.13}$$

That equation enables us to take into account the following corrections to filter out the voluntary blinks [163]:

1. Detection of the closed eye for more than 1s means not spontaneous

closure. Thus, the alarm should be given, and the blinking rate detection should be stopped and restarted as soon as the opened eye is detected again.

2. Detection of two blinks with a short reopening time within 1s should be considered a single blink since it is similar to the voluntary blink. The body's features cause it, and it happens without human control.
3. Detection of more than two consequent closing and reopening eyes means abnormal behavior caused by voluntary blinks or other diseases. Therefore, it should be eliminated from the blink rate detection, and the alarm should be given. Once the expected behavior is detected again, the count restarts.

Having the information about involuntary blinks and their duration, the fatigue level can be measured by calculation of the blink rate or using a PERCLOS method, i.e., by calculating the percentage of frames where the eyes are detected closed in a given time period [164].

In other words, PERCLOS can be defined as a fatigue analysis method that shows the ratio of closed eyes depending on the number of opened and closed eyes [165]. This value can be calculated as in (4.14), where $N_{CloseAndOpen}$ represents the total number of open and n_{close} represents closed eye frames at a given time [97].

$$f_{PERCLOS} = \frac{n_{close}}{N_{CloseAndOpen}} \times 100\% \tag{4.14}$$

According to [166, 167], a fatigue status is determined when the PERCLOS threshold $f_{PERCLOS} > 0.24$. Furthermore, fatigue status can be divided into three levels:

1. **Very Tired Level**: It happens when the eye closure time exceeds 5 seconds, i.e., $n_{CLOSE} > 150$ frames.
2. **Tired Level**: Here $f_{PERCLOS}$ is in the range $(0.15, 0.24)$.
3. **Not Tired Level**: Where $f_{PERCLOS} < 0.15$ and no signs of fatigue are expressed.

- **Positional fatigue component**: Leverages the operators' data, collected by the imaging systems deployed on the workstation and by the biometric sensors worn by operators, to analyze their posture and determine if they assume incorrect postures or wrong ergonomics while performing their job [87]. Specifically, with the imaging systems it is possible to perform hand detection and skeleton identification, as shown in Figure 4.9. [87] proved

Figure 4.9: Example of hand detection and skeleton identification via imaging systems [87].

that operators engaging in repetitive or straining actions or remaining in one position for extended periods may adopt a non-upright posture, indicating signs of fatigue due to work accumulation. Analyzing the hands can determine the time needed to perform a specific task, and the computerized skeleton can estimate operators' body inclination variations [168]. By incorporating these two metrics, fatigue can be detected and its onset assessed to implement proactive actions.

- **Component of the contribution of task time score weights**: By measuring the operation time, it is possible to determine if an operator is taking longer to perform the same assembly information, which can indicate fatigue. The duration taken by an expert individual to accomplish the task is used as a reference. The time scoring task (*tts*) component is calculated as the ratio of time taken by the operator to the reference time taken by the expert:

$$tts = \frac{\text{Time taken by the operator}}{\text{Reference time taken by the expert}} \tag{4.15}$$

This component is then aggregated over all tasks the operator performs to get an average time task score, which is included in the overall fatigue scoring equation. That aggregation is done by summing up the individual task scores and dividing by the number of tasks (*nTask*) to normalize the score:

$$\frac{\sum_{i=1}^{nTask}}{tts_i} nTask \tag{4.16}$$

- **Operator adjustment bias**: this component accounts for individual differences among operators that may influence their fatigue levels. These differences can arise from various factors, including personal health conditions, age, experience, and susceptibility to fatigue. The bias helps personalize the fatigue scoring model, reflecting each operator's unique characteristics.

  To determine the operator adjustment bias, the following factors are considered:

  1. **Personal health conditions**: Operators with certain health conditions, such as chronic fatigue syndrome or cardiovascular issues, may exhibit higher fatigue levels. Medical assessments and health records can be used to adjust the bias accordingly.

  2. **Age**: Age-related factors can significantly influence an operator's endurance and recovery rate. Older operators may require a higher adjustment bias due to declines in natural physical stamina and resilience.

  3. **Experience**: Operators with more experience might perform tasks more efficiently and with less fatigue due to their familiarity and proficiency with the job. On the other hand, less experienced operators may tire more quickly and thus have a different bias adjustment.

  4. **Individual susceptibility to fatigue**: This factor considers how different operators react to the same workload. Some individuals may

have a higher tolerance for repetitive tasks and stressful conditions, while others may exhibit signs of fatigue more rapidly. Surveys, self-reports, and historical performance data can be used to quantify this susceptibility.

The bias (b) is integrated into the fatigue scoring equation as a constant that modifies the final score, providing a personalized adjustment that ensures the fatigue assessment is fair and accurate for each operator.

Therefore, this component enables the continuous monitoring, evaluation, and proactive assessment of operators' physiological and psychological states, recognizing stress, fatigue, uncertainty, musculoskeletal disorders, and incorrect postures.

4.2.3 Environmental Data Analysis

The Environmental Data Analysis focuses on evaluating real-time environmental data to identify and predict potential hazards in industrial settings. By applying advanced ML techniques, particularly Recurrent Neural Networks (RNNs), this component aims to model environmental conditions to signal normal, warning, or alarm states in both a reactive and proactive way [84, 169, 170].

The key metric utilized here is the Comprehensive Environmental Risk Index (CERI), designed to forecast potential dangers based on sensor data. This index builds upon the concept of the Comprehensive Air-quality Index (CAI) and serves as an additional feature of the RNNs to improve prediction accuracy [171].

The specific environmental sensors employed, as detailed in Section 4.1.2, measure critical factors such as dust, oxygen levels, and toxic substances and gases. The standards representing normal conditions for each of these sensors are defined in Table 4.4, which constitute the benchmark for triggering different environmental alerts.

Since each sensor has different degrees of risk depending on its value, a different environment risk index divided into six levels is assigned for each sensor:

1. Good;
2. Normal;
3. Caution;
4. Warning;

Table 4.4: Measured substances and normal criteria [84].

Process	Factors
Oxygen (O_2)	$19.5 \sim 23.5\%$
Carbon Monoxide (CO)	Under 20 ppm
Hydrogen sulfide (H_2S)	Under 0.1 ppm (0.3 ppm - smell)
Methane (CH_4)	Under 1%
Hydrogen (H_2)	Under 1%
Dust (Particulate Matter)	PM 10: $0 \sim 15$ PM 2.5: $0 \sim 15$ PM 1.0: $0 \sim 10$

5. Alarm;

6. Critical.

The score of environment risk index (Ip) is obtained by the following equation [84]:

$$Ip = \begin{cases} \frac{50}{P_H - P_L} \times (C_p - P_L) + 50 \times Level & \text{if} \quad Level \neq 0 \\ 0 & \text{if} \quad Level = 0 \end{cases} \tag{4.17}$$

Where P_H and P_L are the highest and lowest values for a particular sensor level, C_p is the current sensor reading, and $Level$ represents the six-step risk classification from "good" to "critical". When $Level$ is normal, namely when it is 0, the risk level becomes 0. The minimum and maximum range values for each step are, respectively, 0 and 50.

The risk level and the risk range of sensor data for calculating the above values are shown in Table 4.5.

Table 4.5: Risk levels and ranges for environment collected data [84].

(Risk Level)	good(0)		normal(1)		caution(2)		warning(3)		alarm(4)		critical(5)	
Risk range	PL	PH	PL	PH	PL	PH	PL	PH	PL	PH	PL	PH
O2 (%)	19.5	23.5	17	19.5	24.5	25.5	25.5	26	0	17	26	47
CO (ppm)	0	20	20	25	25	30	30	40	40	45	45	60
H2S (ppm)	0	0.1	0.1	0.2	0.2	0.3	0.3	10	10	10.3	10.3	20
CH4 (%VOL)	0	1	1	2	2	3	3	4	4	5	5	100
H2 (%)	0	1	1	1.2	1.2	1.4	1.4	1.6	1.6	1.8	1.8	2
PM-1.0(µg/m^3)	0	10	10	20	25	25	30	50	50	70	70	150
PM-2.5(µg/m^3)	0	15	15	25	25	35	35	55	55	75	75	150
PM-10(µg/m^3)	0	15	15	25	25	35	35	55	55	75	75	150

CERI is calculated as a maximum value among summed weighted environment category as in Equation (4.18), where $W_{*\text{env}*,\#p}$ is a weighted value according to the environment category and the presence or absence of workers, as shown in Table 4.6. FE consists of O_2, CH_4, and H_2 sensor data, which means the work area is vulnerable to fire, explosion, or oxygen deficiency. GE consists of CO, H_2S, and CH_4 sensor data, indicating a work area vulnerable to gas choking or suffocation. DE is measured by PM 1.0, PM 2.0, and PM 10 sensor data. However, since these weights are assigned according to the degree of risk of the environment, when deployed in an actual environment they need to be adjusted to reflect the application scenario.

$$\text{CERI} = \max \begin{pmatrix} W_{FE,\#p} \times \sum_{p \in FE} Ip \\ W_{GE,\#p} \times \sum_{p \in GE} Ip \\ W_{DE,\#p} \times \sum_{p \in DE} Ip \end{pmatrix} \tag{4.18}$$

Table 4.6: Weights of work area type and presence of workers on CERI.

	#p	
Environment	**1**	**0**
Fire Environment (FE)	1.5	1.2
Gas Environment (GE)	1.2	1.1
Dust Environment (DE)	1.05	1.0

4.2.4 Digital Twin Simulation

Digital Twin (DT) technologies in I5.0 enable the creation of detailed virtual replicas of human operators and their interactions within the workplace. These simulations integrate data from various sources, including wearable sensors, environmental and machinery monitoring systems, and operational metrics (e.g., task completion times and error rates) to provide a comprehensive view of operator conditions and interactions [172].

It is possible to have different DTs simulating operators with varying levels of expertise, physical conditions, and even psychological factors, enabling the simulation of different operative scenarios in the working environment to assess the impact of various factors on the operators' performance and well-being and predict potential challenges or improvements that can be made to enhance their overall experience [111].

Specifically, DTs in this context can model a wide range of factors, including:

1. **Operator variability**:

- **Expertise levels**: DTs can simulate operators with varying levels of expertise, exhibiting differences in performance and error rates, to predict how experience impacts performance and error rates. ML models, such as Convolutional Neural Networks and Recurrent Neural Networks, can analyze patterns in the data to differentiate between novice and expert behaviors, helping in the identification of the need for additional training or support for less experienced workers [173].
- **Physical conditions**: By simulating operators with different physical characteristics (e.g., age, height, weight) and health conditions, DTs can predict how these factors affect fatigue and injury risk. Ergonomic analysis tools assess the physical strain on operators, allowing for adjustments in workstation design and personalized work schedules to reduce the risk of musculoskeletal disorders [172].
- **Psychological factors**: Incorporating psychological data, such as stress and cognitive load, enables the simulation of how mental states impact performance. Advanced AI techniques, including Emotion Recognition and Natural Language Processing (NLP), analyze data from EEG sensors and wearable devices to monitor stress levels and cognitive load. This is crucial for developing interventions that mitigate stress and prevent burnouts [174].

2. **Operational scenarios**:

    - **Task complexity**: Simulating various task complexities helps understand the impact on operator performance and identify potential bottlenecks or error-prone activities. Discrete Event Simulation (DES) and Agent-based Modelling (ABM) can be used to create detailed simulations of task workflows, providing insights into efficiency and identifying areas for improvement [173].
    - **Environmental changes**: DTs can simulate different environmental conditions, such as lightning, temperature, or noise levels, to assess their impact on operator performance and safety. Environmental simulation tools and Virtual Reality (VR) environments can be employed to recreate various conditions and evaluate their effects on operators, enabling proactive adjustments in the workplace environment to maintain optimal conditions [172, 173].

The insights derived from DT simulations enable several proactive measures, among which:

- **Training programs**: By analyzing performance data, DTs help in optimizing training programs customized to individual needs. Simulated training environments using VR and AR can provide immersive, hands-on training experiences that improve skill acquisition and retention [172].
- **Task allocation**: Simulations can identify which tasks are best suited for specific operators based on their physical and mental conditions. AI-driven task allocation systems optimize workforce management by assigning tasks that align with each operator's strengths and limitations, enhancing overall productivity and well-being [174].
- **Health and safety interventions**: Predictive insights from DTs help in identifying potential health and safety risks before they occur. For instance, if an operator's DT shows signs of increasing fatigue, interventions such as task rotation or scheduled breaks can be implemented to prevent accidents and injuries [173].

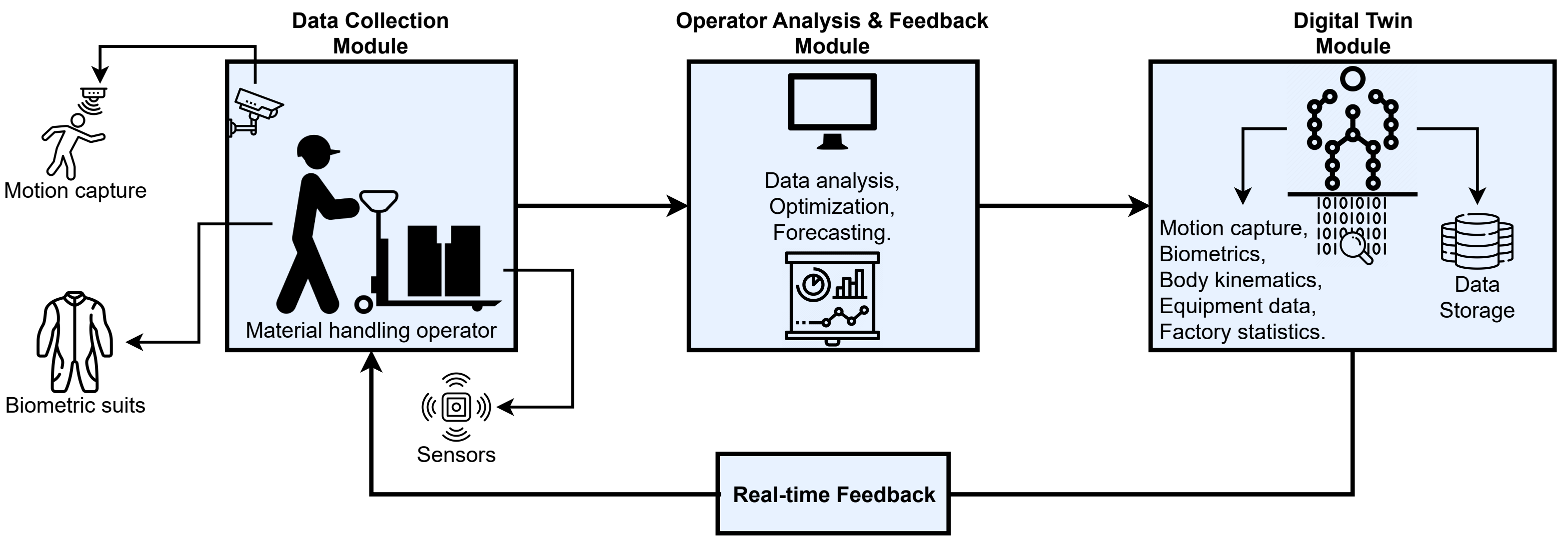


Figure 4.10: A possible framework for the application of DTs on the shop floor [111].

4.3 Intervention Techniques Module

The Intervention Techniques Module is the framework's component in charge of effectively utilizing the insights informed by the Data Analysis Module to proactively manage and mitigate potential risks to human operators' health and safety. It aims to respond to existing challenges and, more importantly, anticipate and prevent potential issues before they escalate, crucial for sustaining high levels of productivity and operator welfare in the advanced industrial landscape of Industry 5.0.

This module includes three main components, each one playing a fundamental role in ensuring that potential risks are mitigated, operators are well-informed and supported, and continuous improvements in operator training and assistance are achieved:

1. **Emergency Action Triggering**: Implements immediate responses to imminent threats, ensuring rapid and effective measures are adopted to safeguard operators.

2. **Personal Notifications, Suggestions, and Recommendations**: Delivers personalized advice and warning to operators based on real-time data analysis, promoting awareness and proactive physical and psychological behavior adjustments.

3. **Training and On-site Assistance**: Enhances operator skills and knowledge through dynamic training programs and real-time support, adapting to evolving workplace demands and individual needs.

4.3.1 Emergency Action Triggering

This component is designed to ensure the immediate safety of operators by responding to potential risks identified through real-time data analysis. When a potential risk or hazard is detected, the system triggers an immediate response to mitigate or eliminate the danger, safeguarding the operators from harm.

The system can monitor proximity to hazardous zones or machinery by utilizing data on operator positions and movements. In case an operator enters a high-risk area, automated protocols are put in action to stop machinery operations or activate warning alarms, preventing accidents and harm to workers [46].

Similarly, by continuously monitoring environmental parameters, it is possible to establish when the critical thresholds defined in Table 4.5 are exceeded and consequently activate immediate evacuation alarms or adjust the ventilation systems, depending on the risk level detected [84].

Furthermore, by leveraging the insights associated with vital signs like heart rate, body temperature, brain activity, and stress and fatigue levels, the system can identify biometric anomalies indicating potential health issues, such as sudden spikes in heart rate, abnormal body temperature, or severe fatigue, and alert medical personnel to provide immediate assistance [96].

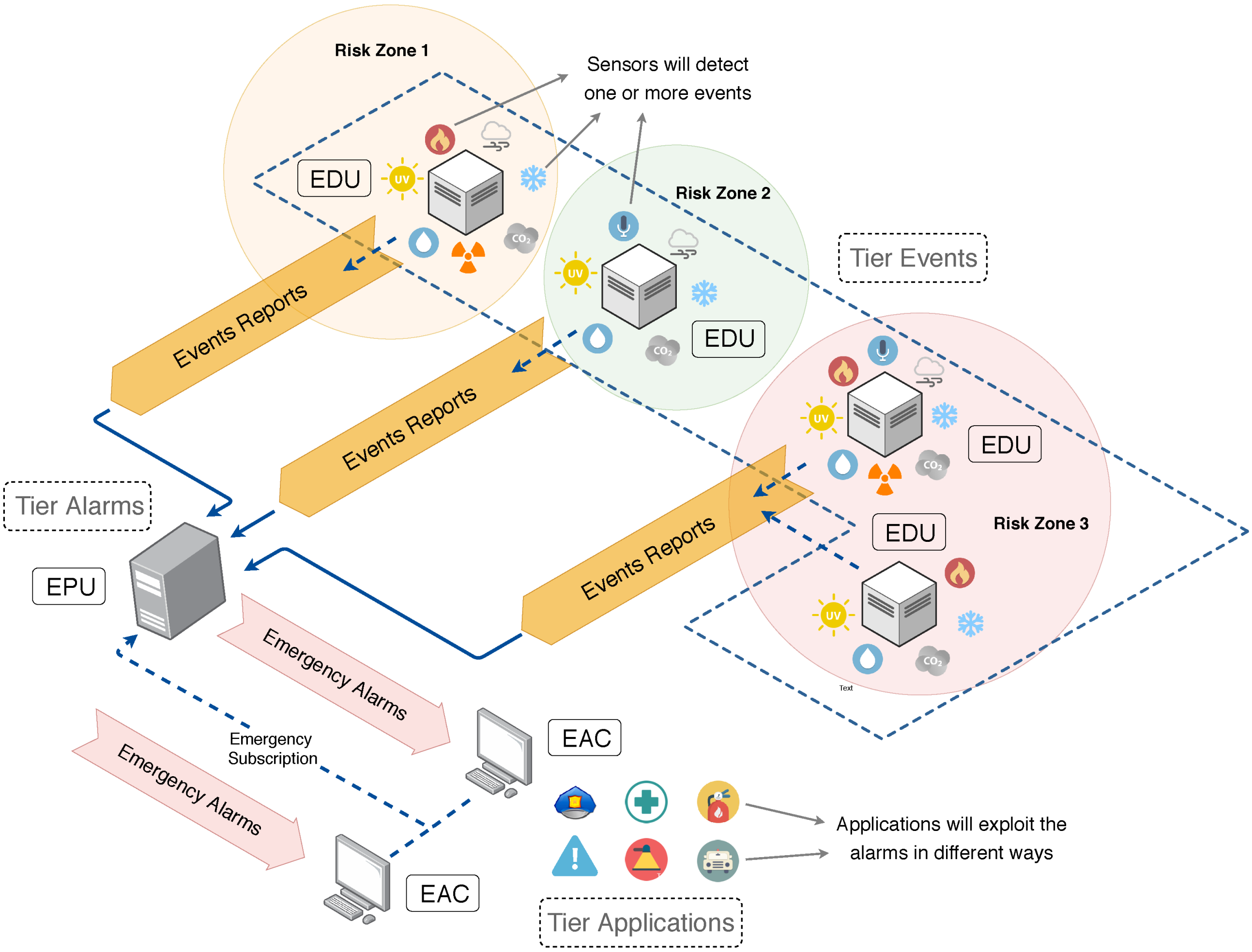


Figure 4.11: Example of emergency action triggering system setup [175].

4.3.2 Personal Notifications, Suggestions, and Recommendations

This part is developed to enhance the well-being and productivity of human operators by providing real-time, personalized feedback based on data collected from wearable and imaging devices, ensuring that operators receive timely and relevant information to maintain their health, optimize performance, and reduce the risk of injuries.

The techniques employed include:

- **Real-time Notifications**: By leveraging continuous data monitoring and predictive analytics, it is possible to send personalized notifications to operators, including:
  - **Break reminders**: When the system detects signs of fatigue, such as increase HRV or prolonged periods of inactivity, it sends reminders to operators to take breaks, helping in preventing burnouts and maintaining high levels of productivity [87].
  - **Posture alerts**: The system monitors operators' postures in real time using data from wearable sensors and imaging devices. If sub-optimal postures that could lead to musculoskeletal disorders are detected, the system provides immediate alerts, suggesting adjustments to reduce strain and improve ergonomics [176].
  - **Hydration and nutrition reminders**: Based on environmental conditions and biometric data, the system can remind operators to stay hydrated or consume snacks to maintain energy levels, especially in physically demanding environments [177].
- **Suggestions for Improved Ergonomics**: By analyzing posture and operation data, it is possible to provide suggestions that enhance ergonomic practices and reduce the risk of injury:
  - **Ergonomic adjustments**: Recommendations for adjusting workstation setups, such as the height of desks and chairs, positioning of monitors, and placement of tools, to ensure that operators maintain proper posture and avoid repetitive strain injuries [176].
  - **Stretching exercises**: Based on activity levels and detected muscle tensions, the system can suggest specific stretching exercises to alleviate stress and improve flexibility. These suggestions help prevent long-term injuries and enhance overall physical health.
- **Mental and Cognitive Health Recommendations**: To support mental well-being and cognitive performance, the system can provide personalized recommendations, including:
  - **Stress-reduction techniques**: When high-stress levels are detected through biometric and behavioral data, the system can suggest mind-

fulness exercises, deep-breathing techniques, or short breaks to engage in relaxing activities. This helps maintain mental clarity and reduce the risk of stress-related health issues [178].

– **Task prioritization**: By analyzing workload and task completion rates, the system can provide recommendations on prioritizing tasks to manage time effectively and reduce cognitive overload, ensuring that operators remain focused and productive without feeling overwhelmed [178].

4.3.3 Training and On-Site Assistance

This component focuses on enhancing operators' skills and providing immediate support when needed. Ensuring operators receive punctual and appropriate training and assistance can significantly improve their performance and reduce the likelihood of errors or accidents.

In that scope, EEG sensors monitor brain activity to detect signs of cognitive overload, fatigue, or stress. At the same time, cameras and imaging systems analyze facial expressions to detect, for instance, feelings of confusion, anxiety, or uncertainty.

Three main methods of assistance can be employed:

1. **Remote Expert Support**: Experts can provide real-time assistance through video calls or audio guidance, offering immediate advice and troubleshooting. This method ensures operators can resolve issues quickly without waiting for on-site personnel [115].

2. **On-site Personnel**: In those situations requiring a physical presence, trained personnel can assist operators directly. This hands-on support helps resolve complex issues and provides immediate relief in high-stress situations [115, 179].

3. **Augmented Reality (AR) and Mixed Reality (MR)**: AR and MR technologies offer immersive and step-by-step guidance. Operators can use AR glasses or MR headsets to receive visual instructions over their physical environment. This method enhances understanding and execution of tasks, reducing errors and improving efficiency [66, 176].

4. **Virtual Reality (VR) training and ergonomic optimization**: VR provides a safe and cost-effective platform for training operators, allowing

them to practice and improve their skills in a controlled environment, making them face various scenarios without the associated risks. This method is beneficial for training on complex machinery or hazardous tasks [66]. Additionally, VR can be used to prototype workstations, allowing for the optimization of ergonomic factors before their implementation in the physical workspace. Doing that reduces waste and improves sustainability, ensuring that workstations are designed to minimize physical strain and maximize comfort and efficiency [176].

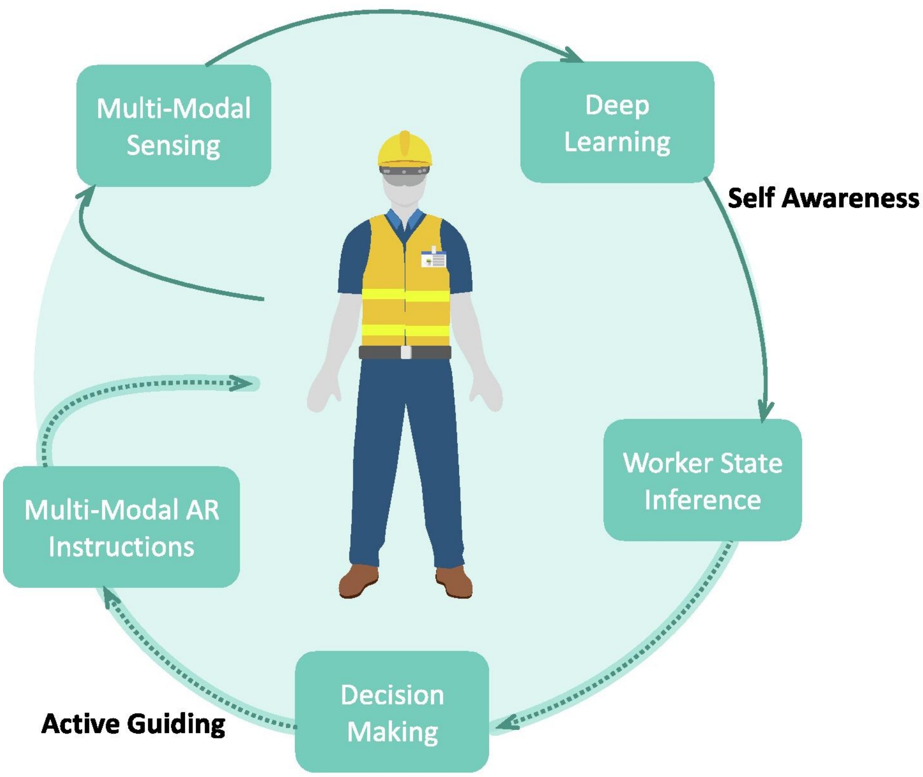


Figure 4.12: The basic workflow to provide on-site assistance to operators [115].

Figure 4.13 illustrates the final version of the conceptual framework developed.

4.4 Discussion

This Chapter presented a novel conceptual framework for the predictive assessment of human operators' condition within the paradigm of Industry 5.0, emphasizing a shift towards more human-centric approaches in industrial environ-

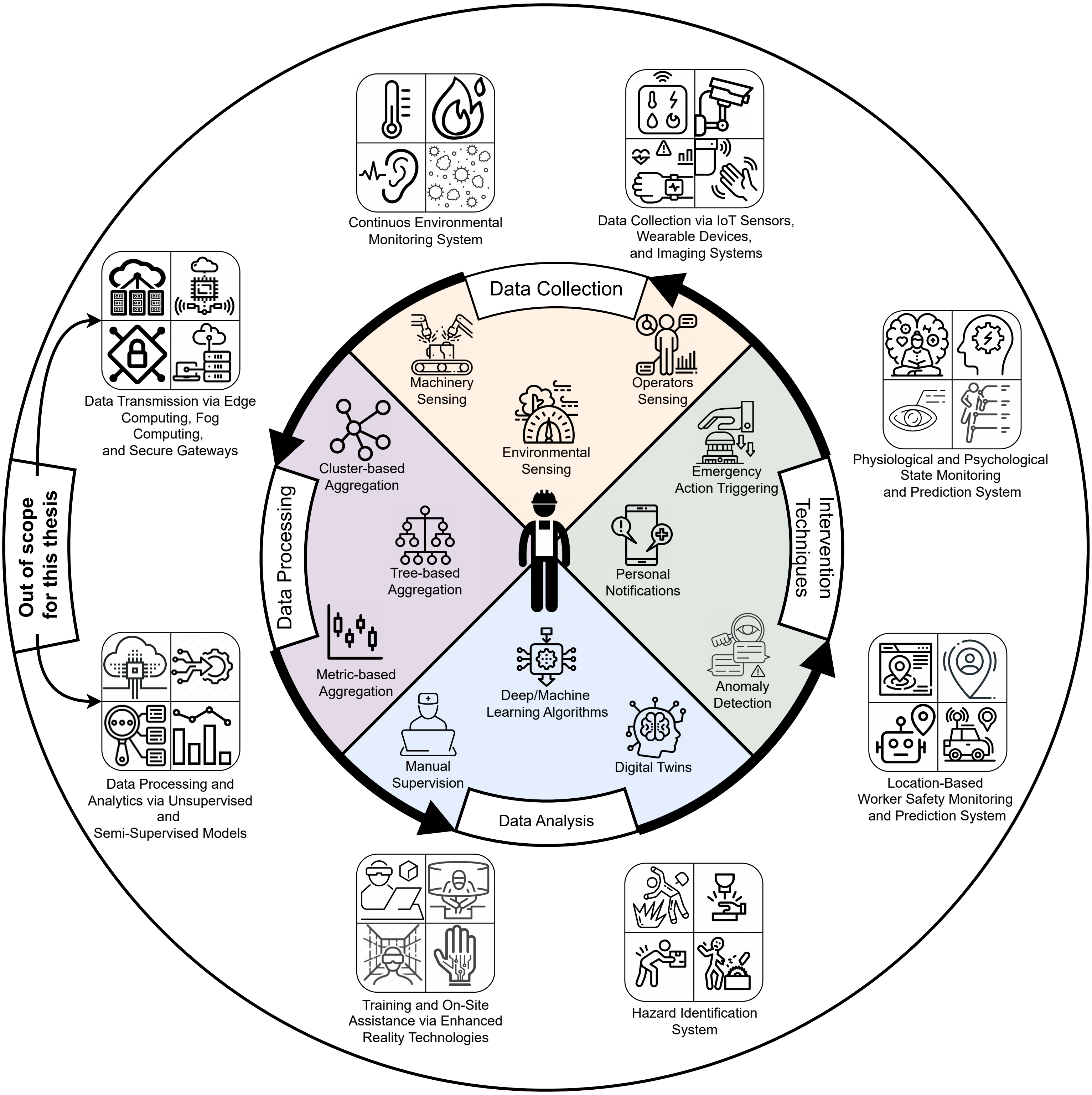


Figure 4.13: A visual representation of the developed framework, showcasing in the inner circle the employed methodologies and on the outer one the component originated from these.

ments. The integration of data collection, analytics, and intervention techniques established a road map toward enhancing human operators' safety, health, and well-being, tackling the current undercoverage of human elements in industrial practices. By prioritizing preventive strategies while maintaining a focus on reactive ones, the framework anticipates potential risks before they occur while being able to respond to critical situations already occurring. That allows for timely interventions that prevent accidents and health issues, promoting a more engaging and satisfying work environment [5].

The first module composing the framework is "*Data Collection*". It comprises the collection of data about operators leveraging wearable devices and imaging systems, about environmental conditions using fixed IoT sensors disseminated over the workplace, about machinery utilizing a combination of various sensors and imaging devices, and about operational status employing cameras and smart wearables.

This wide range of collected information enables a comprehensive assessment of the shop floor, the production lines, and, most importantly, the operators. By continuously collecting all these data, it's possible to automatize almost all of the assessment methodologies presented in Section 3.2, covering the majority of the factors presented in Section 3.1, among which the psychological and physiological status, various criticalities in the heart and breathing rate, possible situations of cognitive and mental overload, stress levels, and so on, emphasizing a solid focus on the human-centricity pillar of I5.0. Furthermore, data collection about environmental and machinery conditions enhances the safety of human workers, fostering a safer, more comfortable, and more satisfying work environment. At the same time, this enables companies to understand what can be improved in their production processes, both in terms of stimulating the operators while relieving them from physically demanding and repetitive tasks, but also in reducing emissions and waste, aligning with the sustainability principle of I5.0.

However, all of that would not be possible without the second module, which is in charge of analyzing the collected data. It concentrates on determining anomalies and potential risks, as well as opportunities and potential enhancements, in both a reactive and proactive way.

Using disseminated and wearable IoT devices and the deployed imaging systems provide much knowledge about positions, occupations, and movements within the shop floor. Regarding the reactive measures, leveraging that knowledge allows for the determination of potential risks to health and safety. For instance, we can detect operators entering certain areas without the proper PPE or proper training or authorization. Moreover, we can enhance the safety of operators working with potentially risky equipment or in more hazardous locations and, more generally, guarantee a safer interaction between humans, machinery, and the overall working environment. All of that culminates in improving the collaboration and cooperation between humans and machines, promoting a working environment having a strong synergy between these two, thus aligning with the goals of I5.0 [10, 31]. For proactive strategies, analyzing the positions and frequent patterns in movements and operations performed makes predicting operators' movements and activities feasible. This strengthens and improves the reactive measures seen above by reducing the time for intervention and allowing the detection of potential optimization in the production processes. By identifying repetitive actions performed by workers, it is possible to spot opportunities for automatizing repetitive or physically demanding tasks, improving the overall welfare of workers in terms of psychological and physiological load and broader well-being and stimulation.

Complementing the breakdown of location data, we have the analysis of the data about operators' body parameters. First of all, that enables an increase in safety and health since, under a reactive point of view, we can identify abnormalities in the heart and breathing rate, but also in the body posture and acceleration, thereby being able to detect a wide range of critical situations: hearth strokes, suffocation, falls, and so on. Additionally, it is possible to assess the variations in stress and fatigue levels, thus promoting an industrial culture in which the interest toward operators is not merely in their physical safety but also in their psychological well-being. Nevertheless, the insights about muscle and joint activity, along with the ones about posture and musculoskeletal load, provide details about the workload perceived by operators and potential incorrect postures being adopted. Again, this allows the identification of possible areas for improvement in the working conditions and production processes and prevents long-term damage to workers.

Further enhancing the welfare of humans in industrial environments, the environmental data analysis provides valuable information about the current and upcoming risk levels of the various areas of the shop floor, monitoring various types of chemicals and gases harmful to humans.

To conclude with this module, all the data collected can be used to perform simulations and feed Digital Twins, to replicate various working conditions and operators with different skills and characteristics, improve training programs and task allocations, but also detect occasions for health and safety interventions.

It is worth noting that the overall analysis of the data strongly focuses on the various aspects of human workers, seeking to improve their overall working experience and enhance their working conditions, fostering a positive, comfortable, sustainable, and satisfying working environment.

Anyway, collecting and analyzing data would mean nothing without establishing appropriate and specific intervention techniques. This is the stage in which prevention comes into play, anticipating potential threats ahead of time and responding to current risks. In that scope, the module defines the triggering of emergency action to respond to upcoming or already-happening dangers, which can be of various natures: unexpected behaviors of machinery and robots, falls and collisions, environmental hazards, etc. The system is also designed to provide real-time notifications about bad habits and wrong postures, break reminders, and hydration and nutrition reminders. At the same time, it delivers suggestions for improved ergonomics and mental health recommendations. Here, the focus is on all the macro-domains defined in Section 3.1, with the formulation of a comprehensive intervention strategy tailored explicitly to the needs of industrial operators.

That last module of the framework also comprises the delivering of training and on-site assistance, being able to detect and offer these timely when the operators need, via remote support, on-site personnel, or employing AR and VR technologies. Doing that can reduce the cognitive overload, fatigue, and stress operators feel when performing their tasks.

However, various challenges need to be faced when validating this framework.

First, data interoperability cannot be assumed as granted. The wide range of devices employed for collecting data exposes the system to the risk of incompatibility in the data sources. Therefore, the system designer should consider that and use strategies that can guarantee the uniformity of the data.

Along with that, there is the challenge of transmitting and storing data. Since the system relies entirely on the collected and analyzed information to respond to risks and threats, it must be assured that the data are correctly transferred (i.e., sent and received) within a certain acceptable interval of time to ensure timely interventions. This is absolutely crucial, especially in critical use cases related to health and safety. Then, the collected data should also be stored securely and efficiently to safeguard the workers' privacy and avoid excessive and useless memory consumption to respect the sustainability principle of I5.0.

Basically, for having a successful collection of data and ensuring the collected data are leveraged appropriately, efficiently, and safely, the framework requires the establishment of a comprehensive architecture that assures the processing, transmission, and storage of the data, defining counter-measures to potential issues that may arise from internal problems (e.g., latency, dispersion of signals, packet losses) and external sources (i.e., IT attacks).

Remaining on the challenges related to data collection, it is mandatory to ensure that the adopted wearable devices don't cause discomfort or any stress to operators and to establish a well-defined internal regulation detailing how the images and videos are used and stored. That regulation must be explained to operators to ensure they don't feel pressure or stress from being constantly monitored. In general, when establishing a system like the one proposed by the framework, the operators should be informed about its overall working logic to make them understand that such a model is thought to improve their working conditions and should not be seen as a menace in any way.

Nevertheless, despite all the efforts system designers can put in, technologies may always have some failure points, making them less reliable. For that reason, redundant safety mechanisms should be established, and these should be technology-independent, meaning that they should be able to provide at least the basic safety measures in case of system failures.

Switching about the data analysis, it cannot be totally unsupervised, especially in the context of I5.0. Suppose we leave machines to determine whether an operator is in imminent or upcoming danger. In that case, it's fundamental to have humans guarantee the accuracy and trustworthiness of the outputs. Moreover, when using ML and AI models for processing vast amounts of data and making decisions, it is fundamental to establish practices assuring these machines respect the ethical and privacy-oriented EU principles. Additionally, the energy consumption of these algorithms should also be considered to fulfill the environmental requirements of I5.0.

Lastly, personalization in the design of intervention techniques cannot be overlooked. In a system that aims to respond in reactive and proactive ways, customization tailored to individuals' needs and specifics is fundamental to ensuring the best possible outcomes. If the model is able to collect, transmit, store, and analyze all the data successfully and effectively but doesn't implement appropriate interventions, then it is not unleashing its full potential. Basic safety measures, such as evacuation alarms or emergency stops on the production line, can be common to most workers, while personal notifications with suggestions and recommendations and on-site assistance cannot be. Every operator needs to receive support specific to his exigencies, characteristics, and physical and mental conditions. Therefore, personalization is something that should be customized for the specific person and also on the particular current situation of that person.

Chapter 5

Conclusions and Future Works

The European economy relies mainly on Industry, which generates wealth and jobs across the continent. Between 2009 and 2019, the Industry continuously contributed about 20% of the EU Gross Domestic Product (GDP), with manufacturing contributing more than 14% of that total [31]. Although the European Industry is strong, it faces ongoing challenges due to the rapidly changing geopolitical environment in which it operates [10]. If this sector wants to continue bringing prosperity to Europe, it must constantly adapt to these ever-changing problems.

This thesis started by investigating the industrial landscape, starting from the three Industrial Revolutions to understand how these originate Industry 4.0 and Industry 5.0. Then, the key characteristics of Industry 4.0 have been detailed, along with the challenges and issues this paradigm originated. Following that, Industry 5.0 has been explained in detail, starting from the Japanese concept of Society 5.0, passing then to the definition and outline of Industry 5.0 formulated by the European Commission, and concluding with the enabling technologies, opportunities, and applications of this new industrial framework.

After explaining the context of Industry 5.0 and outlining the needs for systems enabling the proactive assessment of industrial operators, this work studied the human factors that should be considered to enhance industrial working conditions. These efforts led to the formulation of a taxonomy divided into four primary domains: safety, health, well-being, and human errors. Each domain is extensively detailed and divided into more specific sub-domains.

Following that, another round of literature review was performed to understand the qualitative methodologies currently employed to assess these elements. This enabled the understanding of the metrics and parameters of interest that will be needed to switch to a quantitative assessment leveraging modern technologies.

The core of that thesis is the conceptual framework exposed in Chapter 4, proposing a closed-loop system divided into three modules, enabling the collection and analysis of data used for triggering appropriate responses to enhance the factors defined in the previously mentioned taxonomy.

Future research directions will investigate technologies for aggregating, processing, and transmitting the data collected on the shop floor, something left out of the scope of this thesis but still crucial in realizing the framework's full potential. Following that, various validations of the framework need to be performed. Since it is not feasible to implement a comprehensive system like the proposed one from scratch, the validations should progressively add components, test their effectiveness, and eventually proceed by adding new functionalities and features until the desired complete system is in place. The ideal workflow should first implement some data collections and collect these data locally to build datasets while simultaneously working on the telecommunication infrastructure. At this point, it's possible to start training models if needed and finally test the triggering of the defined interventions.

Efforts should also be made to guarantee the ethical and privacy-oriented collection, processing, and storage of the collected data, establishing security features to protect these from being leaked, obfuscating sensitive data, and developing internal regulations detailing how the data will be collected, leveraged, and stored. It is fundamental that the focus is on adopting approaches that can alleviate the feelings of oppression and over-control that operators may sense by a system, such as the proposed one that, by its definition, is invasive and pervasive. Consequently, training programs explaining how the system works, how the data are used, what is being examined and what is not, and the advantages and benefits should be implemented as complementary to the more standard training programs.

Lastly, to improve the framework's potential, its implementation necessitates interdisciplinary cooperation between engineers, psychologists, ethics experts, and specialists in industrial and manufacturing processes, among other disciplines. Such collaboration will be vital in addressing various issues associated with the predictive assessment itself. It will also help understand the impact of these systems in the industrial environment, namely, how they affect production processes, the shop floor, and operators.

To conclude, the I5.0 paradigm presents a new industrial landscape in which humans and the environment are central. It proposes an industrial future in which operators are satisfied and able to apply their human capabilities, such as critical thinking, reasoning, and creativity, supported by machines in performing those repetitive and physically demanding tasks. In this way, Operator 5.0 should feel satisfied and accomplished, acknowledging his safety and health are guaranteed while his skills and personal talents are fully leveraged. The proposed framework aims to foster a sustainable, effective, and satisfying workplace by promoting an effective integration of people and technology in manufacturing. The final objective is that this work can be used as a starting point for all the following works related to the predictive assessment of industrial operators in the context of Industry 5.0.

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