Predictive Technologies and Methodologies for Human Operator Assessment in Industry 5.0: A Conceptual Framework

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***Abstract*—The advent of Industry 5.0 represents a paradigm shift towards a more human-centric approach in manufacturing, focusing on integrating human operators with advanced technological systems. Despite significant progress in predictive maintenance for machinery, there is a notable gap in predictive assessment technologies to safeguard human operators. This paper introduces a novel conceptual framework designed to fill this gap by leveraging predictive technologies and methodologies to proactively monitor human operators in Industry 5.0 paradigm settings. Our framework emphasizes the importance of human well-being and safety by integrating data collection, advanced analytics, and targeted intervention techniques. Through a literature review of related works and a detailed exposition of our framework, we highlight its potential to enhance operational efficiency, environmental sustainability, and, importantly, the overall welfare of the workforce. This research underlines the critical need for a balanced focus on both technological advancement and the well-being of human operators, proposing a preemptive approach that aligns with the pillars of Industry 5.0. We discuss the implications of our findings for future research, particularly the need for ethical data collection practices, real-time data processing techniques, and personalized interventions. The proposed framework categorizes conceptual approaches and introduces recent innovations in predictive assessment technologies, outlining the way for more sustainable, efficient, and human-centric industrial environments.**

***Index Terms*—IIoT, Industry 5.0, Data-driven Architectures, Industrial Data Value Chain, Human Operators, Predictive Assessment.**

I. Introduction

The paradigm transition from Industry 4.0 (I4.0), characterized by focusing automation and digital interconnectivity, to Industry 5.0 (I5.0) marks a shift towards re-centering human factors in manufacturing, emphasizing sustainability in production systems and worker well-being [1]. Despite the advancements in predictive maintenance for machinery, the domain of predictive monitoring for human operators in industrial environments remains under-explored. This gap highlights a disparity in prioritizing machine efficiency over human health and well-being [2], an issue this paper aims to address.

By leveraging the technological foundations of I4.0 and embracing the human-centric principles of I5.0, this research proposes a novel conceptual framework for assessing the condition of human operators. This framework seeks to proactively identify potential health and safety risks, optimize working conditions, and promote a balanced focus on productivity, environmental sustainability, and social well-being. We aim to enhance operational efficiency but also to safeguard and improve workers' mental and physical health, addressing critical workplace challenges such as stress, fatigue, and demotivation.

Our framework introduces a novel approach by merging various I4.0 technologies into components specifically designed to proactively assess and support the conditions of human operators, thereby prioritizing their well-being. Leveraging the power of these components promotes a more sustainable and human-centric I5.0 environment, aligning technological advancement with the core values of I5.0.

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

Structured as follows, the paper begins with a review of the background and related works that support our conceptual framework (Section II). Section III outlines the proposed framework, detailing its data collection, data analytics, and intervention techniques modules. The discussion and future works (Section IV) explore the framework's potential impacts and avenues for further research. Finally, Section V concludes with reflections on the framework's contributions to promoting more sustainable and human-centric industrial environments.

II. Background and Related Works

Although the prioritization of human health and well-being within industrial settings has been relatively overlooked, some notable studies have highlighted the importance of this issue in the context of Industry 4.0. However, the proposed perspectives show an interest in the operators just as a matter of productivity.

In this paper, we used those previous works as a starting point to formulate a taxonomy of the critical factors influencing the operators' health and well-being within industrial settings. In the following sections, we change the perspective to adapt the existing models to the pillars of Industry 5.0.

Existing models within Industry 4.0 primarily address operational efficiency and predictive maintenance from a machine-centric viewpoint. Our work extends these models by incorporating a human-centric perspective, drawing on interdisciplinary research that intersects with physiological features, mental health, and environmental risks. This extension is crucial for adapting to the pillars of Industry 5.0 [1], where human welfare and technological advancement are not just parallel tracks but integrated paths toward sustainable industrial progress.

We identified three main areas to consider for improving the operators' working conditions: Safety, Health, and Well-Being. These domains encompass both physical and psychological aspects of operator well-being, acknowledging the interconnections of these factors in achieving optimal performance and satisfaction. It's important to remark that these are not isolated factors but rather interconnected and mutually influencing elements that shape the overall well-being of human operators [8]. Another identified area is related to human errors, which are more commonly associated with productivity but still significantly impact operators' well-being. Indeed, it overlaps with emotions and mood states, since errors often reflect and contribute to stress and emotional troubles [27]. Therefore, our framework implicitly addresses human errors as they relate to mood states and emotions, areas already incorporated into our taxonomy.

These three domains can then be decomposed into various more specific sub-domains. Table I presents that decomposition, supported by pertinent literature that underscores their importance in industrial settings.

Furthermore, the taxonomy illustrated in Figure 1 combines these insights, visually emphasizing the relationship between physical safety, health, and psychological well-being. This visualization supports establishing an integrated strategy essential to accomplishing Industry 5.0's ambitions, integrating human factors and technological innovation to foster sustainable, efficient, and fulfilling industrial environments.

Through our critical analysis and elaboration of these studies, we identify a significant gap: integrating these domains into a unified framework customized to meet the various requirements of Industry 5.0. This gap shows that our proposed framework, which seeks to balance these critical variables, could significantly contribute and open the door to a more human-centered, sustainable approach to industrial innovation.

III. Conceptual Framework

The narrative encompassing Industry 5.0 progressively emphasizes the mutually beneficial relationship between human capabilities and technological progress. This paper presents a conceptual framework to enhance worker safety, health, and overall well-being in the industrial workspace. The framework highlights human operators by deviating from the principles of predictive maintenance for machines, indicating a shift towards a more worker-centric industrial future.

Our framework's unique contribution lies in its comprehensive approach, integrating data collection, analysis, and intervention to preemptively address risks to operator welfare. This integration enables a dynamic, closed-loop system that reacts to current conditions and anticipates potential future issues, setting a new standard for predictive assessment systems in industrial settings.

At its core, the framework integrates a closed-loop process comprising three distinct yet interrelated modules: Data Collection, Data Analytics, Intervention Techniques, and Predictive Modelling. Each plays a critical role in advancing proactive and preventive strategies over reactive responses.

- **Data Collection Module**: At the forefront, this module comprises the biometric parameters of workers, the environmental context of the industrial workspace, and the operational status of machinery. The key component of the framework is this wide range of information, which allows for an in-depth analysis of the interactions between the operator and their environment, laying the groundwork for predictive analysis.
- **Data Analytics and Predictive Modelling Module**: Provided with a large amount of knowledge, the analytics module analyses and interprets all of this data, identifying patterns and trends crucial for predicting dangers and enhancing operator welfare. This module changes the paradigm from reactive to preventive by delivering predictive insights to detect potential issues before they materialize.
- **Intervention Techniques**: The intervention techniques are strategically designed responses to improve operator health and workplace safety. These are driven by actionable insights obtained from our analytics. These interventions, adapted to individual needs and workplace dynamics, can range from ergonomic adjustments to emergency action triggering, all purposed to enhance the industrial operation's human aspect.

This dynamic framework depends on an ongoing feedback loop to improve and adapt its methods based on new information. The industrial environment is meant to be both productive and supportive of worker welfare, and it is a living system designed to remain flexible and responsive to the evolving needs of human operators.

Although acknowledged as critical in realizing our framework's full potential, the technical details of data transmission and infrastructure are not within the scope of this article. Instead, we focus on the data's strategic application to support

TABLE I

SUMMARY OF KEY DOMAINS AND SUB-DOMAINS IMPACTING OPERATOR SAFETY, HEALTH, AND WELL-BEING, HIGHLIGHTING THE MULTIFACETED APPROACH REQUIRED TO ADDRESS INDUSTRIAL ENVIRONMENT CHALLENGES.

Domain	Sub-domain	Description	References
Safety	Movement/Collision Situations	The risks associated with the physical movement of operators and machinery within industrial environments. It includes the potential for collisions and accidents due to machinery, vehicles, or other moving objects	[3] [5] [10]
	Environmental Dangers	The risks from the surrounding working environment, including exposure to harmful substances, extreme temperatures, chemicals, noise pollution, and inadequate lighting.	[6] [12]
	Operational Dangers	The risks associated with specific job tasks or operations, including the use of heavy machinery, electrical hazards, and ergonomic risks.	[3] [5] [9] [10] [11] [17] [18]
Health	Physical Health	The physical health of operators, including risks related to musculoskeletal disorders, repetitive strain injuries, and other physical diseases resulting from industrial activities.	[3] [4] [7] [10] [12] [14] [15] [24]
	Mental Health	The psychological well-being of operators, including stress, fatigue, burnout, and other mental health issues originating from workplace conditions.	[7] [13] [15] [16] [20] [24]
Well-being & Satisfaction	Repetitive Manual Material Handling	The impacts of repetitive and manual material handling tasks on operator well-being and satisfaction.	[4] [14] [15]
	Training and On-site Assistance	The provision of training programs and real-time support for operators.	[21] [22] [25]
	Emotions and Mood States	The influence of work on operators' emotions and mood states, recognizing that emotional well-being significantly contributes to overall job satisfaction and productivity.	[13] [16] [17] [18] [19] [20] [21] [23]

Industry 5.0's human-centric principles. Future investigations will explore these technical aspects, exploring robust and secure methods to seamlessly blend our human-centric assessment framework with existing industrial systems for a unified, Industry 5.0-compliant solution.

Figure 2 illustrates the interplay between the framework's modules in a flowchart, facilitating a deeper understanding of their interconnectivity and the continuous, closed-loop process that drives the framework's dynamic evolution.

A. Data Collection Module

The Data Collection Module is the fundamental component of this framework, as it is responsible for gathering real-time data from various sensors that are then used by the Analytics Module for analysis and generating insights. We can split the Data Collection Module into four sub-components:

1) Operators Monitoring and Assessment: For the scope of that paper, the collection of data about human operators is the most crucial component.

Traditional methods such as conducting interviews and compiling surveys [26] provide valuable qualitative insights about the experiences and perceptions of operators. However, considering technological advancements, it is also feasible to leverage modern technologies to automate the data collection process. This would enable the passive and continuous gathering of quantitative data, providing a more comprehensive and accurate picture of operator health and well-being.

a) Wearable Devices: Wearable devices are one of the most prominent technologies that can be adopted for that purpose due to the facts they are in direct contact with operators, they are non-intrusive, and they can be easily embedded in clothing, accessories, and personal protective equipment worn by the operators, making them easily integrated into their daily work routines [16].

We can employ a wide range of different wearables technologies in that scope. For the aspects related to posture and movements, we can adopt Inertial Measurement Unit (IMU) sensors, comprising gyroscopes, accelerometers, and eventually magnetometers, which can accurately measure body positions, orientations, and movements [21].

For capturing biometric data, wearable sensors such as electrocardiography (ECG) sensors for heart rate monitoring, electromyography sensors (EMG) sensors for muscle activity, electroencephalogram (EEG) sensors for brain activity, and skin temperature sensors for monitoring body temperature [16] [24].

Moreover, wearable devices equipped with localization sensors can track the location and movement of operators in real-

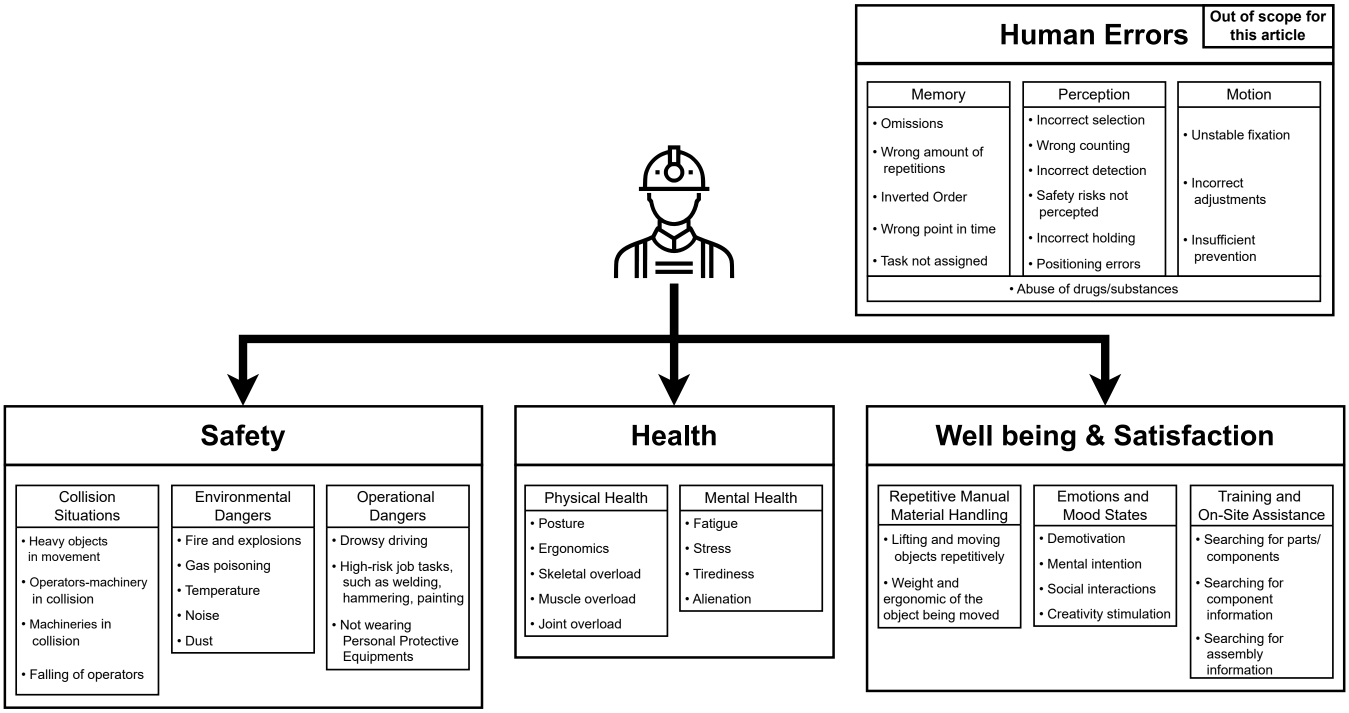

Fig. 1. Taxonomy of the aspects covered by the framework

time, providing valuable insights into the operators' positions and movements. We can also consider smartphones as data sources, as they have built-in sensors like accelerometers and GPS that can track movement and location [9].

It's possible to consider integrating this wide assortment of sensors into a body suit for the workers, enabling a non-intrusive and continuous data collection [14].

b) Imaging Systems: Imaging systems are another promising technology family for operator assessment. Depending on the needs, we can employ standard, thermal, infrared, or depth-sensing cameras to better capture the aspects of interest.

Imaging systems can be employed mainly in two different ways. First, by properly disseminating the cameras throughout the work environment, we can monitor operators' activities, locations, and movements, enforcing the location data collected by the wearable sensors [3] [5]. In addition, we can implement closer monitoring of the operators by mounting cameras on their helmets and glasses or on their workstations [7], allowing the collection of data such as posture, ergonomics, facial expressions, and features and movements of the mouth and the eyes.

This array of wearable sensors and imaging systems enables the continuous monitoring of operators, allowing for the establishment of four data-collection modules: action, posture, face, and biometric collection modules.

However, adhering to ethical guidelines and privacy standards is crucial when employing wearable devices and imaging systems for continuous monitoring. Consent protocols and anonymization techniques must be used to safeguard operator privacy, ensuring that the benefits of predictive assessment are realized without compromising individual rights or autonomy.

2) Environment Monitoring: Environmental factors significantly impact human performance and safety. Here, fixed sensors within the workplace are the technology of choice because of their capability to provide continuous and unobtrusive monitoring. The first family of data we are interested in collecting pertains to more hazardous aspects, such as risks of chemicals, explosions, and electric shocks. However, we are also interested in monitoring environmental factors such as noise levels, lighting conditions, air quality, and vibration levels that can affect the well-being and performance of human operators [6].

By integrating various sensor technologies, such as gas, humidity, temperature, smoke, and noise, we can continuously monitor the environmental factors that impact human operators.

3) Machinery Monitoring: The framework also takes into account the monitoring of machinery. Here, we can consider two different sets: fixed machinery and machinery in motion. Both share the need to monitor potential hazards, abnormal vibrations or sounds, and any deviations from normal operating conditions.

To monitor fixed machinery, we can utilize a combination of vibration sensors, acoustic sensors, temperature sensors, and visual inspection using cameras.

For machinery in movement, additional sensors such as proximity, speed, and current sensors can be used to detect anomalies and potential failures and, more importantly, to ensure the safety of operators nearby, preventing situations such as accidents or collisions. If the machines are used

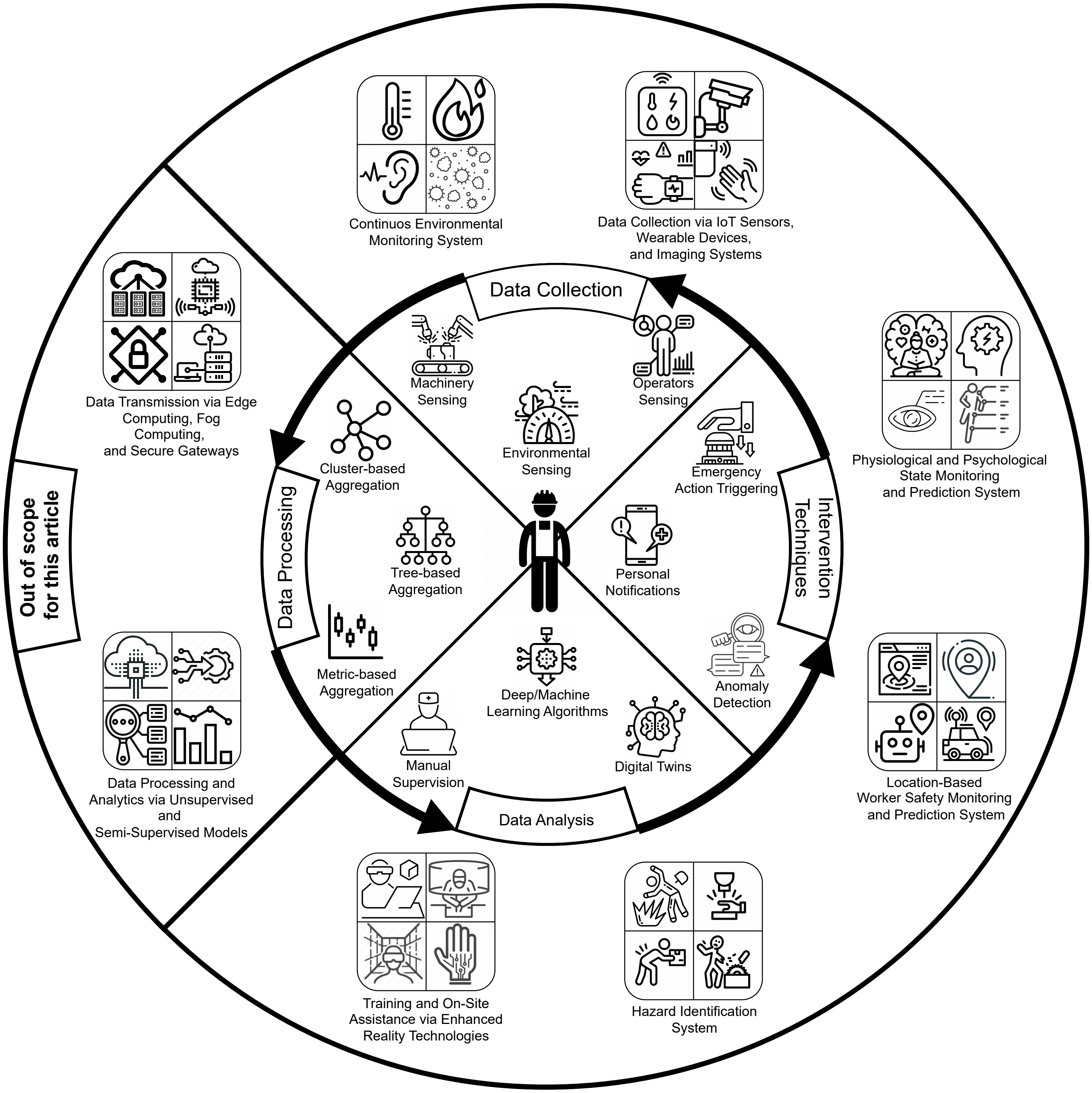

Fig. 2. Flowchart of the proposed conceptual framework

to move objects, monitoring the weight and stability of the objects being moved is crucial to ensure that operators are not at risk of injury.

4) Operation Monitoring: The last framework component for the data collection module is operation monitoring. We want to collect data about those operations performed by operators that can be potentially harmful, e.g., hammering, welding, painting, and lifting objects, and those that can be potentially stressful, e.g., recalling assembly information, locating and screwing small pieces, and verifying the correct outcome of a task. This data can be collected by combining close-look imaging systems, e.g., using smart glasses and cameras installed on the workstations, as well as wearable devices such as smart gloves or wristbands that can track hand movements and muscle activity [21] [25].

In addition, a transversal aspect we must consider is that operations can involve using potentially hazardous components. This tracking can be achieved by utilizing already deployed technologies such as sensors, cameras, or RFID technology, allowing for real-time monitoring and identification of hazardous areas or equipment [11].

B. Data Analysis and Predictive Modelling Module

The Data Analysis Module analyzes the data collected from the Data Collection Module to identify patterns, trends, and potential risks to human operators' safety, health, and well-being. It utilizes algorithms and statistical methods to process the data and extract meaningful insights. These insights are then used to develop predictive models capable of anticipating and forecasting potential health hazards or risks for human operators.

For the conceptual aim of this paper, the authors are not strictly interested in the actual methods applied to extract statistics and patterns but more in the metrics and trends of interest, what information they can provide, and how these insights can be utilized in the scope of predictive modeling so to be able to prevent and not only react.

This module is structured into four key components:

1) Location-Based Worker Safety Monitoring System (WSMS): Starting from the use of positioning and motion data, the first critical component of this framework's module is establishing a Worker Safety Monitoring System (WSMS) to monitor and predict operators' movements and activities within the working environment. By leveraging the operators' positions provided by the wearable devices and the imaging systems deployed on the shop floor, we can detect and count operators in different areas of the shop floor, identify their movements and their proximity in relation to machinery, and also establish some virtual fences for restricted or hazardous areas [5]. Moreover, regarding prevention, WSMS can model repetitive operators' movements to predict the most likely following motion based on the current operators' position.

2) Physiological and Psychological Well-being Analysis: The second component of this module involves the analysis of the physiological and psychological data collected by the wearable devices. These technologies allow for real-time monitoring, ensuring coverage of all the three domains defined in Table 1. Starting with safety, the data collected by IMU sensors and imaging systems allow for the detection of safety hazards, such as sudden falls, abnormal body movements, and proximity to machinery in operation or movement [16] [21]. Then, the data collected by physiological sensors and close cameras allow for more in-depth insights into the operators' health and well-being. First, it is possible to monitor and evaluate the posture and ergonomics of the operators at their workstations, ensuring everyone is working in a safe and comfortable environment, preventing physical strain or injuries [7] [24]. This aspect is particularly critical for Manual Material Handling, especially when repetitive, since the cumulative stress on the musculoskeletal system can lead to long-term health issues. In addition, the data gathered by ECG and EEG sensors merged with the facial features detected by the imaging systems can provide valuable insights into the psychological conditions of the operators. The first valuable information we can extract is the levels of stress, fatigue, and alienation experienced by the operators. In addition, by analyzing the brainwaves and the eye features, we can gain insight into the operators' cognitive state, mental intention, and level of focus, crucial for preventing errors and accidents, and improving the overall workers' satisfaction [13] [17] [18] [19]. This kind of data can also serve to detect when the operators may need assistance or guidance, avoiding potential mistakes, and easing their working conditions.

3) Environmental Data Analysis: The third component of this module is the analysis of the environmental data. For that purpose, we can define a taxonomy of the typologies of collected environmental data. For each of those typologies, we can establish thresholds and patterns that indicate potential risks or opportunities for optimization. One approach is establishing different risk levels, such as good, normal, caution, warning, and alarm, based on predefined limits for each monitored parameter, ensuring the working environment is safe, comfortable, and conducive to optimal performance [6]. In addition, since the monitoring of these data is continuous, it is possible to create a model able to predict the evolution of these parameters, for instance, predicting if a warning level is more probable to change to an alarm or to a caution level in the upcoming times.

4) Digital Twin Simulation: Finally, from the predictive perspective, since we are collecting plenty of data about the operators and the surrounding environment, this module's fourth and last component involves merging all of these into one or more digital twins [14]. We can have different digital twins simulating operators with varying levels of expertise, physical conditions (e.g., age, height, weight, medical history), and even psychological factors. These digital twins can also simulate different operative scenarios in the working environment, allowing us to assess the impact of various factors on the operators' performance and well-being, and predict potential challenges or improvements that can be made to enhance their overall experience and well-being [4]. Furthermore, their outputs can be used to optimize training programs and allocate tasks accordingly, ensuring that each operator is working at their optimal capacity [20].

C. Intervention Techniques Module

The Intervention Techniques Module is a proactive infrastructure within our framework, effectively utilizing the insights identified by the Data Analysis Module. This is the stage in which prevention comes into play, foreseeing potential challenges and establishing interventions specifically designed to preserve and improve the health and well-being of human operators.

This module fully takes advantage of the analytical depth that its preceding module provided to anticipate upcoming dangers and create specific strategies intended to address these issues ahead of time or properly handle current situations. This confirms the dynamic interaction between insights and action in our efforts to build an industrial ecosystem that is safer, healthier, and more fulfilling.

The approaches used in this module include:

1) Emergency Action Triggering: This is the most widely employed intervention technique in most safety systems. When a potential risk or hazard is identified, the system triggers an immediate response to mitigate or eliminate the danger. We want to trigger emergency actions for any situation that is posing or can pose an immediate threat to operators. Regarding the location data, when we predict or detect a worker in a hazardous area, for instance, in the proximity of machinery operating or in movement, or in a zone presenting critical environmental parameters, we can trigger actions such as immediate machinery shut down, evacuating alarm, or alerting the appropriate staff members. In addition, when the insights about biometric parameters predict or display critical situations, such as a notable spike in the heart rate or body temperature, we can alert the medical personnel, prompting immediate intervention [9]. The same holds for situations where the IMU sensors detect substantial changes in posture and movements that can correspond to a slip, a fall, or, more in general, injuries [12].

2) Personal Notifications, Suggestions, and Recommendations: This module aims to provide real-time individualized notifications, suggestions, and recommendations to human operators based on the actual and predicted insights collected from wearable and imaging devices. These notifications can range from reminders to take breaks and stretch to suggestions for better posture or ergonomics to recommendations for adjusting work processes to reduce strain or improve well-being in general. More specifically, when the prediction module detects signs of fatigue or high-stress levels in an operator, personalized notifications can be sent to encourage taking breaks or engaging in stress-reducing activities [7]. Furthermore, when the system identifies sub-optimal postures or ergonomic conditions, real-time suggestions can be provided to guide operators in adjusting their poses and workstations, improving their comfort and reducing the risk of musculoskeletal disorders [15].

Concerning mental intention, the system can provide recommendations to help operators stay focused and maintain their mental clarity, such as suggesting mindfulness exercises or providing reminders for task prioritization [14].

3) Training and On-Site Assistance: This module focuses on providing real-time training and on-site assistance to human operators. The collected data about brain activity and facial features can be leveraged to predict the need for on-site assistance. That can be provided by experts remotely, through video calls or audio guidance, by deploying on-site personnel to assist the operator directly, or by using augmented reality or mixed reality technology to provide step-by-step guidance and instructions [21] [22]. All these approaches can significantly enhance the efficiency and effectiveness of training, improve operators' skills and knowledge, and minimize errors or accidents in real-time situations. In addition, when operators are aware that on-site assistance is implemented, they may feel more confident and supported in their tasks, leading to increased job satisfaction, reduced stress, and improved overall well-being. Furthermore, virtual training can provide operators with cost-effective and safe training experiences, allowing them to practice and refine their skills without being exposed to potentially dangerous situations [25]. In addition, virtual reality can be used to prototype workstations, aiding in optimizing ergonomic factors and design before implementation in the physical workspace, thus reducing waste and improving sustainability [15].

IV. Discussion and Future Works

This paper presents a pioneering conceptual framework for the predictive assessment of human operators' condition within the paradigm of Industry 5.0, emphasizing a shift towards a more human-centric approach in industrial environments. Our proposed framework integrates advanced technologies, predictive analytics, and intervention techniques, aiming to proactively address human operators' health, safety, and well-being, thus promoting a sustainable, efficient, and appropriate workplace.

The novel integration of data collection, analytics, and intervention techniques establishes a road map toward enhancing human operators' safety and well-being, tackling the current gap in industrial practices that often neglect the human element. Our framework anticipates potential risks by prioritizing predictive over reactive strategies. This allows for timely interventions that prevent accidents and health issues and promote a more engaging and satisfying work environment.

Even though our framework offers a strong basis for predictive monitoring, several areas still deserve more investigation and improvement. Future research could explore:

- Ethical and Privacy-Oriented Data Collection: Future research might investigate developing solid ethical guidelines and privacy-preserving technologies to ensure that the benefits of predictive assessment are balanced with respect for individual privacy and autonomy.
- Data Transmission, Aggregation, and Processing Techniques: Exploring advanced techniques for efficient data transmission, aggregation, and real-time processing will be fundamental in handling the vast amounts of data generated by the proposed system.
- Personalization and Adaptation: Improving the efficacy of intervention strategies requires customizing them to the needs and contexts of each individual. Future work could focus on adaptive algorithms that personalize interventions based on real-time data and feedback.
- Interdisciplinary Collaboration: The proposed framework's implementation necessitates cooperation between engineering, psychology, ethics, and information technology, among other disciplines. Such collaboration will be vital in addressing the various issues associated with predictive assessment in industrial environments.

V. Conclusions

This paper introduces a revolutionary framework to improve human operator monitoring in Industry 5.0, emphasizing a human-centric approach. By focusing on worker health, safety, and well-being through integrated predictive analytics and proactive interventions, it expands beyond conventional machine-focused approaches. This strategy aims to reduce risks, enhance work-life quality, and address the oversight of human factors in industrial practices. The research encourages future advancements in predictive monitoring, highlighting the need for ethical, private, and personalized methods. In conclusion, the framework strives to foster a sustainable, effective, and satisfying workplace by promoting an effective integration of people and technology in manufacturing.

Acknowledgments

This work has been done in the context of the Agenda Drivolution – Transition to the factory of the future, Ref. 02/C05-i01.02/2022.PC644913740-00000022, funded by the Portuguese Resilience and Recovery Plan (PRR). M.M. has received funding from the European Union under the Erasmus+ Program.

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