Instituto Tecnológico y de Estudios Superiores de Monterrey

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School of Engineering and Sciences

Influence of Workers' Well-being on Productivity in the Context of Industry 5.0: Applying a Competitive Technology Intelligence Methodology

A thesis presented by

Sofia Pamela Recinos Dorst

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Declaration of Authorship

I, Sofia Pamela Recinos Dorst, declare that this thesis titled, “Influence of Workers' Well-being on Productivity in the Context of Industry 5.0: Applying a Competitive Technology Intelligence Methodology” and the work presented in it are my own. I confirm that:

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- Where I have consulted the published work of others, this is always clearly attributed.
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- I have acknowledged all main sources of help.
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Sofia Recinos

Sofia Pamela Recinos Dorst
Monterrey Nuevo León, February 5 th, 2025

Dedication

I would like to dedicate my thesis to my mom, Barbara, and my grandmother, Griselda, who have always given me their unconditional support throughout all my decisions, for being there during the most difficult times, and for always believing in me. I also want to thank my husband, Jan, who has stayed by my side, pushing and motivating me through the challenging days and nights.

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by

Sofia Pamela Recinos Dorst

Abstract

In the new era of Industry 5.0, a human-centric approach is being adopted, emphasizing the importance of creating workplaces that support efficiency and worker well-being. However, this evolution raises questions about how to create a human-centered work environment that prioritizes the well-being and, consequently, productivity. To address this issue, this thesis applies the Competitive Technology Intelligence (CTI) methodology to offer guidance and recommendations in this context by identifying trends related to the human-centric pillar of Industry 5.0, with a focus on the influence of workers' well-being on productivity. Furthermore, this study proposes the incorporation of the PRISMA methodology into the CTI methodology with the objective of improving the reproducibility and robustness of the CTI process. As a result, the following trends were determined: (i) Facilitating effective and natural communication between robots and humans, (ii) Modifying and optimizing the work environment to enhance workers' well-being, (iii) Customizing technology to meet operators' individual needs, and (iv) Monitoring technologies that assess workers' real-time states and provide accurate feedback. This study offers valuable insights by providing actionable recommendations centered on human-centricity within the framework of Industry 5.0.

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Chapter 1: Introduction

This chapter begins by outlining the motivation behind this research. It then defines the problem statement within the Industry 5.0 framework, emphasizing its human-centric approach. The chapter presents the Competitive Technology Intelligence (CTI) methodology and delineates both general and specific objectives, along with the research questions, scope, and an overview of the proposed solutions.

1.1 Motivation

Industry 4.0 has enabled organizations to achieve significant advancements in automation and performance through the adoption of innovative and transformative technologies (Rahardjo, Wang, Lo, & Chu, 2024). As noted by Polivka & Dvorakova (2021), the nine technological pillars of Industry 4.0 include Big Data, autonomous (collaborative) robots, simulations, system integration, the Internet of things, cyber-physical systems, cloud technologies, additive manufacturing, and augmented reality. These technological developments have revolutionized industries and led to fast growth. Nevertheless, amid these innovations, there is a need for a more holistic approach that considers human factors (Ling, et al., 2024).

Industry 5.0 represents a transformative shift that emphasizes sustainability and work-life balance. It enhances worker well-being by fostering collaboration between humans and machines, enabling both to thrive in harmony (Capponi, Gervasi, Mastrogiacomo, & Franceschini, 2024). Nonetheless, this evolution raises questions about how to create a human-centered work environment that prioritizes well-being and, consequently, productivity.

The motivation behind this research stems from a gap in existing studies concerning Industry 5.0, a relatively new concept that has garnered considerable attention since the European Commission introduced it in 2019. Additionally, the subjective nature of human-centricity within Industry 5.0 creates ambiguity surrounding its practical implementation in industrial settings (Alves, Lima, & Gaspar, 2023). Consequently, this research aims to empower organizations and academic institutions to recognize and seize the opportunities offered by Industry 5.0. by assessing the human-centric approach in industrial environments, with a specific focus on the influence of workers' well-being on productivity.

1.2 Problem Statement

Staying updated on the latest innovations and trends is essential for a company to maintain a competitive edge in the market. Competitive Technology Intelligence is a systematic process that aids decision-making by monitoring the competitive and technological landscape to provide early detection of emerging technologies and innovations (Das, 2010). Ultimately, it supports organizations in maintaining a competitive advantage and navigating the complexities of their industries.

In the manufacturing sector, new technologies should address both individual and collective needs while meeting production requirements (Coronado, et al., 2022). Industry 5.0 introduces a framework that emphasizes a human-centric approach, prioritizing human needs and interests in production processes (Breque, De Nul, & Petridis, 2021). Nevertheless, Alves et al. (2023) highlight that the concept of Industry 5.0 has not been fully integrated into the industry, as it persists in confronting challenges associated with Industry 4.0. Consequently, this situation renders researchers and companies without sufficient guidance to successfully navigate the landscape of Industry 5.0 and facilitate the transition from Industry 4.0 to Industry 5.0 within various organizations and sectors.

By applying the Competitive Technology Intelligence methodology, this research aims to offer guidance and recommendations for companies pursuing Industry 5.0 to adopt a more human-centric approach that prioritizes workers' well-being and productivity.

1.3 Research Context

1.3.1 Industry 4.0

Industrial revolutions have persistently adapted to the necessity for change, leading to increased productivity facilitated by technological advancements and automation (Verma, 2024). Industry 5.0 represents the latest version of this concept. To comprehend its evolution over the years and the introduction of Industry 5.0, a concise summary of the challenges and benefits encountered by its predecessors will be presented.

The Fourth Industrial Revolution centered on Human-Machine Interaction, guiding a wave of technological advancements that transformed industrial manufacturing processes (Sony, Anthony, Mc Dermott, & Garza-Reyes, 2021). It relied heavily on enhancing efficiency and productivity through automation and data exchange technologies (Loizaga, Toichoa Eyam, Bastida, & Martinez Lastra, 2023). In this section, some of the benefits and disadvantages that Industry 4.0 propelled for the creation of Industry 5.0 will be mentioned.

One of the benefits that Industry 4.0 has brought to industries is a broader range of new job opportunities (Grybauskas, Stefanini, & Ghobakhloo, 2022). Consecutively, increasing the demand for human resources with new requirements as traditional job roles undergo significant transformation (Sony, Anthony, Mc Dermott, & Garza-Reyes, 2021). As a result, this leads to the creation of jobs, mostly in engineering, technician roles, production management, and robotics (Macpherson, Werner, & R. Mey, 2022).

Another notable benefit is an increase in collaboration between the government and companies (Grybauskas, Stefanini, & Ghobakhloo, 2022). This is essential for overcoming current obstacles when implementing new technologies or work structures, such as Industry 5.0.

On the contrary, a significant disadvantage is that Industry 4.0 created an unequal division of labor, where high skills and high technological knowledge would be necessary for proper performance in the work areas (Grybauskas, Stefanini, & Ghobakhloo, 2022). The underlying rationale for this phenomenon is that, in the context of Industry 4.0, workers are required to modify and enhance their skill sets in response to advancing technologies. Consequently, in Industry 5.0, the goal is to adapt technology to meet the employees' existing skills and needs. “Rather than asking what we can do with new technology, we ask what the technology can do for us. Rather than asking the industry worker to adapt his or her skills to the needs of rapidly evolving technology, we want to use technology to adapt the production process to the needs of the worker” (Breque, De Nul, & Petridis, 2021).

However, even workers with advanced digital skills may not be safe from digital replacement. Grybauskas et al. (2022) also suggest that these positions could easily be replaced by technologies and algorithms in the future, offering another reason for the industry to evolve.

Furthermore, the problems are present not only in the workplace but also extend to the individual level of employees. In the academic literature, researchers began to mention the influence of Industry 4.0 on workers’ well-being (Zorzenon et al., 2022) and, therefore, on production rates. In 2017, Christensen et al. (2017) claimed that employee well-being is a positive element that can enhance productivity in a company. The International Labour Organization (ILO) also acknowledges that: “productivity growth and improvements in well-being are closely interconnected and can create mutually reinforcing positive feedback loops.” (See Figure 1). In other words, employee well-being can influence their performance at work, and work, in turn, can influence their well-being.

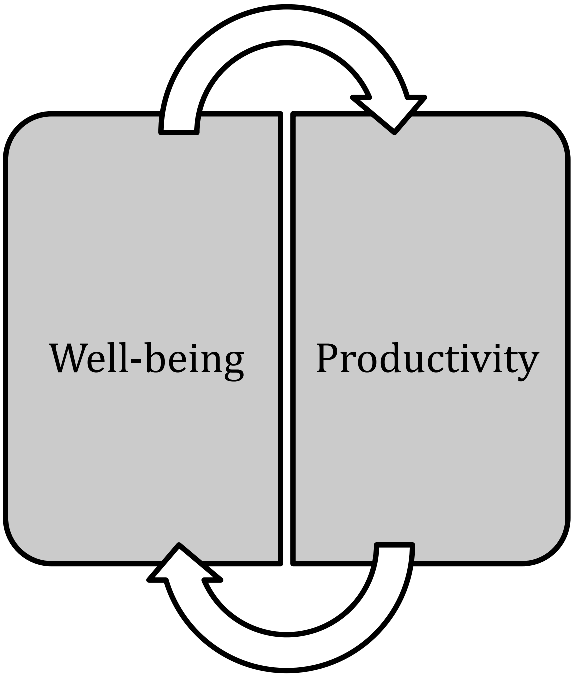


Figure 1. Relation between well-being and productivity.
(Own elaboration, 2024)

This aspect contributed to the list of reasons why a change in organizations was necessary. For example, Kovacs (2018) mentioned that a structural change is needed for sustainable development and promotion of well-being in the complexity of Industry 4.0 and digital transformation.

In summary, Industry 4.0 contributed to the creation of new jobs, higher wages due to increased demands, and higher company productivity. However, over the years, researchers and industry leaders have identified areas for further improvement within this framework. A combination of the gaps in Industry 4.0 and the new needs of the environment and society encouraged the creation of Industry 5.0, which supports a human-centric, sustainable, and resilient approach to technology.

1.3.2 Industry 5.0

Due to automation and the rapid adoption of technology, a growing need for new skill sets, job roles, and work models became necessary (Schwab & Zahidi, 2020). The

Directorate for Prosperity within DG Research and Innovation organized two virtual workshops for participants from research and technology organizations throughout Europe, during which they explored the concept of Industry 5.0 (Müller, 2020).

Industry 5.0 is centered around three key elements: Human-Centricity, Resilience, and Sustainability (See Figure 2) (Breque, De Nul, & Petridis, 2021). Unlike its predecessors, this industry aims to reshape the industrial landscape by becoming a resilient source of prosperity, producing within planetary boundaries and placing workers' well-being at the center of the production center (Xu, Lu, Vogel-Heuser, & Wang, 2021). While Industry 5.0 presents a novel approach, it remains fundamentally rooted in Industry 4.0 and is not entirely independent of its predecessor.

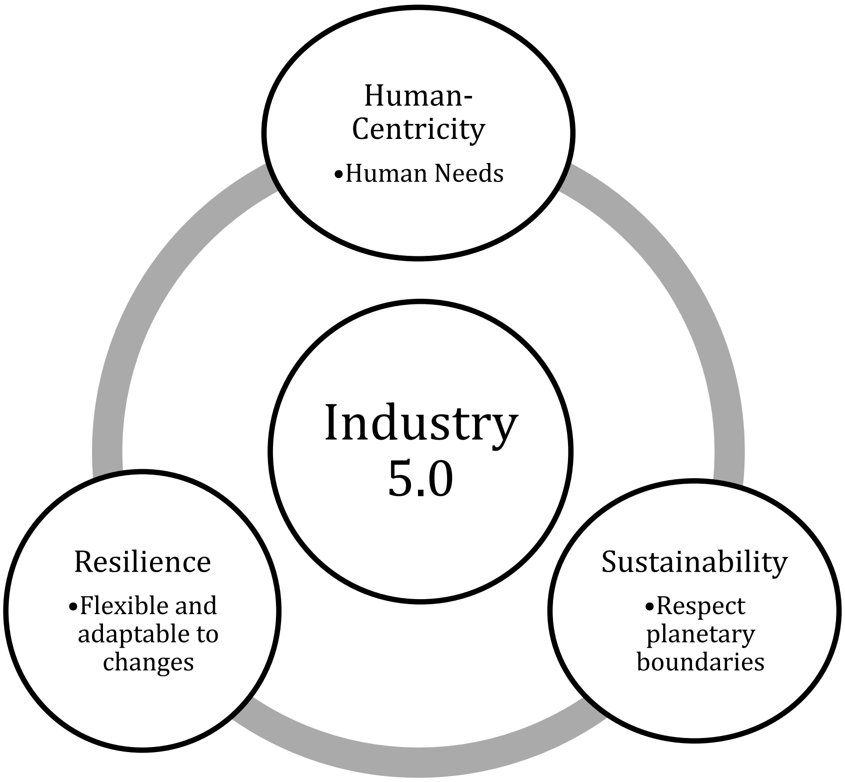


Figure 2. Key Elements of Industry 5.
Adapted from: Breque, M., De Nul, L., & Petridis, A. (2021). Industry 5.0: Towards a sustainable, human-centric, and resilient European industry. European Commission Directorate-General for Research and Innovation, 1st edition, pp. X-X. CC BY 4.0. Available at https://doi.org/10.2777/308407

A human-centric approach aims to center workers' well-being at the center of the production process (Breque, De Nul, & Petridis, 2021). It focuses on evolving technology to adapt to worker skills instead of requiring the worker to acquire new skills to adapt to technology. In addition, it upholds workers' fundamental rights, which correspond to level 1 of the Industrial Human Needs Pyramid, as shown in Figure 4.

Another key element of Industry 5.0 is **sustainability**. Rapid human development, uncontrolled population growth, increased greenhouse gas emissions, and biodiversity loss have disrupted Earth's balance (Barnosell & Pozo, 2024). Planetary boundaries define the limits within which humanity can safely operate by recognizing the constraints of the Earth's systems (Rockström, et al., 2009). Another innovative key element of Industry 5.0 is being sustainable by respecting planetary boundaries to avoid endangering future generations' needs (Breque, De Nul, & Petridis, 2021)

Finally, the authors of Industry 5.0 define **resilience** as "the need to develop a higher degree of robustness in industrial production, arming it better against disruptions and making sure it can provide and support critical infrastructure in times of crisis" (Breque, De Nul, & Petridis, 2021). This implies that production and business processes must be adaptable during unexpected, challenging periods.

To achieve the goals of Industry 5.0, it is important to incorporate the tools of Industry 4.0, as well as to develop new technologies. This requires a unified approach between humans and machines. According to Müller (2020), technologies supporting Industry 5.0 are characterized by providing human-centric solutions and human-machine interaction, bio-inspired technologies and smart materials, real-time-based digital twins and simulation, cyber-safe data transmission, storage and analysis technologies, Artificial Intelligence and Technologies for energy efficiency and trustworthy autonomy (See Figure 3). Each of them can unfold its potential when combined with others (Müller, 2020).

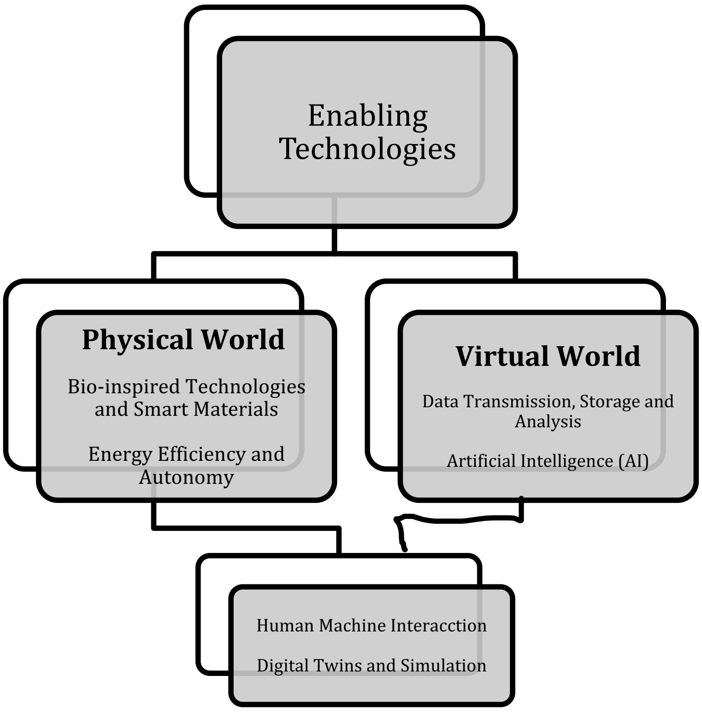


Figure 3. Enabling Technologies for Industry 5.0.
(Own elaboration, 2024)

Furthermore, integrating technologies, particularly in the context of Industry 5.0, can actively support well-being by reducing repetitive tasks, enhancing safety, and encouraging fulfilling work environments (Breque, De Nul, & Petridis, 2021). These technologies are also anticipated to promote sustainability and create a resilient environment.

In conclusion, the European Commission (2021) emphasized that a renewed and broader sense of purpose will characterize Industry 5.0. This new approach will extend beyond merely producing goods and services for profit, focusing instead on promoting prosperity in social, environmental, and societal aspects. However, it is essential to recognize that the fifth revolution complements Industry 4.0 by leveraging the advancements made during that era rather than replacing it (Breque, De Nul, & Petridis, 2021). The new revolution builds upon this foundation to assist in a new era of workers' well-being and environmental consciousness, creating a more resilient industry.

1.3.3 Human-Centric Pillar Focused on Well-being

As previously mentioned, the primary aspects of Industry 5.0 emphasize human centricity, sustainability, and resilience. This section focuses specifically on the human-centric approach.

While the human-centric approach began gaining prominence during Industry 4.0, as exemplified by Romero et al. (2016) concept of “Operator 4.0,” which focuses on integrating technologies to enhance worker satisfaction, creativity, and performance through human cyber-physical systems, its scope has expanded in the context of Industry 5.0. However, human-centric manufacturing is still a relatively new concept that requires standardized definitions and frameworks for discussion (Alves, Lima, & Gaspar, 2023); (Locatelli, et al., 2024).

In the context of Industry 5.0, the human-centric approach emphasizes enhancing human well-being in industrial environments (Alves, Lima, & Gaspar, 2023). The topic of well-being has been widely researched by psychologists, sociologists, public health experts, and organizations such as the World Health Organization (WHO) and the Centers for Disease Control and Prevention (CDC). The WHO states, "Health is a complete physical, mental, and social well-being and not merely the absence of disease or infirmity" (WHO, 2024) . Similarly, the CDC states that enhancing emotional well-being positively affects mental and physical health. It also recognizes that part of the benefits of emotional well-being can include being more resilient, and better productivity and performance at the workplace (CDC, 2024).

Diener & Seligman (2004) studied a correlation between people with higher well-being and their higher incomes, as well as better performance at work, finding positive results. Furthermore, different studies have demonstrated that when companies implement actions that benefit employees’ well-being, their productivity increases (Christensen, Øystein Saksvik, & Karanika-Murray, 2017); (Sagar, Garg, & V. Basavaraddi, 2023); (Loizaga, Toichoa Eyam, Bastida, & Martinez Lastra, 2023); (Sharpe & Mobasher Fard, 2022); (Henri DiMaria, Peroni, & Sarracino, 2020); (Isham, Mair, & Jackson, 2021).

Understanding and assessing well-being in work environments often rely on human factors (Loizaga, Toichoa Eyam, Bastida, & Martinez Lastra, 2023). In 2022, a model was created to categorize human needs in the industrial environment into five levels, ranging from basic safety to self-actualization (Lu, et al., 2022) (See Figure 4). The sequence of levels illustrates the journey from basic safety to personal growth.

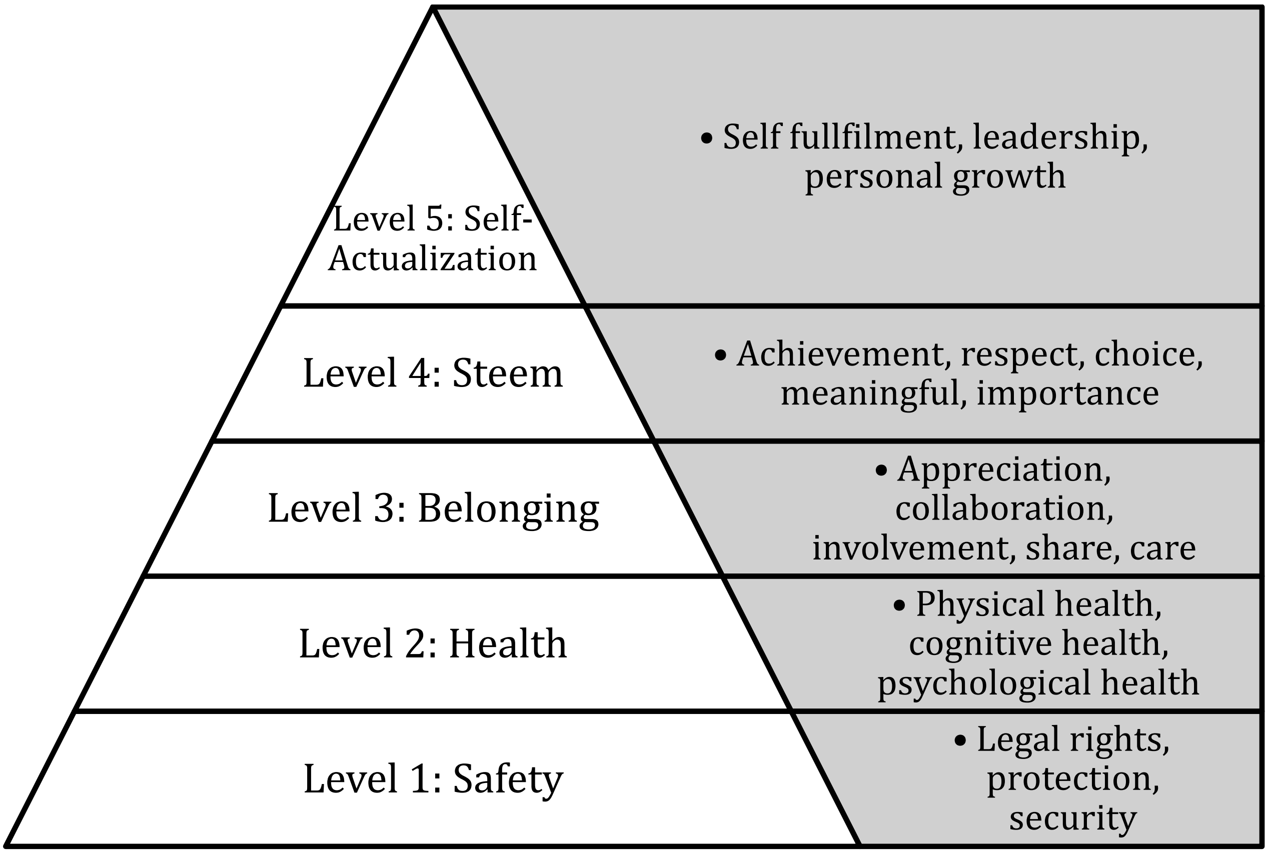


Figure 4. Industrial Human Needs Pyramid.
Adapted from: Lu, Y., Zheng, H., Chand, S., Xia, W., Liu, Z., Xu, X., Wang, L., Qin, Z. & Bao, J. (2022). Outlook on human-centric manufacturing towards industry 5.0. Journal of Manufacturing Systems,62,612-627.
https://doi.org/10.1016/j.jmsy.2022.02.001 CC BY 4.0

Level 1: Safety. At the foundation of the pyramid, worker's physical safety and legal rights are granted, ensuring compliance with labor and safety regulations (Lu, et al., 2022). Traditionally, it has been managed by protocols that combine physical separation between workers and machines with reactive measures that respond to incidents only after they have occurred (Robla-Gomez, et al., 2017). However, the future of industrial safety is moving towards proactive protection (Casalino, Bazzi, Zanchettin, & Rocco, 2019). This approach involves the creation of intelligent environments capable of sensing and predicting worker's actions in real-time, allowing for adaptive safety measures to prevent accidents proactively.

Level 2: Health. At this level, the focus shifts from immediate safety concerns to long-term physical and mental well-being. This level identifies and addresses risks associated with repetitive motions, improper posture, and work practices that may lead to musculoskeletal injuries, as opposed to level 1, which is concerned primarily with reducing immediate hazards (Lu, et al., 2022). To mitigate these risks, it is imperative to implement ergonomic design principles that facilitate the creation of static workstations, operational tools, and control interfaces, all aimed at minimizing physical fatigue (Boulila, Ayadi, & Mrabet, 2017);(Caputo, Greco, Fera, & Macchiaroli, 2019). Moreover, psychological well-being is also prioritized at this level. The work environment should promote worker engagement by offering meaningful tasks that reduce cognitive overload (Lu, et al., 2022).

Level 3: Belonging. Humans are social by nature and need cooperation and connection to flourish (Tomasello & Gonzalez-Cabrera, 2017). This level focuses on the social aspects of the workplace, acknowledging the need for belonging: "Belongingness refers to the emotional need for interpersonal relationships, connection, and being part of a group. This includes needs such as friendship, trust, acceptance, and appreciation" (Lu, et al., 2022). In a manufacturing context, this involves ensuring active and trustworthy collaboration from workers in a human-machine team and playing valuable roles in the overall success of the team grounded in mutual empathy, communication, and shared responsibility for achieving common goals (Lu, et al., 2022). Trust, intimacy, acceptance, and mutual appreciation are essential components of this level.

Level 4: Esteem. On this level, confidence, strength, self-belief, personal and social acceptance, and respect from others are key elements. To achieve self-actualization, fulfilling these needs is critical. This transition represents shifting from being "willing to work" to feeling "happy to work" (Lu, et al., 2022). Although esteem is an internal need, humans are heavily influenced by external factors, such as social validation and approval. An effective way to reinforce an individual's sense of esteem is through methods like gamification which includes rewards and recognition (Lu, et al., 2022).

Level 5: Self-Actualization. "Self-actualization is about reaching your full potential and finding personal fulfillment and growth" (Lu, et al., 2022). At this level, workers experience personal satisfaction in their jobs. They have a clear sense of purpose and are able to embrace and accept themselves and others, fostering deep and meaningful relationships in their daily work. In a manufacturing environment, a personalized experience focusing on co-learning and co-exploration is offered, allowing bi-directional learning coevolution between humans and machines (Lu, et al., 2022).

As previously mentioned, it's crucial to first understand and identify human factors to implement a human-centric approach. Even though identifying the most relevant human factors in Industry 5.0 can be challenging, some authors have identified six that are particularly relevant (Coronado, et al., 2022); (Lu, et al., 2022); (Crnjac Zizic, Mladineo, Gjeldum, & Celent, 2022); (L Russ, et al., 2012). The six mentioned are physical fatigue, attention, cognitive workload, stress, trust, and emotional assessment. These were later categorized into Level 2, according to Loizaga et al. (2023), based on the affected distinct states: physical, cognitive, and psychological, as outlined in the Human Need Pyramid. Organizations need to be aware of these human factors because they influence not only an individual's well-being but also behavior and performance (Aquino, Jalagat, Kazi, & Nadeem, 2020).

In summary, understanding and addressing human factors is crucial to improving well-being. By prioritizing these fundamental elements, organizations can create environments that promote employee satisfaction and sustained productivity, leading to meaningful and lasting outcomes. Human factors facilitate a Human-Centric approach, bringing organizations closer to the new Industry 5.0.

1.4 Objectives

1.4.1 General Objective

Apply a Competitive Technology Intelligence methodology to identify the trends of the human-centricity pillar that characterize the Industry 5.0 paradigm and offer recommendations for companies looking to adopt this human-centric approach with a focus on the influence of workers' well-being on productivity.

1.4.2 Specific Objective

- To employ scientometrics as part of the Competitive Technology Intelligence process for identifying relevant trends.
- Offer recommendations to companies on how to become more human-centric following this Industry 5.0 pillar.

1.5 Research Questions

In line with the objectives of the previous section, the following table outlines the research questions and the corresponding chapter numbers where they are addressed (See
Table 1).

Table 1. Research Questions.
(Own elaboration, 2024)

Research question	Chapter
What are the trends being discussed in the scientific literature regarding the human centricity pilar of the Industry 5.0 paradigm with a focus on the influence of workers' well-being on productivity?	4
What recommendations could companies adopt to become more human-centric, following the Industry 5.0 pillar?	5

1.6 Scope and Limitations

Although Industry 5.0 is defined by three foundational pillars: human-centricity, sustainability, and resilience, this thesis will focus exclusively on the examination of the “human-centricity” pillar. The scope of the findings presented in this research encompasses scientific papers published in Scopus from January 1, 2019, to October 1, 2024. A limitation of this research is that not all criteria of the PRISMA methodology were comprehensively applied, which may have influenced the assessment of potential bias.

1.7 Solution Overview

This document provides an overview of the current state of the influence of workers' well-being on productivity within the context of Industry 5.0. The relevant research and trends are obtained using the Competitive Technology Intelligence methodology. Furthermore, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology is integrated into the Competitive Technology Intelligence approach to ensure adherence to rigorous systematic review standards and enhance the reliability of the findings.

Chapter 2: Competitive Technology Intelligence Theoretical Framework

2.1 Introduction

This chapter presents and describes the chosen methodology for this research, Competitive Technology Intelligence (CTI), and it briefly reviews each stage.

2.2 Competitive Technology Intelligence Methodology

Today, a wealth of information from various sources is available to enhance the competitiveness and innovation of research and development (R&D) units. However, having the right tools to turn this information into actionable intelligence is crucial. One effective approach to meet this challenge is Competitive Technology. According to Pellissier and Nenzhelele (2013), it is defined as “a process or practice that produces and disseminates actionable intelligence by planning and ethically and legally collecting, processing, and analyzing information from both the internal and external competitive environment. This process helps decision-makers in their decision-making and provides a competitive advantage to the enterprise.” In simpler terms, it is a tool that ethically gathers information and transforms raw data into actionable results, ultimately offering a competitive edge. Competitive intelligence can help facilitate new or increased revenues, the development of new products or services, and savings in both cost and time in organizations (Calof & Wright, 2008).

According to Rodriguez-Salvador and Castillo-Valdez (2021), Competitive Technology Intelligence (CTI) refers to the application of competitive intelligence (CI) in scientific and technological research. Furthermore, CTI can be utilized to predict new technologies, develop competitor analyses, forecast market changes, guide innovation strategies, and support decision-making in R&D initiatives (Rodriguez-Salvador & Castillo-Valdez, 2021).

This thesis will apply the CTI methodology developed by Rodriguez-Salvador and Castillo-Valdez (2021) to identify trends and emerging technologies in Industry 5.0. This methodology stands out because it integrates primary and secondary information, utilizes quantitative and qualitative metrics, and involves expert engagement throughout the entire process. This methodology consists of eight interdependent stages that provide and receive feedback from one another (See Figure 5).

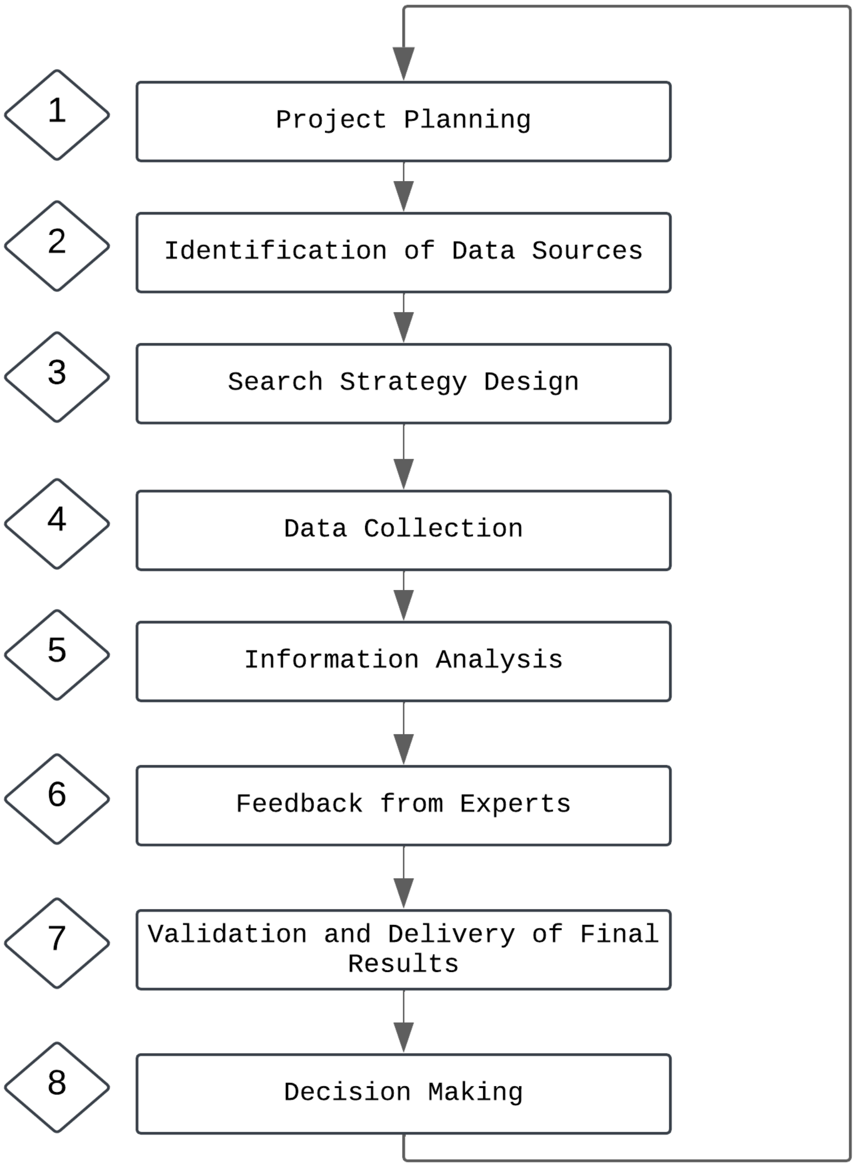


Figure 5. Competitive Technology Intelligence Methodology Cycle.
Adapted from: Rodriguez-Salvador, M., & Castillo-Valdez, P.F. (2021). Integrating science and technology metrics. *JISIB*, 11(1), 69-77. CC BY 4.0. Available at https://ojs.hh.se/index.php/JISIB/article/view/JISIB%20Vol%2011%20Nr%201%202021

2.2.1 Project Planning

This step establishes important elements, including the main activities, scope, participants, roles, resources, and internal policies. In some cases, metrics may also be established during this stage, depending on the research objectives.

2.2.2 Identification of Data Sources

Data constitutes the essential raw material for analysis, while the source denotes the origin from which this data is obtained. Data sources are primarily categorized into two types: primary sources, which come directly from experts in a specific field, and secondary sources, which include scientific papers, technical documents, industry reports, and market research (Rodriguez-Salvador & Castillo-Valdez, 2021). Additionally, establishing metrics can facilitate the selection of the best data sources.

2.2.3 Search Strategy Design

In this stage, a clear search strategy is created to find the information within the data sources identified in the previous step. When working with primary sources involving experts, selecting the appropriate tools for gathering insights is essential. Consider using methods such as Delphi studies, focus groups, and interviews. For secondary sources, especially those obtained from databases, designing a search query that includes the most relevant terms is crucial. These terms can be found in a thorough literature review (Rodriguez-Salvador & Castillo-Valdez, 2021). Additionally, different query designs are recommended to ensure the collection of the most relevant and reliable data.

2.2.4 Data Collection

This stage involves collecting and organizing all essential information for research using primary and secondary data sources. Additionally, the data is analyzed to ensure consistency and the right format, a process known as "normalization”.

2.2.5 Information Analysis

Unlike traditional studies, which emphasize primarily the “what” and “how”, this methodology seeks to explore further questions (Rodriguez-Salvador & Castillo-Valdez, 2021), including the five Ws. According to Hart (1996), the five Ws are: “what”, “who”, “where”, “when” and “why”. The author notes that this method may act as a tool to ensure that the retrieved information aligns with the research needs.

Each data source is assessed differently using its corresponding metrics. For example, scientific literature can be evaluated based on publication counts, growth rates, impact factors, citations, and collaboration networks. Relevant metrics for patents include patent production, classification, inventor distribution, and legal status. Social media and websites are gauged through the number of mentions, downloads, and user interactions.

2.2.6 Feedback from Experts

Unlike in other studies, where expert input might be limited or absent, in CTI, researchers contact experts throughout the process. The methodology suggests involving experts through interviews and questionnaires in the entire CTI process. In addition to interviews, experts may participate in methods like Delphi studies and focus groups.

2.2.7 Validation and Delivery of Final Results

At this stage of the process, a final check will ensure the accuracy of the data, although validation should occur at every stage. Final adjustments may also be made at this point. After this, the validated data will be used to create a report for project decision-makers and stakeholders. It is recommended that the report includes both quantitative and qualitative results, taking into account the project's preferences and needs.

2.2.8 Decision Making

In this phase, the results will be implemented based on the information gathered and analyzed in the R&D area. After evaluating and discussing potential outcomes, action can be taken. Additionally, it will be essential to define what will be continuously monitored, which is a key aspect of this methodology. This stage promotes discussion, which is vital for stimulating conversation and facilitating debates about these decisions, helping to identify ways to gain competitive advantage.

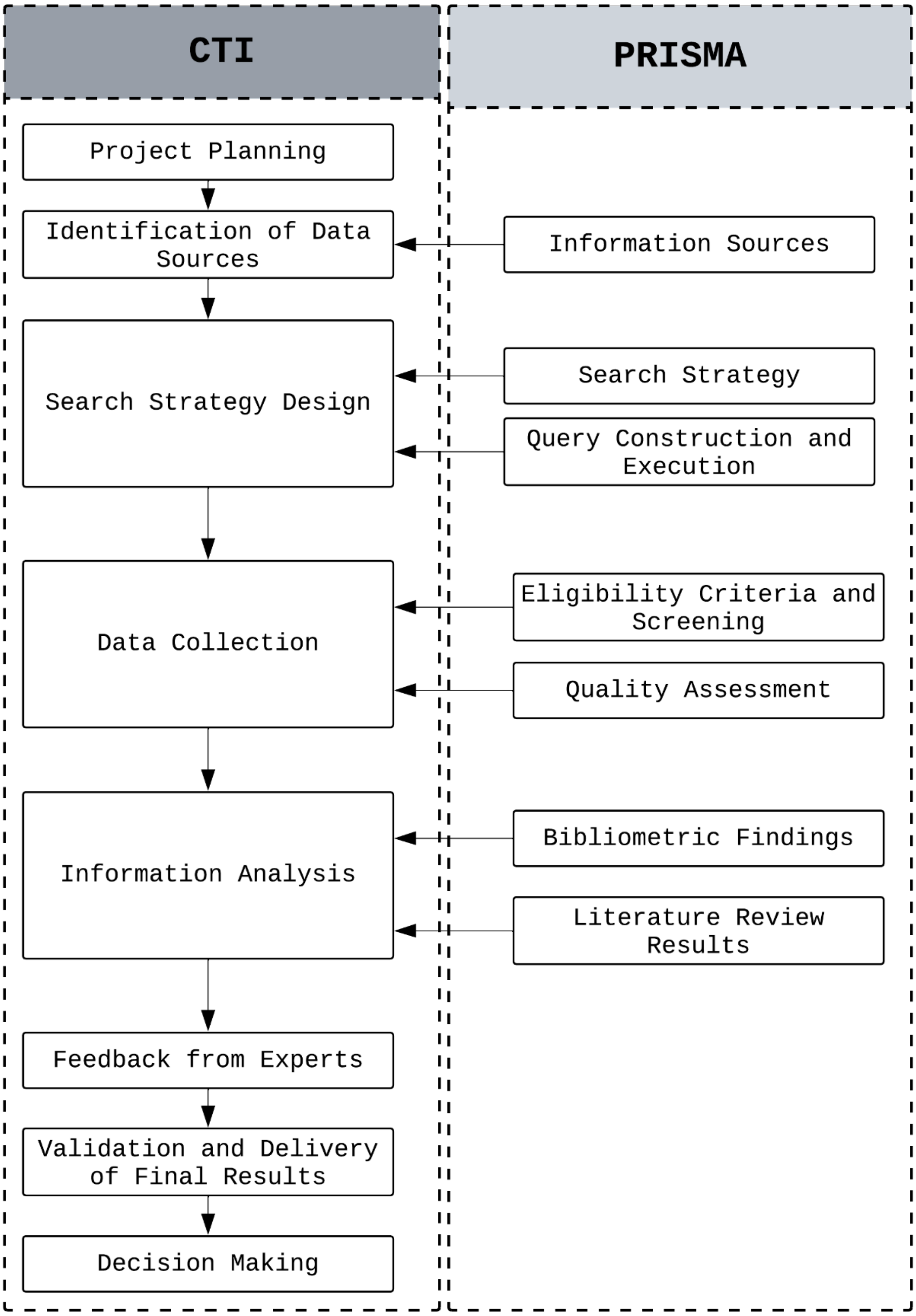
Chapter 3: Competitive Technology Intelligence Execution

3.1 Introduction

The upcoming chapter will implement the Competitive Technology Intelligence (CTI) methodology proposed by Rodriguez-Salvador & Castillo-Valdez (2021). This is done step by step, focusing on how well-being influences productivity in the context of Industry 5.0. This methodology was previously detailed in Chapter 2 and is the foundation of this research. Additionally, scientometrics is utilized as a key component of the CTI approach to enhance precision and depth. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology is a valuable tool to ensure systematic validation and comprehensive data analysis, resulting in a transparent, complete, and accurate literature review (Page, et al., 2021). Therefore, PRISMA was utilized for scientometric analysis as part of the CTI methodology (See Table 2).

While the original specifications of the CTI methodology, as proposed by Rodriguez-Salvador & Castillo-Valdez (2021), do not explicitly reference the use of PRISMA, this research aspires to adhere to stringent systematic review standards and enhance the reliability of its findings.

Table 2. PRISMA integration on Competitive Technology Intelligence.
(Own elaboration, 2024)



3.2 Project Planning

The research topic has been clearly defined and focused. The general and specific objectives and research questions that this thesis aims to address have been established. Additionally, the scope of the study has been clarified.

While Chapter 1 covers this stage of the methodology, a review will be provided to clarify and enhance understanding of its components. The research topic centers on the influence of workers' well-being on productivity in the context of Industry 5.0. In general, this research aims to find trends related to the human-centric pillar of Industry 5.0 and provide recommendations for companies seeking to adopt this approach.

Furthermore, the research has two specific objectives: first, to employ scientometrics as part of the Competitive Technology Intelligence process to identify relevant trends, and second, to offer recommendations to companies interested in becoming more human-centric in accordance with the principle of Industry 5.0.

This research aims to answer the following questions:
Q1: What are the trends being discussed in the scientific literature regarding the human centricity pilar of the Industry 5.0 paradigm with a focus on the influence of workers' well-being on productivity?

Q2: What recommendations could companies adopt to become more human-centric, following the Industry 5.0 pillar?

Ultimately, Industry 5.0 is characterized by three pillars: human-centricity, sustainability, and resilience. This thesis specifically focuses on human-centricity, which defines the scope of this research. The findings are limited to scientific papers published in the Scopus database from 01/01/2019 to 01/10/2024.

3.3 Identification of Data Sources

This research incorporates insights from Industry 4.0 and Industry 5.0 experts as primary sources and scientific literature as secondary sources, in accordance with the CTI methodology, which advocates for using both sources. Experts in the field of Competitive Technology Intelligence also participated.

A specific timeframe was defined between 01/01/2019 and 01/10/2024 due to the “Industry 5.0” official creation in 2019 by The European Commission (Breque, De Nul, & Petridis, 2021). The scientific literature was retrieved from Scopus at the recommendation of the CTI expert due to its high reliability and analytical capacity. Scopus indexes 24.6+ million open-access journals and covers a wide range of disciplines: science, technology, medicine, social sciences, and arts and humanities (Elsevier, 2024). Moreover, in a comparison of the databases Google Scholar, Web of Science, and Scopus, Scopus demonstrated the highest percentage of papers and citations (Harzing & Alakangas, 2016). The database access was granted by Biblioteca TEC 21 of Tecnologico de Monterrey.

3.4 Search Strategy Design

3.4.1 Primary Source Search Strategy Design

In accordance with the CTI methodology proposed by Rodriguez-Salvador & Castillo-Valdez (2021), the collection of insights from experts is a fundamental aspect of the process. Moreover, it is important to thoughtfully select the appropriate tools for gathering this information based on the specific research objectives.

One key objective of this research is to offer recommendations for organizations seeking to embrace a human-centric approach that emphasizes the influence of workers’ well-being on productivity. To support this offering, it's essential to gather insights from experts regarding the information presented in this research. This will help assess the relevance of the results and identify potential interests for organizations that need to make decisions in the context of Industry 5.0, with an emphasis on the influence of workers' well-being on productivity.

According to Masadeh (2012), a focus group is a qualitative research methodology that involves a structured discussion with a small group of individuals. One person or a team of moderators facilitates this discussion, which aims to generate qualitative data on a specific topic of interest. The author further emphasizes that focus groups are an effective and efficient method for data collection, particularly when involving a small group of participants, typically four to twelve individuals.

Due to the novelty of the term Industry 5.0 in research and the limited number of experts in the field, a focus group is considered the most appropriate tool for this study. This thesis proposes conducting a focus group with five Industry 5.0 experts and using a questionnaire (See Table 3) to ensure the relevance of the results, which will serve as the foundation for the recommendations offered.

Table 3. Focus Group Questions with Experts.
(Own elaboration, 2024)

Participant	Question
1	Is the information presented easy to understand?
	Is the information presented sufficient for decision-making?
	Is the information presented useful for decision-making?
	Is there any additional information that would you find needed for decision-making?
2	Is the information presented easy to understand?
	Is the information presented sufficient for decision-making?
	Is the information presented useful for decision-making?

	Is there any additional information that would you find needed for decision-making?
3	Is the information presented easy to understand?
	Is the information presented sufficient for decision-making?
	Is the information presented useful for decision-making?
	Is there any additional information that would you find needed for decision-making?
4	Is the information presented easy to understand?
	Is the information presented sufficient for decision-making?
	Is the information presented useful for decision-making?
	Is there any additional information that would you find needed for decision-making?
5	Is the information presented easy to understand?
	Is the information presented sufficient for decision-making?
	Is the information presented useful for decision-making?
	Is there any additional information that would you find needed for decision-making?

3.4.2 Secondary Source Search Strategy Design

The CTI methodology proposed by Rodriguez-Salvador & Castillo-Valdez (2021) recommends identifying keywords through a literature review. The PRISMA methodology advocates using the PICO framework. However, both frameworks have limitations. For example, keyword selection through a literature review relies heavily on databases, while PICO relies heavily on the discretion of the research expertise (Leem, Shin, Kim, & Ryul Shim, 2024).

To fill this gap, this research proposes to develop a search strategy through a literature review in order to establish a solid basis for the PICO framework. This enhances the robustness of the secondary source search strategy and improves the reliability of the search results.

3.4.2.1 Keyword Selection through Literature Review

During this phase, a search strategy was developed to find the most relevant information. This strategy involved identifying the most suitable terms, which were determined through a preliminary literature review in the Scopus database. The decision to include or exclude a keyword was made through an iterative process. Due to the European Commission's official mention of “Industry 5.0” in 2019, a specific timeframe was defined between 01/01/2019 and 01/10/2024 (Breque, De Nul, & Petridis, 2021).

The keywords were divided into three core categories (See Table 4).

- Industry 5.0 terms.
- well-being terms.
- productivity terms.

These core categories were considered as keywords to search on Scopus, focusing on literature published between 01/01/2019 and 10/01/2024. For each category, 20 papers were selected from the Scopus database, 10 representing high-impact publications and 10 representing the most recent publications within the past five years. The 'Sort by' function in Scopus was used, with 'Relevance' for high-impact publications and 'Date (newest)' for the most recent ones. The objective was to ensure the inclusion of the latest and most relevant terminology. The review considered important sections of each paper, including the title, keywords, and abstracts. This approach revealed variations of the terminology and commonly used synonyms.

The following table presents the core categories and their number of results in Scopus from 01/01/2019 to 01/10/2024, followed by the word variations identified in the previously explained literature review strategy.

Table 4. Analysis of the Core Terms "Industry 5.0", "well-being", and "productivity". (Own elaboration, 2024)

Numbers of results corresponding between 01/01/2019 – 01/10/2024		
Core	**Keyword**	**Scopus**
Industry 5.0	TITLE-ABS-KEY ("Industry 5.0") AND PUBYEAR > 2018 AND PUBYEAR < 2025	2,401
	TITLE-ABS-KEY ("Fifth Revolution") AND PUBYEAR > 2018 AND PUBYEAR < 2025	7
	TITLE-ABS-KEY ("Fifth Industrial Revolution") AND PUBYEAR > 2018 AND PUBYEAR < 2025	230
	TITLE-ABS-KEY ("I5.0 ") AND PUBYEAR > 2018 AND PUBYEAR < 2025	119
	TITLE-ABS-KEY ("human-centric manufacturing") AND PUBYEAR > 2018 AND PUBYEAR < 2025	76
	TITLE-ABS-KEY ("IR 5.0") AND PUBYEAR > 2018 AND PUBYEAR < 2025	21
Well-being	TITLE-ABS-KEY ("well ? being" OR "wellbeing") AND PUBYEAR > 2018 AND PUBYEAR < 2025	210,249
	TITLE-ABS-KEY ("welfare*" OR "well?fare*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	93,321
	TITLE-ABS-KEY ("human ? factor*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	16,634
	TITLE-ABS-KEY ("Health") AND PUBYEAR > 2018 AND PUBYEAR < 2025	2,263,376
productivity	TITLE-ABS-KEY ("productiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	271,128

	TITLE-ABS-KEY ("Efficien*" OR "Effectiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	5,136,909
	TITLE-ABS-KEY ("Performance") AND PUBYEAR > 2018 AND PUBYEAR < 2025	3,253,593

The next phase of the search strategy involved conducting a comparative analysis between "Industry 5.0" and "well-being." Combining the keywords from Table 4. Analysis of the Core Terms, an analysis was carried out to explore the relationship between "Industry 5.0" and "well-being" (See Table 5). This step aimed to ensure that the selected literature sufficiently represented the intersection of both topics.

Table 5. Combination of "Industry 5.0" & "well-being" terms.
(Own elaboration, 2024)

Numbers of results corresponding between 01/01/2019 – 01/10/2024	
Keyword	**Result Scopus**
TITLE-ABS-KEY ("Industry 5.0" AND ("well ? being" OR "wellbeing")) AND PUBYEAR > 2018 AND PUBYEAR < 2025	186
TITLE-ABS-KEY ("Industry 5.0" AND ("welfare*" OR "well?fare*")) AND PUBYEAR > 2018 AND PUBYEAR < 2025	24
TITLE-ABS-KEY ("Industry 5.0" AND ("human ? factor*")) AND PUBYEAR > 2018 AND PUBYEAR < 2025	122
TITLE-ABS-KEY ("Industry 5.0" AND "health") AND PUBYEAR > 2018 AND PUBYEAR < 2025	157
TITLE-ABS-KEY ("Fifth Revolution" AND ("well ? being" OR "wellbeing")) AND PUBYEAR > 2018 AND PUBYEAR < 2025	0

TITLE-ABS-KEY ("Fifth Revolution" AND ("welfare*" OR "well?fare*")) AND PUBYEAR > 2018 AND PUBYEAR < 2025	0
TITLE-ABS-KEY ("Fifth Revolution" AND ("human ? factor*")) AND PUBYEAR > 2018 AND PUBYEAR < 2025	0
TITLE-ABS-KEY ("Fifth Revolution" AND "health") AND PUBYEAR > 2018 AND PUBYEAR < 2025	3
TITLE-ABS-KEY ("Fifth Industrial Revolution" AND ("well ? being" OR "wellbeing")) AND PUBYEAR > 2018 AND PUBYEAR < 2025	14
TITLE-ABS-KEY ("Fifth Industrial Revolution" AND ("welfare*" OR "well?fare*")) AND PUBYEAR > 2018 AND PUBYEAR < 2025	0
TITLE-ABS-KEY ("Fifth Industrial Revolution" AND ("human ? factor*")) AND PUBYEAR > 2018 AND PUBYEAR < 2025	7
TITLE-ABS-KEY ("Fifth Industrial Revolution" AND "health") AND PUBYEAR > 2018 AND PUBYEAR < 2025	14
TITLE-ABS-KEY ("I5.0" AND ("well ? being" OR "wellbeing")) AND PUBYEAR > 2018 AND PUBYEAR < 2025	14
TITLE-ABS-KEY ("I5.0" AND ("welfare*" OR "well?fare*")) AND PUBYEAR > 2018 AND PUBYEAR < 2025	0
TITLE-ABS-KEY ("I5.0" AND ("human ? factor*")) AND PUBYEAR > 2018 AND PUBYEAR < 2025	8

TITLE-ABS-KEY ("I5.0" AND "health") AND PUBYEAR > 2018 AND PUBYEAR < 2025	9
TITLE-ABS-KEY ("Human-centric manufacturing" AND ("well ? being" OR "wellbeing")) AND PUBYEAR > 2018 AND PUBYEAR < 2025	18
TITLE-ABS-KEY ("Human-centric manufacturing" AND ("welfare*" OR "well?fare*")) AND PUBYEAR > 2018 AND PUBYEAR < 2025	1
TITLE-ABS-KEY ("Human-Centric manufacturing" AND ("human ? factor*")) AND PUBYEAR > 2018 AND PUBYEAR < 2025	4
TITLE-ABS-KEY ("Human-Centric Manufacturing" AND "health") AND PUBYEAR > 2018 AND PUBYEAR < 2025	8
TITLE-ABS-KEY ("IR 5.0" AND ("well ? being" OR "wellbeing")) AND PUBYEAR > 2018 AND PUBYEAR < 2025	0
TITLE-ABS-KEY ("IR 5.0" AND ("welfare*" OR "well?fare*")) AND PUBYEAR > 2018 AND PUBYEAR < 2025	0
TITLE-ABS-KEY ("IR 5.0" AND ("human ? factor*")) AND PUBYEAR > 2018 AND PUBYEAR < 2025	0
TITLE-ABS-KEY ("IR 5.0" AND "health") AND PUBYEAR > 2018 AND PUBYEAR < 2025	1

To examine the keyword's relevance to this study's objective, a more detailed evaluation was undertaken when the combinations between "Industry 5.0" and "well-being" and their synonyms had at most five papers (See Table 5). This involved a thorough review of the abstract, introduction, and discussion sections.

From the four combinations with the keyword "IR 5.0" only one resulted in a single paper. Upon analysis, it became clear that this paper did not contribute to the objectives of this research. Among the four combinations with the keyword "Fifth Revolution," only one resulted in three papers. However, these papers did not significantly contribute to the research and were subsequently excluded.

As a result, the keywords "Fifth Revolution" and "IR 5.0" were excluded, as their associated papers did not contribute significantly to the research or show any results (See Table 6).

Table 6. Reasoning for Exclusion of Terms.
(Own elaboration, 2024)

Combination	Reference	Reasoning
TITLE-ABS-KEY ("Fifth Revolution" AND "health") AND PUBYEAR > 2018 AND PUBYEAR < 2025	Sultan, S., Acharya, Y., Zayed, O., Elzomour, H., Parodi, J. C., Soliman, O., & Hynes, N. (2022). Is the cardiovascular specialist ready for the fifth revolution? The role of artificial intelligence, machine learning, big data analysis, intelligent swarming, and knowledge-centered service on the future of global cardiovascular healthcare delivery. *Journal of Endovascular Therapy, 30*(6), 877-884.	The paper focuses on how technologies will shape cardiovascular medicine, which is not the topic of this research.
	Shubhangi, C., Ankit, T., Qasim, M., R.S, W., & Prince, S. (2023). A Critical Review on Industry 5.0 and Its Medical Applications. *2nd International Conference on*	It focuses on Industry 5.0 for medical applications, which is not the topic of this research.

	Industrial and Manufacturing Systems, CIMS 2021. 251-261.	
	Montgomery, D. (2020). Soil health and the revolutionary potential of Conservation Agriculture. *Rethinking Food and Agriculture: New Ways Forward.* Pages 219 - 229	It focuses on the health of the soil, which is not the topic of this research.
TITLE-ABS-KEY ("IR 5.0" AND "health") AND PUBYEAR > 2018 AND PUBYEAR < 2025	Chen, Y., Chen, Y.-q., & Zhang, Q. (2022). Association between vitamin D and insulin resistance in adults with latent tuberculosis infection: Results from the National Health and Nutrition Examination Survey (NHANES) 2011–2012. *Journal of Infection and Public Health, 15*(8), 930–935.	In this paper IR referes to insuline resistance, which is not the topic of this research.

Therefore, the preliminary search query kept only the keywords that significantly contributed to the focus of workers' well-being in the context of Industry 5.0 (See Table 7).

Table 7. Preliminary Search Query.
(Own elaboration, 2024)

Query	Result
TITLE-ABS-KEY (("Industry 5.0" OR "Fifth Industrial Revolution" OR "I5.0" OR "Human-centric manufacturing") AND (("well ? being" OR "wellbeing") OR ("welfare*" OR "well?fare*") OR ("human ? factor*") OR ("health"))) AND PUBYEAR > 2018 AND PUBYEAR < 2025	430

The final step of the search strategy involved performing a comparative analysis combining the keywords from Table 4. In this case, the keywords related to "productivity" were added along with the "Industry 5.0" and "well-being" previous combinations shown in Table 5. The combinations with “Industry 5.0”, “well-being” and “productivity” are presented in Table 8. This step aimed to ensure that the selected literature sufficiently represented the intersection of well-being and productivity in the context of Industry 5.0.

Table 8. Combination of "Industry 5.0", "well-being" & "productivity" terms.
(Own elaboration, 2024)

Numbers of results corresponding between 01/01/2019 – 01/10/2024	
Keyword	**Result Scopus**
TITLE-ABS-KEY ("Industry 5.0" AND ("well ? being" OR "wellbeing") AND "productiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	43
TITLE-ABS-KEY ("Industry 5.0" AND ("welfare*" OR "well?fare*") AND "productiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	2
TITLE-ABS-KEY ("Industry 5.0" AND ("human ? factor*") AND "productiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	25
TITLE-ABS-KEY ("Industry 5.0" AND ("health") AND "productiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	22
TITLE-ABS-KEY ("Industry 5.0" AND ("well ? being" OR "wellbeing") AND "efficiency") AND PUBYEAR > 2018 AND PUBYEAR < 2025	44
TITLE-ABS-KEY ("Industry 5.0" AND ("welfare*" OR "well?fare*") AND	4

"efficiency") AND PUBYEAR > 2018 AND PUBYEAR < 2025	
TITLE-ABS-KEY ("Industry 5.0" AND ("human ? factor*") AND "efficiency") AND PUBYEAR > 2018 AND PUBYEAR < 2025	24
TITLE-ABS-KEY ("Industry 5.0" AND ("health") AND "efficiency") AND PUBYEAR > 2018 AND PUBYEAR < 2025	31
TITLE-ABS-KEY ("Industry 5.0" AND ("well ? being" OR "wellbeing") AND "performance") AND PUBYEAR > 2018 AND PUBYEAR < 2025	52
TITLE-ABS-KEY ("Industry 5.0" AND ("welfare*" OR "well?fare*") AND "performance") AND PUBYEAR > 2018 AND PUBYEAR < 2025	4
TITLE-ABS-KEY ("Industry 5.0" AND ("human ? factor*") AND "performance") AND PUBYEAR > 2018 AND PUBYEAR < 2025	42
TITLE-ABS-KEY ("Industry 5.0" AND ("health*") AND "performance") AND PUBYEAR > 2018 AND PUBYEAR < 2025	34
TITLE-ABS-KEY ("Industry 5.0" AND ("well ? being" OR "wellbeing") AND "Effectiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	24
TITLE-ABS-KEY ("Industry 5.0" AND ("welfare*" OR "well?fare*") AND "Effectiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	3
TITLE-ABS-KEY ("Industry 5.0" AND ("human ? factor*") AND "Effectiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	15

TITLE-ABS-KEY ("Industry 5.0" AND ("health*") AND "Effectiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	42
TITLE-ABS-KEY ("Fifth Industrial Revolution" AND ("well ? being" OR "wellbeing") AND "productiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	4
TITLE-ABS-KEY ("Fifth Industrial Revolution" AND ("welfare*" OR "well?fare*") AND "productiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	0
TITLE-ABS-KEY ("Fifth Industrial Revolution" AND ("human ? factor*") AND "productiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	2
TITLE-ABS-KEY ("Fifth Industrial Revolution" AND ("health") AND "productiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	2
TITLE-ABS-KEY ("Fifth Industrial Revolution" AND ("well ? being" OR "wellbeing") AND "efficiency") AND PUBYEAR > 2018 AND PUBYEAR < 2025	3
TITLE-ABS-KEY ("Fifth Industrial Revolution" AND ("welfare*" OR "well?fare*") AND "efficiency") AND PUBYEAR > 2018 AND PUBYEAR < 2025	0
TITLE-ABS-KEY ("Fifth Industrial Revolution" AND ("human ? factor*") AND "efficiency") AND PUBYEAR > 2018 AND PUBYEAR < 2025	3
TITLE-ABS-KEY ("Fifth Industrial Revolution" AND ("health") AND	2

"efficiency") AND PUBYEAR > 2018 AND PUBYEAR < 2025	
TITLE-ABS-KEY ("Fifth Industrial Revolution" AND ("well ? being" OR "wellbeing") AND "performance") AND PUBYEAR > 2018 AND PUBYEAR < 2025	3
TITLE-ABS-KEY ("Fifth Industrial Revolution" AND ("welfare*" OR "well?fare*") AND "performance") AND PUBYEAR > 2018 AND PUBYEAR < 2025	0
TITLE-ABS-KEY ("Fifth Industrial Revolution" AND ("human ? factor*") AND "performance") AND PUBYEAR > 2018 AND PUBYEAR < 2025	1
TITLE-ABS-KEY ("Fifth Industrial Revolution" AND ("health") AND "performance") AND PUBYEAR > 2018 AND PUBYEAR < 2025	2
TITLE-ABS-KEY ("Fifth Industrial Revolution" AND ("well ? being" OR "wellbeing") AND "Effectiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	1
TITLE-ABS-KEY ("Fifth Industrial Revolution" AND ("welfare*" OR "well?fare*") AND "Effectiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	0
TITLE-ABS-KEY ("Fifth Industrial Revolution" AND ("human ? factor*") AND "Effectiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	1
TITLE-ABS-KEY ("Fifth Industrial Revolution" AND ("human ? factor*") AND "Health") AND PUBYEAR > 2018 AND PUBYEAR < 2025	1

TITLE-ABS-KEY ("I5.0" AND ("well ? being" OR "wellbeing") AND "productiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	5
TITLE-ABS-KEY ("I5.0" AND ("welfare*" OR "well?fare*") AND "productiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	0
TITLE-ABS-KEY ("I5.0" AND ("human ? factor*") AND "productiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	3
TITLE-ABS-KEY ("I5.0" AND ("health") AND "productiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	2
TITLE-ABS-KEY ("I5.0" AND ("well ? being" OR "wellbeing") AND "efficiency") AND PUBYEAR > 2018 AND PUBYEAR < 2025	5
TITLE-ABS-KEY ("I5.0" AND ("welfare*" OR "well?fare*") AND "efficiency") AND PUBYEAR > 2018 AND PUBYEAR < 2025	0
TITLE-ABS-KEY ("I5.0" AND ("human ? factor*") AND "efficiency") AND PUBYEAR > 2018 AND PUBYEAR < 2025	1
TITLE-ABS-KEY ("I5.0" AND ("health") AND "efficiency") AND PUBYEAR > 2018 AND PUBYEAR < 2025	1
TITLE-ABS-KEY ("I5.0" AND ("well ? being" OR "wellbeing") AND "Performance") AND PUBYEAR > 2018 AND PUBYEAR < 2025	2
TITLE-ABS-KEY ("I5.0" AND ("welfare*" OR "well?fare*") AND "Performance") AND PUBYEAR > 2018 AND PUBYEAR < 2025	0

TITLE-ABS-KEY ("I5.0" AND ("human ? factor*") AND "Performance") AND PUBYEAR > 2018 AND PUBYEAR < 2025	2
TITLE-ABS-KEY ("I5.0" AND ("health") AND "Performance") AND PUBYEAR > 2018 AND PUBYEAR < 2025	1
TITLE-ABS-KEY ("I5.0" AND ("well ? being" OR "wellbeing") AND "Effectiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	3
TITLE-ABS-KEY ("I5.0" AND ("welfare*" OR "well?fare*") AND "Effectiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	0
TITLE-ABS-KEY ("I5.0" AND ("human ? factor*") AND "Effectiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	1
TITLE-ABS-KEY ("I5.0" AND ("health") AND "Effectiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	1
TITLE-ABS-KEY ("Human-Centric Manufacturing" AND ("well ? being" OR "wellbeing") AND "productiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	3
TITLE-ABS-KEY ("Human-Centric Manufacturing" AND ("welfare*" OR "well?fare*") AND "productiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	0
TITLE-ABS-KEY ("Human-Centric Manufacturing" AND ("human ? factor*") AND "productiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	0
TITLE-ABS-KEY ("Human-Centric Manufacturing" AND ("health") AND	2

"productiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	
TITLE-ABS-KEY ("Human-Centric Manufacturing" AND ("well ? being" OR "wellbeing") AND "efficiency") AND PUBYEAR > 2018 AND PUBYEAR < 2025	3
TITLE-ABS-KEY ("Human-Centric Manufacturing" AND ("welfare*" OR "well?fare*") AND "efficiency") AND PUBYEAR > 2018 AND PUBYEAR < 2025	0
TITLE-ABS-KEY ("Human-Centric Manufacturing" AND ("human ? factor*") AND "efficiency") AND PUBYEAR > 2018 AND PUBYEAR < 2025	0
TITLE-ABS-KEY ("Human-Centric Manufacturing" AND ("health") AND "efficiency") AND PUBYEAR > 2018 AND PUBYEAR < 2025	3
TITLE-ABS-KEY ("Human-Centric Manufacturing" AND ("well ? being" OR "wellbeing") AND "Performance") AND PUBYEAR > 2018 AND PUBYEAR < 2025	7
TITLE-ABS-KEY ("Human-Centric Manufacturing" AND ("welfare*" OR "well?fare*") AND "Performance") AND PUBYEAR > 2018 AND PUBYEAR < 2025	0
TITLE-ABS-KEY ("Human-Centric Manufacturing" AND ("human ? factor*") AND "Performance") AND PUBYEAR > 2018 AND PUBYEAR < 2025	0
TITLE-ABS-KEY ("Human-Centric Manufacturing" AND ("health") AND "Performance") AND PUBYEAR > 2018 AND PUBYEAR < 2025	3

TITLE-ABS-KEY ("Human-Centric Manufacturing" AND ("well ? being" OR "wellbeing") AND "Effectiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	2
TITLE-ABS-KEY ("Human-Centric Manufacturing" AND ("welfare*" OR "well?fare*") AND "Effectiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	1
TITLE-ABS-KEY ("Human-Centric Manufacturing" AND ("human ? factor*") AND "Effectiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	1
TITLE-ABS-KEY ("Human-Centric Manufacturing" AND ("health") AND "Effectiv*") AND PUBYEAR > 2018 AND PUBYEAR < 2025	1

To examine the keyword's relevance for the objective of this study, a more detailed evaluation was undertaken when the combinations between "Industry 5.0", "well-being", and "productivity" and their synonyms had at most five papers. This involved thoroughly reviewing the abstract, introduction, and discussion sections. As a result of this evaluation, no changes were made to the keywords.

3.4.2.2 Keyword Selection with PEO Framework

The PICO framework, which stands for Population, Intervention, Comparison, and Outcome, is well-known for its effectiveness in framing and answering clinical and healthcare questions (Palaskar, 2017). Additionally, it can be used to develop literature search strategies by breaking down search terms or concepts into PICO elements (Palaskar, 2017). However, there are some cases where the PICO framework cannot be directly applied due to the research scope and design (Topor, et al., 2021).

Several alternatives to the traditional PICO framework have been developed to address its limitations (Booth, et al., 2019). Some examples include SPICE–Setting, Perspective, Intervention, Comparison, and Evaluation—, SPIDER—Sample, Phenomenon of Interest, Design, Evaluation, and Research type— (Stern, Jordan, & McArthur, 2014), and PEO—Population, Exposure, Outcome— (Aboagye, et al., 2021).

Unlike the PICO framework, which focuses on comparing interventions and their outcomes, the PEO framework explores experiences and outcomes related to exposure. Since worker well-being is closely related to their experiences and perceptions, and productivity is viewed as the outcome of these experiences, the PEO framework is a more suitable choice. The keywords in the PEO framework are derived from the prior section, where they were chosen based on a literature review (See Table 9).

Table 9. Keyword Selection via the PEO Framework.
(Own elaboration, 2024)

PEO Element	**Domain: Human-Centricity focused on well-being and productivity within the Industry 5.0 Paradigm**	
	Keywords	**Search Strategies**
Population	Manufacturing environments aiming to adopt Industry 5.0	"Industry 5.0" OR "Fifth Industrial Revolution" OR "I5.0" OR "Human-centric manufacturing"
Exposure	Human Factors focused on well-being	("well ? being" OR "wellbeing") OR ("welfare*" OR "well?fare*") OR ("human ? factor*") OR ("health")
Outcome	Improvements in worker well-being and productivity	("productiv*" OR "efficiency" OR "performance" OR "Effectiv*")

3.4.2.3 Query Construction and Execution

After the keyword selection process, a query with results focusing on Industry 5.0, well-being, and productivity is produced. The results were limited to the dates between 01/01/2019 and 01/10/2024. The following table presents the final query and its results (See Table 10).

Table 10. Final Query.
(Own elaboration, 2024)

Query	Result
TITLE-ABS-KEY (("Industry 5.0" OR "Fifth Industrial Revolution" OR "I5.0" OR "Human-centric manufacturing") AND (("well ? being" OR "wellbeing") OR ("welfare*" OR "well?fare*") OR ("human ? factor*") OR ("health")) AND ("productiv*" OR "efficiency" OR "performance" OR "Effectiv*")) AND PUBYEAR > 2018 AND PUBYEAR < 2025	223

3.5 Data Collection

The previous validated query produced 223 results in Scopus, as shown in the last section (See Table 10). These results include journals, books, and conference papers published between 01/01/2019 and 1/10/2024. No duplicate findings were eliminated since only one database was used. The remaining publications were screened based on their titles, keywords, and abstract information. The inclusion criteria required publications to be all in the English language, publications to be consistent with the research topic of workers' well-being and productivity within the context of Industry 5.0, and the publication stage must be final in the Scopus function of the "Publication stage." Commonly, a publication labeled as "Final" ensures that the article has gone through the entire peer-review process and has been formally accepted (PLOS, 2024).

Moreover, exclusion criteria encompassed publications on well-being and productivity that are not aligned with the Industry 5.0 paradigm, publications primarily pertaining to the healthcare sector, and publications focused mainly on the sustainability or resilience pillars of Industry 5.0. As a result, the number of papers decreased to 149 (See Figure 6).

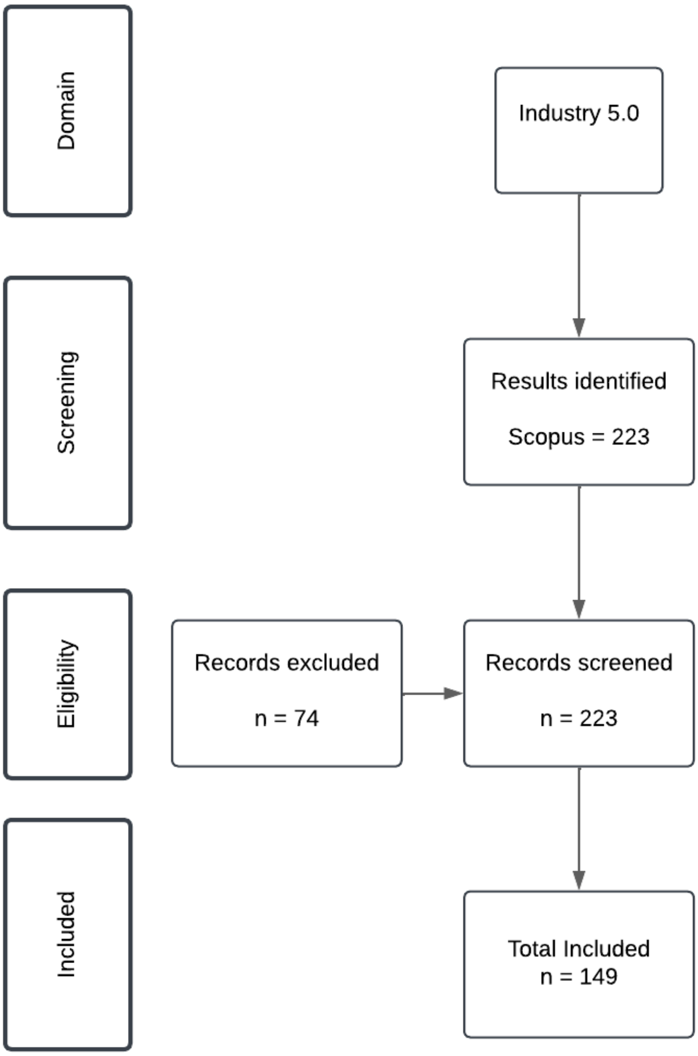


Figure 6. Flow Diagram based on PRISMA Methodology.
(Own elaboration, 2024)

3.6 Information Analysis

An information analysis will be undertaken using the five Ws framework previously introduced in subchapter 2.2.5, Chapter 2. The main aim is to ensure that the information obtained aligns with the research objectives while also uncovering insights that may not be clearly visible in the raw data. The application of the five Ws in this research is as follows: **When**—to analyze temporal patterns; **Where**—to identify the geographical distribution of research effort in the field; **Who**—to determine the key contributors and stakeholders; **What**—to identify the most frequently mentioned keywords and types of publications obtained; and **Why**—to identify the most relevant human factors and trends in Industry 5.0. By applying this framework, the goal is to achieve a detailed and comprehensive understanding of the data at hand.

3.6.1 When

The publication years are critical for comprehending the evolution of research interest over time. The subsequent chart illustrates the annual publication production through the years (See Figure 7). The chart encompasses only complete years. Given that data collection for this research concluded in October 2024, the year 2024 has been omitted to avoid potentially misleading results.

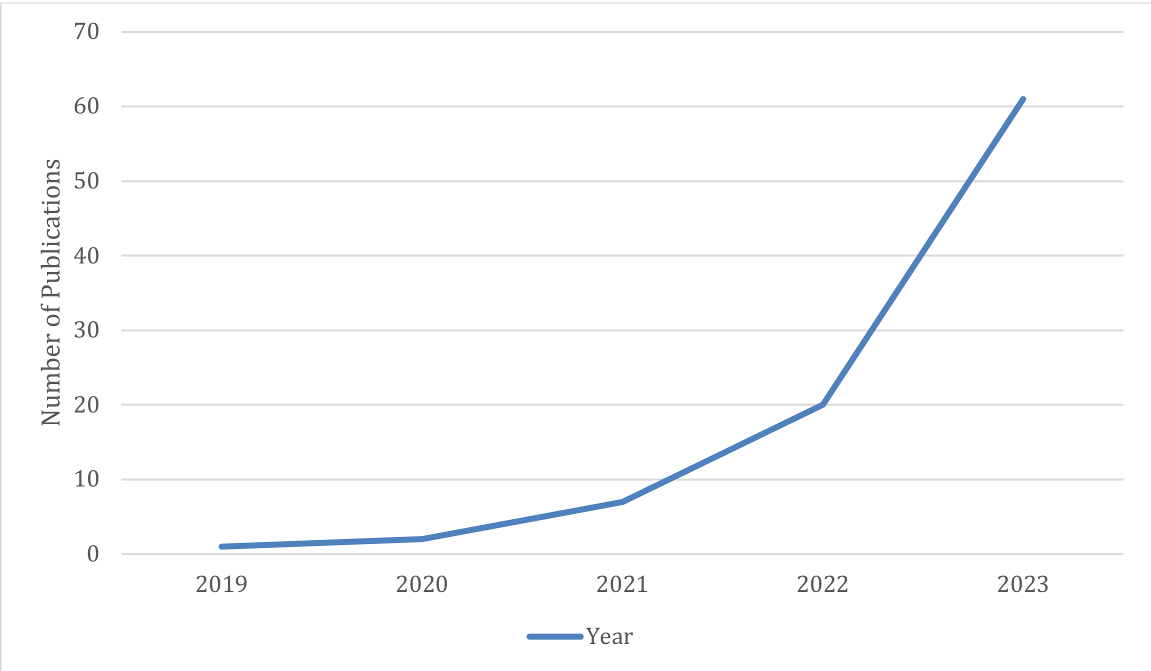


Figure 7. Number of Publications per Year.
(Own elaboration, 2024)

As observed, there is a consistent increase from 2019 to 2021, indicating an exploratory phase in this field, while the sharp rise from 2022 to 2023 implies accelerated research engagement. This corresponds with the period when the European Commission officially introduced Industry 5.0 in 2019. Furthermore, this notable increase may indicate a transition from exploring concepts to actively adopting and implementing the principles of Industry 5.0. Decision-makers can view this as a sign of growing opportunities for collaboration, funding, and innovation in this rapidly expanding sector.

3.6.2 Where

Subsequently, the publications were organized according to the first author's country of affiliation in order to identify the geographical distribution of research efforts within the field. The chart below displays the publications by the country of the first author (See Figure 8).

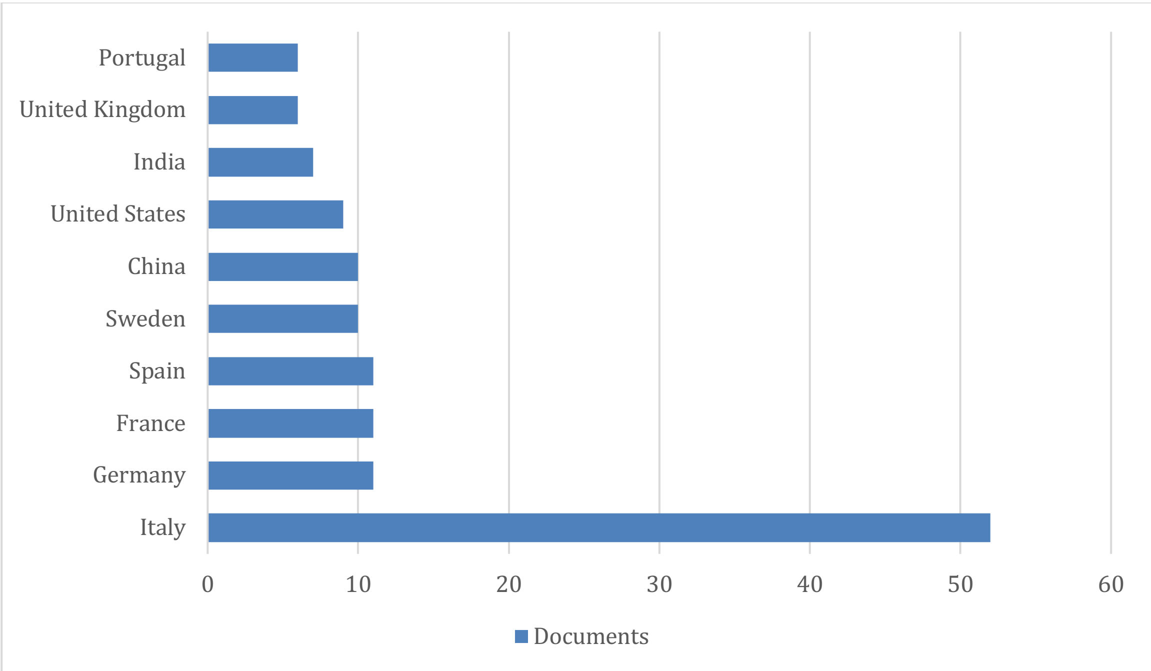


Figure 8. Number of Publications by Country.
(Own elaboration, 2024)

As a result, the ten leading countries with publications related to the relationship between well-being and productivity in the Industry 5.0 field are Italy (52), Germany (11), France (11), Spain (11), Sweden (10), China (10), the United States (9), India (7), the United Kingdom (6), and Portugal (6).

This chart shows Italy's dominance as the primary contributor of papers in the field, accounting for 35%. This underlines its significant role in advancing research on the influence of workers' well-being on productivity within Industry 5.0. This finding is consistent with Italy's pioneering role in the implementation of Industry 5.0 initiatives. For instance, the project "Piano Transizione Industry 5.0," which was launched in March 2022 (Ministero delle Imprese e del Made in Italy, 2022). Furthermore, another significant factor that may have served as a catalyst for Italy to lead Industry 5.0 focused on the influence of workers' well-being on productivity, is that it was the first European country to be impacted by COVID-19 in January 2020 (Masino & Enria, 2023).

Furthermore, Germany, France, and Spain each account for 7%, establishing a significant secondary group of contributors. This underscores European leadership in the domain, as seven of the top ten countries are situated in Europe. Additionally, these countries demonstrate a substantial level of industrial development, thereby presenting considerable potential for research and innovation.

In Asia, China and India emerge as notable contributors, while the United States leads in the Americas. This regional distribution underscores the potential for global collaboration regarding workers' well-being and its influence on productivity within the context of Industry 5.0.

3.6.3 Who

The primary authors will be identified to highlight the key contributors in Figure 9, and the funding sponsors will be identified to highlight key stakeholders in Figure 10. The following chart presents the primary contributors (See Figure 9).

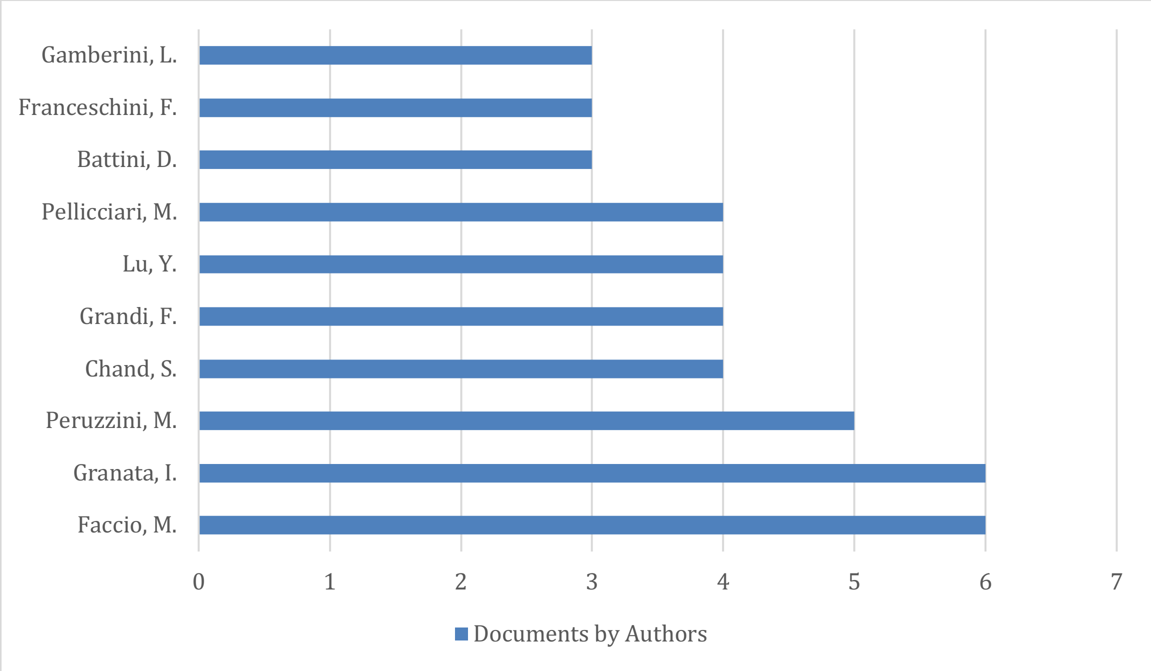


Figure 9. Publications by Author.
(Own elaboration, 2024)

The bar chart indicates that Faccio, M. and Granata, I. are the most active contributors to research on the influence of workers' well-being on productivity in the context of Industry 5.0. Organizations and researchers looking to deepen their understanding or establish collaborations in this area should consider engaging with these key contributors to enhance their expertise and insights. Moreover, the consistent contributions from authors like Peruzzini, M., Chand, S., and Grandi, F. showcase a strong secondary tier of expertise, highlighting a robust network of researchers in the field. Furthermore, these findings can help decision-makers identify leaders and potential collaborators in innovation projects.

Additionally, the following treemap displays the ten main funding sponsors (See Figure 10).

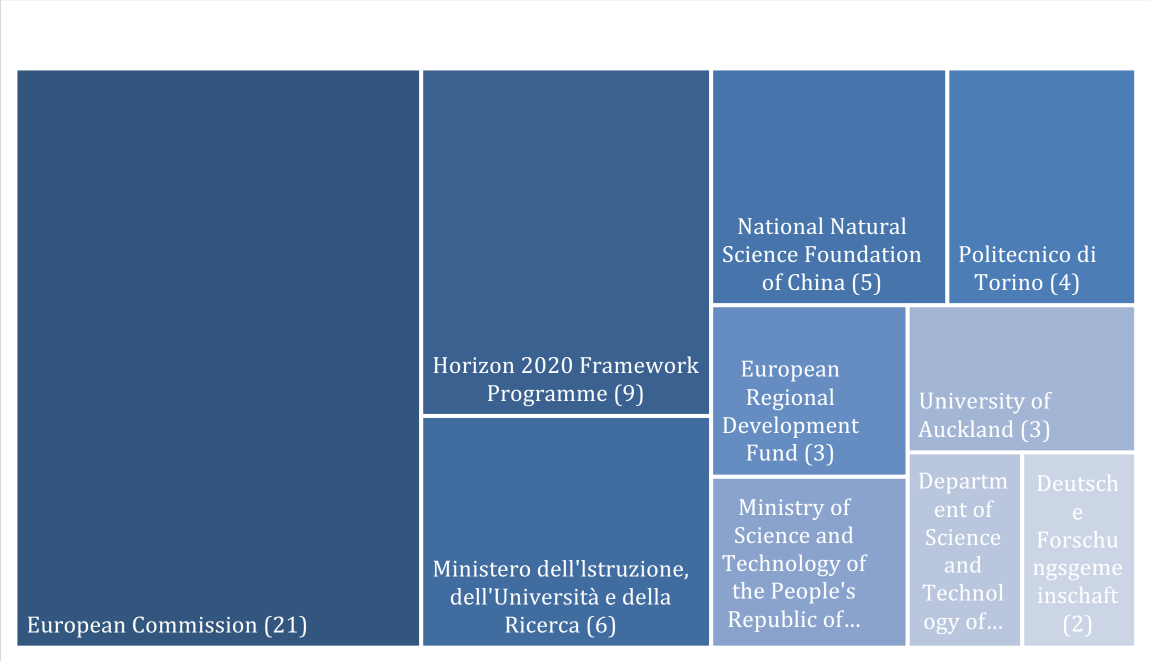


Figure 10. Number of Publications by Funding Sponsor.
(Own elaboration, 2024)

Evidently, the European Commission plays a dominant role in funding research related to the influence of workers' well-being on productivity in Industry 5.0 (See Figure 10). Notably, it contributes to 59% of the publications through initiatives such as the Horizon 2020 Framework Programme (Commission, Horizon 2020, 2020) and the European Regional Development Fund (Commission, European Regional Development Fund, 2024). This significant funding dominance can be attributed to the European Commission's leadership in defining the concept of Industry 5.0. Additionally, this substantial European funding is closely connected to the prominence of European countries in well-being and productivity within the context of Industry 5.0.

3.6.4 What

Figure 11 highlights key topics in this research field and frequently mentioned keywords. Meanwhile, Figure 12 presents an overview of the various types of publications and categorizes them accordingly.

A word cloud (see Figure 11) illustrates the most commonly referenced topics. This word cloud was created using keywords extracted from the 149 analyzed papers. It was created using an online tool called “wordcloud.com” (Schoonhoven, 2003), and it highlights the most prominent topics in the research field.

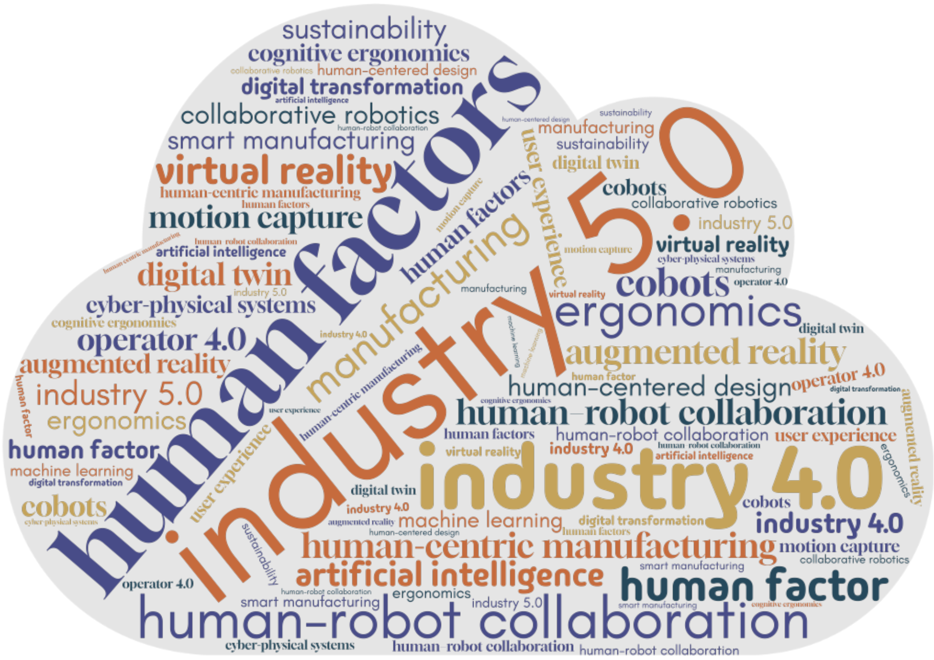


Figure 11. Word Cloud Distribution.
(Own elaboration, 2024)

Keywords like ‘Industry 5.0’ and ‘human factors’ are crucial elements of the discourse, emphasizing their importance in shaping the focus of current studies. These insights also enabled the validation of the alignment between the research objectives and the information gathered.

Furthermore, the presence of keywords such as ‘human-robot collaboration’, ‘virtual reality, and ‘augmented reality’ in the cloud highlights a significant interest in technology-driven approaches to enhancing well-being within the context of Industry 5.0. The word cloud provides valuable insights by emphasizing key research priorities and emerging technologies. For instance, the prominence of terms like ‘cobots,’ ‘digital twin,’ and ‘ergonomics’ underscores areas where resources can be allocated to promote innovation and collaboration, especially concerning the influence of workers’ well-being on productivity in Industry 5.0. Additionally, it identifies potential gaps in topics that receive less focus, encouraging further examination of these lesser-emphasized areas.

Furthermore, the doughnut chart provides an insightful overview of the publications organized by type. (See Figure 12).

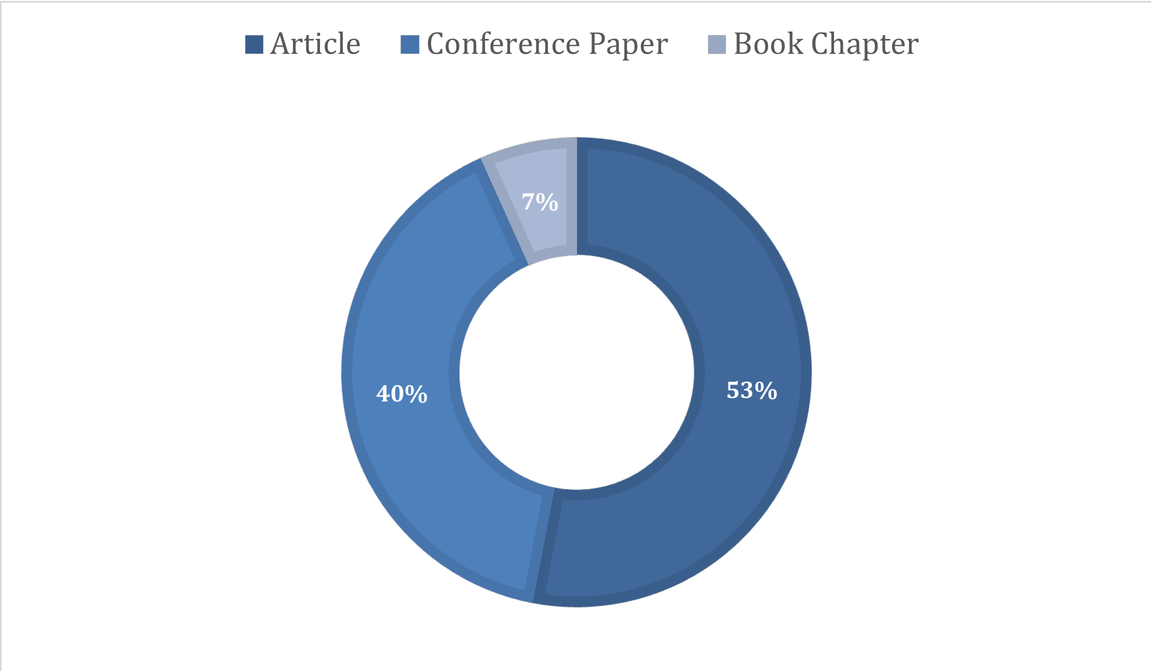


Figure 12. Publication Type Distribution.
(Own elaboration, 2024)

The doughnut chart offers a clear overview of the distribution of document types in the analyzed research papers. Research articles dominate the landscape, accounting for 53% of the total, emphasizing the academic field's strong reliance on peer-reviewed articles for credible information. Conference papers closely follow at 40%, reflecting the crucial role that conferences play in sharing the latest trends and fostering discussions in the field. Finally, book chapters contribute a modest 7% to the overall mix. The substantial presence of articles highlights the importance of engaging with peer-reviewed literature for reliable insights, while the high percentage of conference papers indicates the need to attend conferences to stay informed and make valuable connections.

3.6.5 Why

Figure 13 illustrates the most relevant human factors in Industry 5.0, and Figure 14 highlights the latest technological trends. The following pie chart categorizes these key human factors.

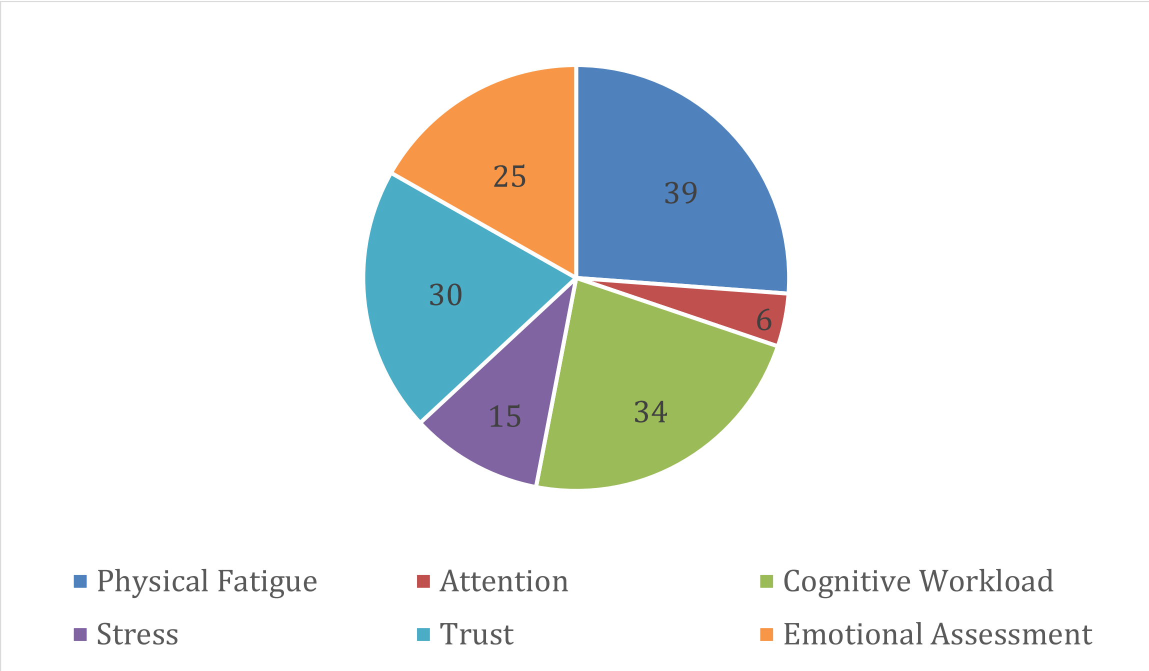


Figure 13. Human Factors.
(Own elaboration, 2024)

The chart highlights the distribution of six key human factors in Industry 5.0. Notably, ‘Physical Fatigue’ and ‘Cognitive Workload’ stand out as the most significant, with 39 and 34 publications in these areas, respectively. These two factors account for half of the total publications, underscoring their prominence in the field. This suggests that physical strain and mental load are critical challenges impacting worker well-being and productivity, making them key priorities for intervention.

Furthermore, ‘Trust’ also stands out as a crucial element, highlighted by 30 publications in this area. This underscores the goals of Industry 5.0, which focuses on fostering closer collaboration between humans and robots. It’s essential to understand that Industry 5.0 aims to cultivate a human-centric environment where robots are not merely tools but rather collaborative partners that enhance human potential.

Lastly, even though ‘Attention’ and ‘Stress’ make up a smaller portion of the pie chart, it's crucial not to underestimate them, as they may be underlying issues that affect other factors.

Furthermore, the latest technological trends are presented in the pie chart below (See Figure 14).

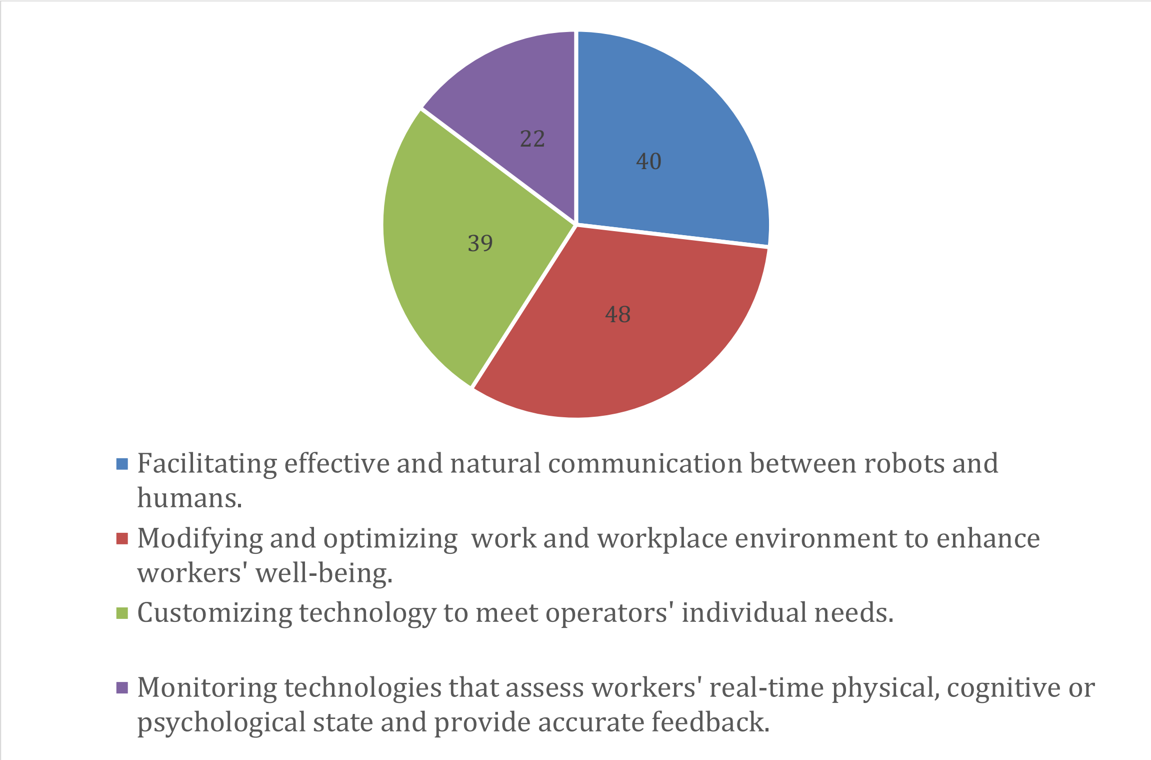


Figure 14. Technological Trends.
(Own elaboration, 2024)

The predominant trend, encapsulated in 48 publications, underscores the integration of technology to modify and optimize work and workplace environments. This enhances well-being, which in turn contributes to heightened productivity levels among the workforce. This trend evidences a robust commitment to creating adaptive work and environmental settings that prioritize the holistic well-being of employees.

Another notable trend, characterized by 40 publications, centers on facilitating effective and natural communication between robots and humans, thereby facilitating seamless human-robot collaboration within the framework of Industry 5.0. Following closely, a total of 39 publications suggest a burgeoning interest in the design of customized technology design to meet operators' individual needs. Lastly, while it constitutes a smaller segment of the overall analysis, real-time monitoring technologies that provide accurate feedback are attracting increased attention, thereby presenting a promising opportunity for further exploration.

As demonstrated in the analysis above, Europe has emerged as the primary region for researching the Industry 5.0 human-centric approach, focusing on well-being and productivity, driven by the European Commission's financial support. Italy is currently at the forefront, although global players like China and the United States are also making significant contributions. The rise in publications since 2022 indicates a continually increasing interest and investment in this research area. Moreover, technologies that promote human-robot collaboration, such as virtual and augmented reality, are gaining traction in the field of Industry 5.0.

3.6.6 Literature Review Results

This section offers a concise summary of each paper. This step aligns with the PRISMA methodology, which seeks to emphasize relevant characteristics and support the comparison of study methodologies and results. Furthermore, it helps in recognizing patterns, similarities, and differences among the studies.

Result 1:

Digital Twin Technology of Human–Machine Integration in Cross-Belt Sorting System by Qu et al. (2024)

This research examines the increased workload imposed on workers in the Chinese express delivery sector in light of significant automation. It also presents a human-machine integrated digital twin framework designed to balance employee well-being with productivity. By integrating physiological data to monitor operator fatigue and utilizing real-time simulations for optimization, this framework enhances worker welfare and boosts the efficiency of cross-belt sorting systems.

Result 2:

Human-centric robotic assembly line design: a fuzzy inference system approach for adaptive workload management by Ghorbani et al. (2024).

This study highlights the shift to Industry 5.0 by introducing an innovative fatigue model that focuses on ergonomic risk management in robotic assembly lines. The model employs a fuzzy inference system to address ergonomic complexities. It evaluates fatigue at both the task and worker levels, incorporating supportive robots to enhance productivity and well-being. Empirical validation demonstrates its effectiveness in reducing system costs by up to 47% while lowering fatigue and ergonomic risks. This underscores Industry 5.0's dedication to sustainable productivity and worker satisfaction.

Result 3:

Achieving productivity and operator well-being: a dynamic task allocation strategy for collaborative assembly systems in Industry 5.0 by Calzavara et al. (2024).

This paper investigates the role of collaborative robots (cobots) in enhancing productivity while simultaneously safeguarding worker well-being within the framework of Industry 5.0. It emphasizes the importance of designing work environments with a human-centric paradigm, considering critical factors such as ergonomics, mental workload, and individual competencies to optimize both human performance and systemic efficiency. Furthermore, the study introduces a flexible, real-time multi-objective task allocation strategy for collaborative systems that adjusts the workload distribution between the human operator and the cobot in accordance with the operator's stress or energy levels. This methodology contributes to the equilibrium between system performance and employee well-being by mitigating stress, consequently leading to an overall increase in productivity.

Result 4:

A framework for human-robot collaboration enhanced by preference learning and ergonomics by Mergalli Falerni et al. (2024).

This study concentrates on improving employee well-being and efficiency in the context of Industry 5.0 by suggesting a human-centered framework for human-robot collaboration. It presents a preference-based optimization algorithm (AmPL-RULA) that combines ergonomic evaluations (RULA) to enhance the configurations of collaborative robots during tasks involving object handling. The research emphasizes how incorporating user feedback and ergonomic factors boosts physical well-being by alleviating workload, which in turn promotes enhanced working conditions and productivity in joint assembly tasks.

Result 5:

Workplace Well-Being in Industry 5.0: A Worker-Centered Systematic Review by Antonaci et al. (2024).

This paper provides a comprehensive review of methods for monitoring and evaluating both physical and cognitive ergonomics within the framework of Industry 5.0, where enhancing worker well-being is essential for boosting productivity and ensuring safety. The research tackles three primary questions: the technologies employed to evaluate worker well-being, the process of data analysis, and the objectives of these assessments. Wearable inertial measurement devices and RGB-D cameras are highlighted as the most prevalent tools for monitoring physical ergonomics, whereas cardiac activity stands out as the key physiological metric utilized for cognitive ergonomics. The review indicates that future investigations should aim at creating multi-modal systems that combine both physical and cognitive evaluations, with a focus on their practical implementation in actual industrial settings to enhance worker well-being and productivity.

Result 6:

Maximizing efficiency and collaboration: Comparing Robots and Cobots in the Automotive Industry- A Multi-Criteria Evaluation Approach by Mouhib et al. (2024)

This paper investigates the role of collaborative robots (cobots) in Industry 5.0, focusing on their relationship with traditional robots in assembly lines. The research compares cobots and traditional robots using a case study from an automotive factory and the Fuzzy AHP methodology. The findings reveal that cobots are effective for low-volume, high-variability tasks, improving flexibility and worker well-being, but they do not match the reliability, precision, or productivity of traditional robots in repetitive tasks. The study proposes a decision-making framework to help industries choose the right technology for specific tasks, balancing productivity and worker well-being.

Result 7:

Real-time Monitoring of Human and Process Performance Parameters in Collaborative Assembly Systems using Multivariate Control Charts by Verna et al. (2024).

This paper explores the challenges of manufacturing customized products in small quantities, highlighting the need for adaptable Human-Robot Collaboration (HRC) systems. The research introduces multivariate control charts as diagnostic tools to monitor key factors such as assembly duration, quality assessment, defect rates, and worker stress, providing a comprehensive view of both operational efficiency and employee well-being. By incorporating real-time tracking of these elements, the system can identify and address inefficiencies while prioritizing the welfare of operators. This approach is demonstrated in the assembly of custom electronic boards and can be automated through the HRC system's software or its digital twin. This enhances performance without overloading operators, achieving a balance between productivity and employee well-being in customized manufacturing environments.

Result 8:

An innovative integrated solution to support digital postural assessment using the TACOs methodology by Khamaisi et al. (2024).

This paper introduces an innovative solution for ergonomic assessment in Industry 5.0 that overcomes the challenges of manual methods, which are often time-consuming and reliant on ergonomist expertise. By integrating wearable sensors and digital posture assessments, the study aims to enhance worker well-being and productivity through real-time monitoring of ergonomic risks. The proposed system features a wearable suit and a software tool based on the Time-Based Assessment COmputerized Strategy (TACOs) method, enabling even non-expert users to conduct reliable postural evaluations. Preliminary tests in simulated industrial settings demonstrate that this system provides more accurate and efficient results than traditional methods, highlighting its potential for proactive intervention to reduce musculoskeletal disorders and improve workplace safety and productivity.

Result 9:

Digital Twins in Industry 5.0 – a systematic literature review [Gemelos Digitales en la Industria 5.0 – una Revisión Sistemática de Literatura by Domínguez (2024).

This study explores the role of digital twins in advancing Industry 5.0, focusing on their effects on worker safety, human-robot collaboration, and manufacturing efficiency. Digital twins improve safety through real-time monitoring and proactive risk management while also enhancing collaboration and boosting production efficiency. However, there are challenges that need to be addressed, including data quality, computational complexity, cybersecurity risks, and the consideration of human and socio-economic factors. Overall, the study emphasizes the potential of digital twins to create safer and more efficient industrial environments in the context of Industry 5.0.

Result 10:

Human-Centric Assistive Technologies in Manual Picking and Assembly Tasks: A Literature Review by Lucchese et al. (2024).

The authors explore the role of Industry 4.0 assistive technologies in production and logistics systems, focusing on their impact from a human-centric perspective. The study reviews various assistive technologies, categorizing them by task type (e.g., picking, assembly), the type of support they offer (cognitive or motor), and potential drawbacks. The findings highlight the importance of considering worker well-being and performance when developing and implementing these technologies, advocating for a comprehensive, human-centric approach to enhance both productivity and operator health.

Result 11:

“CANTINA 5.0”—A Novel, Industry 5.0-Based Paradigm Applied to the Winemaking Industry in Italy by Venturi et al. (2024)

This document examines how Industry 5.0 concepts can be implemented in the Italian winemaking sector, emphasizing the importance of sustainability, human-centered approaches, and innovation. The winemaking sector, characterized by small and medium enterprises (SMEs) as well as large companies with varying approaches, faces challenges due to climate differences and seasonality. The CANTINA 5.0 project aims to bridge these gaps by integrating human well-being, environmental monitoring, and advanced technologies across diverse production conditions. Furthermore, the study uses smart tools and questionnaires to monitor the health and well-being of workers, as well as adopt novel environmental monitoring techniques, such as IoT-based sensors and gas chromatography, to improve the production process. Additionally, sensory analysis of the wine, considering both chemical and emotional characteristics, is utilized to optimize quality in alignment with Industry 5.0 principles.

Result 12:

Advancing human–robot collaboration in handcrafted manufacturing: cobot-assisted polishing design boosted by virtual reality and human-in-the-loop by Ciccarelli et al. (2024).

This article examines the use of collaborative robots (cobots) in the handcrafted manufacturing sector, with a focus on the fashion industry and the reduction of work-related risks. Unlike traditional manufacturing, handcrafted processes, such as leather shoe polishing, present challenges due to the need for precision, adaptability, and nuanced decision-making. The study suggests utilizing collaborative robots (cobots) during the initial polishing phase to manage physically demanding tasks. This approach allows artisans to concentrate on the finalization and quality control processes. Additionally, the research incorporates the concept of human-in-the-loop (HITL) and virtual reality simulations to enhance human-robot collaboration, ensuring safety, ergonomics, and efficiency. By addressing human factors in the design and development of cobot systems, this study provides insights for effectively integrating collaborative robotics into craftsmanship, aligning with both industrial performance goals and worker well-being.

Result 13:

RHYTHMS: Real-time Data-driven Human-machine Synchronization for Proactive Ergonomic Risk Mitigation in the Context of Industry 4.0 and Beyond by Ling et al. (2024)

The challenges associated with human-machine work systems (HMWS) within the frameworks of Industry 4.0 and 5.0 are examined, with an emphasis on the necessity for real-time synchronization between humans and machines. HMWS combines human cognitive flexibility with machine precision, but the lack of real-time information sharing, human instability, and complexities in smart networking environments can hinder synchronous coordination. RHYTHMS is a solution proposed by the authors that utilizes a service-oriented human-to-machine architecture (SOH2M) along with model reference adaptive fuzzy control to facilitate real-time data sharing and enhance synchronization. A real-life assembly case study demonstrates how this approach proactively mitigates ergonomic risks, supporting a human-centric manufacturing model aligned with the principles of Industry 5.0.

Result 14:

Updating design guidelines for cognitive ergonomics in human-centred collaborative robotics applications: An expert survey by Gualtieri et al. (2024).

The discussion centers on the significance of cognitive ergonomics in designing collaborative human-robot systems within the framework of Industry 5.0. The goal is to create and validate guidelines that aid non-experts in developing user-centered assembly applications, highlighting the factors that enhance workers' cognitive responses. The guidelines were created through an extensive review of scientific literature and validated through feedback from field researchers and a survey of 108 international experts. The results confirm that integrating human factors into the design of collaborative applications can enhance system adaptability and resilience, improving worker safety, ergonomics, and well-being.

Result 15:

Navigating HR industry 5.0: Seizing opportunities and confronting challenges by Shukla et al. (2024).

The strategic HR value chain model is introduced within the context of Industry 5.0, emphasizing the necessity for HR practices to align with organizational goals to drive sustainable growth. This model highlights the importance of measurable outcomes, continuous improvement, and a people-centric approach. It also underscores the role of technological integration in optimizing core HR functions such as talent acquisition, learning and development, performance management, and total rewards. Focusing on employee well-being and development fosters a positive workplace culture that drives innovation and success in the digital era. The model serves as a guide for navigating the changing HR landscape, allowing organizations to effectively address challenges and seize opportunities in today's business environment.

Result 16:

Development of a novel machine learning-based approach for brain function assessment and integrated software solution by Qu et al. (2024).

The integration of cybernetic principles and data-driven methods seeks to enhance rehabilitation processes in healthcare, particularly within the framework of Industry 5.0, which emphasizes human-centered solutions. This research concentrates on developing a comprehensive multimodal approach to combine rehabilitation data through the utilization of electroencephalogram (EEG) and functional near-infrared spectroscopy (fNIRS) for evaluating motor imagery (MI) tasks. By incorporating techniques such as Granger causality and a brain region adjacency matrix, this study integrates electrophysiological and hemodynamic data, enhancing the complementarity and understanding of neural processes. The findings indicate that the multimodal fusion method provides higher accuracy and stability, suggesting its potential for broader research applications. These results have been used to develop an intelligent rehabilitation platform that supports personalized medicine and enhances medical practices by offering a personalized and more effective approach to patient care. This research contributes to rehabilitation modeling, equipment design, and the application of cybernetics in healthcare.

Result 17:

Determining Cognitive Workload Using Physiological Measurements: Pupillometry and Heart-Rate Variability by Ma et al. (2024).

This study introduces a new method for measuring cognitive workload in manufacturing environments that are highly digitalized and human-centered. This method links task complexity, operator expertise, and cognitive workload to overall operator performance. The approach was tested through experiments in which operators performed assembly tasks on a Wankel engine block. During these tasks, physiological signals were recorded, including heart rate variability and pupillometry. The results indicated statistically significant differences in cognitive load across different task complexities. Experts typically demonstrated lower cognitive load compared to others. This approach provides a more accurate assessment of cognitive load than traditional methods, highlighting its potential use in optimizing workplace design.

Result 18:

Information Technology based on Industry 5.0 Human Place into IoT-and CPS-based Industrial Systems by Noori et al. (2024).

This study explores the intersection of art design and Human-Cyber-Physical Systems (HCPS) within the context of Industry 5.0, with a specific focus on applications of

Emotional Intelligence (EI). The research explores how HCPS can improve EI by integrating system design, theoretical evaluation, and methodology development with the human-in-the-loop concept. This integration enhances system efficiency and performance. The results underscore the synergistic relationship between technology, art, and the creative industries, suggesting future research directions and applications that utilize digital transformation to promote enhanced human-centric design and creativity.

Result 19:

A human-centric system combining smartwatch and LiDAR data to assess the risk of musculoskeletal disorders and improve ergonomics of Industry 5.0 manufacturing workers by Pistolesi et al. (2024).

These authors present a privacy-preserving system aimed at monitoring the posture of workers engaged in assembly and disassembly tasks, addressing the widespread issue of back pain and its associated costs. The system utilizes artificial intelligence to track both the upper and lower body postures of workers during repetitive activities such as screwing and soldering. It incorporates inertial sensors in smartwatches and LiDAR technology while adhering to the ISO 11226 European standard. The system collects data, including information on posture and movement, in a way that ensures it is non-identifiable, meaning it cannot be traced back to specific individuals. This approach preserves worker privacy. The results indicate an impressive 98% accuracy in detecting posture, which helps identify poor posture habits and reduce the risk of musculoskeletal disorders.

Result 20:

Analyzing psychophysical state and cognitive performance in human-robot collaboration for repetitive assembly processes by Gervasi et al. (2024).

The research investigates how human-robot collaboration (HRC) affects worker well-being, specifically looking at stress, cognitive load, and fatigue during repetitive assembly tasks. By employing non-invasive biosensors to monitor the operator's psychophysical state in real-time, the study underscores the significance of understanding cognitive workload in order to improve both worker well-being and performance. The results indicate that using a collaborative robot (cobot) decreases stress and cognitive load, particularly during the initial phase of a shift, and results in fewer process failures compared to manual methods. This approach underscores the potential of using non-invasive monitoring to improve collaboration, reduce physical and mental strain, and enhance productivity in Industry 5.0 environments.

Result 21:

Human Digital Twin in the context of Industry 5.0 by Wang et al. (2024).

This paper examines the concept of the Human Digital Twin (HDT) in the context of Industry 5.0. HDTs are digital representations of individuals that incorporate human characteristics into system design and performance, with the goal of improving human-system collaboration. The study tackles the absence of standardized frameworks and architectures for HDTs in practical applications, offering a thorough review of their evolution, proposed definitions, and conceptual frameworks. It also offers insights into how HDTs can help realize human potential, meet diverse needs, and support human-centric goals in manufacturing systems.

Result 22:

Evaluating the Impact of AI-Based Sustainability Measures in Industry 5.0: A Longitudinal Study by Valeriya et al. (2024).

The study emphasizes the role of AI-driven sustainability metrics in Industry 5.0, demonstrating how artificial intelligence and human expertise collaborate to enhance sustainability, financial performance, and employee satisfaction. The human aspect saw significant improvements, with employee satisfaction rising from 4.2 to 4.7 and work-life balance scores increasing from 4.1 to 4.6.

Result 23:

Human-Centric AI Adoption and Its Influence on Worker Productivity: An Empirical Investigation by Shchepkina et al. (2024)

This empirical study explores the effects of human-centric AI deployment in the industrial sector, highlighting transformative changes in the workplace. It highlights a 35.5% increase in productivity due to AI's ability to automate repetitive tasks, provide data-driven insights, and enhance decision-making. Additionally, employee satisfaction improved by 20.6%, with better work-life balance and job happiness. Structured AI training programs resulted in a 29.6% boost in skill development, and departments experienced significant cost reductions of up to 40%.

Result 24:

Human-Centered Edge AI and Wearable Technology for Workplace Health and Safety in Industry 5.0 by Nguyen et al. (2024).

This research explores how human-centered edge AI and wearable technology can be integrated to enhance workplace health and safety in Industry 5.0. It emphasizes the significance of real-time monitoring through wearable sensors that utilize Industrial Internet of Things (IIoT) technologies. These sensors track physiological and environmental conditions to prevent hazards and enhance overall efficiency. Moreover, AI allows for immediate decision-making by processing data locally, reducing latency, and addressing privacy concerns. Despite limited computing power and battery life, the study highlights the potential of these technologies for a safer, more productive work environment.

Result 25:

Digital Transformation Towards Human-Centricity: A Systematic Literature Review by Crnobrnja et al. (2024).

This study examines the intersection of "Human-Centricity" and "Industry 5.0" in manufacturing and identifies key research directions for future development. It emphasizes the essential role of worker well-being in improving productivity within the

Industry 5.0 framework. Specific areas for further exploration include human-robot interaction, AI integration, ergonomics, safety, and training for skills development. The paper proposes that a human-centric approach, which focuses on both well-being and skill enhancement, is essential for improving productivity and promoting sustainable manufacturing practices in Industry 5.0.

Result 26:

Designing Augmented Reality Assistance Systems for Operator 5.0 Solutions in Assembly by Cimini et al. (2024)

The integration of Augmented Reality (AR) into human-centered smart manufacturing systems within Industry 5.0 has the potential to significantly enhance operator performance, especially in assembly and disassembly tasks. This approach utilizes AR technology to provide real-time information and guidance, enhancing efficiency and accuracy in manufacturing. It highlights the importance of human-centered design in AR applications and recommends integrating AR into manual workstations to boost operator productivity and well-being. Key findings highlight the importance of considering user groups, selecting suitable devices for usability, and creating clear instructions.

Result 27:

A Meta-heuristic Approach for Industry 5.0 Assembly Line Balancing and Scheduling with Human-Robot Collaboration by Zhang et al. (2024).

This research examines how human-robot collaboration (HRC) can improve assembly line balancing in Industry 5.0, focusing on enhancing productivity and operator well-being. It presents an adaptive simulated annealing (SA) framework with innovative task allocation mechanisms, including a new fitness value calculation and a heuristic approach for optimizing workload distribution between human and robot operators. The findings indicate that this meta-heuristic approach significantly boosts productivity, reduces cycle times, and enhances operators' welfare by strategically balancing tasks and decreasing the number of operators required at each workstation.

Result 28:

Promoting human-centered manufacturing through Lean Ergonomics–a structural equation model for ergonomics and management data by Brunner et al. (2024).

The Stress-Strain Concept (SSC) is utilized to explore the relationship between ergonomics and productivity on the shop floor, drawing on empirical data from manual work processes in chemical reactor operations. By analyzing ergonomic factors such as physical strain, health, and age alongside business data like work process times, the study finds that stress and physical strain significantly affect productivity, particularly when considering health. The results indicate that ergonomic improvements can lead to lasting benefits that enhance productivity. This suggests that focusing on worker well-being can result in more efficient work processes.

Result 29:

A Review of HRV and EEG Technology Applications in Industry 5.0: Emphasising Manufacturing Efficiency and Worker Well-Being by Chulakit et al. (2024).

This review paper examines the application of physiological monitoring techniques, specifically Heart Rate Variability (HRV) and Electroencephalography (EEG), in the manufacturing industry within the framework of Industry 5.0's human-centric approach. The text emphasizes the significance of biometric tools in enhancing worker well-being, managing cognitive workload, and improving human-machine interactions. It outlines the benefits of heart rate variability (HRV) in monitoring autonomic nervous system activity and assessing health outcomes. Additionally, electroencephalography (EEG) is highlighted for its capability to map psychological states and support Brain-Computer Interface technologies. By integrating these monitoring techniques, the paper suggests that manufacturing operations can prioritize both worker health and operational efficiency.

Result 30:

The Impact of New Technologies on Occupational Safety and Health from the Point of View of Their Academic Interest by Cuadrado-Cabello et al. (2024).

This study examines how emerging technologies from Industry 4.0 and 5.0 enhance Occupational Safety and Health (OSH) for workers. By analyzing articles from SCOPUS and Web of Science, the research reveals that the main focus of these technologies is on risk assessment. Wearable technology and artificial intelligence (AI) are identified as the most relevant technologies for improving OSH. The paper highlights the significant potential of these technologies to enhance worker safety and well-being, particularly through their applications in monitoring health metrics and predicting risks.

Result 31:

Gamification for Manufacturing (GfM) Towards Era Industry 5.0 by Baroroh et al. (2024)

This research examines Gamification for Manufacturing (GfM) in the context of Industry 5.0, emphasizing its potential to improve workers' well-being and productivity. By prioritizing human-centric values, GfM offers a promising approach to achieving these objectives. The framework is intended to assist professionals and researchers in effectively integrating GfM into Industry 5.0.

Result 32:

The Importance of Soft Skills for Computing Graduates in the Context of the Fifth Industrial Revolution by Enakrire et al. (2024).

A systematic literature review was conducted to examine the changing demands of the Fifth Industrial Revolution on computer science curricula. It emphasizes the need for graduates to possess both technical skills and essential soft skills, such as collaboration and interpersonal abilities. The findings support a competency-based education framework that integrates these skill sets to prepare graduates for a future centered on human-machine collaboration. The paper suggests that educational programs should regularly update their curricula to promote the integration of human-machine interaction, organizational change, and increased productivity while also fostering graduates’ self-confidence and overall development.

Result 33:

Challenges in Developing Digital Twins for Labor-intensive Manufacturing Systems: A Step towards Human-centricity by Götz et al. (2024).

This paper examines the challenges of developing Digital Twins in labor-intensive manufacturing systems that depend on human workers. While Digital Twins can enhance efficiency and improve decision-making, their integration is complicated by the unpredictable nature of human involvement. The study identifies key obstacles in creating data-driven Digital Twins and proposes a framework to support their implementation. A case study conducted with two companies illustrates the application of Digital Twins for decision support in job scheduling within hybrid machine-worker environments, with a focus on worker well-being. The findings emphasize the need to consider both technological and human factors for effective Digital Twin solutions in labor-intensive manufacturing.

Result 34:

MetaStates: An Approach for Representing Human Workers' Psychophysiological States in the Industrial Metaverse by Toichoa Eyam et al. (2024).

The concept of MetaStates is introduced as digital representations of a human worker’s psychophysiological states, aiming to address the challenge of accurately simulating human factors in industrial contexts. Enhancing photo-realistic avatars with detailed graphical representations of physical and mental states improves the simulation of human workers during tasks. By integrating MetaStates into industrial simulations, companies can better utilize the Industrial Metaverse. This approach keeps human workers central to the system while also increasing the accuracy and effectiveness of simulations for decision-making and operational improvements.

Result 35:

Surveying the landscape of Human-Centric Manufacturing in Lombardy: Insights from the practices and perspectives of Italian enterprises by Locatelli et al. (2024).

This paper analyzes the technological readiness and human-friendliness of several Italian companies through a survey that evaluates technology development, funding allocation, and worker integration. The findings reveal a positive attitude toward innovation and human involvement, though a fully realized human-centric approach remains a work in progress. Ultimately, the insights gained provide valuable best practices to facilitate the transition toward more sustainable and human-centered digital manufacturing systems.

Result 36:

Industry 5.0: prioritizing human comfort and productivity through collaborative robots and dynamic task allocation by Granata et al. (2024).

This paper introduces a dynamic multi-objective task allocation system aimed at optimizing the use of collaborative robots (cobots) in production environments. It monitors human well-being through physiological and performance data and reallocates tasks in real-time to prevent overwork and fatigue, thereby enhancing both efficiency and human involvement.

Result 37:

Towards Coordinating Machines and Operators in Industry 5.0 through the Web of Things by Picone et al. (2024).

This paper introduces a groundbreaking architecture for Industry 5.0, emphasizing the integration of human-centric technologies through the Web of Things (WoT) standard. A central element of this architecture is the Operator Thing (OT), which serves as a digital replica of the human operator. The OT continuously monitors well-being factors such as stress and discomfort. The system adjusts in real-time to improve the synergy between humans and machines while prioritizing worker comfort. By incorporating human conditions into operational procedures, this approach creates a more empathetic industrial environment. The solution has been validated through interdisciplinary evaluations and aligns with the human-centered principles of Industry 5.0.

Result 38:

Revolutionizing Industry 5.0: Harnessing the Power of Digital Human Modelling by Donmezer et al. (2024).

This paper explores the transformative potential of Digital Human Modelling (DHM) in advancing Industry 5.0, highlighting its applications across various sectors such as manufacturing, textiles, robotics, and energy. DHM facilitates the design and optimization of human-centered systems that enhance ergonomics, safety, and productivity. In manufacturing, it optimizes production processes by focusing on human factors to create smart factories. In textiles, DHM improves ergonomic workstation design for better worker comfort and efficiency, while in robotics, it ensures safe and productive human-robot interactions. In the energy sector, it aids in optimizing energy consumption and promoting sustainable practices. Overall, the integration of DHM into these sectors can lead to significant advancements in efficiency, safety, productivity, and sustainability, offering valuable insights for researchers and practitioners seeking to harness its full potential.

Result 39:

Enhancing Human Safety in Production Environments Within the Scope of Industry 5.0 by Aksoy et al. (2024).

The study proposes an AI-assisted system that analyzes sensor data to proactively identify hazardous situations and risky behaviors in production environments, such as machine malfunctions, gas leaks, and falls, facilitating timely interventions. It focuses on developing a system for real-time risk detection and utilizes predictive capabilities to enhance worker safety in the context of Industry 5.0.

Result 40:

A Framework for Enhancing Human-Agent Interaction in Cyber-Physical Systems: OCRA Measurement Perspective by Meza et al. (2024).

This paper introduces a Cyber-Physical System (CPS) framework designed for Industry 5.0. The framework incorporates human factors to enhance both human and system performance. By utilizing the OCRA index to evaluate ergonomic impacts, the system dynamically adjusts task planning and workloads to minimize physical strain by aligning tasks with human capabilities. The approach was tested in a simulated flexible manufacturing system using a multi-agent systems paradigm.

Result 41:

Exploiting Immersive Virtual Reality for Investigating the Effects of Industrial Noise on Cognitive Performance and Perceived Workload by Evangelista et al. (2024).

The investigation into the impact of auditory stimuli on cognitive performance and the well-being of operators within confined environments underscores the human-centric approach characteristic of Industry 5.0. Immersive Virtual Reality (IVR) serves as a tool to simulate conditions endemic to confined spaces, thereby facilitating the comparison of effects between stationary and intermittent noise on cognitive load. The Stroop Test, in conjunction with a modified noise-induced task load index, provides a framework for evaluating cognitive performance and perceived exertion. Additionally, Heart Rate Variability (HRV) is employed to quantify physiological responses. The findings reveal a significant influence of noise on cognitive performance.

Result 42:

Identification of Criteria for Enabling the Adoption of Sustainable Maintenance Practice: An Umbrella Review by Vasić et al. (2024).

This study examines the transition from traditional industrial maintenance to sustainable maintenance (SM) within existing industrial ecosystems by utilizing an umbrella review (UR) methodology. It identifies 43 key criteria in maintenance decision-making (MDM) and highlights the most discussed factors, such as environmental pollution, energy consumption, and worker health and safety. The study also employs Bayesian Network Analysis to determine that labor costs, employee satisfaction, and resource consumption are the most influential criteria. Additionally, it notes a shift in research focus after 2021 from economic and technical factors toward a more balanced approach that includes social and environmental considerations.

Result 43:

The realities of achieving a Smart, Sustainable, and Inclusive shopfloor in the age of Industry 5.0 by Bonello et al. (2024).

This study investigates integrating Industry 5.0 principles—sustainability, human-centricity, and resilience—into the manufacturing sector to address the challenges faced by workers with disabilities. It identifies three primary issues: the tension between engineers and the inclusion of disabled workers, insufficient design knowledge for creating inclusive workstations, and a lack of social sustainability in disability employment. The study proposes future research and action focused on enhancing inclusive design knowledge and promoting social sustainability for individuals with disabilities in the manufacturing industry.

Result 44:

Industry 5.0 Adoption Among Heavy Machinery Producers: The Potential of Artificial Intelligence in Social Sustainability Facilitation by Valtonen et al. (2024).

The exploration focuses on how artificial intelligence (AI) can enhance social sustainability and worker well-being in the context of Industry 5.0, particularly for heavy machinery operators. It identifies challenges such as cognitive and physical strain, safety concerns, and skill gaps. AI-driven solutions are presented that improve operators' health, safety, emotional well-being, work efficiency, and access to training. The findings indicate the significant potential of AI to boost worker productivity and well-being in industrial settings.

Result 45:

Augmented Reality Towards Industry 5.0: Improving Voice and Tap Interaction Based on User Experience Feedback by Carrança et al. (2024).

To examine the role of Extended Reality (XR), particularly Augmented Reality (AR), in industrial operations, this study focuses on preventive and reactive maintenance while emphasizing the importance of user-friendly design to enhance efficiency and decrease dependence on specialized technicians. This research involved the development and testing of an AR application with 27 participants, including both experienced and novice users. The findings highlighted significant improvements in user experience, particularly in areas like fluidity, responsiveness, and intuitiveness. Furthermore, the study showed that voice commands were as effective as tap commands, emphasizing the importance of user interaction in optimizing AR applications for Industry 5.0.

Result 46:

UX and Industry 5.0: A Study in Repairing Equipment Using Augmented Reality by Margolis et al. (2024).

For the study of an Augmented Reality (AR) application for industrial equipment diagnostics, this study involved 18 participants from different professional backgrounds. The diverse expertise of the participants aimed to provide varied insights into the application’s effectiveness and usability in real-world scenarios. Overall, the system received positive feedback; however, several areas for improvement were identified. User experience (UX) varied among different profiles, with human-centered design experts giving more critical feedback. These findings emphasize the importance of user-centered design and its impact on interactions with new technologies in Industry 5.0.

Result 47:

The Effect of Digitalization and Human-Centric on Companies’ Production Performances by Wan et al. (2024).

This study stated that aligning digitalization with human-centricity is essential for improving production performance. It revealed an S-shaped relationship between production throughput and process flexibility, indicating that higher levels of human-centric approaches combined with digitalization can enhance overall performance. The research emphasizes the importance of a balanced approach to human-centricity in production systems, considering the roles of managers and engineers.

Result 48:

A framework to design smart manufacturing systems for Industry 5.0 based on the human-automation symbiosis by Peruzzini et al. (2024).

This study introduces a framework for Smart Manufacturing Systems Design (SMSD) within the context of Industry 5.0, with a particular focus on the collaboration between humans and automation. It utilizes an "Augmented Digital Twin" (ADT) to create a digital representation of all factory components—machines, robots, personnel, and the surrounding environment—facilitating AI applications that enhance productivity as well as employee well-being. By fostering knowledge sharing and co-evolution between human operators and machines, this methodology significantly improves collaboration and mutual understanding. The approach has been validated through partnerships with four industrial firms, seeking to rectify the deficiencies observed in Industry 4.0 by integrating human factors into the architecture of smart manufacturing systems.

Result 49:

Rooting out the root causes of order fulfillment errors: a multiple case study by Helm et al. (2024).

This study investigates the fundamental causes of errors in warehouse operations utilizing intelligent video analysis (IVA). Through the examination of numerous case studies from companies implementing IVA in outbound processes, such as order picking, packing, and sorting, the research determines that many errors frequently regarded as human mistakes actually arise from erroneous customer claims, inbound warehouse inaccuracies, or malfunctioning technology. The findings underscore the intricate interplay of technical, organizational, and human factors, yielding insights for the enhancement of error reduction strategies.

Result 50:

A scoping review of human robot interaction research towards Industry 5.0 human-centric workplaces by Panagou et al. (2024).

This scoping review explores how the design features of robots affect human operators in the context of Industry 4.0 and 5.0. By analyzing 32 articles, complex relationships between various robot design elements were revealed—such as appearance, capabilities, and communication features—and operators' perceptions of reliability, safety, and teamwork. Robot appearance and capabilities shape operators' perceptions of performance, while effective collaboration relies on strong communication skills. The results provide practical guidance for designers and practitioners, highlighting the significance of operator involvement, awareness of robot capabilities, and effective training.

Result 51:

Application of supportive and substitutive technologies in manual warehouse order picking: a content analysis by Grosse (2024).

The research examines the use of supportive and substitutive technologies in manual warehouse order picking, a labor-intensive and time-consuming process that affects supply chain efficiency. It underscores the importance of human factors and the interaction between workers and technology within socio-technical systems. The study explores the potential benefits and challenges of technologies such as augmented reality and exoskeletons, highlighting the need for further research on their integration.

Result 52:

Unravelling human-centric tensions towards Industry 5.0: Literature review, resolution strategies and research agenda by Pacheco et al. (2024).

This study identifies 20 key tensions related to automation, well-being, safety, education, and value creation. These tensions are categorized into four dimensions: learning, organizing, belonging, and performing. The research develops a framework to address these tensions, offering resolution strategies aimed at enhancing worker well-being and performance. The findings emphasize the critical role of shop floor workers in adapting to Industry 5.0 and provide actionable insights for manufacturing companies seeking to integrate human-machine collaboration effectively.

Result 53:

A comprehensive STPA-PSO framework for quantifying smart glasses risks in manufacturing by Karevan et al. (2024).

This study aims to quantify the risks associated with using smart wearables, such as smart glasses, in complex systems under Industry 5.0. It addresses a gap in the existing literature concerning the risks of human error by proposing a methodology called STPA-PSO. This approach combines Systems-Theoretic Process Analysis (STPA) to identify hazards with Particle Swarm Optimization (PSO) to optimize risk assessments. Through a case study focused on refrigerator assembly, the methodology proves effective in evaluating risks related to industrial, financial, and occupational health and safety aspects.

Result 54:

Enhancing Workplace Safety through Personalized Environmental Risk Assessment: An AI-Driven Approach in Industry 5.0 by Lemos et al. (2024).

This paper introduces a comprehensive system designed to monitor environmental risks in the workplace, with a specific focus on personalized health assessments aimed at improving worker well-being. The system tracks various environmental factors, including dust, noise, radiation, and temperature, while also considering workers' health histories. This allows for customized risk assessments and recommendations tailored to individual needs. Utilizing machine learning algorithms, the system provides actionable alerts to enhance safety and inform decision-making. Additionally, it prioritizes data privacy and protection, addressing the critical issue of managing sensitive health and exposure information.

Result 55:

Enhancing worker-centred digitalisation in industrial environments: A KPI evaluation methodology by Abril-Jiménez et al. (2024).

This paper proposes a new methodology for Industry 5.0 that integrates human workers as key participants in the digitalization process. It addresses gaps in existing Industry 4.0 evaluation methods. Unlike KPI-driven approaches that focus mainly on technology, this methodology assesses the direct and indirect benefits of technological transformations for both workers and stakeholders. It includes tools for evaluating technological integration, process optimization, and human factors. A real case study demonstrates its application by comparing the digitalization processes of three companies.

Result 56:

Integrating AI with Lean Manufacturing in the Context of Industry 4.0/5.0: Current Trends and Applications by Boursali et al. (2024).

This article explores the role of Artificial Intelligence (AI) in improving lean manufacturing processes. It highlights AI's influence on smart manufacturing, sustainability, maintenance optimization, production efficiency, and quality enhancement. The study also emphasizes the importance of integrating human factors and digitalization. It reviews relevant literature from the SCOPUS database and advocates for further research into sustainable, human-centered manufacturing practices.

Result 57:

Metaverse for Industry 5.0 by Majumder & Dey (2024).

This book chapter explores the metaverse in the context of Industry 5.0, emphasizing its connection to the human-centric vision of Web 4.0. It presents the metaverse as a digital ecosystem that enables collaboration between individuals and organizations, leveraging technologies like AI, VR, AR, MR, and IoT. The integration of the metaverse aims to enhance worker well-being and productivity through tailored solutions. The chapter covers the metaverse's evolution, advantages, challenges, ethical issues, and applications in sectors such as healthcare, construction, and manufacturing, concluding with a framework for its human-centric integration in Industry 5.0.

Result 58:

Human in the loop: revolutionizing industry 5.0 with design thinking and systems thinking by Dehbozorgi et al. (2024).

This study examines Human-Centric Manufacturing and Systems (HCM and HCS) in the context of Industry 5.0, with a focus on worker welfare and sustainability. It highlights key principles such as safety, inclusivity, and empowerment within the human-centric approach. The paper discusses the effective integration of Design and Systems Thinking into HCM. It proposes a workshop at the MADE Competence Centre aimed at raising awareness and promoting these principles throughout the system life cycle. The goal is to encourage the development of HCS that prioritize both worker well-being and system efficiency in Industry 5.0.

Result 59:

Informing User-Centered Approaches To Augmented Custom Manufacturing Practices by Franze et al. (2023).

This study examines how augmented and mixed reality (AR/MR) technologies can boost productivity and efficiency in Australian small-to-medium (SME) custom manufacturers while addressing workforce challenges in Industry 4.0. It also considers how AR/MR can aid the transition to a human-centric Industry 5.0 model that prioritizes fabricator well-being. Findings from industry expert interviews highlight the benefits of reducing task uncertainties and improving fabrication practices. The research identifies future development areas, emphasizing the need for tailored solutions to enhance accessibility and competitiveness in custom manufacturing.

Result 60:

Artificial Intelligence for Smart Manufacturing in Industry 5.0: Methods, Applications, and Challenges by Nguyen et al. (2023).

This study examines the role of Artificial Intelligence (AI) in Industry 4.0 and its evolution into Augmented Intelligence (AuI) in Industry 5.0, where AI is integrated with human intelligence to enhance manufacturing processes. It surveys AI-based methods, applications, and challenges in smart manufacturing within the Industry 5.0 framework. The study demonstrates how these technologies can improve productivity while ensuring the well-being of human workers. Additionally, it provides valuable insights into the potential benefits and concerns related to AI and AuI in advancing smart manufacturing.

Result 61:

Empowering People in Human-Robot Collaboration: Why, How, When, and for Whom by Johansen et al. (2023).

This workshop focuses on empowering individuals in human-robot collaboration (HRC) within Industry 5.0 by addressing the genuine empowerment offered by HRC applications. It promotes a comprehensive approach involving user modeling, adaptive interfaces, interaction design, and situational awareness. The goal is to explore when HRC empowers humans and the benefits for all involved. Experts from fields such as robotics, engineering, ethics, psychology, and artificial intelligence are invited to contribute to the future of human-robot partnerships, aiming to enhance performance and work quality.

Result 62:

Evaluation of Lean Off-Site Construction Literature through the Lens of Industry 4.0 and 5.0 by Hadi et al. (2023).

This study investigates the implementation of lean manufacturing principles within the context of off-site construction (OSC). The review accentuates significant interactions between lean-OSC tools and the principles of Industry 4.0 and 5.0, identifying resilience as a critical integrative concept. Furthermore, the study delineates research deficiencies in social and environmental domains, encompassing mental health, assistive technologies, and end-of-life design. Human-centered technologies, including collaborative robots and exoskeletons, have the potential to enhance worker empowerment, diversity, and inclusion.

Result 63:

Multimodal Assessment of Cognitive Workload Using Neural, Subjective and Behavioural Measures in Smart Factory Settings by Zakeri et al. (2023).

The mental workload and stress of human workers in collaborative robot (cobot) environments within Industry 5.0 are examined, focusing on how task complexity, cobot speed, and payload capacity influence stress levels. The results indicate that task complexity and cobot speed significantly affect mental stress, with physiological measures such as EEG and fNIRS providing more accurate assessments than traditional methods. Utilizing regression analysis and artificial neural networks (ANN), the research highlights the potential of these physiological measures to replace conventional stress evaluation methods, particularly in predicting missed beeps, where the highest correlation and accuracy were observed.

Result 64:

Development of a Neuroergonomic Assessment for the Evaluation of Mental Workload in an Industrial Human–Robot Interaction Assembly Task: A Comparative Case Study by Caiazzo et al. (2023).

This study explores the mental workload of operators engaged in human-robot interaction (HRI) tasks, specifically in the context of collaborative robots (cobots) within Industry 5.0. It compares two assembly task scenarios: one without robot interaction and one with it. To assess mental workload, a combination of subjective (NASA TLX) and objective (EEG) measurements is used, with cognitive workload characterized by analyzing brainwave power ratios. The results show that interacting with robots significantly reduces mental workload and improves task performance, as evidenced by a higher number of components assembled correctly when robots are involved. This research contributes to the field of neuroergonomics by providing insights into how collaborative robots can enhance operator well-being and efficiency in industrial settings.

Result 65:

A human-cyber-physical system for Operator 5.0 smart risk assessment by Simeone et al. (2023).

This paper presents the development of a human-cyber-physical system (HCPS) designed to assess operator risk in the context of Industry 5.0. The HCPS offers an advanced method for risk assessment by integrating various types of sensing data, including physiological, environmental, and manufacturing variables. It analyzes complex patterns and interactions, dynamically adjusting to changing conditions to create real-time risk profiles for operators and work processes. The system provides timely alerts that enable proactive safety interventions and optimize work processes. A simulated case study validates this framework.

Result 66:

Heart Rate Variability Measurement to Assess Acute Work-Content-Related Stress of Workers in Industrial Manufacturing Environment - A Systematic Scoping Review by Tran et al. (2023).

This study evaluates heart rate variability (HRV) as a real-time indicator of acute work-content-related-stress (AWCRS) in industrial environments. After analyzing 14 studies conducted between 2000 and 2022, it is clear that, although HRV and AWCRS were measured in several instances, there is not enough evidence to establish a link between them in industrial work. Additionally, no randomized controlled trials were identified, leaving the relationship between HRV and AWCRS still unclear. The review emphasizes the necessity for more rigorous research to validate HRV as a reliable indicator of worker stress, highlighting its potential role in monitoring well-being within the Operator 4.0 framework.

Result 67:

Safety At Work Within Industry 5.0-QUO VADIS [ZAŠTITA NA RADU U SKLOPU INDUSTRIJE 5.0-QUO VADIS] by Kralj et al. (2023).

Since the introduction of Industry 4.0 in 2011, a global digital transformation has been underway, characterized by advanced ICT solutions, robotics, and new expert roles that enhance production. In 2015, Industry 5.0 emerged, emphasizing the importance of human potential alongside the Internet of Things (IoT) and Big Data to improve job quality and workers' skills. This study performs a literature review alongside a secondary data analysis, incorporating theoretical discussions, reports, and academic studies to strengthen its exploration of technological advancements in Industry 5.0.

Result 68:

Human-centred data-driven redesign of simulation-based training: a qualitative study applied on two use cases of the healthcare and industrial domains by Brunzini et al. (2023).

This paper explores simulation-based training in both industrial and healthcare sectors, within the context of Industry 5.0. It evaluates simulations from the learner's viewpoint, aiming to enhance performance and the learning process by taking into account physical, cognitive, and emotional factors. It includes data-driven guidelines for optimizing and redesigning training, applicable to both traditional and virtual/augmented reality systems. Two use cases are presented: a healthcare simulation for lumbar puncture procedures and an industrial simulation for replacing tractor engine oil filters. Despite the differences in content, the results reveal similarities in performance, cognitive processes, and emotional states. This allows for the development of a common set of guidelines to optimize simulations across various sectors.

Result 69:

An Experimental Protocol for Human Stress Investigation in Manufacturing Contexts: Its Application in the NO-STRESS Project by Apraiz et al. (2023).

This paper presents a human-centered protocol for measuring stress in manufacturing environments. The protocol integrates physiological signals, performance metrics, and individuals' perceptions of stress. To capture physiological responses, it employs advanced techniques, including EEG (electroencephalogram), HRV (heart rate variability), GSR (galvanic skin response), and EMG (electromyography). It also assesses performance metrics such as task completion time, error rates, and production rates. Additionally, subjective self-assessments are included to reflect individual experiences of stress. Applied in both the automotive and plastic component industries, this protocol offers a comprehensive understanding of stress and provides valuable insights to inform interventions aimed at enhancing employee well-being.

Result 70:

Multi-objective task allocation for collaborative robot systems with an Industry 5.0 human-centered perspective by Calzavara et al. (2023).

This paper proposes a multi-objective optimization model for task allocation in Industry 5.0. The model aims to minimize makespan while also reducing operator energy expenditure and mental workload. With the growing use of collaborative robots (cobots) alongside human operators, the goal is to optimize task distribution. The methodology presents a novel approach for assessing mental workload and introduces a constraint related to resource idleness. Implemented in a real-world assembly scenario, the results indicate that this approach is effective.

Result 71:

Dual task scheduling strategy for personalized multi-objective optimization of cycle time and fatigue in human-robot collaboration by Chand & Lu (2023).

This study presents a dual scheduling strategy designed to optimize task allocation in Human-Robot Collaboration (HRC). The primary goals are to reduce both cycle time and worker fatigue. The approach recognizes that workers in HRC environments have varying capabilities and muscle strengths, leading to different levels of fatigue response. The model integrates two objectives for minimizing fatigue: one aimed at reducing the overall fatigue of the team and the other focusing on individual workers. Balancing fatigue accumulation across the team and incorporating targeted rest and recovery periods maintains production efficiency while prioritizing worker well-being.

Result 72:

Augmented Reality in a Lean Workplace at Smart Factories: A Case Study by Pereira et al. (2023).

This study applies a methodology called RAES-Log to explore the integration of Augmented Reality (AR) into material handling processes. The primary focus is on improving workers' ergonomic conditions and reducing risks, in alignment with Industry 5.0's human-centric approach. By minimizing human effort, preventing Musculoskeletal Disorders (MSD), and enhancing workplace efficiency, the research aims to create a safer and more effective working environment. Positive feedback from workers indicated improvements in well-being, engagement, and motivation, suggesting that augmented reality (AR) could greatly enhance productivity while fostering safer and waste-free work environments.

Result 73:

Effects of Presence on Human Performance and Workload in Simulated VR-based Telerobotics by Nenna et al. (2023).

This paper investigates the impact of the Sense of Presence (SoP) in Virtual Reality (VR)-based telerobotics and examines its effects on industrial task performance and operator workload. Using a simulated teleoperation task with an industrial robotic arm, the study reveals that a higher SoP positively influences task performance, resulting in greater efficiency. However, the SoP had little impact on the operators' mental workload, indicating that while presence may boost productivity, its connection to workload needs further investigation.

Result 74:

Industry 5 and the Human in Human-Centric Manufacturing by Briken et al. (2023).

This systematic literature review revealed that engineering experts are increasingly acknowledging workers as essential "end-users" in manufacturing innovations. However, published practices frequently neglect workers' perspectives. The findings suggest that Industry 5.0 has the potential to improve worker well-being and productivity by aligning technological development with human-centered design and practices.

Result 75:

Dynamic muscle fatigue assessment using s-EMG technology towards human-centric human-robot collaboration by Chand et al. (2023).

The authors developed a theory to quantify localized muscular fatigue by considering task load, muscle strength, and the number of repetitive operations. They used surface electromyography (s-EMG) technology to monitor operator fatigue in environments where humans collaborate with robots. This method allows for non-invasive, real-time monitoring of fatigue during dynamic manufacturing tasks. The system can continuously monitor operator fatigue using sensors like cameras, establishing a framework for integrating fatigue monitoring into human-robot collaboration systems.

Result 76:

An experimental focus on learning effect and interaction quality in human–robot collaboration by Gervasi et al. (2023).

This paper investigates how the learning process acquired through interaction with robots affects user experience. It focuses on several factors, including robot speed, task control, and proximity to the robot's workspace. Participants performed assembly tasks in 12 different configurations and provided feedback about their experience, alongside physiological measures such as skin conductance and heart rate variability. The results indicated that the learning process significantly impacted user experience, with participants' perceptions of the robot configuration factors changing over time.

Result 77:

Passive Exoskeletons to Enhance Workforce Sustainability: Literature Review and Future Research Agenda by Ashta et al. (2023).

This paper examines the use of passive exoskeletons in manufacturing and logistics (M&L) systems. It categorizes exoskeleton performance based on different M&L tasks, providing insights into their practical applications, efficiency, and cost-effectiveness.

Additionally, it presents a maturity heat map to assess the development stage of various exoskeleton models in both scientific and industrial contexts. The paper offers recommendations for integrating exoskeletons into modern workplaces.

Result 78:

Manual assembly and Human–Robot Collaboration in repetitive assembly processes: a structured comparison based on human-centered performances by Gervasi et al. (2023).

This study investigates the impact of Human-Robot Collaboration (HRC) on user experience and performance during a repetitive assembly task, with participants working in both manual assembly and HRC settings across two 4-hour shifts. Data were collected on affective states, body discomfort, workload, stress (measured via heart rate variability and electrodermal activity), and the quality of processes and products. The results revealed that HRC significantly reduced upper limb exertion, demonstrating its physical ergonomic advantages. Additionally, HRC led to decreased cognitive effort, lower stress levels, and fewer defects in the assembly process, indicating that collaborative robots enhance not only physical ergonomics but also cognitive performance and the overall quality of repetitive tasks.

Result 79:

Biomechanical Assessments of the Upper Limb for Determining Fatigue, Strain and Effort from the Laboratory to the Industrial Working Place: A Systematic Review by Brambilla et al. (2023).

This study analyzes 288 articles out of 1375 identified in scientific databases to evaluate current approaches for assessing fatigue, strain, and effort in the workplace, specifically regarding upper limb performance. It compares laboratory-based assessments with those conducted in real workplace settings. Laboratory studies typically utilize instrumental methods to assess upper limb biomechanics, while workplace evaluations often depend on questionnaires and rating scales. The findings indicate that future research should integrate both instrumental and self-reported methods to develop multi-domain approaches. This would help expand the use of instrumentation in real-world settings and support the implementation of more structured trials. Such efforts are essential for translating laboratory findings into practical solutions aimed at improving worker health, reducing fatigue, and enhancing productivity.

Result 80:

How to Measure Stress in Smart and Intelligent Manufacturing Systems: A Systematic Review by Blandino (2023).

This review examines the stress indicators affecting workers in smart and intelligent manufacturing systems. The analysis outlines various objective measures of stress, such as physical and physiological indicators, as well as subjective assessments, including psychological factors. It also discusses the experimental protocols and the environmental and demographic influences on stress. The study reveals that while many stress indicators have been thoroughly examined, there is a lack of standardized measurement techniques. Furthermore, it highlights the need to better consider environmental and demographic variables that could enhance the accuracy of stress assessments. It emphasizes the need for comprehensive, multi-faceted approaches to stress evaluation in advanced manufacturing systems to enhance understanding and mitigation of work-related stress.

Result 81:

Flexible job shop scheduling problem under Industry 5.0: A survey on human reintegration, environmental consideration and resilience improvement by Destouet et al. (2023).

The authors introduce the Sustainable Flexible Job Shop Scheduling Problem, which integrates human and energy-efficiency considerations into the traditional flexible scheduling framework. The review evaluates the literature on Flexible Job Shop Scheduling Problems that include human and environmental factors, outlining future research directions for improving scheduling models that consider these aspects.

Result 82:

Biomechanical Modeling of Human–Robot Accident Scenarios: A Computational Assessment for Heavy-Payload-Capacity Robots by Asad et al. (2023).

This study focuses on the potential for injuries in human-robot collaboration (HRC) environments, addressing safety concerns particularly with medium- and low-payload robots, while also extending the analysis to high-payload, high-speed robots within Industry 5.0 contexts. This study employs quasi-static and dynamic simulations based on ISO TS 15066 standards to evaluate injury thresholds in scenarios with collaborative robots. The model of a human hand indicates that high-payload robots should operate at a maximum speed of 80% of that used by low-payload robots to minimize injury risk. The results highlight the significance of biomechanical analysis in creating safer collaborative environments and encouraging the use of heavy-payload robots.

Result 83:

Happy and Engaged Workforce in Industry 4.0: A New Concept of Digital Tool for HR Based on Theoretical and Practical Trends by Salvadorinho & Teixeira (2023).

This study introduces BoosToRaise, a technological tool designed to improve and monitor workforce engagement. By combining a systematic literature review with benchmarking of existing applications, the tool was developed around key engagement predictors, including employee roles, skills and career management, supervisory support, and social relationships. It incorporates coaching and gamification to promote a happier and more engaged workforce, ultimately enhancing productivity, innovation, and competitiveness.

Result 84:

Fall Detection and Efficiency Enhancement via Wearable Technology by Enis Isik et al. (2023).

The paper discusses a technology called the smart glove, developed by the company Thread In Motion. This innovative device aims to integrate human-centric technologies to enhance worker capabilities instead of replacing human labor. The smart glove combines conductive thread with advanced electronic and mechanical components, all designed to optimize human physiology. A key project involves using Inertial Measurement Unit (IMU) sensors along with machine learning algorithms to capture and analyze human motion. A notable accomplishment is the ability to differentiate between the fall of a glove and the fall of the user. This advancement has led to the creation of a health emergency alarm system, commonly referred to as a "man-down" feature. The primary goal of this system is to enhance workplace safety, particularly in settings such as warehouses, by monitoring physical movements and minimizing human error.

Result 85:

Human-Centered Design in Industry 5.0: Leveraging Technology for Maximum Efficiency by Granata & Faccio (2023).

This paper presents a dynamic multi-objective task allocation system that utilizes real-time physiological and performance data to evaluate the well-being of human operators. By monitoring factors such as fatigue and stress, the system can dynamically reallocate tasks to prevent overwork, ensuring a balance between efficiency and human well-being. It emphasizes that to fully harness the potential of collaborative robots, workspaces should be designed to optimize the contributions of both humans and robots.

Result 86:

The Road to Industry 5.0: The Challenges of Human Fatigue Modeling by Zanoli et al. (2023).

This paper presents an experimental analysis utilizing unsupervised learning on real-world data to address the limitations of traditional fatigue assessment methods. Fatigue can negatively impact cognitive and motor functions, leading to decreased productivity and increased safety risks. Although wearable devices offer a promising solution for continuous and non-intrusive monitoring of fatigue, challenges such as individual variability can reduce the effectiveness of traditional machine-learning models. This highlights the need for more sophisticated, personalized models to improve fatigue detection.

Result 87:

A Real-Time Double Flexible Job Shop Scheduling Problem under Industry 5.0 by Aribi et al. (2023).

This paper examines how human factors like fatigue and energy consumption affect production efficiency within the Industry 5.0 framework. It focuses on a real-time double flexible job shop scheduling issue and proposes a dynamic strategy that utilizes an improved genetic algorithm. The paper emphasizes the significance of incorporating human well-being factors, such as energy management and fatigue control, into the optimization of productivity. It presents a comprehensive experimental analysis that demonstrates the effectiveness of the proposed solution in enhancing both worker well-being and operational efficiency within a flexible and dynamic production environment.

Result 88:

Research on the Visual Search Ability Decline Caused by Different Types of Noise by Yin & Li (2023).

By analyzing the performance and physiological responses—such as reaction time, task completion time, pupil diameter, and visual hotspots—of 30 participants exposed to different types and levels of factory noise, this study investigates how such noise affects workers' visual search abilities within the context of Industry 5.0. The findings highlight the negative impact of noise on work efficiency and worker well-being, underscoring the importance of addressing these factors in industrial environments. Additionally, it finds that both composite and random noise, particularly for individuals sensitive to noise, significantly impair visual search performance.

Result 89:

A review of work-related stress detection, assessment, and analysis on-field by Ciccarelli et al. (2023).

This paper addresses the growing issue of work-related stress by analyzing its effects on both performance and health. It underscores the importance of accurately measuring mental stress in workplace settings, especially as production processes become more complex. While stress detection in controlled environments has been extensively studied, there is a significant gap in research focusing on stress detection in real-world work settings. The paper also highlights the need for innovative tools and methods to identify stress in dynamic work environments. The findings emphasize the necessity of adopting objective, multi-modal approaches to better understand stressors and to effectively alleviate them.

Result 90:

Advanced workstations and collaborative robots: exploiting eye-tracking and cardiac activity indices to unveil senior workers' mental workload in assembly tasks by Pluchino et al. (2023).

This study delves into how various human factors—such as task performance, mental workload, and subjective well-being—interact with the use of collaborative robots (cobots). It pays particular attention to dual-task scenarios that heighten cognitive demands, especially in senior workers who may face hurdles due to declining work capabilities. Results show that senior workers demonstrated a strong acceptance of the cobot and positive experiences, even when faced with higher mental strain. However, their performance was affected, resulting in increased errors and longer task duration during dual-tasking situations. Eye-tracking and cardiac data partially reflected the increased mental demand. The study highlights the need to understand human factors to build trust, reduce fatigue, and improve performance in collaborative manufacturing environments. The findings suggest that a holistic approach is vital for integrating cobots, especially for senior workers in Industry 5.0.

Result 91:

The NASA-TLX Approach To Understand Workers Workload In Human-Robot Collaboration by Javernik et al. (2023).

This paper examines how the motion parameters of robots influence worker utilization and workload. An experiment was conducted using the NASA-TLX questionnaire to analyze two scenarios with different robot motion parameters tailored for each participant, ensuring consistent conditions. The results demonstrated that individual differences, such as workers' abilities and skills, significantly affected both workload and utilization. This highlights the need for personalized approaches in Human-Robot Collaboration (HRC) settings. The findings underscore the importance of developing guidelines that consider these individual differences to enhance worker well-being and improve productivity in collaborative environments.

Result 92:

Data-Driven Human Factors Enabled Digital Twin by Kolesnikov et al. (2023).

This paper presents the implementation of human factors-enabled digital twins to improve human-centered production systems. The proposed system collects real-time data related to human factors from various sources and employs a decision-making algorithm to schedule tasks based on the worker's condition dynamically. A digital twin model visualizes both the worker's status and the production system in real-time, utilizing a Visual Components simulation environment. The results demonstrate that production systems can adapt flexibly to changes in worker conditions, optimizing workflows and task distribution with automated guided vehicles (AGVs) and collaborative robots while also modifying workplace ergonomics to enhance worker safety and performance.

Result 93:

From Human to Robot Interaction towards Human to Robot Communication in Assembly Systems by Kambarov et al. (2023).

This study explores the changing relationship between humans and robots in assembly systems, with a particular focus on the transition from physical to cognitive collaboration in Industry 5.0. It emphasizes how advanced communication technologies allow humans to guide robots, thereby improving flexibility, productivity, and worker well-being. The shift toward a human-centered environment, where skilled operators engage in both physical and cognitive tasks alongside robots, results in a safer, more efficient, and more fulfilling workplace. This form of collaboration is crucial for enhancing the efficiency of assembly operations and improving the overall well-being of human workers.

Result 94:

Abrupt Movements Assessment of Human Arms Based on Recurrent Neural Networks for Interaction with Machines by Polito et al. (2023).

This study aims to identify sudden and unpredictable human movements during collaborative human-machine tasks. It utilizes magneto-inertial measurement units (MIMUs) placed on the forearms. The research employs deep learning, specifically a recurrent neural network, to differentiate between normal gestures and abrupt movements that occur during a pick-and-place task. The results show a high accuracy of 99.25% in detecting these abrupt movements, which is essential for improving worker safety and operational efficiency.

Result 95:

Perceptual Computing Based Framework for Assessing Organizational Performance According to Industry 5.0 Paradigm by Tavrov et al. (2023).

This paper presents a framework for evaluating organizational performance that uses perceptual computing to assess criteria related to a person's functional state, an essential aspect of worker well-being. Unlike traditional performance metrics, which can be subjective and imprecise, this framework allows regulators to express their opinions using natural language. It also addresses the uncertainties involved in measuring physiological, psychological, and physical characteristics, making it adaptable for monitoring and improving human-centric industrial practices in Industry 5.0.

Result 96:

A novel quality map for monitoring human well-being and overall defectiveness in product variants manufacturing by Verna et al. (2023).

This paper introduces a new method called the "Quality Map," which combines two key indicators: production quality and worker well-being in the context of mass customization within Industry 5.0. By evaluating the overall defects in product variants alongside the stress responses of operators, this tool provides a comprehensive approach to monitoring both manufacturing quality and worker well-being during the production process. The study demonstrates the application of this method in a collaborative human-robot assembly setting, highlighting its ability to help companies balance the demands of high-quality, customized production with the necessity of ensuring worker well-being.

Result 97:

Quantifying the contribution of single joint kinematics to the overall ergonomic discomfort by Scalona et al. (2023).

The correlation between joint displacement during straightforward reaching tasks and employee discomfort is examined, as it is essential for the prevention of work-related musculoskeletal disorders (WMSDs) in industrial environments. This research utilizes wearable inertial measurement units to capture comprehensive whole-body kinematics. It contrasts established ergonomic assessment frameworks, including RULA, REBA, and MMGA, with a quantitative index derived from joint kinematics termed W1. The study underscores the necessity for subject-specific, quantitative methodologies to accurately assess the risks associated with WMSDs.

Result 98:

A Self-quantified Based Dashboard for Supporting Aged-Workforce in Industry 4.0 by Abril-Jimenez et al. (2023).

This paper explores how self-quantification tools can help tackle the challenges posed by an aging workforce in Industry 5.0. It emphasizes the importance of adapting factory workflows to meet the evolving needs of older workers. The focus is on empowering these workers by helping them understand and develop their skills while promoting a more flexible, inclusive, and well-being-oriented work environment.

Result 99:

Reactive Flexible Job Shop Problem with Stress Level Consideration by Yadegari et al. (2023).

This study investigates the flexible job shop scheduling problem (FJSSP) within the context of Industry 5.0, highlighting the significance of worker well-being, especially stress levels, on scheduling performance. It examines how the need to reschedule due to new job arrivals can increase worker stress. The study focuses on three types of changes: shifting operations, altering machine assignments, and changing operation sequences. To address this NP-Hard problem, a Genetic Algorithm (GA) is proposed to minimize stress while ensuring that the schedules remain efficient and compact despite the considerations for worker well-being.

Result 100:

Video-Based Fatigue Estimation for Human-Robot Task Allocation Optimisation by Zheng et al. (2023).

This paper introduces a video-based method for estimating human fatigue in human-robot collaboration systems, which overcomes the limitations of traditional wearable sensors. The method employs the boundary-aware dual-stream MS-TCN algorithm to identify operation types and repetitions from video footage. The data is input into a fatigue model to assess worker fatigue levels. This estimated fatigue is then integrated into a human-robot task allocation optimization model, which aims to minimize cycle time while ensuring that fatigue remains within acceptable limits. The results highlight the effectiveness of both the fatigue estimation and the optimization methods.

Result 101:

The Role of Human Factors in Zero Defect Manufacturing: A Study of Training and Workplace Culture by Psarommatis et al. (2023).

This review explores the importance of human factors in achieving Zero Defect Manufacturing (ZDM) within the context of Industry 5.0. It highlights key elements that contribute to the success of ZDM, including employee training, workplace culture, effective communication, and the utilization of assistive tools. The paper highlights the significance of human-centered approaches in enhancing manufacturing processes and minimizing defects. By prioritizing worker engagement, training, and motivation, industry professionals can improve zero-defect management outcomes. Moreover, the authors advocate for additional research on the impact of HF across various industries to develop more effective strategies for implementing ZDM.

Result 102:

Investigating Human Factors Integration into DT-Based Joint Production and Maintenance Scheduling by Franciosi et al. (2023).

This study explores the integration of Digital Twin (DT) technology with Joint Production and Maintenance Scheduling (JPMS) within the contexts of Industry 4.0 and 5.0. It specifically focuses on human factors that affect worker safety, well-being, and performance. Through a systematic literature review, the study identifies gaps in current research, particularly noting that aspects related to humans, such as workforce scheduling, adjustments due to worker absences, and the impact of human factors on stochastic parameters, are often overlooked. Based on these insights, the paper proposes a framework for incorporating human factors into digital twin-based Job Performance Management Systems.

Result 103:

Dynamic Task Allocation for Collaborative Robot Systems by Granata et al. (2023).

The paper presents an online approach for dynamic, multi-objective task allocation that allows for real-time adjustments to design human-centered workplaces integrating collaborative robots. (cobots) into production systems. By allowing cobots to work alongside human operators, the authors aim to achieve a balance between productivity and worker well-being. This approach represents an early effort to simultaneously assess human wellness and productivity in real-time, enabling immediate adjustments during task performance and creating a more effective and supportive work environment.

Result 104:

Human-centric production and logistics system design and management: transitioning from Industry 4.0 to Industry 5.0 by Grosse et al. (2023).

This paper introduces a special issue of the International Journal of Production Research, which features ten articles that examine the human-centric aspects of Industry 5.0 and their implications for the design of production and logistics systems. It highlights the necessity for a more systemic, data-driven, and ethically conscious approach in future research. This approach should integrate human diversity and factors affecting system operators, addressing the limitations of Industry 4.0.

Result 105:

The Human Factor and the Resilience of Manufacturing Processes: A Case Study of Pharmaceutical Process Toward Industry 5.0 by Rubini et al. (2023).

This paper presents a methodology for assessing the vulnerability of human factors in production processes, with particular emphasis on the potential risks associated with weaknesses in both cyber and physical systems. Through the execution of an industrial case study, this research examines the interaction between human skills, specifically Operator 5.0, and cyber systems, particularly in scenarios where system performance is adversely affected. The study underscores the critical importance of the synergy between human actions and cyber systems for the recovery of overall system functionality capabilities.

Result 106:

Development of a new set of Heuristics for the evaluation of Human-Robot Interaction in industrial settings: Heuristics Robots Experience (HEUROBOX) by Apraiz et al. (2023).

This paper introduces the HEUROBOX tool, a new set of heuristics designed to evaluate Human-Robot Interaction in industrial environments, with a focus on User Experience, Technology Acceptance, and overall worker well-being. With the growing collaboration between humans and robots, enhancing these interactions is essential for achieving optimal performance and a satisfying user experience. The HEUROBOX tool categorizes 84 basic heuristics and 228 advanced heuristics into four key areas: Safety, Ergonomics, Functionality, and Interfaces. Additionally, it incorporates important elements such as trust, perceived safety, inclusivity, and workload. The tool was validated by experts using the System Usability Scale questionnaire and prioritized through the Analytic Hierarchy Process. This provides a comprehensive framework for evaluating human-robot systems in industrial settings.

Result 107:

Integration of Industry 5.0 requirements in digital twin-supported manufacturing process selection: a framework by Papacharalampopoulos et al. (2023).

This paper introduces a framework that utilizes digital twin technology, essential enabling technologies, and the concept of the micro factory to automate process selection and scheduling. A case study evaluates two manufacturing components produced through Additive Manufacturing and laser welding under various scenarios. The study concludes that integrating Industry 5.0 criteria not only enhances worker well-being but also improves energy and time efficiency. This integration leads to higher profit margins and more sustainable production processes.

Result 108:

Role of Cobots over Industrial Robots in Industry 5.0: A Review by Sahan et al. (2023).

This paper discusses the increasing role of collaborative robots in industrial automation, emphasizing their advantages compared to traditional industrial robots. Collaborative robots, or cobots, are specifically designed to work safely alongside human operators. They provide flexibility, are easy to program, and are cost-effective, making them particularly appealing to small and medium-sized businesses. Unlike industrial robots, which excel in repetitive tasks, collaborative robots, or cobots, are designed to operate in dynamic environments and manage more complex, cooperative activities. The authors highlight several benefits of cobots, including enhanced safety, greater adaptability, and reduced operational costs. The text also examines the current state of cobot technology and its potential to revolutionize manufacturing by improving efficiency, sustainability, and worker well-being.

Result 109:

A Framework for Human-aware Collaborative Robotics Systems Development by Montini et al. (2023).

This paper introduces a framework aimed at enhancing human-aware collaborative robotics systems. It enables the development of a collaborative screw-driving application where both the operator and the robot actively perceive one another and provide support. The objective is to boost task efficiency while prioritizing the well-being of human workers. The authors acknowledge that, despite the promise of collaborative robots working alongside humans, their actual use in manufacturing settings has been limited.

Result 110:

Performance optimisation of pick and transport robot in a picker to parts order picking system: a human-centric approach by Vijayakumar & Sobhani (2023).

This study presents a mathematical model designed to optimize the performance of Picker-to-Parts systems in e-commerce warehouses that utilize Pick and Transport Robots (PTRs). The model takes into account not only productivity and quality but also the well-being of order pickers, a consideration that is frequently overlooked in previous research. By using data from a case company, this model provides valuable insights for managerial decision-making, enabling the design of more efficient and worker-friendly order-picking systems.

Result 111:

A Smart Manufacturing Ecosystem for Industry 5.0 using Cloud-based Collaborative Learning at the Edge by Javed et al. (2023).

The authors present a value-driven manufacturing process automation ecosystem for Industry 5.0, where each edge automation system operates on a local cloud and utilizes a service-oriented architecture. This ecosystem integrates cloud-based collaborative learning (CCL) across diverse fields, including building energy management, logistics robot oversight, production line coordination, and support for human workers. By fostering shared learning and collaboration, it aids the development of efficient manufacturing workflows that align with Industry 5.0 principles. The workflow management system not only optimizes processes for sustainability and cost-effectiveness but also prioritizes the well-being of human workers. Overall, this adaptable ecosystem holds significant implications for the future of various industrial applications.

Result 112:

Industry 5.0 and Operations Management - the Importance of Human Factors by Lindner & Reiner (2023).

This paper emphasizes the importance of human cognition in operations management during the transition from Industry 4.0 to Industry 5.0. It argues that the increasing reliance on digital technologies in manufacturing requires human-centered approaches to leverage both human strengths and technology. The paper provides examples of how technology can support or hinder decision-making and explores the potential of human-AI interaction and explainable AI, particularly through visualizations, to improve operational performance.

Result 113:

A Cost-Effective Thermal Imaging Safety Sensor for Industry 5.0 and Collaborative Robotics by Barros et al. (2023).

This paper presents a cost-effective thermal imaging Safety Sensor specifically designed for Industry 5.0 applications, aimed at enhancing human safety in environments characterized by collaborative robots and flexible manufacturing systems. The sensor utilizes a hybrid detection method to identify human presence adjacent to active machinery, thereby automatically engaging safe mode settings to prevent potential accidents. When evaluated under controlled conditions, the sensor demonstrated a remarkable accuracy rate of 97%, all while maintaining minimal computational costs. This positions the sensor as a practical solution for improving safety without undermining efficiency on the factory floor.

Result 114:

Wearable Technology for Smart Manufacturing in Industry 5.0 by Nguyen et al. (2023).

This chapter examines the role of wearable Internet of Things (IoT) devices, highlighting their potential to enhance human tasks and address new industrial demands. The integration of artificial intelligence and IoT with wearable technologies has led to significant innovations in areas such as manufacturing, healthcare, and sports. Despite facing challenges like security, privacy, and connectivity, the implementation of federated learning algorithms has bolstered data security, improved computing power, and increased accuracy. It also reviews the applications of wearable IoT devices in manufacturing, discusses their challenges, and presents case studies that utilize machine learning, deep learning, and federated learning for fall and fatigue classification.

Result 115:

A Comprehensive Study of Human Factors, Sensory Principles, and Commercial Solutions for Future Human-Centered Working Operations in Industry 5.0 by Loizaga et al. (2023).

This study investigates the measurement of human factors in the workplace, which are essential for understanding workers' well-being. Human factors are the physical, cognitive, and psychological conditions affecting worker efficiency, effectiveness, and mental health. The paper identifies six key human factors: physical fatigue, attention, mental workload, stress, trust, and emotional state. It examines how these factors influence physiological responses, including brain activity, cardiovascular reactions, muscular responses, electrodermal activity, and eye changes. Additionally, the study reviews technologies for measuring these factors in workplace environments and highlights available commercial solutions for such assessments.

Result 116:

Challenges in introducing automated guided vehicles in a production facility– interactions between human, technology, and organisation by Thylén et al. (2023).

This paper uses the Human, Technology, and Organization (HTO) model to investigate the complexities of integrating Automated Guided Vehicles (AGVs) into production environments. It seeks to emphasize the often-overlooked human and organizational aspects in discussions about Industry 4.0, which usually focus on technological innovations. By addressing challenges such as developing new work procedures, ensuring operator knowledge, and gaining employee acceptance, the study aims to provide insights for successfully incorporating AGVs into existing workflows. The results highlight that overcoming these challenges is vital for enhancing AGV performance and employee well-being, underscoring the need for a balanced approach that aligns human factors with technological advancements in Industry 5.0.

Result 117:

Human-Centered Design for Productivity and Safety in Collaborative Robots Cells: A New Methodological Approach by Boschetti et al. (2023).

This research explores how collaborative robots (cobots) can merge the flexibility of manual systems with the productivity of automation by working alongside human operators in the context of Industry 5.0. It investigates control methodologies, such as computer vision and augmented reality, to enhance productivity by minimizing idle times and reducing the effort required from operators. Furthermore, it highlights the significance of establishing a safe, human-centered workspace through real-time monitoring, which ensures secure interactions between humans and robots. The paper also covers the optimization of task allocation to achieve a balance between productivity, operator well-being, mental workload, and energy expenditure.

Result 118:

Predictive maintenance for industry 5.0: behavioural inquiries from a work system perspective by van Oudenhoven et al. (2023).

This paper examines the challenges of adopting Predictive Maintenance (PdM) solutions, with a specific focus on how changes in the roles of decision-makers impact their acceptance of these systems. Using the Smith-Carayon Work System model, the study investigates the human, task, and organizational factors that are involved in implementing PdM. Furthermore, it identifies four key factors that enhance the adoption of PdM: trust in the system, control over the decision-making process, availability of cognitive resources, and appropriate allocation of organizational decision-making responsibilities. The findings of this study provide valuable insights aimed at improving the acceptance of PdM systems.

Result 119:

Multi-ResAtt: Multilevel Residual Network With Attention for Human Activity Recognition Using Wearable Sensors by Al-Qaness et al. (2023).

The Human Activity Recognition (HAR) system utilizes a deep learning architecture known as Multi-ResAtt. This architecture combines a multilevel residual network with attention mechanisms to improve activity classification. The model processes data from inertial measurement units and features a recurrent neural network, enabling it to recognize complex human activities captured by wearable sensors effectively. Furthermore, the model utilizes three public datasets (Opportunity, UniMiB-SHAR, and PAMAP2). Multi-ResAtt surpasses existing human activity recognition models, showcasing its potential for Industry 5.0 applications such as smart homes and e-health by enhancing activity recognition accuracy and efficiency in human-centric systems.

Result 120:

Future of industry 5.0 in society: human-centric solutions, challenges and prospective research areas by Adel (2022).

This paper analyzes potential applications of Industry 5.0 with a focus on the collaboration between humans and machines in the context of smart factories. With the advent of Industry 5.0, there is a strong focus on delivering personalized products and enhancing customer satisfaction through cutting-edge technologies. The paper emphasizes key technological drivers of Industry 5.0, including big data analytics, the Internet of Things (IoT), collaborative robots, blockchain, digital twins, and the emerging 6G systems. Finally, the study addresses the challenges and issues faced by organizations involving robots and people on the assembly line.

Result 121:

UX assessment strategy to identify potential stressful conditions for workers by Khamaisi et al. (2022).

This paper presents a strategy for evaluating workers' User Experience (UX) within the framework of Industry 5.0, with an emphasis on human-centric design. The study utilizes noninvasive wearable devices to monitor human activities and physiological parameters in conjunction with self-assessment questionnaires. The goal is to improve workers' well-being and optimize industrial outcomes. A virtual reality (VR) simulation of heavy-duty tasks at an oil and gas pipe manufacturing site is utilized to identify potential physical and mental stressors that may affect operator performance.

Result 122:

Beyond playful learning – Serious games for the human-centric digital transformation of production and a design process model by Brauner & Ziefle (2022).

This article explores the use of serious games as a human-centered approach to facilitate digital transformation in manufacturing, specifically the transition from Industry 4.0 to Industry 5.0. It discusses how serious games can help operators manage complex and uncertain information while improving their responses to dynamic production environments. The paper provides an adaptable process model for designing serious games and tests this model through a serious game focused on supply chain and quality management. Additionally, the study presents empirical research indicating that serious games can serve as an effective learning environment for evaluating the interfaces used by industrial workers. Ultimately, the paper advocates for the use of serious games as a methodology to support the transition from Industry 4.0 to Industry 5.0 in manufacturing settings.

Result 123:

Employee-centric innovation: Integrating participatory design and video-analysis to foster the transition to Industry 5.0 by Orso et al. (2022).

This paper highlights the significance of involving workers in the early stages of design to achieve the objectives of Industry 5.0. It presents a case study on the redesign of technology in a validation laboratory, emphasizing a human-centric approach and the well-being of workers within the context of Industry 5.0. By combining self-reported data from employees with objective event-based data from video analysis, the study provided a comprehensive understanding of work activities and the associated challenges. The findings led to a set of redesign recommendations, which included updating the application and introducing portable devices. A preliminary usability evaluation of the revised application showed promising results, demonstrating the effectiveness of this mixed-method approach.

Result 124:

Digital Twin as Industrial Robots Manipulation Validation Tool by Kuts et al. (2022).

This study investigates how Virtual Reality interfaces can be integrated into Digital Twin (DT) systems for industrial applications, especially in the context of Industry 5.0, where human operators are integrated into automated systems. This research compares the performance of industrial robot control using traditional teach pendants and virtual reality (VR)-based DT interfaces. It evaluates several factors, including task completion time, stress levels, physical and mental effort, and user perceptions of both real and virtual robots. The findings indicate that while virtual reality (VR) interfaces may provide efficiency similar to traditional methods, they can also increase stress levels among users. Furthermore, the study emphasizes the potential of VR DT interfaces to enhance worker well-being and productivity. However, it recommends further research to confirm their long-term effects in collaborative industrial systems.

Result 125:

Evaluating quality in human-robot interaction: A systematic search and classification of performance and human-centered factors, measures and metrics towards an industry 5.0 by Coronado et al. (2022).

This article presents a literature review on measuring quality in Human-Robot Interaction (HRI), specifically in manufacturing environments, within the context of Industry 5.0. The review systematically analyzes 102 peer-reviewed articles and provides a taxonomy of performance aspects and a Venn diagram illustrating common human factors in HRI. The study clarifies often overlapping or confusing concepts in HRI research and identifies seven emerging research topics that are essential for advancing human-centered smart environments in Industry 5.0.

Result 126:

Design of Cognitive Assistance Systems in Manual Assembly Based on Quality Function Deployment by Pokorni et al. (2022).

This research develops a method for designing cognitive assistance systems (CAS) in the context of Industry 5.0, where human-machine collaboration is key. The cognitive assistance system-QFD (CAS-QFD) combines business and worker requirements to improve productivity, quality, and worker well-being. The CAS-QFD methodology, which is based on Quality Function Deployment (QFD), consists of six phases. It focuses on addressing workers' information needs, defining support functions, and selecting appropriate interaction technologies. An industrial evaluation has shown that this method is effective in systematically designing cognitive assistance systems that meet comprehensive requirements across the worker, workplace, production, and enterprise levels.

Result 127:

Balancing and scheduling assembly lines with human-robot collaboration tasks by Nourmohammadi et al. (2022).

This study focuses on the assembly line balancing problem with human-robot collaboration (ALBP-HRC) in advanced manufacturing, aiming to enhance productivity and worker well-being within the framework of Industry 5.0. The research develops a mixed-integer linear programming (MILP) model that incorporates the task times for both humans and robots, the joint tasks they may perform, and the possibility of having multiple humans and robots working at the same stations. The model is solved using a neighborhood-search simulated annealing (SA) algorithm that incorporates an adaptive neighborhood selection mechanism. Computational results applied to real-world scenarios in the automotive industry demonstrate that the proposed SA algorithm produces promising solutions when compared to MILP and other optimization techniques. This indicates significant productivity gains when humans and robots collaborate at workstations.

Result 128:

KIDE4I: A Generic Semantics-Based Task-Oriented Dialogue System for Human-Machine Interaction in Industry 5.0 by Aceta et al. (2022).

This paper presents KIDE4I (Knowledge-driven Dialogue framework for Industry), a semantic-based task-oriented dialogue system designed for Industry 5.0. KIDE4I enables workers to interact naturally with industrial systems, thereby reducing cognitive load and enhancing system acceptance. KIDE4I is distinct from traditional systems in that it can adapt to new scenarios without needing extensive training data. This framework has been applied to four industrial use cases, with two of them evaluated through user studies. The results indicate that users perceive the system as accurate, efficient, flexible, and easy to use.

Result 129:

Ikigai Robotics: How Could Robots Satisfy Social Needs in a Professional Context? a Positioning from Social Psychology for Inspiring the Design of the Future Robots by Sartore et al. (2022).

This study presents the concept of "ikigai robotics," focusing on the mutually beneficial relationship between worker well-being and performance in railway maintenance. By combining aspects of both industrial and service robotics, the research highlights the importance of the need for affiliation as a key factor that positively affects both well-being and performance in this field. The findings emphasize that integrating robots designed with human well-being in mind can enhance productivity. Additionally, the authors provide initial guidelines for designing "ikigai robots" and suggest that this concept could have broader applications beyond just railway maintenance.

Result 130:

Roadmap to Implement Industry 5.0 and the Impact of This Approach on TQM by Chaabi (2022).

This paper develops a roadmap for implementing the transition to Industry 5.0, emphasizing a human-centric, sustainable, and resilient approach. It focuses on prioritizing the health and safety of workers while outlining strategies for embracing collaboration between workers and advanced technologies. This roadmap aims to foster a positive integration of robotics into the workforce by addressing concerns about job loss and enhancing productivity and efficiency. The roadmap integrates the ADKAR change management model with Quality Circles to enhance worker engagement and facilitate the transition to Industry 5.0. Furthermore, the paper examines the potential effects of Industry 5.0 on Total Quality Management, highlighting the importance of workers in promoting continuous improvement within industrial environments.

Result 131:

Impact of Meditation on Quality of Life of Employees by Sagar et al. (2022).

This study investigates the effects of virtual meditation and mindfulness programs that incorporate artificial intelligence (AI) on promoting organizational health and enhancing mental well-being. The focus was on young engineers at PPS International in Greater Noida, India, who participated in an eight-week meditation intervention. The experimental group consisted of 30 males. The results showed significant improvements in quality of life across various domains, including perception, physical health, psychological health, social relationships, and environmental factors, when compared to a control group. This research contributes to the limited literature on AI-integrated wellness programs and highlights their positive effects on employee efficiency, emotional stability, and stress reduction.

Result 132:

An IoT-based Wireless Sensor Network for Lighting Control Systems by Pierleoni et al. (2022).

This study introduces a lighting control system aimed at enhancing worker well-being in the context of Industry 5.0, with a focus on both physical and mental health. The system utilizes a wireless sensor network, integrating with standard lighting controls to extend their functionality. It also allows for remote monitoring through a web platform. The proposed solution seeks to regulate workers' circadian rhythms by modifying the lighting in the work environment, thereby enhancing their psychophysical well-being. The system has been tested in industrial settings, with its performance evaluated using metrics such as round-trip time, packet loss, and goodput. The results demonstrate the system's versatility and scalability, accommodating various node densities, network topologies, and sensor units.

Result 133:

Investigating exoskeletons applicability in manufacturing and logistics systems: state of the art and future research directions by Ashta et al. (2022).

This paper explores the role of exoskeletons in the manufacturing and logistics sectors, aiming to improve worker well-being and increase productivity by reducing the risk of musculoskeletal disorders, particularly among an aging workforce. As modern industries shift towards human-centered workplaces, exoskeletons are regarded as promising solutions for enhancing ergonomics and safety. The study reviews various exoskeleton designs and their applications, categorizing them by task type, including simulated and real tasks, as well as by application field and evaluation methods.

Additionally, it highlights the growing interest in using tools such as electromyography, motion capture, and questionnaires to assess the effectiveness of these devices.

Result 134:

Promoting operator's wellbeing in Industry 5.0: detecting mental and physical fatigue by Villani et al. (2022).

This paper investigates the detection of mental and physical fatigue in workers, in line with the human-centric approach promoted by Industry 5.0. By utilizing wearable devices to monitor operators' physiological conditions, specifically their cardiac activity, the study aims to identify fatigue at an early stage. Early detection of fatigue will enable the implementation of supportive strategies that enhance productivity and maintain the well-being of workers.The experiment subjects participants to both mental and physical fatigue, analyzing heart rate variability to distinguish between rest, mental fatigue, physical fatigue, and combined fatigue. The results reveal significant differences in time-domain metrics; however, identifying mental fatigue in conjunction with physical fatigue remains a challenge. These findings offer valuable insights into how fatigue detection can improve worker health and efficiency within Industry 5.0 environments.

Result 135:

Review of Human-Machine Interaction Towards Industry 5.0: Human-Centric Smart Manufacturing by Yang et al. (2022).

This paper explores the role of Human-Machine Interaction (HMI) in Human-Centric Smart Manufacturing (HCSM), a vital aspect of Industry 5.0. It presents a framework for HMI focused on the interaction process and examines research in several key areas: sensors and hardware, data processing, transmission mechanisms, and interaction and collaboration. The paper analyzes current developments in each of these fields and investigates their potential applications in HCSM, where the emphasis shifts from merely enhancing productivity to prioritizing worker well-being and sustainability. The paper concludes by discussing the challenges and opportunities for future HMI research in smart manufacturing systems.

Result 136:

Supporting Resilient Operator 5.0: An Augmented Softbot Approach by Zambiasi et al. (2022).

This paper examines the "Resilient Operator 5.0" concept within Industry 5.0. The aim is to enhance human adaptation, productivity, and mental health by creating intuitive, human-centered work environments. It introduces a novel approach, called an "augmented softbot", that combines softbots and augmented reality to improve preventive maintenance processes. A software prototype was developed, and three evaluation scenarios were analyzed within a specific company. The findings demonstrate the potential of this technology to support operational resilience, showing promising benefits for productivity and employee well-being.

Result 137:

An IIoT Platform For Human-Aware Factory Digital Twins by Montini et al. (2022).

This paper discusses the need for new Digital Twins in Industry 5.0, which includes human workers alongside traditional system representations. It introduces an industrial IoT-based platform that addresses the current limitations of Digital Twin solutions, such as issues with reusability, scalability, and extensibility. The platform enables the creation of customized data models for both production systems and human workers, facilitating improved interaction modeling. Tested in a laboratory environment, it provides a flexible and modular infrastructure for easy instantiation of digital twins.

Result 138:

Outlook on human-centric manufacturing towards Industry 5.0 by Lu et al. (2022).

This paper introduces a framework grounded in the Industrial Human Needs Pyramid, which encompasses a comprehensive range of human needs—from safety to self-actualization. The discussion highlights the progression of human-machine relationships, moving from mere coexistence and cooperation to deeper levels of compassion and coevolution. This evolution underscores the importance of bidirectional empathy, proactive communication, and collaborative intelligence. The authors suggest that future research should aim to create transparent and trustworthy technologies to enhance the effectiveness of high-performance human-machine teams.

Result 139:

Disruptive Technologies and Operations Management in the Industry 4.0 Era and Beyond by Choi et al. (2022).

This study investigates disruptive technologies such as AI, robotics, blockchain, 3D printing, 5G, IoT, digital twins, and augmented reality, focusing on their impact on operations management (OM) in the context of Industry 4.0. It delves into their current applications while weighing the benefits against the potential drawbacks of these innovations. The paper also addresses the possible conflicts that may arise between human and machine interactions. Additionally, it introduces the idea of "sustainable social welfare," which includes considerations for worker well-being and privacy, emphasizing the crucial role of policymakers in maintaining a proper balance.

Result 140:

A preliminary experimental study on the workers' workload assessment to design industrial products and processes by Bruzini et al. (2021).

This paper discusses the role of human-centered design (HCD) in advancing Industry 5.0, focusing on improving worker well-being while maintaining sustainable production.

It proposes an ergonomic assessment method to analyze workers' physical and cognitive workload during tasks. The method utilizes wearable devices to monitor physiological parameters and questionnaires for subjective assessments, enabling companies to optimize product and process design to enhance worker well-being. The method has been preliminarily tested in a real industrial case.

Result 141:

Device for monitoring the influence of environmental work conditions on human factor by Onofrejova et al. (2021).

The paper emphasizes EU-OSHA's commitment to preventing work-related diseases, following the EU Strategic Framework on Health and Safety at Work for 2014-2020. It highlights the significant influence of the work environment on worker productivity, health, and safety. The paper advocates for the implementation of miniaturized technology to monitor working conditions, which can help build resilience against disruptions like the COVID-19 crisis.

Result 142:

Neuro-competence approach for sustainable engineering by de Miranda et al. (2021).

This paper examines the Quintuple Helix innovation model and emphasizes the importance of engineers developing the right competencies, especially through the lens of connectivism learning theory. A bibliometric analysis was performed to pinpoint the key factors influencing the design of neuro-competencies in engineering education. The paper introduces the Neuro-Competence Engineering (NCE) model, which combines neuro-competence, activity theory, and neuroscience to better align engineering tasks with human capabilities, thereby promoting lifelong learning in a sustainable manner.

Result 143:

Accelerating Time to Competency in an Industry 5.0 World by Kedzierski & Willetts (2021).

This paper emphasizes how companies like Shell create more personalized experiences for their workers that align with business objectives and human welfare. It discusses innovations such as mobile, on-demand training, collaborative learning through Operator Training Simulators, AI-driven microlearning tailored to individual worker profiles, and Virtual Reality platforms that provide training for decision-making in real-time scenarios. Additionally, the paper highlights how tools like Microsoft Power Apps enable workers to develop their own solutions, marking the emergence of mass personalization in Industry 5.0. This approach aims to enhance both safety and individual performance.

Result 144:

Next Generation Auto-Identification and Traceability Technologies for Industry 5.0: A Methodology and Practical Use Case for the Shipbuilding Industry by Fraga-Lamas et al. (2021).

This paper examines the impact of Auto-Identification (Auto-ID) technologies within the framework of Industry 5.0. It underscores how these innovations can boost worker productivity by facilitating transparent and human-centered traceability across the entire value chain. By investigating the latest Auto-ID solutions and implementing a selection methodology specifically for the shipbuilding sector, the paper highlights that a thoughtful evaluation and selection of technologies—such as RFID tags—can effectively address challenges posed by complex industrial settings. These technologies not only enhance product tracking and identification but also support production processes focused on the workers themselves.

Result 145:

Influence of emotional intelligence on the workforce for industry 5.0 by Chin (2021).

This study examines the role of emotional intelligence in improving workforce performance within the framework of Industry 5.0. Unlike Industry 4.0, which emphasizes technological advancements, Industry 5.0 focuses on human intelligence and emotional skills in the workplace. The research, which involved 110 executives, reveals that emotional intelligence—especially the abilities to recognize emotions, express them, and direct them cognitively—significantly influences workforce performance. This underscores the importance of soft skills, such as emotional intelligence, in equipping workers for the challenges and demands of Industry 5.0, ultimately promoting both personal well-being and productivity.

Result 146:

The Entropic Complexity of Human Factor in Collaborative Technologies by Panagou et al. (2021).

This paper examines the role of human operators in the evolving workplace environments shaped by Industry 4.0 technologies, such as automation, collaborative robots, and cyber-physical systems. It also looks ahead to Industry 5.0, which focuses on human sustainability within these technological frameworks. The study highlights the critical importance of human operators, especially considering the challenges posed by an aging workforce. It suggests that these operators need to adapt to new tasks, improve their skills, and prioritize safety and productivity in increasingly complex environments. Furthermore, the research presents a model derived from the concept of entropy in statistical mechanics to evaluate human capabilities and the potential for errors.

Result 147:

Walrasian Equilibrium-Based Multiobjective Optimization for Task Allocation in Mobile Crowdsourcing by Wang (2020).

This paper focuses on improving task allocation in mobile crowdsourcing systems. It proposes a Markov and Collaborative Filtering-based Task Recommendation (MCTR) model that considers worker similarities, trajectory prediction, dwell time, and trust levels. This approach aims to encourage crowd workers to participate in tasks and provide accurate data. The research also investigates the optimal solution using Walrasian equilibrium to maximize social welfare within mobile crowdsourcing systems. Comparison experiments demonstrate that the proposed task allocation model enhances the efficiency and adaptability of these systems.

Result 148:

Human Failures on Production Line as a Source of Risk of Non-conformity Occurrence by Nagyova et al. (2020).

This paper explores how organizations implement automation to meet production needs, enhance performance, minimize costs, and satisfy customer demands. However, certain activities and processes cannot be fully automated and require a human-machine interface. These processes may introduce risks that are not easily predictable, and if identified too late, they could lead to inconsistent product quality. Such inconsistency may ultimately result in a loss of competitiveness and a decline in company profits. Additionally, the paper emphasizes risk analysis related to non-conformity arising from the manual placement of components in automotive production processes. The causes of non-conformity were identified using quality tools, and system solutions for their elimination were proposed. In alignment with the Industry 5.0 strategy, these solutions include investing in operator training programs to address the significant impact of the human factor within the human-machine system.

Result 149:

An automatic procedure based on virtual ergonomic analysis to promote human-centric manufacturing by Grandi et al. (2019).

This paper highlights the importance of integrating human factors into manufacturing processes to improve worker well-being, prevent illnesses, reduce errors, and mitigate excessive workloads. It outlines a systematic approach for the automatic extraction of data from virtual analyses performed by digital manufacturing tools to evaluate manufacturing ergonomics. The research establishes a set of indicators specifically designed for assessing manual operations, with a particular focus on assembly tasks. Additionally, it presents a methodology for the automatic extraction of this data. An application developed in Visual Basic generates task lists and corresponding ergonomic assessments. This procedure was applied in a case study that examined the manual assembly of tractor cabin supports. The results led to a redesign that enhanced ergonomics by decreasing the EAWS (Ergonomic Assessment Worksheet Score). This approach allows for an early evaluation of worker well-being during the design phase, promoting the development of human-centric manufacturing processes.

3.7 Feedback from Experts

Following the CTI methodology presented in Chapter 2, experts in Industry 5.0 and Competitive Technology Intelligence were contacted via email during the process. The experts provided feedback to help construct the search query.

3.8 Validation and Delivery of Final Results

The expert’s feedback contributed to the final validation in parallel to the previous step. Vital aspects were validated, such as selecting the database, choosing keywords, formulating the final query, categorizing the results, and accurately analyzing the data. The publications utilized in the theoretical framework for Competitive Technology Intelligence, well-being, and Industry 5.0 provided additional reassurance for this study's findings.

3.9 Decision Making

The findings in this thesis provide a strong basis for informed decisions for research and development (R&D), and innovation.

Chapter 4: Discussion

4.1 Introduction

In the subsequent section, the 149 papers sourced from Chapter 3 will be detailed. Each human factor includes a brief description of its characteristics, its impact on workers' well-being and productivity, and the approaches discussed in this research. Lastly, the trends in technology and research related to how workers' well-being influences productivity within the context of Industry 5.0 are presented.

4.2 Human Factors

The papers were categorized into six key human factors for assessing well-being and productivity in Industry 5.0: physical fatigue, attention, cognitive workload, stress, trust, and emotional assessment.

4.2.1 Physical Fatigue

Physical fatigue occurs when the body decreases its physical capabilities due to exertion (Loizaga, Toichoa Eyam, Bastida, & Martinez Lastra, 2023). It can cause tiredness and mental, cardiovascular, or muscular fatigue that can affect any body part (Mahdavi, Dianat, Heidarimoghadam, Khotanlou, & Faradmal, 2020).

Mahdavi et al. (2020) mention that fatigue can have both short-term and long-term consequences. In the short term, it may result in decreased strength, localized muscle fatigue, and impaired motor control, while long-term effects can include musculoskeletal disorders (MSDs) (Mahdavi, Dianat, Heidarimoghadam, Khotanlou, & Faradmal, 2020). The impact of physical fatigue, whether immediate or prolonged, can significantly affect a worker's productivity and overall well-being. MSDs are a recurring health issue among operators, often arising from the physical demands of their work (Pistolesi, Baldassini, & Lazzerini, 2024). Moreover, MSDs substantially impact employee well-being and overall task performance (Ling, et al., 2024). Therefore, organizations that take a proactive approach to addressing ergonomic concerns can enhance productivity and performance while fostering the well-being of their employees.

Various approaches have been explored to address physical fatigue in the workplace. This research categorizes the information into ergonomic interventions, advanced monitoring technologies, and dynamic task allocation systems to enhance understanding.

4.2.1.1 Ergonomic Interventions

Grandi et al. (2019) propose Human Modeling Software that simulates worker movements and postures in a virtual environment. This software enables ergonomic adjustments to workstation layouts, task sequences, or tools before physical implementation. They also present the EAWS (Ergonomic Assessment Worksheet), a tool for calculating the ergonomic risks associated with specific tasks. The EAWS tool is expected to help redesign tasks to improve worker comfort and safety.

Ghorbani et al. (2024) developed a fuzzy fatigue model by combining Potvin's fatigue model with the Fuzzy Inference System (FIS). Based on rules derived from ergonomic specialists' insights, this model provides actionable insights for managing ergonomic risks. The study assessed three scenarios with different thresholds for maximum allowable fatigue levels, referred to as Fmax. The scenarios included Fmax values of 1, 0.75, and 0.5. The findings revealed a reduction in fatigue of 30%, 52%, and 81%, respectively, for each scenario. Moreover, it helps in work cell planning by categorizing fatigue levels, enabling designs that minimize potential fatigue.

Falerni et al. (2024) introduce a novel approach called AmPL-RULA. This approach combines the Active Multi-Preference Learning (AmPL) algorithm with the Rapid Upper Limb Assessment (RULA). The AmPL algorithm offers qualitative feedback on user preferences, while RULA aids in assessing the ergonomic aspects of a task. The authors state that postural comfort and ergonomics are different; ergonomics emphasizes postures that prevent health issues, while comfort encompasses various factors, including cognitive, physiological, and environmental. This research considers both user preferences and ergonomic principles.

4.2.1.2 Advanced Monitoring Technologies

In 2023, Chand et al. (2023) developed a personalized muscle fatigue profile using Surface Electromyography (s-EMG) technology to measure muscle strength and fatigue changes during dynamic manufacturing tasks in human-centric human-robot collaboration (HHRC) environments. The aim was to improve real-time monitoring of muscle performance through a noninvasive method. The research was conducted in three case scenarios: static hold, vertical handling, and pick and place operations. The results showed that static hold and pick and place operations present higher muscle fatigue with 25-50% relative task load. Furthermore, individuals with varying muscle strengths exhibited similar fatigue profiles under the same task load. This research, which effectively tracks muscle fatigue during dynamic operations, has potential applications for dynamic task allocation.

Khamaisi et al. (2024) used a wearable motion capture suit to measure body postures in real-time during a standardized lifting task. The gathered data was utilized in the TACOs (Time-Based Assessment Computerized Strategy) methodology, which the authors proposed. This methodology emphasizes analyzing both the duration and severity of postures adopted by the spine and lower limbs during tasks.

Pistolesi et al. (2024) propose a privacy-preserving posture-tracking system that uses a LiDAR (Laser Imaging Detection and Ranging) sensor and a smartwatch to monitor workers' postures. The system is designed to comprehensively assess the alignment of the trunk, shoulders, arms, and legs. It monitors the worker's posture with an impressive 98% accuracy, offering an alert mechanism that notifies users when their posture deviates from the ISO 11226 standard. Moreover, it safeguards privacy, as the system is designed to prevent the retention of sensitive information.

4.2.1.3 Task Allocation Systems

Dynamic task allocation involves the real-time and adaptable assignment of tasks based on changing conditions in a collaborative workspace between humans and robots (Calzavara, et al., 2024). This system can monitor factors such as worker fatigue, performance metrics, and robot availability (Calzavara, et al., 2024). On the other hand, in static allocation systems, tasks are pre-assigned at the beginning of the shift and do not change under real-time conditions, which often fails to support operator well-being and environmental variability (Granata, Faccio, & Boschetti, Industry 5.0: prioritizing human comfort and productivity through collaborative robots and dynamic task allocation, 2024).

Both Calzavara et al. (2023) and Boschetti et al. (2023) propose a multi-objective task allocation model to minimize the makespan, energy expenditure, and mental workload, using a static task allocation method as input (Boschetti et al., 2023). The model offers a range of options based on the makespan, energy expenditure, or mental workload. According to the authors, this method effectively balances productivity and well-being by optimizing task distribution between humans and collaborative robots. Furthermore, Calzavara et al. (2023) introduce a saturation constraint that allocates more tasks to the cobot, aiming to minimize the operator's effort, even though it increases the makespan.

Calzavara et al. (2023) describe the makespan as "the total time required to complete all tasks that must be performed", the energy expenditure as "the energy required to both maintain the posture and to perform the job, which is measured by the duration, level, and repetitiveness of a physical job", and mental workload as "the combination of all elements, both cognitive and emotional, that are related to the complexity of the tasks, limited resources, and feelings during work", under this context mental workload is estimated through the CLAM (Cognitive Load Assessment for Manufacturing) index.

Granata et al. (2024) and Calzavara et al. (2024) propose a dynamic task allocation system by monitoring real-time data on human variability. Unlike the multi-objective method, this method allows the reassignment of tasks between humans and cobots under unexpected conditions such as the operator’s energy and stress levels. In both studies, only makespan and energy expenditure were considered. The results showed that this method can avoid overworking the operator, potentially improving well-being and productivity and preventing operator fatigue and the risk of stress.

In conclusion, multi-objective task allocation presents an effective methodology for optimizing task assignments through the careful balancing of various objectives within a static framework. Conversely, dynamic task allocations facilitate adaptability and real-time adjustments, enabling them to respond effectively to immediate fluctuations and alterations in the task environment.

Furthermore, while static systems are valuable for predetermined, stable environments, dynamic task allocation systems are essential for enhancing productivity and well-being. A human-centric task allocation system must be adaptive and prioritize both operational efficiency and human factors. Nevertheless, it's important to recognize that while implementing assistive technologies can support operators, these solutions may also present drawbacks, such as increased fatigue, workload, or injury risk (Lucchese & Mummolo, 2024). Therefore, it is essential to consider a range of different strategies for effectively assessing fatigue in the workplace, as this can significantly contribute to overall employee well-being and productivity.

4.2.2 Attention

Chun et al. (2011) define attention as the brain's capacity to focus on and process specific external or internal stimuli. According to them, this ability is essential due to the brain's limited capacity to handle information simultaneously. Under this context, attention serves as a mechanism that allows for the selection and concentration of information relevant to ongoing tasks. Forster and Lavie (2008) explain that a distraction occurs when attention shifts from one task to another due to external or internal stimuli that are unrelated to the task. On the contrary, concentration is the state of sustained attention on a specific task that requires both effort and cognitive resources (Chun, Golomb, & Turk-Browne, 2011).

This mechanism becomes especially important in industrial settings. Distractions or the operator's loss of attention can lead to significant safety risks (Simeone, Grant, Ye, & Caggiano, 2023), increased errors, and lower performance (Tortora, Pasquale, Franciosi, Miranda, & Iannonne, 2021). Therefore, continuously monitoring the operator’s attention (Simeone, Grant, Ye, & Caggiano, 2023) and addressing human factors like attention and focus (Tortora, Pasquale, Franciosi, Miranda, & Iannonne, 2021) are critical to maintaining a secure workplace environment for the operator, minimizing errors, and increasing productivity.

Various approaches have explored the impact of attention in the workplace. This research categorizes the information into concentration and distractions to enhance understanding.

4.2.2.1 Concentration

Rykala (2023) developed an algorithm for analyzing brain electrical activity through electroencephalography (EEG) signals. The aim of this evaluation was to assess the concentration levels of operators in real-time, especially during periods of extended working hours or in elevated temperature conditions while interacting with heavy machinery, such as unmanned ground vehicles (UGVs). The author employed EEG-based biofeedback to monitor operators' concentration levels and provide feedback for increased awareness. The feedback was provided when concentration appeared to drop, and it could be delivered directly through notifications or indirectly by reviewing focus trends. Results accurately reflected the participants' conditions, indicating that the methodology was correct. This solution may provide an overview of machine operator concentration levels.

In 2023, Helm et al. (2023) examined the source of errors in a warehouse using Intelligent Video Analysis (IVA). The IVA is a tool for recording, tracking, and analyzing warehouse operations. Cameras were strategically installed, synchronized with the Warehouse Management System (WMS), and analyzed by human operators. This tool was implemented in six case companies identified as A, B, C, D, E, and F.

The results indicated that confusion, lack of experience, distraction, stress, and carelessness are the main causes of errors. The authors also noted that the presence of cameras appeared to reduce errors, suggesting that operators tend to concentrate more when they feel they are being monitored. This conclusion was made after observing an 80% decrease in errors at Company F when using the IVA tool.

4.2.2.2 Distraction

Yin & Li (2023), Polito et al. (2023), and Al-qaness et al. (2023) examine how external stimuli affect human performance through attention. Although they use different experimental methods, both studies aim to evaluate the impact of distractions during task execution.

Yin & Li (2023) explore how auditory noise affects attention in participants performing visual tasks using fan noise alone, fan with human noise, and fan with striking noises. Results indicated that under noisy conditions, participants, particularly those sensitive to noise, experienced longer task completion times and increased pupil dilation, which serves as an indicator of stress. This conclusion was reached after observing that individuals sensitive to noise took longer to complete tasks, with their time increasing from 1.74 seconds in a quiet environment to 2.77 seconds in the presence of fan noise combined with human sounds. Similarly, for individuals who are less sensitive to noise, their task completion time increased from 2.20 seconds in a quiet setting to 2.84 seconds when exposed to noise from a fan along with striking sounds.

Polito et al. (2023) examine how distractions, stress, or fatigue can lead to sudden movements during Human-Machine Interactions (HMI), potentially compromising safety. The authors propose wearable Magneto-Inertial Measurement Units (MIMUs) to monitor precise movement data. These MIMUs integrate accelerometers, gyroscopes, and magnetometers. The findings indicated a 99.25% accuracy rate with a precision of 85.23%, highlighting an effective method for detecting abrupt movements and enhancing operator safety in industrial settings.

Similarly to Polito et al. (2023), Al-qaness et al. (2023) focus on the importance of human activity recognition. The authors develop a model called Multi-ResAtt (multilevel residual network with attention) that utilizes data from wearable sensors, specifically Inertial Measurement Units (IMUs). The model processes and learns from IMU data to recognize complex human activities. The results showed that the Multi-ResAtt model can reach up to 84.99% accuracy.

Distractions that negatively impact attention, as demonstrated by Yin & Li (2023), can cause sudden movements during Human-Machine Interaction (HMI), jeopardizing the operator's safety. For this reason, Polito et al. (2023) and Al-Qaness et al. (2023) emphasize the importance of identifying human activities, such as abrupt movements in the workplace.

These proposals emphasize the need for continuous monitoring of both attention and concentration to ensure safety, well-being, and optimal performance, particularly in environments where humans and machines work closely together.

4.2.3 Cognitive Workload

Cognitive workload refers to the balance between the resources the operator requires and those required by the task (See Figure 15) (Wickens, Gordon, & Liu, 2004). Cognitive workload is key to preserving a healthy and high-performing working environment (Ma, Monfared, Grant, & Goh, 2024).

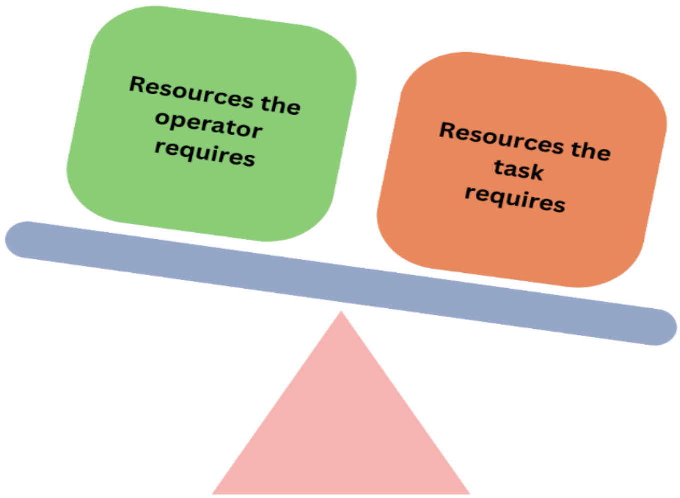


Figure 15. Graphical Representation of Cognitive Workload Balance.
(Own elaboration, 2024)

An imbalance between these two resources could impact the operator's well-being and performance. For example, consider the amount of time a task requires compared to the time available to complete it. If the time needed for a task exceeds the time available for the operator to finish it, this results in an overload (Wickens, Gordon, & Liu, 2004). Equally, if the time needed for a task is low and the time available is too high, it can result in an underload. Although this example oversimplifies the complexities of the concept, it still serves as a useful starting point, given that other factors such as attention, information processing capacity, memory, and decision-making (Ma, Monfared, Grant, & Goh, 2024) influence it.

Even though a newly implemented system in a work environment shows good performance, task performance can be reduced, and errors can increase if the operator experiences an excessive workload while using it (Wickens, Gordon, & Liu, 2004). This reinforces the importance of constantly monitoring the operator's cognitive workload to maintain their well-being and performance.

Various approaches have been explored to address cognitive workload in the workplace. This research categorizes the information into subjective, objective and a combination of both to enhance understanding.

4.2.3.1 Subjective

Javernik et al. (2023) used the NASA-TLX questionnaire to take a completely subjective approach. The authors found that Human-robot collaboration (HRC) significantly influenced worker workload. The study involved two case scenarios: 60% and 100% worker utilization, with the difference being the time given by the robot. The results showed a 34.7% increment in perceived workload when worker utilization increased from 60% to 100%. Additionally, the highest workload reported was in the TD (temporal demand) dimension of the questionnaire, which relates to the time pressure experienced by respondents. They recommend personalized guidelines for HRC workplaces that consider the operator's abilities, skills, and personalities. This focus is aligned with Gualtieri et al. (2024), emphasizing guidelines for non-experts in Human-Robot Collaborative (HRC) assembly tasks to create effective, human-centered HRC environments.

4.2.3.2 Objective

Cardiac activity and visual scanning are consistent and reliable parameters for measuring cognitive workload (Wickens, Gordon, & Liu, 2004). Cardiac activity is, however, the physiological metric most commonly utilized (Antonaci, et al., 2024).

The authors Pluchino et al. (2023) and Ma et al. (2024) follow these parameters for their research. Pluchino et al. (2023) used eye-tracking and cardiac activity alongside the NASA-TLX questionnaire in an assembly task experiment with senior workers and a cobot. The authors evaluated mental workload under single-task, where only one assembly task was evaluated, and dual-task conditions, where two assembly tasks were required simultaneously. The results indicate that participants experienced a higher level of mental workload during the dual-task condition, with a median score of 100 and an average of 5.64 errors. In contrast, during the single-task condition, the median score was 45, and the average number of errors was just 0.81. Additionally, Senior operators exhibited a greater willingness to work with cobots, even though their cognitive workload and error rates increased.

Ma et al. (2024) conducted an experiment involving the assembly of a Wankel Engine, utilizing pupillometry and heart rate variability (HRV) measurements. The tasks were designed with varying complexities categorized as rest, low, medium, and high, and included both experts and non-experts. The results indicated that cognitive load increased with task complexity, accompanied by a decrease in heart rate variability under higher cognitive workloads. Furthermore, the authors discovered that experts experienced lower cognitive workloads compared to non-expert participants despite the task complexity.

Both studies provide valuable strategies for designing and optimizing a workplace environment that considers operators' cognitive workload.

4.2.3.3 Combined

Zakeri et al. (2023) and Caiazzo et al. (2023) evaluated cognitive workload using the NASA-TLX questionnaire and electroencephalography (EEG). However, Zakeri et al. (2023) also integrated functional near-infrared spectroscopy (fNIRS) and auditory signals, referred to by the authors as beeps, to evaluate attention and reaction time. Both studies found reduced cognitive workload and enhanced performance when the participants worked with cobots.

Zakeri et al. (2023) conducted an experiment involving a sorting task in which a collaborative robot (cobot) would present participants with a box. The participants had to decide where to place the box. Additionally, an extra task was introduced: participants would hear a beep and were required to press a foot pedal in response. The authors found that NASA-TLX scores were higher in conditions of high complexity compared to those of low complexity, indicating an increased mental workload. Reaction times also increased under high-stress conditions, especially when both task complexity and cobot speed were elevated, which pointed to a rise in cognitive workload and stress levels. Furthermore, in high-complexity scenarios, a greater number of beeps were missed, demonstrating how cognitive workload affects task performance.

Caiazzo et al. (2023) conducted an assembly task experiment in a standard scenario, where no robotic assistance was provided, and collaborative scenarios, with the same assembly task but with the assistance of a cobot. The authors observed a higher number of components correctly assembled in the collaborative scenario, resulting in higher productivity and a significant reduction in mental workload, as evaluated by EEG data and NASA-TLX scores.

Nenna et al. (2023) studied the connection between cognitive workload, performance, and the Sense of Presence (SoP) in a VR-based telerobotic environment. Participants who reported a higher SoP completed the pick-and-place tasks faster than participants who reported a lower SoP. During the "pick" operation, the average time was 2.37 seconds for the high SoP group, while the low SoP group took 3.05 seconds. Similarly, for the "place" operation, the high SoP group completed it in 1.86 seconds, compared to 2.51 seconds for the low SoP group. The investigation concluded that a higher Sense of Presence (SoP) positively affects task performance and has a 'little to no impact' on cognitive workload. The results were obtained by administering the NASA-TLX for workload evaluation and the MEX-SPQ for SoP evaluation questionnaires to participants. Additionally, pupil size variation was measured using an eye headset integrated with an eye-tracking system.

In summary, the subjective approach provides valuable insights into cognitive workload from the operator's perspective, whereas the objective approach employs data obtained through instrumentation. While the objective method is generally more suited for tasks requiring precise measurements, the subjective method effectively captures the operator's experiences and perceived workload. Therefore, integrating both approaches may be beneficial for achieving a more comprehensive evaluation.

4.2.4 Stress

The authors Loizaga et al. (2023) define stress as "a condition in which unpredictability (absence of anticipatory response) and uncontrollability (delayed recovery of the response and presence of a typical neuroendocrine profile) are involved". In other words, stress is a reaction to feeling unprepared and lacking control over events. Additionally, the author Blandino (2023) defines the work-related phenomenon originating from stress as “a phenomenon that occurs when the work demands exceed the worker’s capacity to perform them”.

This phenomenon is associated with several health issues, including an increased risk of musculoskeletal symptoms, mental health challenges like depression (Kim, et al., 2023) as well as decreased productivity at work (Chung, et al., 2023); (Blandino, 2023); (Tran, et al., 2023). Therefore, organizations that take a proactive approach to addressing work-related stress concerns can enhance productivity and performance while fostering the well-being of their employees.

Given stress's significant impact on well-being and productivity, numerous authors have conducted research to address this issue. Blandino (2023) and Ciccarelli et al. (2023) conducted a literature review on stress indicators, measurement methodologies, and the contextual factors influencing stress in smart and intelligent manufacturing systems. The measurement methods identified by the authors are categorized into three groups (See Figure 16):

1. **Physical:** The physical evaluation includes indicators related to both posture and behavior. Posture is assessed using the Ovako Working Posture Analysis System (OWAS), the Rapid Entire Body Assessment (REBA), and the Rapid Upper Limb Assessment (RULA). Behavior indicators are determined by analyzing body language and indicators of hyperactivity.

2. **Physiological:** The physiological evaluation includes various measures such as cardiac activity, electrodermal responses, respiratory rates, and indicators of brain activity. Key metrics used in this evaluation are Heart Rate Variability (HRV) and heart rate (HR) to assess cardiac function, along with Electrodermal Activity (EDA), which is measured through skin conductance to reflect nervous system responses.

3. **Psychological:** The psychological assessment includes subjective measures, such as self-assessment questionnaires like the State-Trait Anxiety Inventory and the Perceived Stress Scale (PSS).

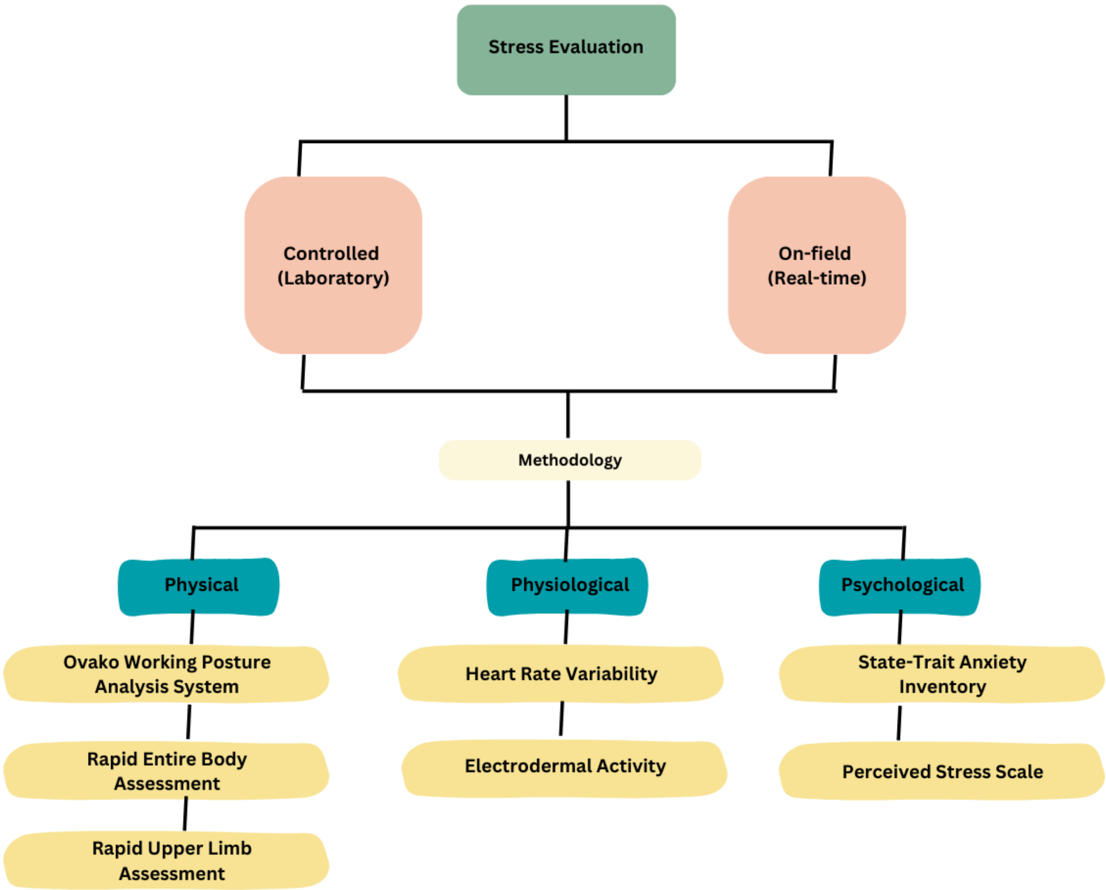


Figure 16. Stress Evaluation Elements.
(Own elaboration, 2024)

Ciccarelli et al. (2023) expand on these elements by exploring multimodal approaches to stress detection through integrating multiple methodologies and data types to increase accuracy.

Studies discuss the influence of contextual and demographic factors on stress. For instance, Blandino (2023) and Gervasi et al. (2023) note how factors such as age, gender, experience level, and familiarity with collaborative robots impact stress perception and physiological responses. Similarly, Ciccarelli et al. (2023) emphasize that factors in the environment, such as time of day, temperature, and weather, can affect stress levels in real-world environments.

Furthermore, Ciccarelli et al. (2023) note that examining real-world environments can be particularly challenging due to unpredictable environmental factors. Similarly, Tran et al. (2023) conclude that assessing stress in real-world settings presents greater difficulties. They explain that this challenge arises because factors such as the work context, as well as individual physical and mental health, are often not considered in experiments conducted in real-world environments.

This research categorizes the information into a real-world environment and laboratory-controlled environment to enhance understanding.

4.2.4.1 Real-World Environment

In 2023, Apraiz et al. (2023) proposed a protocol for measuring stress in a manufacturing environment in the "NO-STRESS Project". The protocol consists of three phases that integrate physiological signals, performance indicators, as well as the operator's perception of stress. Techniques such as self-assessment reports, electroencephalography (EEG), heart rate variability (HRV), galvanic skin response (GSR), and electromyography (EMG) are used to gather comprehensive data on stress levels. Additionally, performance indicators like task execution time, error rates, and production rates are evaluated. This protocol has proven effective for assessing stress levels in operators within manufacturing environments. As Blandino (2023), Apraiz et al. (2023) highlight the importance of standardizing and refining protocols to ensure measurement consistency across different industries.

Furthermore, Verna et al. (2023) introduce a "Quality Map" as a proactive tool for monitoring product defectiveness and operator stress. The map enables the identification of critical points in production and facilitates real-time quality adjustments. The authors found these critical points often occur at stages of high task complexity, repetitive strain, or limited resources. This approach supports maintaining high standards while actively promoting worker health. As task complexity increases, worker stress levels also tend to rise.

4.2.4.2 Laboratory-Controlled Environment

Aceta et al. (2022) introduced the KIDE4I (Knowledge-driven Dialogue framework for Industry) system designed to enhance natural language communication. The system allows workers to interact with machines through voice commands, reducing the need to memorize specific phrases. The authors conducted two case studies. The first involved a guide robot designed to provide navigation and information in response to user voice commands. The second involved a bin-picking robot that was programmed to sort items based on user specifications given through voice commands. The results indicated high completion rates for both use cases: 84% for the guide robot and 82% for the bin-picking robot. This suggests that the system effectively supported task execution in most instances. Additionally, the response times were approximately 1.25 seconds for the guide robot and 0.75 seconds for the picking robot, contributing to increased productivity through a faster workflow. The authors highlight the importance of human-machine interactions in the context of Industry 5.0, noting that these interactions can either reduce or increase stress, depending on how intuitive the communication between workers and machines is.

4.2.5 Trust

Interactions between humans and robots are intended to reduce the operator's workload (Kambarov, Inoyatkhodjaev, Kunz, Brossog, & Franke, 2023). Building trust in interactions between operators and robots is essential for cultivating a secure and comfortable work environment alongside robots, which in turn enhances efficiency and productivity (Montini, et al., 2023). Additionally, trust is the second most frequently evaluated aspect in collaborative robotics environments (Coronado, et al., 2022).

Trust in human-AI teams is built on transparency and a shared understanding. According to Hosain et al. (2023), reducing the “black box” effect by providing clear explanations of how AI makes decisions can enhance user confidence. Endsley (2023) emphasizes that establishing a shared situational awareness within human-AI teams enables the AI to act in a predictable manner. This predictability supports teamwork and fosters trust. Complementing these views, Balasubramaniam et al. (2023) point out that trust can be reinforced through ethical guidelines that ensure users can understand not only the actions of the systems but also the reasoning behind them.

A lack of trust can lead to disengagement and decreased motivation, reducing worker’s willingness to put effort into their tasks (Fulmer & Gelfand, 2012). In automation, distrust can increase cognitive workload. Workers may allocate additional mental resources to verify the AI's actions, which can lead to faster fatigue and reduced situational awareness (de Visser, Pak, & Shaw, 2018). The authors Lee & See (2004) expand on the importance of establishing an appropriate level of trust in human-automation interaction, noting that both under-reliance and over-reliance can compromise safety and operational success.

Therefore, organizations that take a proactive approach to addressing concerns about trust between workers and machines can enhance productivity and performance while fostering the well-being of their employees.

Various approaches have been explored to address human-automation trust in the workplace. Some approaches involve both humans and robots, where the robot responds to the operator’s needs or feedback. Others focus solely on the operator's perspective, allowing trust to develop without needing the machine to adapt or respond. This research categorizes the information into dual-focus trust and operator-only trust to enhance understanding.

4.2.5.1 Dual-Focus

Montini et al. (2023) and Kambarov et al. (2023) propose a structured framework for cultivating trust between humans and collaborative robots (cobots) by ensuring a human-aware, adaptable, and safe system.

The framework of Montini et al. (2023) focuses on developing human-aware collaborative robotic systems through three key pillars: Humanization, Smartification, and Automation & Equipment. Humanization emphasizes the integration of cobots into human work environments by addressing human factors such as safety, well-being, and ergonomics. Smartification highlights the use of sensors and the Industrial Internet of Things (IIoT) to collect and analyze data, enabling informed decision-making, adapting to environmental changes, and ensuring trust in collaborative systems. Lastly, Automation and Equipment focuses on selecting and configuring automation tools like cobots to ensure flexibility and adaptability in the work cell. This enhances productivity and operational effectiveness while maintaining human control.

Kambarov et al. (2023) propose a human-centric human-robot communication (HCHRC) framework to boost productivity and support well-being in assembly operations. In this framework, humans and robots communicate in real-time through sensors, utilizing the following technologies: Human Speech Recognition, Aided Virtual Reality, Work Instruction Guiding, Assembly Object Recognition, Human Motion Prediction, and Hand Gesture Control (See Figure 17).

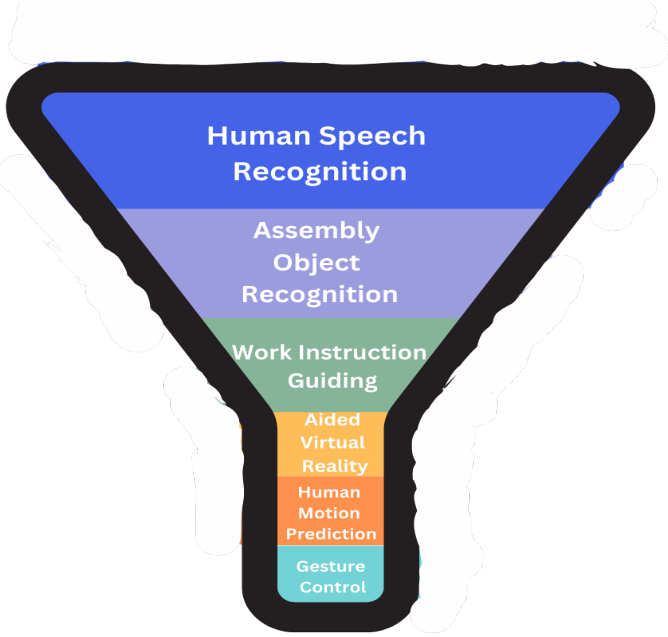


Figure 17. Technologies for a Human-Centered Human-Robot Communication. (Own elaboration, 2024)

Peruzzini et al. (2024) propose a Smart Manufacturing Systems Design (SMSD) framework that explores the concept of mutual learning between humans and machines to enhance trust. This framework fosters a cooperative relationship inspired by natural ecosystems, utilizing digital replicas of humans, machines, and the environment to simulate and manage factory operations in real-time.

Isaza Dominguez (2024) adds that digital twin technologies are crucial for improving worker safety, enhancing human-robot collaboration, and optimizing efficiency in manufacturing cells. However, these technologies are still limited in their ability to validate models in real-world settings (Isaza Domínguez, 2024).

Barros et al. (2023) present a thermal imaging safety sensor that allows for real-time and cost-effective safety monitoring by detecting human presence around machinery, thereby preventing accidents. This method is low complexity, consumes little energy, and has a small footprint, avoiding reliance on complex algorithms that require training.

4.2.5.2 Operator-Only

Locatelli et al. (2024) and Panagou et al. (2024) discuss the significant impact of involving operators in the robot integration process on building trust. To achieve this, Locatelli et al. (2024) recommend using bottom-up strategies that encourage employees to participate in the innovation process. Additionally, they emphasize the importance of providing workers with evidence of effectiveness through experimentation and education about the technologies.

Furthermore, Panagou et al. (2024) found that the robot’s appearance greatly influences human comfort and perceived reliability, which is why it is essential to include operators in the design and implementation phase. The authors recommend training operators before implementation to improve perceptual safety and reliability.

Perceived safety plays a crucial role in building trust, as operators need to believe that robots will prioritize their interests and well-being (Apraiz, Mulet Alberola, Lasa, Mazmela, & Ngoc Nguyen, 2023).

In conclusion, building trust between humans and robots is essential for ensuring safe, productive, and efficient collaboration. Trust can be established through transparency in AI, shared situational awareness, and ethical guidelines that clarify robot actions (Hosain, et al., 2023); (Endsley, 2023); (Balasubramaniam, Kauppinen, Rannisto, Hiekkanen, & Kujala, 2023). Frameworks proposed by Montini et al. (2023) and Kambarov et al. (2023) incorporate human-centric designs and real-time adaptability to enhance operator comfort and trust. The involvement of the operator in the design process, as advocated by Locatelli et al. (2024) and Panagou et al. (2024), further improves perceived reliability. Additionally, technologies such as the thermal imaging safety sensor suggested by Barro et al. (2023) reinforce trust in collaborative environments through real-time monitoring.

4.2.6 Emotional Assessment

Emotions are mental states that occur in response to stimuli and are expressed through physical and physiological changes, influencing how individuals perceive and react to their environment (Ekman, 1992); (Loizaga, Toichoa Eyam, Bastida, & Martinez Lastra, 2023). According to Ekman (1992) emotions can be recognized through specific facial expressions specific to each emotion. Emotions play a significant role in work efficiency, decision-making, and interpersonal relationships, all of which directly affect industrial operations. (Loizaga, Toichoa Eyam, Bastida, & Martinez Lastra, 2023)

Emotional assessment as a human factor in Industry 5.0 explores how human emotions influence interactions with external stimuli in industrial workplaces. It can be achieved through technology and robotic interactions that recognize human emotions and adjust accordingly (Tao, et al., 2023). Although technology plays a crucial role, it is not the only way to achieve emotional assessment.

In 2021, Chin et al. (2021) studied emotional intelligence in the manufacturing industry workforce. They found that emotional management, which refers to “the ability to regulate positive and negative emotions within oneself and others”, and emotional control, which refers to “the ability to control strong emotional states”, are strongly related to organizations’ performance. Similarly, Salvadorinho et al. (2023) state that happier, engaged, and empowered workers enhance competitive advantage by retaining human capital, which leads to more productive practices and innovative solutions, ultimately resulting in greater performance.

Therefore, organizations that take a proactive approach to addressing emotional assessment can enhance productivity and performance while fostering the well-being of their employees.

Various approaches have been explored to address emotional assessment in the workplace. This research categorizes the information into emotion-supportive and emotion-responsive to enhance understanding.

The emotion-supportive category refers to how human emotions affect workplace interactions, focusing on the worker's perspective. In this context, technology does not need to respond to emotions directly; instead, it may serve as a tool for emotional assessment, improving understanding without necessitating an immediate reaction.

On the other hand, the emotion-responsive category refers to how technologies react to workers' emotions. In this approach, the emphasis is on enhancing the technological response. Utilizing human emotions as a tool aims to enhance technology's sensitivity and response, ultimately fostering emotional well-being. In these applications, human emotions are assessed through real-time physiological metrics.

4.2.6.1 Emotion-Supportive

Sagar et al. (2023) emphasize meditation as a valuable organizational resource that enhances employee well-being and performance. The study employed the World Health Organization Quality of Life (WHOQOL) scale to evaluate meditation's impact on manufacturing company employees. The results showed significant improvements across all assessed areas: physical health, psychological well-being, social relationships, and the work environment. The authors suggest that even if meditation does not improve employee performance, workers can still be trained in meditation techniques to address any shortcomings. They also recommend future research on virtual meditation programs integrating artificial intelligence (AI).

Shukla et al. (2024) developed a Strategic HR Value Chain Model to evaluate human resource (HR) practices in relation to organizational objectives. The authors outline strategies for integrating remote work and worker skill development, supported by case studies. They suggest future use of the Metaverse to enhance virtual recruitment, engagement, and training, leading to technological innovation emphasizing empathy and inclusivity.

Although the research conducted by Sagar et al. (2023) and Shukla et al. (2024) primarily emphasizes approaches that do not rely on technology, it also provides valuable insights into how these methods can be effectively enhanced through technological integration.

Baroroh et al. (2024) analyze the advantages of Gamification for Manufacturing (GfM) in enhancing workers' psychological well-being while also promoting productivity. Based on their analysis, the authors propose a framework to guide the implementation of Gamification for Manufacturing (GfM) in Industry 5.0. This framework addresses both psychological well-being and productivity through game components. The framework is expected to enhance commitment, satisfaction, motivation, engagement, enjoyment, competition, collaboration, and social connectedness. Additionally, it is expected to improve productivity, efficiency, transparency, learning flow, and servitization.

4.2.6.2 Emotion-Responsive

Pierleoni et al. (2022) and Noori et al. (2024) explore an emotion-responsive approach that utilizes sensors and IoT devices to react to real-time data and adjust systems accordingly. Both studies primarily focus on dynamically modifying systems or environmental responses based on workers' data.

For instance, Pierleoni et al. (2022) examine the effects of lighting in industrial environments where workers often have limited exposure to natural daylight. They further state that variations in natural light influence emotions, mood, perception of space, concentration, and performance. Their study focuses on aligning artificial light with natural circadian rhythms, which are “internal processes that regulate the sleep-wake cycle”. The goal is to develop a wireless sensor network based on the Internet of Things (IoT) that can control lighting systems in industrial settings according to these circadian rhythms. According to the authors, the system contributes positively to worker comfort, focus, and productivity. This approach is recommended for organizations with both day and night shifts.

Noori et al. (2024) emphasize the importance of integrating human-in-the-loop (HiTL) and human Cyber-Physical Systems (CPS) within industrial environments. This integration allows systems to identify cognitive traits, roles, and interfaces in human-machine interactions. As a result, the systems can adapt to meet human needs by monitoring worker emotional or physical conditions through real-time data.

Abril-Jimenez et al. (2023) propose a self-quantified dashboard to improve emotional well-being and productivity through personalized self-management tools. The dashboard receives data through wearable devices and processes it with an algorithm developed by the authors that, as a result, provides personalized feedback and motivational messages. This promotes positive behavioral changes, enhancing well-being and productivity.

In conclusion, emotion-supportive strategies such as meditation, human resources guidelines, and gamification can help create healthier environments by enabling individuals to understand, control, and manage their emotions. Furthermore, emotion-responsive approaches, like IoT-driven lighting adjustments, can adapt to real-time emotional states to improve comfort and concentration. Assessing emotional well-being in the workplace will boost motivation, enhance worker well-being, and improve overall performance.

4.3 Technologies

The 149 papers discussed in Chapter 3 were categorized according to four key technological trends:

1. The first trend emphasizes the importance of **facilitating effective and natural communication between robots and humans**. This section refers to this trend as "Facilitating natural communication" to help readers better understand it.
2. The second trend focuses on **optimizing work and workplace environments to enhance workers' well-being**. In this section, this trend is referred to as "Modifying work environment" to help readers better understand it.
3. The third trend relates to **customizing technology to meet operators' individual needs**. This section refers to this trend as "Customizing individual needs" to help readers better understand it.
4. Lastly, the fourth trend concentrates on integrating **monitoring technologies that assess workers' real-time physical, cognitive, or psychological state and provide accurate feedback**. In this section, this trend is referred to as "Monitoring states and providing feedback" to help readers better understand it.

Additionally, the relationship between human factors, previously discussed in Chapter 4, section 4.2, and these trends will be examined and analyzed. The following bar chart presents each trend along with its associated human factors (See Figure 18). In other words, the graphic below illustrates the number of papers categorized under human factors that correspond to each specific trend.

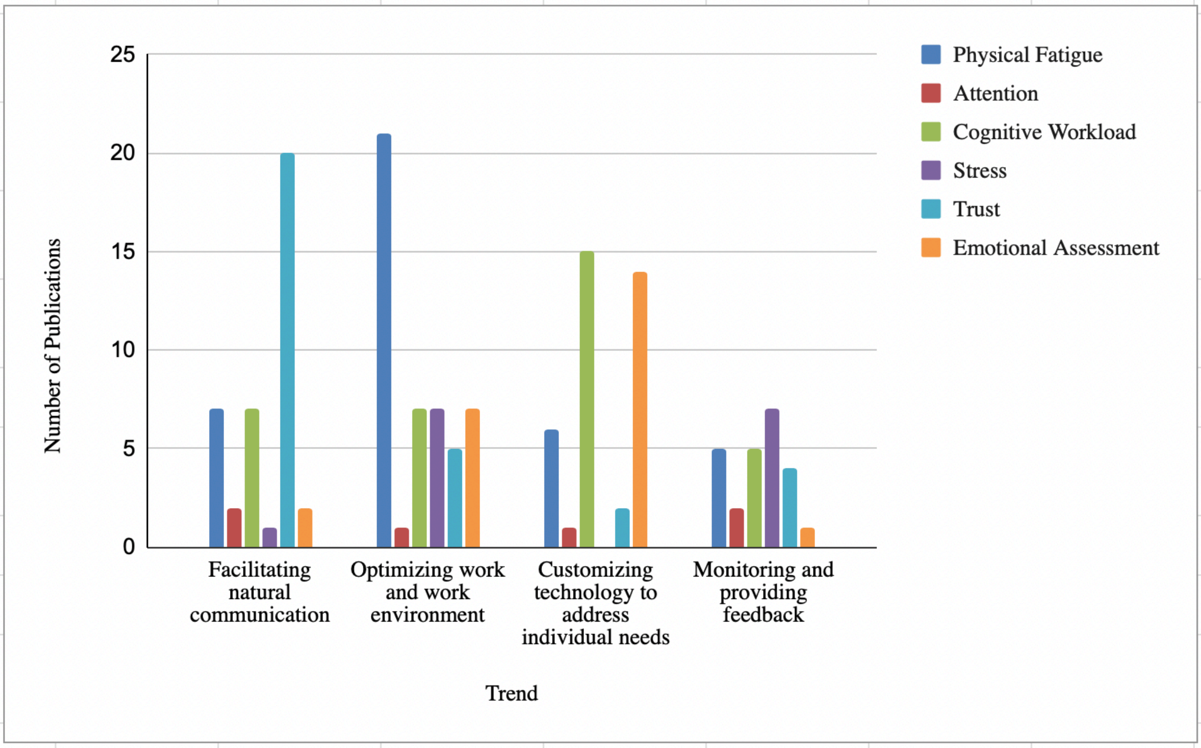


Figure 18. Human Factor per Trend.
(Own elaboration, 2024)

The Y-axis represents the number of papers within each human factor, categorized according to the four identified trends. **Facilitating** effective and natural communication between robots and humans. **Optimizing** work and workplace environments to enhance workers' well-being. **Customizing** technology to meet operators' individual needs. **Monitoring** technologies that assess workers' physical, cognitive, or psychological states in real-time to provide accurate feedback.

4.3.1 Facilitating effective and natural communication between robots and humans

There is a growing trend of enhancing effective and natural communication between robots and humans. The aim is to develop technologies and strategies that bridge the gap between human communication styles and robotic systems, ensuring seamless communication.

According to Alves et al. (2023), human-robot interaction can facilitate the transition from digitally system-centric to operator-centric production. The authors further state that human-robot interaction, collaborative robots, digital twins, augmented reality, and virtual reality are technologies primarily centered on communication, signifying that their foremost objective is to facilitate interaction with the operator.

Improving communication between robots and humans is essential for fostering trust among workers in the workplace. A higher level of trust creates a safe and comfortable environment for human-robot interactions, which, in turn, increases employee engagement and motivation. As a result, workers feel encouraged to put in more effort and fully utilize the systems available to them, leading to improved productivity.

Conversely, when trust is lacking—known as under-reliance—employees face a heavier cognitive workload as they expend extra mental energy verifying the system's decisions. On the other hand, excessive trust—referred to as over-reliance—can compromise worker safety. To address these challenges, it is crucial to enhance communication between humans and robots.

Lu et al. (2022) introduce the concept of "short-term human intent understanding" (See Figure 19), which describes how robots interpret and respond to human intentions at three distinct levels of understanding: Instruction Understanding (IU), Action Understanding (AU), and Goal Understanding (GU). Instruction Understanding involves decoding explicit instructions from the operator. Action Understanding refers to predicting an action or motion, enabling the machine to infer meaning based on the operator's actions. Finally, Goal Understanding entails inferring a human's objective by identifying a set of associated actions.

To achieve this, Lu et al. (2022) identify two types of communication between humans and robots: direct communication and indirect observation. In direct communication, humans interact directly with the robot, while in indirect observation, the robot observes human behaviors to determine how to respond (See Figure 19). Each type of communication relies on specific devices to facilitate interaction, including microphones, cameras, and sensors that capture biological or motion data.

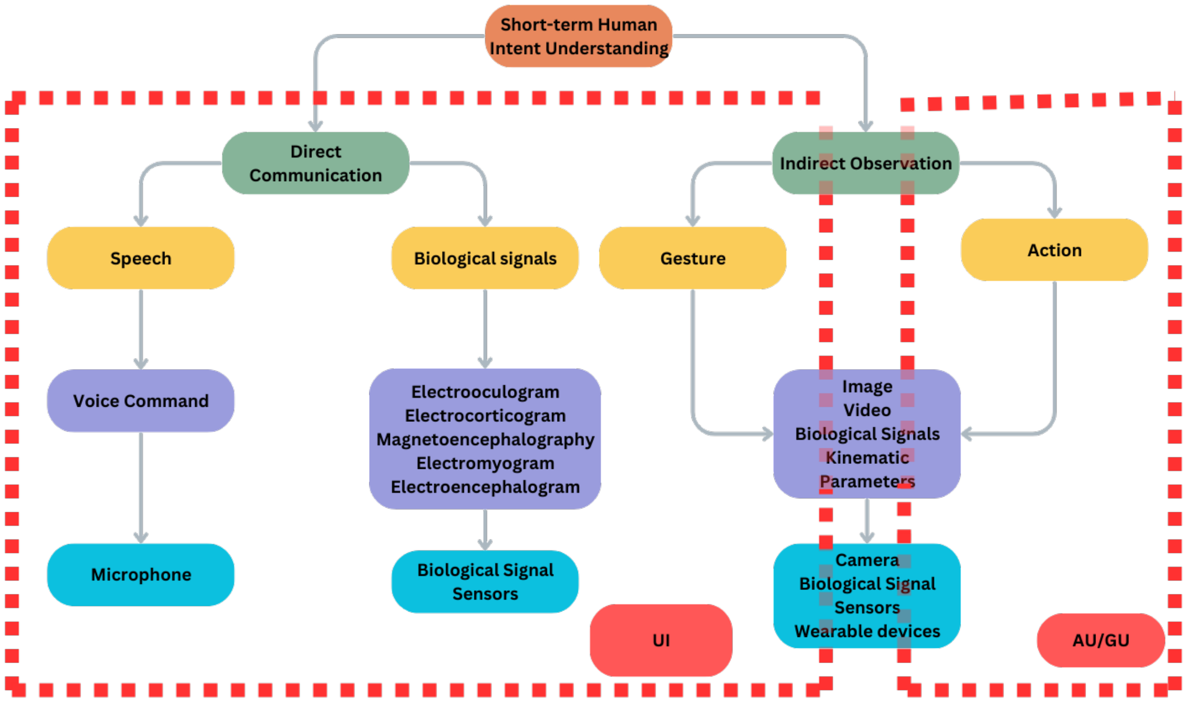


Figure 19. Short-term Human Intent Understanding visualization.
(Own elaboration, 2024)

These tools facilitate effective communication between robots and humans, supporting Industry 5.0's vision of intuitive and collaborative human robots. Furthermore, it closes the gap between human communication styles and robotic systems.

Building on the concept presented by Lu et al. (2022), Aceta et al. (2024) propose a method for seamless direct communication, specifically through the operators' speech. The authors introduce the Knowledge-driven Dialogue Framework for Industry (KIDE4I), allowing workers to interact smoothly with industrial systems. Through voice commands, operators can communicate directly with the KIDE4I, which intelligently extracts essential elements from these commands and implements them in the target system. This study aims to facilitate communication between humans and robots, enabling workers to see the system as a valuable tool that boosts productivity.

Helm et al. (2023) propose Intelligent Video Analysis (IVA) as a method for monitoring and detecting operator errors. While current research focuses solely on detection without providing feedback, this serves as a strong foundation for developing a real-time IVA system. This system would utilize artificial intelligence to offer feedback to operators. According to the model presented by Lu et al. (2022), IVA falls under the category of indirect observation communication, specifically through action.

Kambarov et al. (2023) emphasize the importance of designing user-friendly interfaces that enhance communication between operators and robots. The authors further assert that providing input to the robots should be intuitive for the workers. Additionally, the information provided by the robots should be sufficient to create situational awareness, enabling interventions in unexpected situations. Thus, the authors propose the Human-Centered Human-Robot Communication (HCHRC) framework, which consists of a set of technologies that aid the communication between humans and robots (See Figure 17).

Moreover, the necessity of establishing trust profoundly affects the tendency toward fostering effective and natural communication between humans and robots. Figure 18 illustrates this, indicating that trust is the most notable human factor in this trend. As Chapter 4, Section 4.2.5 articulated, this underscores the significance of developing communication systems that enhance confidence through dual-focus interactions and operator-exclusive scenarios.

4.3.2 Optimizing work and workplace environments to enhance workers' well-being

There is a growing trend of dynamically using technology to modify and optimize work and workplace environments to enhance employee well-being. This shift emphasizes developing adaptive, human-centered workplaces where technology enhances health, comfort, and productivity through task or environmental adjustments.

This direction is significant, especially for organizations where employees experience high levels of physical fatigue. Embracing this trend has the potential to enhance employee well-being by reducing the likelihood of musculoskeletal disorders (MSDs). As discussed in Chapter 4, Section 4.2.1, MSDs adversely affect the speed and accuracy of work tasks, leading to a rise in errors and an increased risk of injury, ultimately impacting overall employee performance.

Pokorni et al. (2022) developed a Cognitive Assistance System based on Quality Function Deployment (CAS-QFD). This system aims to design and implement assistance tools centered around workers' needs while optimizing their work environment to enhance productivity and well-being. The authors identify three changeable environmental influences impacting workers' well-being and in consequence their productivity (See Figure 20). Each type of influence comprises different factors that can be adjusted through inputs. These inputs gather information from the worker, analyze it, and produce an output that optimizes the environment. This system proposes to involve workers throughout all the steps of the process.

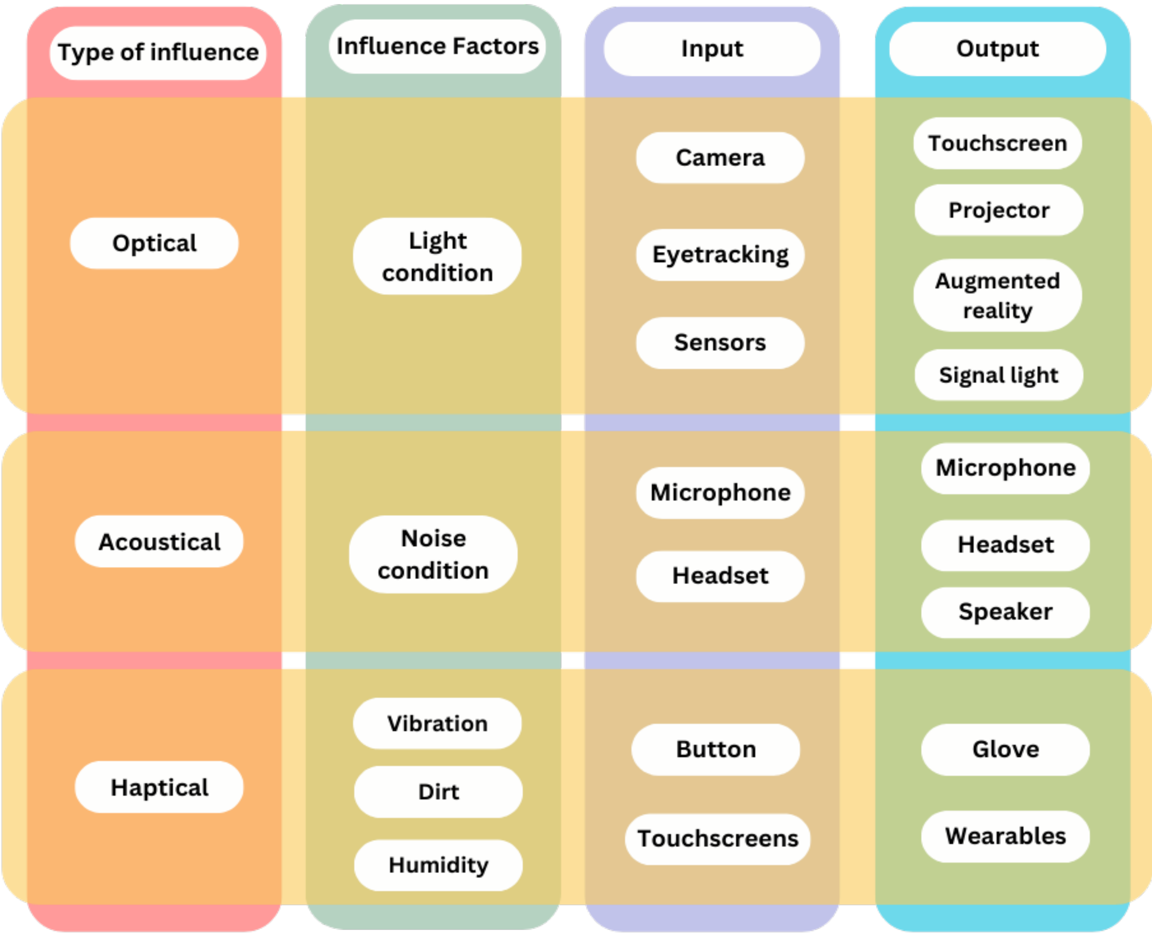


Figure 20. Environmental influence factors, inputs, and outputs.
(Own elaboration, 2024)

The case study Pokorni et al. (2022) investigated a manual assembly process within an industrial environment, highlighting the key challenges faced by workers. These challenges include difficulties understanding complex instructions, high error rates caused by poor lighting and noise, and insufficient guidance for inexperienced employees. Data collected from interviews and surveys revealed that workers prioritized clear instructions, while the business emphasized reducing errors and enhancing task efficiency. This information was analyzed and mapped to specific assembly tasks, identifying necessary environmental adjustments to improve overall performance. The cognitive assistance system was prototyped and implemented to address these specific needs in assembly tasks. In this case, the system provided real-time visual instructions through augmented reality and alerted workers to potential errors. Interaction methods include touchscreens and voice commands, while outputs comprise projectors, augmented reality overlays, and wearable devices. The prototype led to adjustments based on worker feedback, such as adding detailed overlays for clarity, switching from auditory to visual instructions when noise interfered, and adjusting lighting to reduce eye strain. Additionally, the prototyped system led to three key findings: increased productivity as workers completed tasks faster, enhanced quality with reduced error rates from real-time guidance, and improved worker satisfaction, marked by lower stress and greater confidence in skills.

In addition, Pierleoni et al. (2022) introduced an IoT-based wireless sensor network highlighting the importance of lighting control systems in regulating circadian rhythms. This IoT solution utilizes sensor networks for real-time control and monitoring of lighting systems. Its primary goal is to enhance visual comfort, boost worker well-being, and improve productivity in industrial environments. By dynamically adjusting artificial lighting to mimic natural light, the system regulates light intensity and color temperature to create optimal conditions focused on adapting to workers' needs. The study reveals that variations in natural light affect emotions, concentration, and overall performance. Ultimately, this system improves industrial workflows and worker conditions for both day and night shifts.

However, improving and optimizing the work environment can be achieved not only by adjusting the factors identified by Pokorni et al. (2022), such as lighting, humidity, and noise, but also by considering other important variables. These include the distribution of tasks between humans and robots and adjustments to machine operations, such as speed, stiffness, and workload distribution.

Picone et al. (2024) introduce the Operator Thing (OT) concept, which digitalizes human operators and machines to create a responsive industrial environment that adapts to human needs in real-time. This system acts as a digital twin, collecting and analyzing biometric and behavioral data, including parameters such as heart rate and stress indicators. It responds dynamically by offering physical assistance, such as adjusting the stiffness of robots or modifying their load-carrying behavior. The system can also adjust operational speed to slow down processes when the operator shows signs of being overworked or stressed. Depending on the operator's assessed fatigue or stress levels, the system may also reassign tasks as needed.

As shown in Figure 18, physical fatigue is the most prominent human factor that this trend should address. This aligns with the categorized approaches for that factor: ergonomic interventions, advanced monitoring technologies, and dynamic task allocation systems, presented in Chapter 4, section 4.2.1. Nevertheless, integrating cognitive workload, stress, and emotional assessment considerations is essential for effectively addressing the modification and optimization of the work environment.

4.3.3 Customizing technology to address individual needs

There is also a growing trend toward customizing technology to meet operators' individual needs. This trend emphasizes personalized technologies and systems that cater to individual workers' unique physical, mental, and emotional characteristics. The goal is to foster inclusive and supportive work environments.

In this context, Chand et al. (2023) highlight the necessity of personalized fatigue assessment for manufacturing workers, considering their differences in operator muscle strength, operation type, and task loads. The authors explain that assessing different capabilities and muscle strengths can minimize long-term injuries. To achieve this, the authors developed a personalized muscle fatigue profile using s-EMG technologies to measure operators' neuromuscular activity. Later that same year, in the NAMRC 51,2023 conference, Chand and Lu (2023) incorporated the personalized muscle fatigue profile to enhance their approach to managing fatigue accumulation across teams. They focused on balancing fatigue accumulation and recovery rates to balance these factors better.

Yin & Li (2023) researched the impact of various noise types in manufacturing environments on individuals with different sensitivities to sound. The authors identified fan noise, noisy human voices, and striking workpiece noise as the most common types. The participants of the experiment were divided into two groups: “noise-sensitive” and “noise-insensitive”. Each participant completed a visual search task while wearing headphones that played different noise types, and an eye tracker monitored pupil changes and visual focus areas. The key findings revealed that the noise-sensitive group experienced longer delays in completing the task and had slower reaction times compared to their noise-insensitive counterparts. Additionally, there were significant increases in pupil diameter among the noise-sensitive participants, indicating elevated anxiety levels. The analysis of visual focus also demonstrated that this group tended to shift their attention away from the target more significantly during noisy conditions. These findings highlight the need for personalized tools and systems to accommodate individual differences in noise sensitivity and cognitive responses.

Javernik et al. (2023) propose personalized guidelines to better meet the needs of individual workers by adjusting robot motion parameters. This personalization involves modifying aspects like the speed and timing of the robot's movements to align with each worker's physical and cognitive abilities. The authors conducted an experiment involving two scenarios, each with different robot motion parameters and varying levels of worker utilization. In the first scenario, robot parameters were adjusted to enable workers to operate at 60% of their capacity, while in the second scenario, workers operated at 100% capacity. Worker utilization is calculated based on the time spent by workers on preparation and final assembly, relative to the robot’s operating time. The key findings indicate that an increase in worker utilization resulted in a significant 35% increase in workload. These findings underscore the importance of personalized guidelines in collaborative workplaces, which consider workers' differing abilities, skills, and personalities.

Margolis et al. (2024) conducted an experiment to evaluate how different backgrounds can affect a worker's perspective on technology, particularly, on augmented reality. The authors analyzed and compared three distinct user profiles. The first user profile, known as the Human Factors (HF) participants, consisted of individuals experienced in usability and perception. The second user profile, referred to as the System Development (SD) group, was composed of individuals with backgrounds in IT, engineering, or computing. Finally, the third user profile, called the General Users (GU) group, included individuals from various backgrounds, excluding those with expertise in IT, design, or user experience. All distinct user profiles utilized an augmented reality application with the intention of analyzing and comparing the user experiences based on their profiles. The results demonstrated differences in how each user profile perceived the use of the augmented reality application, depending on their backgrounds. These findings highlight the importance of personalizing technology that considers individual worker backgrounds to enhance employee satisfaction and, in turn, improve overall output.

As shown in Figure 18, cognitive workload and emotional assessment are the most significant factors that this trend should address. This aligns with the approaches discussed in Chapter 4, sections 4.2.3 and 4.2.6. These approaches primarily focus on analyzing workers' perspectives, which is consistent with the trend of directing technology to meet individual workers' needs.

When technology or systems are customized to meet the specific needs of individual workers, their overall well-being is improved by reducing cognitive workload and preventing overload. Overload can lead to stress, while the opposite—underload—can result in disengagement and diminished motivation at work. By effectively managing workers' cognitive workloads, productivity tends to rise and error rates tend to drop. Therefore, customizing technology can be particularly advantageous for companies with fluctuating task volumes, as it helps balance instances of cognitive overload and underload.

Another significant advantage of customizing technology to fit workers' individual needs is its ability to aid in emotional management. When operators feel more comfortable with the tools and systems they use, they can better navigate their emotions. Since emotions play a crucial role in efficiency and decision-making, which directly impacts productivity, organizations can benefit from offering technologies that match each worker's unique characteristics. This approach is especially relevant for roles that involve frequent decision-making, as it helps ensure that emotional states do not negatively affect performance.

4.3.4 Monitoring workers' physical, cognitive, or psychological state in real-time to provide feedback

There is a growing trend to integrate technologies that monitor workers' conditions in real-time. These technologies offer precise feedback to enhance employee awareness and well-being through notifications and recommendations based on their states, which, according to Lu et al. (2022), can be categorized as physical, cognitive, or psychological. The aim is to deliver actionable insights or real-time alerts regarding their well-being.

Pistolesi et al. (2024) present a privacy-preserving posture-tracking system that monitors workers' postures and provides feedback whenever deviations from the ISO 11226 standard are detected. The tracking system employs Laser Imaging Detection and Ranging (LiDAR) to assess the lower-body postures, while a smartwatch assesses the upper-body positions. The data collected from both the LiDAR and the smartwatch is then processed using machine learning algorithms to identify risky postures and suggest improvements. Alerts are sent directly to the smartwatch, enabling users to take immediate action to correct their posture when it strays from the ISO 11226 standard. Furthermore, the system was tested on 30 participants engaged in six different manufacturing tasks, yielding impressive accuracy rates of 98%. The system successfully preserves workers' privacy without sacrificing functionality by utilizing inertial data from a smartwatch and LiDAR instead of cameras. Additionally, workers receive real-time notifications on their smartwatches to adjust their posture; these posture records are stored and analyzed for long-term ergonomic improvements, potentially paving the way for personalized training programs.

Lemos et al. (2024) introduced a system for assessing personalized environmental risks through the use of monitoring devices. This system includes an alert and recommendation feature to reduce workplace exposure risks. It continuously tracks environmental factors such as dust, noise, ultraviolet radiation, illuminance, temperature, humidity, and the presence of flammable gases. In addition, the system gathers workers' health data, focusing on diseases and symptoms linked to these monitored environmental factors. The development of criteria for identifying these diseases and symptoms was informed by recent research and collaborations with two physicians. A central server plays a key role by cross-referencing environmental factors with workers’ health histories, which are classified as risks or non-risk environments, using a random forest machine learning model. Furthermore, the recommendation system is also powered by a machine-learning model that generates alerts based on environmental classifications. The authors' primary objective is to enhance workplace safety by merging individual health histories with real-time monitoring of environmental conditions. This integration offers actionable insights for both companies and employees, optimizes safety practices, and minimizes exposure to harmful environmental elements. Notably, the system’s key findings highlight the effective personalization of risk assessment through generated alerts and recommendations, alongside its potential for scalability and adaptability, allowing expansion into other work environments by incorporating additional sensors.

Nguyen et al. (2024) integrate concepts proposed by Pistolesi et al. (2024) and Lemos et al. (2024). This integration involves monitoring workers' postures and environmental factors to promote proactive prevention. The collected data is then analyzed, providing real-time notifications through wearable devices when workers’ postures deviate from recommended ergonomic standards, thereby reducing health risks such as musculoskeletal disorders (MSDs). Additionally, workers are alerted to take corrective actions when immediate risks are identified, such as extreme temperatures, high noise levels, or poor air quality. The authors propose integrating Artificial Intelligence to offer personalized, real-time insights and decision-making capabilities, reducing latency and enhancing worker safety. Moreover, the combination of real-time interventions and data insights may aid in designing safer work environments.

As shown in Figure 18, stress is the most significant factor that this trend should address. This aligns with the approaches discussed in Chapter 4, Section 4.2.4, which primarily focus on assessing real-time conditions to facilitate both immediate and long-term adjustments. However, attention is also crucial for this trend due to the necessity of immediate risk assessments, which can help identify safety risks arising from distractions or lack of concentration, as discussed in Chapter 4, Section 4.2.2.

Stress arises from employees having limited ability to anticipate and control their circumstances. One effective approach to reduce stress-related issues is the implementation of enhanced real-time feedback methods. These methods give workers greater autonomy over their health in the workplace. Organizations need to address stress within their environments, as its prevalence among employees can lead to various health problems, including musculoskeletal disorders and depression. Additionally, the effects of stress go beyond employee well-being; it also negatively impacts performance by increasing task completion times and error rates, which ultimately leads to decreased productivity. This is specially relevant for companies facing high production pressures, such as those using the just-in-time (JIT) manufacturing model.

Chapter 5: Conclusions and Recommendations

5.1 Introduction

This chapter delineates the research conclusions regarding the influence of workers' well-being on productivity within the framework of Industry 5.0, accompanied by recommendations for academics and companies derived from the findings of this thesis.

5.2 Conclusions

This research utilized the Competitive Technology Intelligence (CTI) methodology to identify the trends related to the human-centricity pillar of Industry 5.0. Scientometrics was used as part of the CTI methodology combined with PRISMA guidelines to reveal these trends. Additionally, the research provided recommendations for companies aiming to become more human-centric and suggested areas for further research for academics.

The academic sources were obtained from the Scopus database and cover the period from January 1, 2019, to October 1, 2024. This research focused on Industry 5.0, specifically on the influence of workers' well-being on productivity.

Furthermore, to improve the work's reproducibility, the PRISMA methodology was incorporated into the CTI methodology (See Table 2). During this process, it was observed that the CTI methodology already covered some of the PRISMA steps, but PRISMA complemented some of the CTI steps.

1. The Information Sources stage outlined by the PRISMA methodology includes database selection and time filters. This task is addressed in the identification of data sources stage from the CTI.
2. While the Search Strategy phase outlined by the PRISMA methodology recommends selecting keywords using the PICO framework, this research utilized one of its variants, the PEO framework. Additionally, the CTI

methodology advocates selecting keywords through a literature review. By integrating these two methodologies, the robustness and reliability of the keyword selection for the secondary source search were enhanced.

3. The query construction and execution stage from the PRISMA methodology involves the final composed query and its results. This task is part of the search strategy design outlined by the CTI methodology.
4. The CTI methodology outlines a process for normalizing and preparing information to ensure data consistency and proper formatting. The PRISMA methodology effectively complements CTI by providing standardized guidelines. PRISMA includes the eligibility element, which involves inclusion and exclusion criteria, and defines the screening process necessary to apply them. This process involves analyzing the study's titles and abstracts to identify those that may not align with the research topic.
5. The Quality Assessment phase of the PRISMA methodology is included in the Data collection stage of the CTI methodology.
6. The PRISMA methodology features a bibliometric findings phase, which is part of the information analysis stage within the CTI methodology. Both offer quantitative data. The PRISMA methodology highlights the time distribution of publications, the distribution of document types, the distribution of publication sources, and a word cloud representation. The CTI methodology expands on this by addressing fundamental questions, known as the five Ws, that are relevant to the research.
7. The PRISMA methodology encompasses a literature review results stage that highlights each study's essential characteristics. While PRISMA generally works with a smaller volume of data, CTI is designed to analyze larger datasets and offers more flexible criteria. In this research, the detailed literature review guidelines from PRISMA were implemented. This approach proved beneficial by facilitating the identification of similarities and differences across the studies, ultimately fostering deeper insights.

Six key human factors are crucial in shaping well-being and productivity in Industry 5.0 (Loizaga, Toichoa Eyam, Bastida, & Martinez Lastra, 2023). This research focuses on the factors identified by Loizaga et al. (2023): physical fatigue, attention, cognitive workload, stress, trust, and emotional assessment. Additionally, it found that each factor assesses workers' well-being and productivity differently and requires customized approaches combining technological and human-centered strategies (See Table 11).

Table 11. Summary Human Factors.
(Own elaboration, 2024)

<table>
<tr><th>Number of Papers</th><th>Human Factor</th><th>Well-being impact</th><th>Productivity impact</th><th>Approaches</th></tr>
<tr><td rowspan="3">39</td><td rowspan="3">Physical Fatigue</td><td>Short-term: Decreased strength, localized muscle fatigue, and impaired motor control</td><td rowspan="3">MSDs are recurrent among industrial operators; they arise from work demands. Reduced speed, and precision, and increased errors and risks of injury</td><td>Ergonomic interventions: Task and workplace re(designs)</td></tr>
<tr><td rowspan="2">Long-term: Musculoskeletal disorders (MSDs)</td><td>Advanced monitoring technologies: Wearables to identify bad postures or muscle fatigue</td></tr>
<tr><td>Dynamic task allocation systems: Strategic assigment of tasks according to metrics such as makespan, energy expenditure, and mental workload</td></tr>
<tr><td rowspan="2">6</td><td rowspan="2">Attention</td><td rowspan="2">Safety risks</td><td rowspan="2">Increased errors, anxiety</td><td>Distraction: Eliminate external stimulation that can lead to safety risks through distractions. Technology that reacts to signs of distractions, such as abrupt movements</td></tr>
<tr><td>Concentration: Increase concentration awareness through notifications or the sensation of being monitored</td></tr>
</table>

34	**Cognitive Workload**	**Overload:** Time needed for a task exceeds the time available for the operator may lead to stress	Task performance decreases and errors increase when operators percieve excessive workload	**Subjective:** Evaluation of perceived work overload by the operator through questionnaires
				Objective: Frequently evaluated through cardiac activity and visual scanning – Heart rate variability (HRV), Pupillometry, Electroencephalography (EEG), Auditory signals, and Near-infrared spectroscopy (fNIRS)
		Underload: Time needed for a task is too low compared to the time available for the operator may lead to disengagement, lack of motivation		**Combination:** Integratin both approaches may be beneficial for achieving a more comprehensive evaluation
15	**Stress**	Feeling unprepared and lack of control which is related with health issues such as MSDs and depression	Task execution time and error rates increase, production rates decreased	**Real-world environment:** The goal is to assess real-time conditions in order to make immediate adjustments.
				Laboratory-controlled environment: Evaluation of stress and performance in a controlled environment. It does not consider external factors. The goal is to make long term adjustments
30	**Trust**	Disengagement and decreased motivation, reducing worker's	**Under-reliance:** Increase cognitive workload because they may give	**Dual-focus:** Involve humans and robots, where robots respond to

		willingness to put effort in their tasks	additional mental resources to verify the system actions, this leads to faster fatigue and reduced situational awareness	the operator’s needs or feedback
			Over-reliance: can compromise safety	**Operator-Only:** Develop trust through the operator’s perspective, without the need for the machine to respond
25	**Emotional Assessment**	Lack of ability to regulate positive and negative emotions within oneself and other	Poor work efficiency, decision-making, and interpersonal relationships. Happier, engaged and empowered workers enhance competitive advantage by retaining human capital	**Emotion-supportive:** Technology serves as a tool for emotional assessment, helping operators enhance their understanding of emotions instead of reacting to them
				Emotion-responsive: Technologies react to workers’ emotions. Humans emotions are used as a tool to enhance technology’s sensitivity and response

In the "**physical Fatigue**" factor, ergonomic interventions focus on designing or adjusting workspaces that minimize potential fatigue. Additionally, advanced monitoring employs real-time tracking technologies to analyze data and enables personalized feedback that prevents overexertion or bad postures. Dynamic task allocation systems adjust task assignments based on workers' physical conditions, ensuring a balanced workload with the help of collaborative robots.

The **" attention"** factor encompasses technological methods that enhance operators' awareness of their concentration level, allowing them to adjust as necessary. An alternative approach to address attention is minimizing external stimuli that can lead to distractions, which could endanger the operator's safety.

Pertaining to "**cognitive workload**," trends can be categorized into subjective, objective, and combined approaches. Subjective methods include qualitative tools, such as the NASA-TLX questionnaire, which gathers insights from the operator's perspective. Meanwhile, objective methods provide precise data using technologies like eye tracking, heart-rate variability (HRV), and pupillometry. Currently, the most adopted technology for objectively measuring cognitive workload is cardiac activity. Lastly, combined approaches integrate both methods to achieve a more comprehensive evaluation.

The " **stress** " factor can be measured through physical, physiological, and psychological assessments. Physical assessments evaluate posture and behavior using tools such as the OWAS and RULA systems. Physiological assessments track bodily responses, including heart rate variability (HRV) and electrodermal activity (EDA). Lastly, psychological measurements involve self-assessment questionnaires, such as the Perceived Stress Scale (PSS). These assessments are used in both real-world and controlled laboratory experiments. It was found that real-world stress monitoring presents greater challenges due to variable environmental conditions.

Concerning “**trust**”, dual-focused and operator-only approaches were outlined. Dual-focus is based on building mutual trust between humans and robots through technologies proposed in the human-centric human-robot communication (HCHRC) framework shown in section 4.6.1, Figure 17. Operator-only focuses on involving operators directly in the robot design and integration process by incorporating the operator’s feedback and training in the early stages.

Finally, “**emotional assessment**” approaches were outlined and categorized into emotion-supportive and emotion-responsive. Emotion-supportive focuses on fostering emotional well-being, whether it’s without technology, through strategies like meditation, or by using technology as a tool, such as gamification. The main point is that emotion-supportive technology does not expect real-time reactive responses. On the other hand, emotion-responsive approaches use real-time data from sensors or

IoT devices to dynamically adjust environmental conditions to aid workers' emotional states.

Many studies propose innovative approaches that have yet to be tested in laboratory or field settings. As a result, not all research includes quantitative data regarding the impact of these approaches on workers' well-being or their measurable effects on productivity.

Based on the human factors analysis, the following trends have emerged:

1. The first trend emphasizes the importance of **facilitating effective and natural communication between robots and humans**.
2. The second trend focuses on **modifying and optimizing work and workplace environments to enhance workers' well-being.**
3. The third trend relates to **customizing technology to meet operators' individual needs**.
4. Lastly, the fourth trend concentrates on **monitoring workers' physical, cognitive, or psychological state in real-time to provide feedback.**

In conclusion, the analysis of human factors underscores four principal trends focused on enhancing the well-being of workers while also influencing productivity. These trends indicate an increasing emphasis on human-centered methodologies within technological frameworks, prioritizing the well-being of employees in Industry 5.0 settings.

5.3 Recommendations for Academics

5.3.1 General Recommendations

- Due to the rapid development of Industry 5.0, it is recommended that ongoing exploration of Industry 5.0 focus on advancing human-centric manufacturing, specifically worker well-being and productivity.
- It is suggested that organizational reports on strategies for enhancing worker well-being and their influence on productivity be explored to gain valuable insights and estimate costs.
- It is advisable that additional academic sources, such as the Web of Science or Google Scholar be utilized. This thesis focused on the Scopus database.
- Further investigation into attention and stress as human factors in industrial environments is desirable. These factors are often overlooked, highlighting a significant gap that could lead to more research discussions.

5.3.2 Specific Recommendations

- There is a need for further research into how to effectively integrate senior workers with collaborative robots without increasing their cognitive workload or error rates. A study by Pluchino et al. (2023) indicates that although senior workers are willing to collaborate with robots, this partnership can lead to greater mental strain. Therefore, this thesis suggests conducting experimental research to devise and test adaptive human-robot interaction strategies that minimize cognitive burden while ensuring both efficiency and accuracy. To achieve this, it is recommended to follow the approach outlined in the first trend, which emphasizes the importance of fostering effective and natural communication. Since trust is a crucial human factor in this context, it is possible that senior workers may exhibit either an over-reliance or under-reliance on robots during their collaborative efforts.
- The concept of emotion-supportive technology, as defined in this thesis, refers to using technology as a tool for emotional assessment. This thesis recommends further research into integrating technology to assist operators in improving their understanding and management of emotions, as Sagar et al. (2023) and Shukla et al. (2024) indicate. To achieve it, this thesis emphasizes

the potential for personalized technologies or systems that address the unique characteristics of individual workers, as emotional assessment is the most prominent human factor in the third trend.

- Recent findings by Ma et al. (2024) indicate that non-experts experience higher cognitive workloads than experts, regardless of task complexity. This aligns with the study of Gualtieri et al. (2024), as the authors emphasize the need for guidelines for non-experts considering individual operators' cognitive abilities. On the other hand, research by Javernik et al. (2023) also reveals that cognitive workload varies between different levels of "worker utilization" a parameter calculated based on the time spent by workers on preparation and final assembly, relative to robot's operating time. Acknowledging that operators have different cognitive abilities and that non-experts experience greater cognitive workload. Therefore, this thesis recommends further investigation into effective guidelines tailored for non-experts. Emphasizing the need for individualized training approaches to ensure that the training is effective for all operators, regardless of their cognitive skills. Furthermore, this recommendation is reinforced by the observation that cognitive workload is the most prominent human factor influencing this trend.

5.4 Recommendations for Companies

5.4.1 Technological Recommendations

- This thesis recommends considering dynamic task allocation systems, such as those proposed by Granata et al. (2024) and Calzavara et al. (2024), in high-workload industrial environments. The authors suggest a system that utilizes real-time data on human variability, allowing for task reassignment based on operators' physical and cognitive states. Companies that implement these technologies have the potential to address both physical fatigue and cognitive workload. By doing so, companies can improve their workers' well-being and mitigate issues such as decreased strength, stress, musculoskeletal disorders, cognitive overload, disengagement, and lack of motivation. Additionally, these companies benefit through faster processing speeds, increased precision, reduced errors, and a lower risk of injury. This proposal is particularly relevant for medium—to high-complexity industrial environments, where managing operators can be challenging.
- It is advisable to consider technologies aimed at proactive protection, such as those developed by Barros et al. (2023) and Polito et al. (2023). These innovations emphasize the importance of detecting human presence to prevent accidents before they potentially occur. As Lu et al. (2022) noted, the future of industrial safety appears to be shifting towards a more proactive methodology. Furthermore, the sensor introduced by Barros et al. (2023) is characterized by its low complexity, energy efficiency, and small footprint. Meanwhile, the wearable technology presented by Polito et al. (2023) showcases remarkable accuracy and precision rates. The implementation of proactive safety will reduce workplace accidents, lower costs, and increase productivity as workers can perform with greater confidence. These advancements hold great promise, not only in enhancing worker safety but also in aligning with the sustainable principles of Industry 5.0.
- In work environments where stress is a significant issue, this thesis recommends adopting one of three approaches, listed in order of priority. First, implement technologies that can monitor the worker's physical state using physiological measurements, such as Heart Rate Variability (HRV) or Heart

Rate combined with Electrodermal Activity (EDA), to provide real-time alerts for stress-reducing interventions like meditation. Second, optimize work processes when higher stress levels are detected in employees or make adjustments to the workplace that contribute to reducing stress. Third, incorporate technologies that facilitate communication between operators and robotic systems, as research by Aceta et al. (2022) has shown the potential for natural language communication to alleviate stress significantly. Additionally, to assess the effectiveness of this approach, a self-assessment questionnaire, such as the State-Trait Anxiety Inventory or the Perceived Stress Scale (PSS), can be used. This is consistent with the study by Ciccarelli et al. (2023), which highlights that exploring multiple methodologies and data types can improve the accuracy of stress detection; this is expanded in Chapter 4, section 4.2.4.

- If a company faces multiple challenges related to the human factors mentioned in this thesis, i.e., physical fatigue, attention, cognitive workload, stress, trust, and emotional assessment, it is advisable to invest in wearable technology. Wearables provide extensive coverage for addressing various human factors. By improving these factors, the company can enhance both employee well-being and productivity (See Table 11), ultimately resulting in a strong return on investment. Furthermore, wearables can address the four identified trends in this research (See Chapter 4), with one example presented for each trend in the following section:
  - Trend 1: Lu et al. (2022) suggest that wearables can enhance communication by recognizing gestures and actions between robots and humans across three levels of understanding: Instruction, Action, and Goal Understanding. These levels were previously discussed in Chapter 4, Section 4.3.1.
  - Trend 2: Picone et al. (2024) suggest gathering and analyzing biometric and behavioral parameters, including heart rate and stress indicators. These measurements can be collected through wearable devices. Based on these parameters, the environment responds to human operators by offering physical assistance.

  - Trend 3: Chand et al. (2023) suggest personalized fatigue assessment that considers muscle strength. Muscle strength can be measured using s-EMG sensors, which are classified as wearables.
  - Trend 4: In this trend, wearables are particularly significant due to their potential to offer real-time feedback on workers' well-being. A notable example is the study by Pistolesi et al. (2024), which not only assesses upper-body positions using a smartwatch—considered a wearable—but also delivers real-time notifications through the same device, encouraging workers to adjust their posture as needed.

5.4.2 Management Recommendations

- Companies interested in adopting a human-centric focus, specifically on the influence of workers' well-being on productivity, within the context of Industry 5.0 should consider key collaborators with prominent researchers such as M. Faccio and I. Granata, both from Università degli Studi di Padova in Padua, Italy.
- This thesis proposes a well-being program tailored for industrial environments. Based on a study by Sagar et al. (2023), an eight-week meditation program was implemented in an experiment, demonstrating positive outcomes in employee efficiency, emotional stability, and stress reduction. The authors noted significant improvements in workers' physical and psychological health, as well as in their social relationships. Referring to the human needs pyramid proposed by Lu et al. (2022), this program has the potential to address the third and fourth levels, focusing on aspects such as belongingness and personal and social acceptance. Overall, this program advances the human-centric pillar of Industry 5.0.

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