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SURVEY

A Comprehensive Study of Human Factors, Sensory Principles, and Commercial Solutions for Future Human-Centered Working Operations in Industry 5.0

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ABSTRACT The purpose of this study is to explore the measurement of human factors in the workplace that can provide critical insights into workers' well-being. Human factors refer to physical, cognitive, and psychological states that can impact the efficiency, effectiveness, and mental health of workers. The article identifies six human factors that are particularly crucial in today's workplaces: physical fatigue, attention, mental workload, stress, trust, and emotional state. Each of these factors alters the human physiological response in a unique way, affecting the human brain, cardiovascular, electrodermal, muscular, respiratory, and ocular reactions. This paper provides an overview of these human factors and their specific influence on psycho-physiological responses, along with suitable technologies to measure them in working environments and the currently available commercial solutions to do so. By understanding the importance of these human factors, employers can make informed decisions to create a better work environment that leads to improved worker well-being and productivity.

INDEX TERMS Human factors, industry 5.0, psycho-physiological signals, human physical and cognitive states, signal acquisition, measuring techniques, human-in-the-loop, industrial applications.

I. INTRODUCTION

Industry 4.0, also known as the Fourth Industrial Revolution, relied heavily on automation and data exchange in manufacturing technologies to increase efficiency and productivity. However, this has also raised concerns about job displacement and the need for new skills and training. Industry 5.0, on the other hand, builds on the principles of Industry 4.0 and focuses on the integration of human skills and values in order to create a more sustainable and human-centric industry model. This includes the use of technology more closely aligned with human needs and behaviour, as well as the incorporation of ethical and social considerations into the design and implementation of technology. At the general level, the goal of Industry 5.0 is to create a more harmonious relationship between humans and technology in order to address the challenges and issues that have arisen with the increasing reliance on automation and data exchange.

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II. MOTIVATION

Industry 4.0 focuses on all system-centric manufacturing, placing system optimization at the core of manufacturing [1]. The humanization of the built technological workplace for Industry 4.0 was one of the first steps in the evolution towards *Industry 5.0*. According to the European Commission (EC), *the power of Industry 5.0 is a societal goal beyond jobs and growth to become a resilient provider of prosperity by making production respect the boundaries of our planet and placing* *the well-being of the industry worker at the centre of the production process* [2].

Industry 5.0 represents a shift from a strategy of high industrial performance (Industry 4.0) to a strategy of *human centricity* (Industry 5.0) [3], placing the worker's well-being at the centre of the production process [4]. In summary, Industry 5.0 presents itself as a strategy that puts the *human factor (HF) at the centre of production*, where the well-being of the worker is prioritized, as well as more sustainable and resilient production systems.

Human centricity begins with understanding human factors and satisfying human needs in manufacturing. According to the *Industrial Human Needs Pyramid* (Figure 1), a conceptual framework for classifying human needs in Industry 5.0 [5], human state monitoring, assessment, and optimization should directly address Level 2 of human needs, which refers to a healthy working environment.

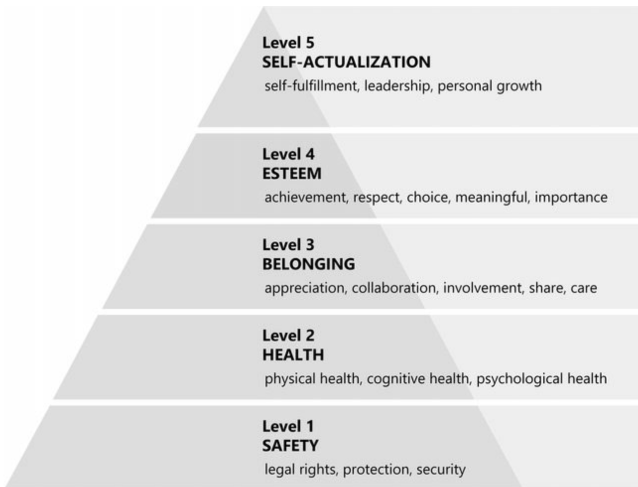

FIGURE 1. Industry human needs pyramid (source: [5]).

Enabling Industry 5.0 workplaces to identify human factors unobtrusively and continuously is the first step in closing the symbiosis loop between humans and industrial systems while providing an adaptive environment. Human factors can be identified by a combination of *physical, cognitive and psychological states* [6], which plays a crucial role in the performance of companies owing to their direct impact on the efficacy and efficiency of the duties that each worker develops [7].

Furthermore, Industry 5.0 is characterized by the integration of advanced technologies such as Artificial Intelligence (AI), Internet of Things (IoT) and Human Factors. Therefore, it is important to consider how the integration of advanced technologies may bring new types of stressors, negative impacts and challenges for workers in the workplace. By addressing this impact on human states and providing support for workers, organizations can *optimize employees' well-being, working conditions, and industrial results*.

III. HUMAN FACTORS AT WORKPLACE

Although it is difficult to identify the most relevant human factors in Industry 5.0, as this will depend on the specific context and goals of each organization, there are six specific human factors that have been identified as particularly relevant and critical in Industry 5.0 [5], [8] [9]. We classified these human factors based on the affected distinctive states as detailed in Level 2 of the Industrial Human Needs Pyramid: physical, cognitive, and psychological states.

- **Physical states: Physical fatigue**
  Physical states include an individual's physical and motor health as well as the capability to perceive the external environment's stimuli. Physical skills significantly influence human performance. The physical state worsens as the worker gets older, but there are cases in which this state can also be affected by the worker's health condition (for example, the worker has the flu). Postural impact and **physical fatigue** are central concerns to a human's physical state. Considering this, supporting physical health refers to enabling an environment that minimizes risky movements, postures, or working patterns to avoid long-term musculoskeletal injuries and minimize physical fatigue. Measuring physical fatigue in a dynamic manufacturing environment is challenging.
- **Cognitive states: Attention and Mental workload**
  Cognitive states represent the cognitive skill sets that enable the worker to act and experience the workplace, including the process of acquiring knowledge and understanding through thoughts, experiences, and senses. This is a particularly important concept in the workplace, where employees with cognitive skills can make all the difference. An industrial worker (e.g. a disassembly worker) is constantly exposed to a large amount of data that must be properly handled to make rapid and suitable decisions (e.g. remembering disassembly instructions, recognising the component to disassemble, commencing the work and identifying the next step). Attention and mental workload are central concerns in a human's cognitive state.
  - Attention is the cognitive state that allows a worker to choose among different stimuli in a dynamic and changing workplace and to concentrate on a specific task. Attention from workers in manufacturing environments is important and requires a higher demand as it can impact productivity and performance (for example, doing repetitive tasks can result in products slipping out on the line because the worker was not paying attention). The integration of multimodal interactive systems can be an effective way to divide attention or to direct the focus of attention towards relevant objects.
  - Mental workload has become a key topic in optimizing the cognitive states of industrial workers and increasing manufacturing performance. The manufacturing environment should also provide

high-value tasks to maintain worker engagement while minimizing the cognitive workload to keep workers mentally healthy. Mental workload is a subjective parameter influenced greatly by an individual's cognitive capabilities at different tasks that could lead not only to errors, safety risks, and performance inefficiency [10] but also has negative effects on workers' behaviour, motivation and well-being [11].

- **Psychological states: Stress, Trust and Emotional Assessment**
  The psychological states include all those innate (un)conscious expressions of inner nature and personality related to emotions and feelings that influence human cognition and behaviour.
  - Stress is a psychological state that occurs when the requirements and demands of a job are excessive and greater than the capabilities, resources, or needs of a worker. Stress may cause burnout (deriving into fatigue and frustration), job dissatisfaction, low commitment, and a high propensity to resign [12], [13].
  - Trust is the ability to rely on and place confidence in someone or something (e.g. a collaborative robot called cobot) and give him/her/it greater responsibilities and authority. In human-centric work environments, one core challenge is acceptance and trust in technology. Human-robot collaborative systems need to be transparent, reliable, intelligent, and friendly.
  - Emotions are faithful descriptors of a worker's feelings and personality. Moving to human-centric manufacturing, empathetic machines and systems that sense human emotions, needs, and preferences are expected to provide adaptive assistance and collaboration to humans.

  In general, as an open challenge, the primary approach to assessing the human psychological state has been focused on detecting stress, trust, or emotions from (i) external human behaviours (such as gestures, body pose, and facial expressions), or (ii) physiological signals (such as heart rate, skin conductance or respiration).

The human-centred approach focuses on designing technology and systems that are easy to use and intuitive for humans. This includes understanding the human factors or status when interacting with various systems under different conditions. It is certainly true that workplace events can influence and trigger human factors, which are psychological, social, and organizational factors that can affect an individual's behaviour, performance, and well-being [14]. That's why it is important for organizations to be aware of these human factors and how workplace events may influence them. Therefore, being able to measure aspects of human factors (such as the physical, cognitive and psychological states of employees) could improve the quality of employees' working lives, reducing the mental and physical impact of the workload, increasing safety in the work field, and improve the performance of the company.

As mentioned before, the physical, cognitive and psychological needs of humans are considered the main components of human status detection and have been widely investigated in the Human Factors domain [15]. The psycho-physiological responses of humans are considered valuable indicators of human states, which are accompanied by changes relevant to human organs and tissues such as the brain, heart, skin, blood flow, muscle, facial expressions, voice, etc. The nervous system plays a central role in regulating those responses of the body, together with the hormones segregated by the Endocrine System [16].

The nervous system is involved in a wide range of functions, including controlling movement, regulating body systems (such as the cardiovascular and respiratory systems), and influencing behaviour and emotion. It is also closely linked to the endocrine system, which produces hormones that can influence the body's response to various stimuli [17]. The nervous system is divided into two parts: Central and Peripheral Nervous Systems (CNS and PNS). The PNS consists of Autonomic and Somatic Nervous Systems (ANS and SNS). The autonomic nervous system is composed of sensory and motor neurons, which operate between the CNS and various internal organs, such as the heart, lungs and viscera. Among the signals generated by the Nervous System, those triggered by the ANS have special relevance as they are harder to influence voluntarily, in contrast to other signals such as facial expressions, body gestures or speech which could be easier to control.

On the other hand, the hormones segregated by the Endocrine System are generated in the different glands of the human body. Hormones are a set of chemical compounds that contain information that must be carried around the body to coordinate certain functions and generate changes and adaptations to prepare the body for the situation that is experiencing [18]. The process of continuously regulating the amount of hormones required to maintain the body in a correct balance is called homeostasis. Additionally, the balancing act performed by the brain to preserve homeostasis and make changes in the organism anticipating the body's needs to prepare it to face a certain situation is called allostasis [19]. These concepts are relevant for understanding why in certain situations the body reacts by segregating different hormones and sending specific body signals, which lead to determinate emotional and cognitive states and vice versa [18]. Most of these body signals are controlled by the ANS which regulates critical aspects such as brain, cardiovascular, electrodermal, muscular, respiratory and eye activity response.

Consequently, using appropriate techniques and sensor technologies, it is possible to detect and measure these aspects to achieve a better understanding of human factors inside and outside industrial workplaces.

The field of psychophysiological signal analysis encompasses a wide range of algorithms used for calculating physiological and psychological signals. While a comprehensive listing of all algorithms is beyond the scope of this paper, it is valuable to highlight some commonly used examples in the literature, such as Fast Fourier Transform, Wavelet Transform, Principal Component Analysis, Independent Component Analysis, Hidden Markov Models, Neural Networks, and Time-Frequency Analysis. These algorithms have demonstrated effectiveness in various research domains and, thus, researchers and practitioners can refer to these algorithms as a foundation for analyzing psychophysiological signals related to human factors. However, it is important to consider the specific research objectives, signal characteristics, and contextual factors when selecting and adapting these algorithms for individual studies.

It is important to recognize that assessing factors such as fatigue, attention, and stress often require the use of various psychophysiological signals, which may lead to conflicts when combining information from different measuring instruments each with its own accuracy and data structure. Additionally, demographic factors, including race and age, can influence psychophysiological responses, further contributing to variations in the processed signals. While acknowledging the presence of such conflicts, addressing them in a universal way is challenging as are affected by the accuracy and quality of the measurement instruments, contextual variables, and environmental conditions. Understanding the complexities associated with these conflicts, researchers and practitioners can make informed decisions when designing and conducting studies on human factors.

IV. IDENTIFICATION OF HUMAN FACTORS

This section provides a detailed description of the six specific human factors identified in Subsection III physical fatigue, attention, cognitive workload, stress, trust, and emotional assessment.

A. PHYSICAL FATIGUE

Physical fatigue is defined as a sub-optimal psychophysiological condition caused by exertion. Muscular fatigue tends to appear in any part of the body. Even if traditionally linked to exercise conditions, physically demanding working tasks or conditions may provoke muscles to temporarily lose their ability to produce force, thus leading to a state of fatigue. Fatigue is a crucial factor that affects task performance [20], therefore it is relevant to determine fatigue in its diverse forms.

Under normal conditions, the brain manages muscular movement through electrochemical signals produced by the positively charged sodium. The brain creates a signal that travels through the neural spine and when it reaches the muscle, it provokes muscular contraction. If the signal is mitigated in the proximity of the muscular end, muscle strength is limited, thus, it provokes peripheral fatigue [21], [22]. However, signal mitigation in the central neural system causes central fatigue [21], [23]. The authors in [24] described several factors that affect the signal transmission between the brain and muscular chains.

Nevertheless, there is a direct connection between the intensity of the electrochemical signal at the muscle end and the movement's strength or lack thereof. Therefore, measuring such signals using passive electrodes is widely used to detect fatigue [23], [25], [26], [27], [28]. Additionally, owing to the direct link between the electrical signal and the muscular strength, the muscular chains may also be stimulated by external electrical signals using active electrodes, thus forcing muscular contraction. Among a wide variety of applications, this may be used to determine the origin of fatigue as peripheral [29] or central [30]. In any case, correct electrode placement is critical for achieving satisfactory results [31].

Considering the link between the brain and muscular chains, muscular fatigue is also reflected in brain activity. In this sense, [32] described that muscular fatigue causes neurons in the posterior cingulate cortex to align their positive-negative directions, creating equivalent current dipoles (ECP). Other authors have pointed out a reduction in the peak alpha frequency in the frontal/prefrontal cortex [33] and around the motor cortex area [34].

Similarly, physical fatigue also affects cardiac activity in individuals. Studies such as [33] and [35] have established that a significant increase in heart rate (HR) is a fair indicator of physical fatigue. However, [36] affirmed that heart rate had no significant difference before and after fatigue and identified blood pressure as an alternative valid indicator of fatigue. Other authors, such as [35], point out that heart rate variability (HRV) is a better feature for assessing physical fatigue, as the ratio of low-frequency (LF) to high-frequency (HF) components of cardiac activity increases due to fatigue. Furthermore, the authors in [37] used heart rate variability entropy to assess fatigue in real-time.

Muscular fatigue and the corresponding lack of strength in certain muscular chains may also lead to changes in movement dynamics [38], [39], [40]. Therefore, a detailed analysis of body acceleration may be used for fatigue assessment [41], [42]. Recent studies, such as [43], studied the changes in dynamics by direct observation of body movement and bio-mechanical analysis to create fatigue assessment models.

Ocular fatigue may be considered a particular case of physical fatigue. The oculomotor system and, particularly, the extraocular muscles are responsible for provoking eye movements and are particularly resistant to fatigue due to their inner structure [44], [45], [46]. However, visual fatigue affects eye movement kinematics and dynamics. Longer fixations [47], slower saccadic movements [48], [49], [50], appearance of glissading undershoots [51], [52], and longer and more frequent blinks [48], [53], [54], [55] are the most common fatigue-caused behavioral alterations. Based on these effects, several studies [48], [56], [57], [58] have created ocular biomechanical models to assess visual fatigue. In recent years, these biomechanical models are of particular interest to assess visual fatigue in unnatural environments like Virtual Reality (VR) or 3D animation environments [59], [60], [61], [62].

B. ATTENTION

Attention is one of the most popular areas of brain study, as it represents the capacity of the brain to focus and process environmental information. However, as pointed out by [63], this concept is broad and ambiguous, as it comprises different specific competencies, including, but not limited to the ability to mantain a focused state of mind during long periods (sustained attention) [64], the capacity to process simultaneous events (divided attention) [65], and the proficiency to focus on certain items while blocking irrelevant stimuli (selective attention) [66]. The time-related nature of attention, especially in the case of sustained attention, also relates to the personal capacity to maintain engagement in a specific task [67].

Brain activity is sensitive to variations in cognitive states. When these changes affect attention and task engagement, they are mainly reflected in the prefrontal and the parietal cortices [68]. In addition, high-frequency brain activity is often related to awareness and higher cognitive activity, whereas low-frequency activity is associated with relaxation and lower vigilance. Therefore, many studies have examined the ratio of high- and low-frequency brain activity as a direct indicator of attention. For instance, [69] found that reaction time on the Stroop Color Test correlates both with the alpha/gamma band power ratio ($\frac{P_\alpha}{P_\gamma}$) in the frontal area and with the theta/beta band power ratio ($\frac{P_\theta}{P_\beta}$). Similarly, [70] points out three indices for asses attention, all of them composed as a ratio between high- and low-frequency spectral power indices: ($\frac{P_\beta}{P_\alpha}$), ($\frac{1}{P_\alpha}$), and ($\frac{P_\beta}{P_\alpha+P_\theta}$). Also, [71] establishes yet another indicator of attention in the so-called "engagement index" expressed as the following ratio: ($\frac{P_\beta}{P_\alpha+P_\beta}$).

In addition, when a person is performing an activity that requires certain levels of attention, this mental state usually produces changes in the cardiac activity [72], [73]. In fact, higher heart rate variability is related to better cognitive performance [74]. However, the amount of work regarding the use of cardiac activity as an indicator of cognitive attention is scarce and mainly aimed at specific demographics, such as the elderly [75] or children with attention-deficit disorders [76], [77]. Therefore, studies regarding healthy adult individuals are limited. According to [78], high-frequency heart rate variability favours the attention rate in highly anxious individuals. Similarly, [79] demonstrated that sustained attention is associated with higher heart-rate variability in the resting state. Some studies have shown that cardiac activity has the capacity to assess attention, but with slightly inferior accuracy than using brain activity as an indicator [80], [81].

Ocular behaviour is closely related to attention, as gaze acts as a proxy for attention [82]. Gaze fixation represents a focused cognitive state, while gaze instability may also be a measure of hyperactivity and lack of attention [82], and saccadic eye movements are considered indicators of attention in tasks that require visual action such as object manipulation, search, examination, or reading [83]. It has also been observed that changes in pupil diameter are markers of attention performance [84], [85]. In addition, [86] shows the capacity of eye vergence information to assess attention.

C. COGNITIVE WORKLOAD

Cognitive workload also referred to as mental workload, is one of the most important human factors to assess effective performance in human-machine interaction, as it identifies the amount of mental resources required to perform a certain task efficiently. Traditionally, the mental workload has played a main role in safety-critical situations, such as air traffic control, automotive, and defense. However, the digitization of workplaces has allowed further research on industrial environments [87], [88].

Mental workload is a multidimensional human factor that may lead to an ambiguous definition of the term. One possible approach to identifying the mental workload is to objectively analyze the work to be performed by the user. From this perspective, the number and complexity of tasks produces a higher workload demand. However, certain circumstantial causes, such as time constraints or environmental risks increase the mental resources necessary to undertake a certain task. Finally, from a subjective perspective, different users may require greater mental resources to overcome the same task, even if the circumstances are the same. These three factors were first identified by Sweller in the late 80s [89], [90] under the names of "Intrinsic cognitive load", "Extraneous cognitive load" and "Germane cognitive load", are related to the inner nature of the task, the external factors and the personal characteristics, respectively. Some modern approaches use the term "Taskload" to identify the intrinsic cognitive load and "Workload" as a term to encompass both the extraneous and the germane factors of the cognitive load. However, even if different researchers do not consider exactly the same concept of workload, the internal consistency of the studies should be considered a guarantee for the different results to identify correctly the human psychophysiological responses regarding the mental resources involved in the experimental procedures.

Recent studies have investigated the use of brain activity to identify mental workload states. Several studies have shown that there are changes in brain activity, particularly as a decrease in alpha band power, also referred to as alpha suppression, when the workload increases [91], [92], [93], [94], [95]. However, [96] points out that whereas alpha suppression is present in increasingly difficult mathematical calculations, it may not be a valid feature to distinguish major workloads from other tasks. Other authors also pointed to variations in the activity of beta [97] and theta [98], [99] bands. Additionally, [88] pointed out significant differences between veteran and novice workers in the beta and gamma bands, as well as in the brain activity asymmetry index. These differences are related to the germane cognitive workload identified by Sweller [89].

An increase in mental workload leads to an increase in physiological arousal [100], and therefore, variations in electrodermal activity may act indirectly as a measure of workload. However, according to a recent systematic review [101], skin measures are rarely used in metal workload detection, although they seem to provide promising results. Out of the more than 400 studies reported in the review, only seven of them employed skin conductance to assess mental workload, but a majority of them (six out of seven) found this feature as a significant indicator of mental workload. Subsequent studies further validated the usability of electrodermal signals as a solid indicator of the mental workload level [102], [103].

High demand for cognitive resources also leads to changes in cardiovascular activity. According to [101], a wide variety of cardiovascular features are used in current research to infer workload information. Among them, heart rate in terms of beats per minute and heart rate variability in both the time and frequency domains are the most popular metrics for assessing mental workload. The heart rate increases accordingly to task complexity [95], [97], [104]. Similarly, several studies [105], [106], [107] have shown a reduction in the interbeat interval as the mental workload demands increase. In the frequency range, higher mental workload increments the low-frequency components of cardiovascular activity, while reducing the high-frequency components [108], [109]. Therefore, the ratio between these two components is a solid assessment feature of the mental workload [110], [111]. In addition to cardiac activity, systolic blood pressure [109], [112] and blood oxygenation [113], [114] are rarely used but have proven to be valid workload evaluation features.

Eye movements and ocular behaviour are sensitive and non-occlusive indicators of cognitive load. This approach has been widely used in the evaluation of Human-Machine interactions (HMI) [115]. The authors in [116] used pupil diameter, blink, and gaze metrics to evaluate the cognitive workload in surgery and determined that pupil diameter and gaze entropy are suitable indicators of mental load. Similarly, [117] employed both pupil diameter and eye movements (saccades) as indicators of the mental workload. Among other indicators, increased blinking latency and decreased blinking duration are related to high workload demands [115]. However, the same authors pointed out the blinking rate is an ambiguous indicator. This phenomenon is further explained by [118] and [119], which stated that the visual demand of the work can interfere with the blinking rate and thus compromise the use of this feature as a valid indicator of mental workload.

D. STRESS

Taking into consideration the work of [120] stress can be defined 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.

Every day, people encounter various sources of stress that can impact their mental and physical well-being. Stress can arise from a variety of personal, social, environmental, and situational factors, including financial troubles, job-related issues, conflicts in relationships, and significant life events, such as the death of a loved one. The effects of stress can be categorized as either acute or chronic, with the latter having a particularly harmful impact on both physical and mental health outcomes. While manageable levels of stress can be beneficial for individuals, prolonged exposure to stress can lead to a range of health problems. Therefore, there has been a significant effort among researchers to identify effective methods for detecting and predicting mental stress, as early intervention is critical for mitigating the negative effects of stress.

From a biological perspective, the Autonomic Nervous System regulates automatic bodily functions, including the hormonal system and is divided into sympathetic and parasympathetic nervous systems, responsible for stress and relaxation responses, respectively. Normally, both systems are balanced, but the continuous release of hormones under continuous stress conditions distorts harmony. As stress hormones increase the heart and respiration rates as well as blood pressure, a long-lasting effect of such hormones is associated with an increased risk of stroke and heart attack [121], [122].

Among stress-related hormones (cortisol and catecholamines [123], [124]), the presence and levels of cortisol are the most frequently used stress indicators [125]. Cortisol can be measured in various body fluids such as urine and saliva. Cortisol levels are normally high in the morning and low at night. An alteration in these levels, such as abnormally high levels at night or small variation between day and night cycles points towards a time-sustained stress level situation [126], [127].

Even if salivary cortisol is considered a reliable indicator of stress levels, as indicated in [128], salivary cortisol analysis requires several days to obtain results. Therefore, alternative methods have been implemented to infer stress levels more quickly and simply. Among other physiological variables, cortisol level affects the heart rate [129], [130], [131], skin temperature (ST) [132], blood pressure [133], and galvanic skin response [134], [135].

Heart rate is a well-known marker of the sympathetic nervous system under mental stress [136], involving both time-domain analysis and frequency-domain analysis techniques. Traditionally, time domain analysis for stress detection involves studying the mean and standard deviation of the respiration rate (RR) peak. On the other hand, frequency analysis works by obtaining the high- and low-frequency powers of heart rate variation. The high-frequency component is related to vagal activity, whereas the low-frequency spectrum modulates sympathetic nervous activity [137], [138], [139], [140]. Mental stress induces a reduction in the high-frequency component while increasing the low-frequency component [141], [142].

Brain activity analysis is also used to measure stress levels, especially under the hemispheric specialization (HS) theory. According to this model, cognitive, sensory, and motor functions are related to brain structure [143], [144]. Research performed in [145] showed an association between right hemisphere activation and electrodermal activity in stress situations. Finally, stress can be assessed by measuring pupil diameter [146].

E. TRUST

Trust is a critical aspect that rules social relationships and plays an essential role in understanding inter-character dynamics. It influences both physical and non-physical interpersonal bonds [147], [148], [149], as well as human relations with organizations [150], [151], [152] and technology [153], [154], [155]. Owing to the interest in understanding trust dynamic, it has been extensively studied in many different fields such as psychology [156], sociology [157], economics [158], philosophy [159], and several technological fields, such as automatization [160] and network computing [161], [162].

As it is a complex and widely used social construct, there are a wide variety of definitions of trust according to different areas of application. On the one hand, some researchers, such as [163], focus on synthesizing the nature of trust, based on previous academic definitions in different fields of application, and, by doing so, they aim to identify the core intrinsic elements of trust. On the other hand, the main academic stream adopts the analytical perspective and focuses on defining different dimensions to establish the nature, origin, and dynamics of trust. For instance, research in [164] distinguishes moralistic trust based on previous beliefs about others' behaviour and strategic trust based on individual experiences. In addition, in [165] and [166] the authors identified three distinct types of trust: dispositional, situational, and learned. Dispositional trust is grounded in individual characteristics such as culture, gender, and age. Situational trust is influenced by contextual factors such as the difficulty or importance of the task, which may modify the otherwise natural response. Finally, learned trust is shaped by accumulated experiences. Each of these dimensions interacts to shape the overall dynamics of trust in any given interaction between a trustor and trustee. Similarly, [161] considered trust as a combination of individual trust (which is derived from personal characteristics and conformed by logical trust and emotional trust) and relational trust, referred to as the dimensions of trust that arise from relationships with other entities.

The complex nature of trust hinders the capacity to measure it accurately. Questionnaires and self-report instruments such as those described in [167], [168], and [169] are commonly used, but these kinds of instruments lack both objectivity and the possibility to use them to obtain a real-time response, which is why they focus mainly on steady long-term features of trust, such as the individual and situational dimensions. However, recent technological advances in the field of sensors have led to an increased interest in the research of objective methods to evaluate trust. From this perspective, trust is a subconscious state of mind, bound to the actions of the peripheral and the central neural systems. Therefore, changes in psycho-physiological signals can be used to objectively assess the state of trust.

The use of signals from the central nervous system for trust assessment is based on brain activity [170], [171], [172].

In contrast, other works studies have assessed trust based solely on a single psycho-physiological signal from the peripheral nervous system. For instance, [173] and [174] analysed how the electrodermal response is significantly affected variations in trust. Regarding pupillometry and eye behaviour, [175] revealed that humans trust partners with dilating pupils and withhold trust from partners with constricting pupils. Research in the field of Human-Robot Interaction shows a similar reaction, although, in this particular field, pupillometry is a better indicator of a high cognitive workload state [176], [177]. Similarly, [178] uses gaze behaviour to check the frequency in which the automatic system is being monitored and infer the dispositional, situational, and learned trust levels of the participants. Heart rate has also been used as an individual indicator of trust, for instance, in [179]. Furthermore, this study found greater levels of behavioural trust in the trust game among the participants when the HR was being measured.

However, the complex nature of trust makes it virtually impossible to assess trust using a single signal [180]. Therefore, most studies tend to combine signals from the central nervous system (mostly brain activity) with those from the peripheral nervous system. Works such as [173] and [181] employed brain and electrodermal responses to obtain real-time trust assessment while [182] included cardiovascular responses. However, owing to the limited temporal resolution of signals from the peripheral nervous system, it is infrequent to combine more than three different psycho-physiological responses for trust assessment [183].

F. EMOTIONAL ASSESSMENT

Emotions frequently refer to a mental state that occurs naturally rather than via conscious effort and is frequently accompanied by physical and physiological changes. In contrast, mood refers to the sustained cognitive state of mind or the long-lasting emotional state for a certain time.

Emotions, which affect the physiological and psychological status, play a key role in human life. Human emotions are how each individual deals and interact with stimuli (matters, situations or thoughts) that they find personally significant. These emotions are defined as complex reaction patterns involving experiential, behavioural and physiological elements and play a key role in human life [184].

Human emotions are psychological states formed in the process of perceiving and interacting with external stimuli, such as environmental changes [185]. Emotions reflect the underlying motivation and consciousness of human behaviours and have a direct impact on the establishment and maintenance of interpersonal relationships, cognition, decision-making, work efficiency, and other interactive activities [186], [187]. For example, emotions have a strong influence on modulating attention sensibility, which can reduce the focus on relevant information. Furthermore, emotions also facilitate efficient encoding and retrieval of information. This is why we remember more emotionally charged events (the flashbulb memory phenomenon). While long-term exposure to unpleasant emotions might eventually harm physical and mental health, positive emotions benefit health and productivity.

According to Cannon-Bard's theory of emotion [188], also referred to as the thalamic theory of emotion, the psycho-physiological reactions in CNS and ANS of the body relate to emotional changes. According to this theory, humans experience emotions together with physiological responses including sweating, shaking, and muscular tension. For example, when an individual encounters a potentially dangerous or stressful situation, their body automatically activates a series of physiological changes that prepare them to fight or flee. These changes include an increase in heart rate, blood pressure, and respiration, as well as the release of hormones such as adrenaline and cortisol. More accurately, it's been proposed that emotions emerge when the thalamus and limbic system communicate with the brain in response to a stimulus, causing a physiological response. [189], [190].

To avoid mistakes in emotion recognition and to design a reliable set up (according to [191]), a deeper understanding of emotion modelling, processing and its expression is necessary. For this purpose, emotions should be defined and quantitatively assessed. Yet, the precise concept of fundamental emotions is not universally recognized by psychologists. Thus, emotional modelling often divides emotions into two distinct philosophies [192]: The discrete or categorical emotional model, which understands each emotion as an isolated self, and the multidimensional emotional model, which uses several affective dimensions to label and categorize the broad emotional spectrum.

- Discrete/categorical emotion model (DEM): Discrete model theory states that people's emotions are composed of basic emotions. All human emotions can be formed by combining one or more of these basic emotions [193]. Furthermore, the discrete emotion models have traditionally used word descriptors to identify emotions than quantitative analyses. This method has proven to be challenging in analyzing complex emotions, including mixed emotions that are difficult to articulate verbally and require a quantitative research approach. Ekman's seminal work in 1992 identified six fundamental emotions, namely anger, pleasure, sorrow, disgust, fear, and surprise, which have been extensively studied in the literature [194]. Additionally, Ekman posited that other emotions arise from combinations and reactions of these fundamental emotions. The wheel of emotion, first introduced by Plutchik in 2001, represents another popular framework employed to categorize emotions, incorporating two more emotions, acceptance and anticipation [195].
- Affective (multi)dimensional emotion model (ADM): The (multi)dimensional theory outlines that emotion is constantly changing, such as the two-dimensional emotion model composed of valence and arousal and the three-dimensional emotion model composed of valence, arousal, and dominance. This model can be useful because similar emotions can have overlapping parameters and emotions with the same descriptions may have different intensities. These factors led to focus on other classifications including dimensions of emotions, in most cases valence (describes the polarity of emotion, from negative to positive emotions) and arousal (points out the intensity of emotion, from the active to passive scale), together with analysing only basic emotions which can be defined more easily. Most research uses variations of Russel's circumplex model of emotions [196], [197], which provides a distribution of basic emotions in two-dimensional space with respect to valence and arousal. Such an approach allows the definition of a desired emotion and assesses its intensity by analysing only two dimensions. Although the 2D emotion space effectively distinguishes between positive and negative emotions, it fails to differentiate similar emotions, such as fear and anger, which are both situated within the zone of negative valence and high arousal. To address this issue, Mehrabian [198] extended the emotion model to include a third dimension, named dominance, which ranges from submissive to dominant and reflects an individual's control over the emotion. The inclusion of dominance gives form to the PAD model (Pleasure, Arousal, Dominance) and allows for easier identification of emotions. Following the previous example, in this model anger is located along the dominant axis while fear is situated on the submissive axis. This model represents an improvement over previous 2D models by providing a more nuanced and comprehensive approach to understanding human emotions.

In the emotional spectrum, the right hemisphere is more prone to process negative and withdrawal emotions, whereas the left hemisphere specializes in positive and approach-related emotions [199], [200]. Studies as [201] show increased prefrontal activity in the left hemisphere when processing positive emotions and greater prefrontal activity in the right hemisphere when processing negative moods.

If negative emotions are provoked, the heart beats rapidly, thereby narrowing the R-peak (maximum amplitude of the R wave) intervals [202]. Blood pressure also correlates with emotions, with emotional intensity raising blood pressure. Heart Rate Variability decreases with happiness, sadness, and fear, while pleasant stimuli might increase the peak heart rate response [203]. It has been established that breathing is a reliable indication of emotion. It is easy to discriminate between emotions like anger or fear (which create irregular rhythms, quick variations and cessation of respiration) and calm (represented by slow breathing). Furthermore, it is possible to detect the laughing state due to high-frequency fluctuations in the HRV signal [204]. Electrodermal activity is actually a sensitive and convenient method of measuring indexing changes in sympathetic arousal associated with emotion [205], [206]. Notably, both positive (such as happy or joyful) and negative (such as threatening or saddening) stimuli can result in increased arousal and skin conductance.

Finally, there is an increase in pupil size as a reaction to emotionally toned or fascinating visual stimulus viewing [207]. The pupil diameter will dilate if a person is frightened or excited owing to the natural adrenaline response of the body [208]. Blink [209] and gaze patterns [210] have also been related to emotional reactions, such as defensive or negative reactions.

V. RECOGNITION OF HUMAN FACTORS

Human factor recognition can be performed using two complementary methods: i) human internal signals, also known as psycho-physiological signals, and ii) human physical signals (such as facial expression or body posture). Spontaneous human internal signals can be used to evaluate the activities of the central and autonomic nervous systems and provide more objective and effective detection of emotional states from the perspective of internal physiology [17], [211]. The main internal processes of human beings can be categorised as follows: 1) brain, 2) cardiovascular, 3) electrodermal (or skin conductance), 4) muscular, 5) respiratory and 6) ocular activities. Human physical signals (such as facial expressions, speech, gestures and postures) have the advantage of easy collection and have been studied for years. However, the main issue is related to reliability, which cannot be guaranteed, because it can be easy for some persons to control the physical signals (e.g., facial expressions or body pose) to hide their real human state.

Each of these physical and internal signals can be quantified using different measurement techniques, sensors and devices. The specific positions of the sensors and devices depend on the parameter being measured and the technique used. The following figure 2 shows examples of the sensor positions for different physiological measurement techniques.

The following subsections provide an analysis of each signal, measurement techniques and relevant features.

A. BRAIN ACTIVITY

Several brain areas are activated when the body is influenced by both sympathetic and parasympathetic nervous system regulation [212]. Electroencephalography (EEG) is a non-invasive technique for determining neurophysiological functions in the brain. By placing electrodes on the scalp, the electrical activity of large populations of neurons firing synchronously in the brain is measured [213]. The electrodes are commonly placed following the 10-20 system, which refers to a conventional way of identifying anatomical points of reference, such as nasion, inion, and preauricular points, with the consecutive arrangement of electrodes at fixed distances from these points in steps of 10 or 20%, considering head size variations [214]. The electrodes register the electrical potential differences generated by the currents flowing during synaptic excitations of the dendrites of pyramidal neurons in the cerebral cortex [215]. The electrical activity detected by the electrodes is amplified and displayed on a screen, computer or paper.

EEG cannot measure every event triggered by brain neurons. The majority of the neural activity is not measurable using EEG or other brain-imaging techniques. Consequently, it is crucial to select the correct brain-imaging technique to better suit the nature of an investigation. In addition, the results should be interpreted by considering what can be measured using the selected technique. For instance, EEG may not be able to measure electrical fields even if they have sufficient power to reach the scalp. If potential fluctuations form from opposing sides of a sulcus and have similar strengths, they could counteract and cancel each other, rendering the signal imperceptible from the scalp, as shown in figure 3 [216].

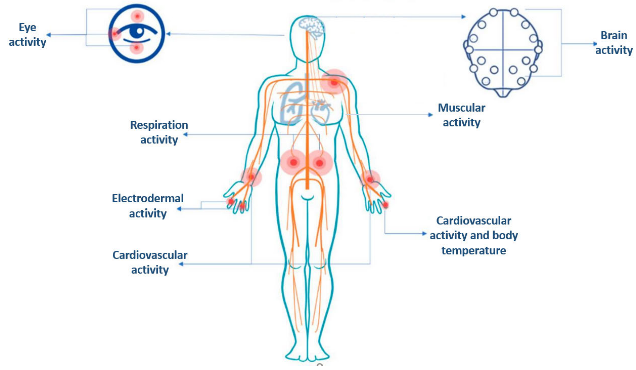

FIGURE 2. Example position of sensors and devices (adapted from [184]).

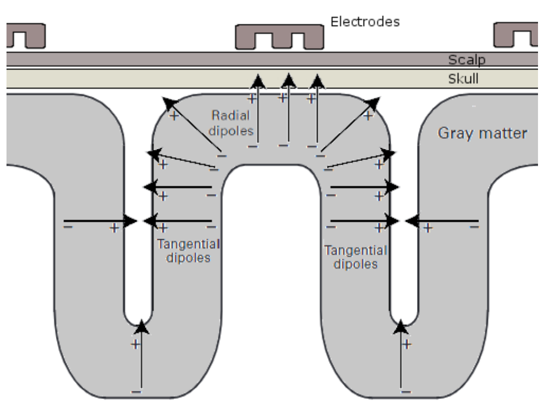

FIGURE 3. Illustration of dipoles in different orientations with respect to the skull, adapted from [216].

Electrodes used in EEG headsets can be divided in great scale into two main types: wet/gel and dry electrodes.

- Wet/gel electrodes generate a conductive zone between the skin and electrodes using an electrolyte gel or liquid solution, thereby decreasing the electrode-skin impedance. These are more commonly used in EEG applications [217]. Despite its broad use, they have some disadvantages as it is time-consuming to prepare the electrodes before each use, the gel might get dry during the test it is necessary to hydrate the electrodes again, or in cases where the gel might be a bit abrasive, it could affect the subject.
- Dry electrodes have emerged as an alternative option to the issues presented by wet/gel electrodes, allowing the use of EEG devices for longer periods and reducing time consumption as there is no need for laborious skin or electrode preparation. Dry electrodes can be contact, non-contact or other approaches such as solid gels or foams [218]. Among the different types, the most commonly used because of their lower impedance levels are dry contact electrodes. These electrodes usually have a metallic surface made of multiple tiny spikes in direct contact with the scalp. Dry electrodes also have some drawbacks, they tend to have lower conductive levels than wet/gel electrodes, meaning higher impedance which results in a more significant amount of noise and interference in the signal. In addition, contact dry electrodes with spikes can be uncomfortable for the subjects after wearing the headset for long periods [218], [219].

Even though there are differences between wet and dry electrodes, as technology advances, more studies are considering that both approaches could yield similar results, depending on their specifications [217].

Brain activity changes depending on the functional status of a subject, being different in the alertness or relaxation state [215]. In addition, brain signals follow a pattern forming a sinusoidal wave. Commonly, brain waves are measured from peak to peak and have an amplitude ranging from 0.5 to 100 (μV). A Fourier transform on the raw EEG signal provides its power spectrum, showing the contribution of different frequency brain waves contribute [215]. Brain waves have been classified into four frequency groups [220], [221]:

- Delta rhythm (0.5-4 Hz): This usually occurs during the dreamless state of sleep, known as deep sleep.
- Theta rhythm (4-8 Hz): Generated in deeply relaxed states and during inward focus.
- Alpha rhythm (8-13 Hz): The dominant frequency in adult humans. Alpha waves are predominantly produced during wakefulness. Their observation improves when the subjects are relaxed and with their eyes closed. On the contrary, they are attenuated or stopped especially by visual attention.
- Beta rhythm (13-30 Hz): Generally, beta waves are associated with alertness, focused attention, engagement and stress.
- Gamma rhythm (30-45 Hz): Connected with information processing, concentration, and performing voluntary movements.

In summary, the slowest cortical rhythms are associated with an idle brain state and the fastest rhythms to information processing.

EEG has been widely used to determine human states and emotion recognition. To achieve this, brain activity generated in the different lobes (frontal, parietal, temporal and occipital) is tracked. Subsequently, the registered brainwaves are correlated with human states and classified using the valence-arousal or PAD model. Researchers have found the following relations between brainwaves and mental states:

- Alpha waves have been associated with pleasure (valence) and relaxed conditions [222], [223].
- The Beta rhythm has been related to alertness and an active state of mind [222], [223].
- The Beta to Alpha ratio reales to the arousal dimension of the PAD model [222], [223].
- An increment of Beta to Alpha ratio in the frontal lobe with an increase of Beta waves at the parietal lobe has been linked to determine the dominance dimension [223].

The detection and recognition of human emotions using EEG has been used to improve communication, in the industrial field, between humans and cobots, having a positive impact on the stress and engagement levels of an operator [224].

A key factor in using EEG technology for emotion recognition is the presence of accurate signals without noise. However, this can be challenged by several factors. First, EEG signals are weak which makes them more easily disturbed by external factors such as environmental noise or the subject movement. It is also relevant to use proper and precise stimulation methodologies to evoke the target's emotions. There are various methods of stimulation (e.g., pictures, music, video clips, games, and environmental elicitation such as lighting, temperature, and humidity). Additionally, the system performance is affected by the signal processing platform used to handle the EEG data, which should consider other aspects such as data denoising, filtering, feature selection and classification algorithms [225].

B. CARDIOVASCULAR ACTIVITY

The activation or deactivation of the ANS can be appreciated by checking for variations in the heart rate. Heart rate is defined as the number of times that the heart beats per minute. On average, an adult's heart beats between 60-100 times per minute [226].

An electrocardiogram (ECG) enables an accurate measure of the heart rate. ECG is a non-invasive test which measures the electrical activity and rhythm of the heart. Conventional ECG machines have 12 leads divided into two groups, limb leads and precordial leads. The limb leads record the heart information in a vertical plane, whereas the precordial leads provide the heart's electrical activity in the horizontal plane.

The combination of both groups of limbs is captured in a graph representing the cardiac electrical activity. In the conventional 12-lead ECG, electrodes are placed on the arms, legs, and surface of the chest. ECGs recordings are based on electromagnetic currents with magnitude and direction. The ECG device records a positive deflection when a current travels towards an electrode, on the other hand, there is a negative deflection each time that the current moves away from an electrode. Additionally, if the current travels perpendicular to the sensor, it produces a biphasic wave [226]. A normal ECG signal cycle consists of three segmented waves. The first is the P wave, generated by atrial depolarization. Second, the QRS (a wave complex) can be found, which contains the highest amplitude produced by ventricular depolarization. Finally, the T wave is formed owing to ventricular repolarization. Usually, the distance between R peaks is used to calculate the heart rate [227] (see figure 4 for more details).

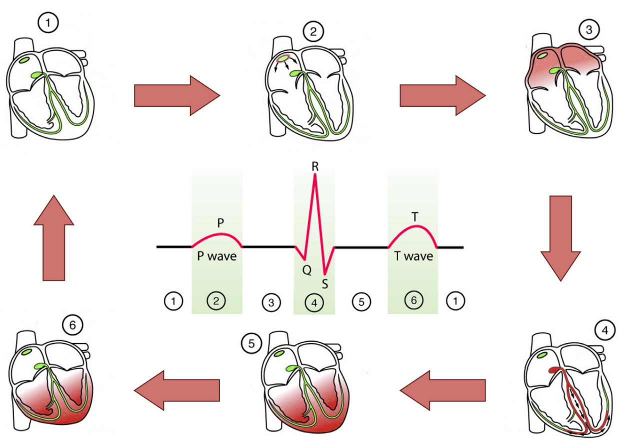

FIGURE 4. ECG cycle in a normal and healthy heart (based on [228]).

ECG has been used in several experiments for emotion recognition [229], [230]. The detection of cognitive and emotional states such as stress via heart rate traditionally involves the time domain analysis of ECG, which includes the maximum, minimum, medium, mean, and standard deviation of inter-beat characteristics (HR or RR-interval) as well as within-beat features (PR-interval, QRS-interval, ST-interval, QT interval, PR segment, and ST segment) [231]. On the other hand, frequency analysis works by obtaining the high- and low-frequency power of the heart rate variability. The high-frequency component is related to the vagal activity, whereas the low-frequency spectrum modulates the sympathetic nervous activity [232].

ECG has several benefits for emotion recognition. First, the ANS stimulation towards emotions leads to rhythm changes in the heart. Second, it is quite versatile as it can retrieve data from several parts of the body such as the arms, legs and chest. Third, ECG signals have higher amplitudes than other biosignals. Finally, there are a great variety of wearable devices that can be used to extract ECG data with accuracy which provides versatility for application in different scenarios [227].

To achieve maximum accuracy in an ECG clinical devices should be used. On the other hand, in other scenarios where emotion recognition could be crucial and users need to be comfortable performing movements such as in industry, construction, primary sector, etc. ECG clinical devices could be cumbersome, restricting mobility at the workplace and annoying the users. Consequently, commercial devices are more practical in these cases as they provide the necessary accuracy for extracting ECG signals that can later be used for emotion recognition and research purposes.

While utilising ECG, there are some challenges to be faced. One of the main challenges is the signal acquisition stage. ECG signals can be easily corrupted by noise if the electrodes are incorrectly placed. Some factors that can influence the signal at this stage are power line interference, breathing movements, electrical impulses, contractions of other muscles, the subject's movements, and electrode misplacement. Additionally, other generic aspects such as posture, the subject's attributes such as age or weight, heart rate variability, emotional states or fatigue. [228] should be taken into consideration.

Apart from ECG, one of the most commonly used techniques to measure cardiac activity is photoplethysmography (PPG). PPG is an optical measurement technique that commonly uses red or near-infrared light to illuminate the target tissue and photodetectors measure small changes in light intensity related to variances in perfusion in the catchment volume [233]. PPG is commonly used in wearable devices to track cardiac variables such as heart rate, HRV, blood pressure, and blood oxygen saturation (SpO2) [234].

C. ELECTRODERMAL ACTIVITY

The activation of the sympathetic nervous system, also known as the fight or flight response, induced by physical or cognitive challenges can be detected by a significant increase in skin conductance (SC) levels [235]. SC is detected by measuring the electrodermal activity (EDA) which serves as an indicator of the activation of the sympathetic nervous system in healthy subjects [236]. EDA (traditionally known as galvanic skin response [GSR]) can be described as a biofeedback signal of tiny variances in the electrical activity of the skin. EDA signals comprise of two main parts related to the SC [237], [238] (see figure 5 for more details):

- Skin Conductance Response (SCR) refers to the phasic or short-term changes produced in the humidity levels of the skin before and after a stimulus.
- Skin Conductance Level (SCL) that is related to the tonic or long-term average level of conductivity created by sweat during a specific time frame.

EDA devices are composed of a set of electrodes usually placed on the limbs. An electrical microcurrent passes through the electrodes, the signal is amplified, and variations in the conductivity are registered in the device. The electrodes measure the differences in the electrical activity of the skin provoked by changes in the activity of the sudoriferous (sweat) glands, in particular, the eccrine glands, which

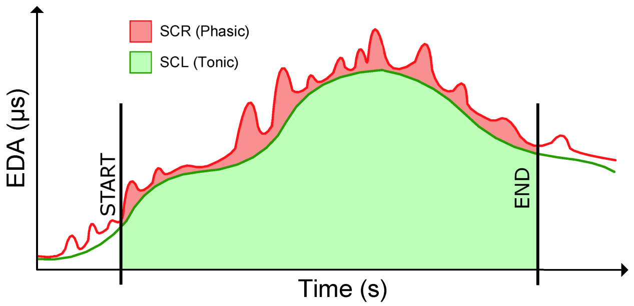

FIGURE 5. **Difference between SCR and SCL in an EDA raw signal (based on [239]).**

open onto the skin surface. Depending on the amount of sweat segregated by the glands, the skin's conductivity varies. The higher the sweat response, the higher the conductivity (μS), which indicates lower electrical resistance ($k\Omega m$) of the skin [240].

Considering the valence-arousal space for emotion recognition [196], EDA has been used in several studies, to determine both the arousal and valence levels [241], [242]. Also, SC has been commonly used in studies that research human fear [243].

EDA can be influenced by several factors that cause technical challenges in the measurements. Environmental factors such as humidity and temperature can affect skin properties, leading to inaccurate results. Additionally, other aspects such as skin hydration can significantly influence the EDA data [244].

D. MUSCULAR ACTIVITY

The muscles can be activated voluntarily or involuntarily. Both types of activation are handled by the nervous system, which controls movement, thoughts, automatic responses, and other body functions. It is the somatic nervous system, part of the peripheral nervous system, which leads and handles skeletal muscles to perform voluntary movements [245]. On the other hand, the sympathetic nervous system (fight or flight response), part of the ANS, plays a role in performing short and intense tasks as the Wingate test [246], and it has also an influence on regulating skeletal muscle motor innervation and neuromuscular junction structure and function (chemical synapses between motor neurons and skeletal muscle fibres) [247], [248].

Considering that muscle activity plays a crucial role in the quality of human movement, it can influence the abilities of operators to perform tasks. Consequently, it becomes relevant to measure the muscular activity of a person, as it can determine several physiological or psychological conditions that the person might experience, such as fatigue or stress.

Electromyography (EMG) is one of the most utilised methods to determine muscle activity. EMG records the electrical signals controlled by motor neurons that generate muscle contraction [249]. EMG can be performed in an invasive or non-invasive manner. In the invasive case, known as needle EMG, a needle electrode is inserted into the target muscle recording its electrical activity. Needle EMG provides more precision to determine the structure of the muscles and can register activity from individual muscle fibres or entire motor units. Usually, needle EMG is used in the clinical field [250].

On the other hand, surface EMG uses non-invasive electrodes placed on the surfaces of the muscles to track their electrical activity. Contraction occurs when muscles are activated. Therefore, their length decrease and surface electrodes move with respect to each other [249]. Surface EMG is more commonly used outside the medical field (e.g., engineering, research) because it can be conducted by personnel other than medical specialists, and it is more comfortable and less risky for the subject [251].

Electro-oculography (EOG) is a particular type of EMG where sensors are placed near the eyes and used to measure their muscular activity. The equipment in both cases is identical, as will be detailed later in the ocular activity section.

Several aspects shape the EMG signal characteristics, which depend on the subject's internal structure, skin temperature, blood flow velocity, skin formation, and tissue structure, among others. These characteristics generate diverse types of noise and artifacts found in the EMG signals. Consequently, it is crucial to eliminate the noise from the signal improving the feature extraction and usability of EMG signals [249].

Regarding human factors, EMG has been broadly used to detect muscular fatigue [23], [26], [28]. Muscular fatigue can appear in all body parts, affecting task performance and attention, as mentioned in the previous sections. Another habitual use of EMG is to determine facial expressions. By measuring the activity of the zygomatic and corrugator muscles it is possible to detect if the subject is experiencing a positive valence emotion (increased zygomatic activity) or negative valence emotion (increased corrugator activity) [252], [253].

E. RESPIRATORY ACTIVITY

The central and peripheral nervous systems play crucial roles in the regulation of voluntary and involuntary breathing. Because of this strong bond, respiration analysis contains useful information regarding diseases and emotional states [254], [255]. Additionally, there is a relationship between agitated states of respiration and the activation of the sympathetic nervous system, and slow, deep and calm breathing techniques with parasympathetic nervous system activation. Concerning this topic, it has been studied the treatment of emotional states with a sympathetic dominance such as stress, anxiety, or depression, with breathing techniques that can shift from sympathetic to parasympathetic dominance [256].

Considering the complexity and impact of respiration, reducing its study to a single parameter, such as respiratory rate, seems to be insufficient, being necessary more variables. These parameters are based on respiratory gases, particularly oxygen uptake (VO2) and carbon dioxide output (VCO2), which are sensitive to cognitive load and can be influenced by emotional processes [257]. Other aspects such as respiration rate, velocity, and depth, should be considered due to their alteration in different mental states and diseases.

Human emotion typically affects both the depth and speed of breathing. For example, deep breathing indicates excitement brought on by happiness, anger, or fear; shallow breathing denotes tension; relaxed people frequently have deep breathing; shallow breathing shows a calm or negative attitude. According to [258], a person typically breathes 20 times per minute when they are calm and 40 times per minute when they are excited. Due to the complexity of the respiratory processes and the fact that they have an impact on a significant portion of the body, there are numerous approaches for evaluating respiration.

Spirometry is a lung test that evaluates the amount of air inhaled and exhaled, and the speed of exhalation. There are several types of spirometers that measure the volume of air in different ways such as using pressure difference, ultrasonics, water, or a wright peal flowmeter spirometer. This technique can be useful for determining VO2 and VCO2 levels [257], [259].

Capnography is a minimally invasive measurement of the partial pressure of CO2 from the airway during inspiration and expiration [260]. This technique uses sensors to measure the carbon dioxide (CO2) present in exhaled gases. It provides physiological information on ventilation, perfusion, and metabolism, which is important for airway management.

Other techniques are non-invasive and easier to apply, even though they are more focused on measuring variables such as respiratory rate, or respiratory effort, instead of O2 or CO2 levels. One of the most commonly used techniques is based on plethysmography. Plethysmography techniques use instruments to measure the increase in blood flow in a region of the body, and determine its volume differences [261]. Non-invasive plethysmography techniques are commonly used to measure respiratory rate. The use of PPG to determine the respiratory rate and respiratory effort could enhance the availability of respiratory data in wearable devices [262], [263].

On the other hand, respiratory inductance plethysmography (RIP) involves the use of elastic bands or belts wrapped around the chest and abdomen, detecting variances in the circumference of the thoracoabdominal area during breathing. Regularly, RIP is performed with two bands, because single-band approaches may not provide the same level of detail as the dual-band approach [264]. Similar to RIP, other respiratory motion monitoring (RMM) techniques include strain gauges, textile-based/resistive strain sensors, wire strains, or foam-based pressure sensors to record and analyze chest wall movements, thus obtaining several respiratory activity variables [265].

Thermal cameras can also be used to measure the respiratory rate, helping to analyse temperature fluctuations near the mouth and nose areas caused by exhaled air [266].

Apart from the non-invasive RMM techniques described previously, and other less intrusive methodologies, the majority of the techniques for assessing respiration activity considering parameters related to respiratory gases, are difficult to be applied in industry. The main reason is that these methods require subjects to wear a mask or perform intubation to collect the gases, which is not practical in industrial scenarios. Consequently, the use of respiration activity for analysing human factors in the industry requires more research and technology development to be performed in a more comfortable and suitable way for operators.

F. OCULAR ACTIVITY

The ANS also influences several features of the eyes such as pupillary response, blink ratio, percentage of eyelid closure (PERCLOS), and saccadic movements. Pupillary response refers to the difference in pupil diameter. Variances in pupil size could be derived from three main aspects, adjustments to brightness levels of the environment (light response), modifications due to fixation (near fixation) and variations in arousal and mental effort [267]. The eyelid is controlled by a complex system of muscles and nerves that work together to facilitate its opening and closing. The levator palpebrae superioris muscle is responsible for opening the eyelid, while the orbicularis oculi muscle is responsible for closing it. The levator palpebrae superioris muscle is innervated by the oculomotor nerve, while the orbicularis oculi muscle is innervated by the facial nerve. Additionally, the trigeminal nerve is responsible for detecting sudden, unexpected stimuli and initiating the protective blink reflex, which is also controlled by the orbicularis oculi muscle. The blink ratio is the interval between blinks, which may vary, depending on the conditions, from averages of spontaneous blinking of 12-15 blinks/min to 22 blinks/min in calm conditions [268]. Similarly, PERCLOS considers the slow drop of the eyelid over the pupil over time instead of a usual rapid and involuntary blink, and it is frequently used to study drowsiness [269]. Finally, saccades are rapid conjugate eye movements that shift the line of the sight (centre of gaze) from one part of the visual field to another and are mainly used for orienting towards objects of interest [270].

The technology that studies and identifies all these concepts is called eye-tracking. Eye-tracking can be defined as the study and measurement of eye movements in certain conditions and stimuli to extract and evaluate eye characteristics such as point of gaze, and pupil diameter, among others.

There are two main methods of performing eye-tracking: measuring the eye's position relative to the head, and determining the orientation of the eye in space also known as point of regard. The last one is more commonly used when the main interest is to track the position where a user is presumed to be observing rendered content on screens or other interfaces [271]. Considering these two eye-tracking methods, three major techniques have been developed to study this field: the scleral search coil technique, electro-oculography (EOG) and video-oculography (VOG).

- The scleral search coil technique is an invasive technique based on recording electrical currents induced by a magnetic field in a coil formed by thin wires situated in a circular plastic embedded in a contact lens, placed in the eye [272]. The signal produced by the induced voltage represents the eye position, allowing to achieve a three-dimensional recording of the eye movements. This methodology is precise and allows the measurement of eye position relative to the head, but at the same time, it has some disadvantages as it is intrusive, wearing lenses could cause discomfort, and it is not convenient for measuring the point of regard [271], [273].

- Electro-oculography is one of the most commonly used methodologies for capturing eye movements. On EOG a set of sensors are attached around the area encircling the eye, which records the skin's electric potential differences generated while the eyes are rotating [273]. The range of recorded potentials is between $15-200\mu V$ with nominal sensitivities on the order of $20\mu V/deg$ of eye movement [271]. EOG calculates eye movements by taking into consideration the head position, if there are no eye movements, the signal can be altered. Also, EOG is not usually employed in daily uses, however its application is more suitable for medical fields and laboratories [271], [273].
- Video-oculography systems have as their principal component a video that sends recorded images to a computer to process the data [274]. The first VOG devices and previous techniques had issues in providing the point of regard. It was necessary to have the head fixed or to measure multiple eye features to disassociate head movement from eye rotation [271]. Nowadays, the majority of the devices use high-resolution cameras and near-infrared technology To provide VOG with the capacity to offer the point of regard. It is crucial to detect the above-mentioned features of the eyes to precisely detect the pupil region. If there is an inaccurate segmentation of the pupil by the camera, the extracted data and its analysis can be compromised [56]. The most common technique to provide the point of regard is called pupil centre corneal reflection (PCCR). PCCR uses a camera to track the pupil's centre and light reflection in the cornea. Corneal reflection, or glint, is used as a fixed reference point. Later, the vector composed of the angle between the two features, pupil centre and corneal reflection is calculated, which combined with other geometrical data, gives the point of regard, solving the related issues of head movement sensitivity [273], [275].

Among the presented methodologies for extracting eye features, the more used in industry and research is infrared oculography (IOG). Among this category, there are two types of eye trackers: remote and mobile. Depending on the use case, one could be more suitable than the other, having both benefits and drawbacks.

- Remote eye trackers: They are usually comprised of a camera and infrared source. The most common are the screen-based ones used in cases where the operator spends most of the time in front of a screen. The eye tracker device is positioned at the bottom of the screen, where it records a functional working region known as the head box. The device captures the eye movements when the user is within the boundaries of the head box.
- Mobile eye trackers: These devices are worn by the subjects and employed in dynamic environments where they have to look in different planes and move in real-life scenarios, facilities, or virtual environments. Typically, the device has the form of glasses or a headband which contain small cameras targeting the eye and the view field or scene.

Using eye-tracking technology might be challenging in some scenarios. In cases where the user is not wearing the eye-tracking device, such as in screen-based eye trackers, the eye trackers could struggle to calculate accurately where the users are looking. For example, if the users are not looking directly at the screen, their faces leave the detection area, or even if they are moving, screen-based eye trackers might face difficulties in the detection. To solve those aspects, it is required fast calibrations, which apart from the user's movement, they should also consider demographic features, lighting, among other parameters.

Additionally, in several studies of human factors, eye-tracking is used with other technologies such as EEG. In particular, when Extended Reality (XR) with eye-tracking is combined with EEG, an arising challenge is the placement of the XR headsets with the EEG headset. Usually, XR headsets have bands that attach the glasses to the user's head. These bands cover positions where the EEG electrodes should be placed. To solve this issue, several companies are combining

TABLE 1. Physical and ocular fatigue: main psycho-physiological alterations and measurement techniques.

Physiological activity	Features	Techniques
Brain	Apparence of ECPs in the posterior cingulate cortex	MEG *
	Reduced peak alpha frequency near the motor cortex	EEG
	Reduced peak alpha frequency in frontal and prefrontal cortexes	
Cardiovascular	Significant increase in HR	ECG
	Increased low-frequency components in HRV	PPG
	Increased LF/HF ratio of components of HRV	
	Variations in heart rate entropy	
Muscular	Limited electrochemical signal	EMG
	Altered dynamics	Computer vision (CV) **
Ocular	Longer fixations	VOG
	Slower saccades	IOG
	Glissading undershots	EOG
	Increased blink frequency	

* Magnetoencephalography (MEG) is an intrusive technique, incompatible with workspaces.
** CV techniques are wide and require specific knowledge, therefore CV is beyond the scope of this article.

XR headsets with EEG headsets, which can be helpful because if the XR headsets include eye-tracking, there will not be any sensory data lost.

VI. CLASSIFICATION OF RESULTS

This section provides a condensed summary of the previous sections, creating a bridge between Sections IV and V. The tables presented in this section aim to offer a comprehensive reference for researchers and practitioners working in the field of human factors.

These tables summarize the psycho-physiological alterations associated with each human factor discussed in the previous sections, including physical fatigue (Table 1), attention (Table 2), cognitive workload (Table 3), stress (Table 4), trust (Table 5), and emotional state (Table 6). Each table provides a concise overview of the main physiological signals affected by a particular factor, highlighting the complex relationships between human factors and physiological responses. These tables serve as useful references for readers to quickly

TABLE 2. Attention: main psycho-physiological alterations and measurement techniques.

Physiological activity	Features	Techniques
Brain	Increased high-frequency activity Decreased low-frequency activity Increased HF/LF spectral power ratio	EEG
Cardiovascular	Higher HRV at rest	ECG PPG
Ocular	Longer gaze fixation More frequent saccades * Pupil diameter Gaze convergence	VOG IOG EOG

* Only if the task requires visual attention.

TABLE 3. Cognitive workload: main psycho-physiological alterations and measurement techniques.

Physiological activity	Features	Techniques
Brain	Decreased theta band power Decreased alpha band power Increased beta band power Increased gamma band power Higher asymmetry between hemispheres	EEG
Cardiovascular	Increased heart rate Decreased inter-beat interval Increased low-frequency activity Decreased high-frequency activity Increased systolic blood pressure Increased blood oxygenation	ECG PPG SPH *
Electrodermal	Increased sweat gland activity	GSR
Ocular	Changes in pupil diameter Increased gaze entropy Increased microsaccade magnitudes Increased blinking latency Decreased blinking duration	VOG IOG EOG

* Sphygmomanometry(SPH) is not suitable for continuous monitoring because it requires the person to remain still and applies an uncomfortable amount of pressure. Thus, this technique is beyond the scope of this study.

TABLE 4. Stress: main psycho-physiological alterations and measurement techniques.

Physiological activity	Features	Techniques
Brain	Increased right hemisphere activity	EEG
Cardiovascular	Increased heart rate Increased blood pressure Increased low-frequency activity Decreased high-frequency activity	ECG PPG SPH
Electrodermal	Increased skin conductance Decreased high-frequency activity	GSR Skin thermometry (ST)
Respiratory	Increased respiration rate Variations in chest wall movement	RMM Spirometry Capnography
Ocular	Increased pupil diameter	VOG IOG

TABLE 5. Trust: main psycho-physiological alterations and measurement techniques.

Physiological activity	Features	Techniques
Brain	Heterogeneous variations in several areas and wavelengths	EEG
Cardiovascular	Increased heart rate	ECG PPG
Electrodermal	Increased peak values of skin conductance	GSR
Muscular	Changes in facial expression	MEG CV
Ocular	Increased pupil diameter Gaze direction and behaviour *	VOG IOG

* Indicator of the automation monitor checking frequency

TABLE 6. Emotional state: main psycho-physiological alterations and measurement techniques.

Physiological activity	Features	Techniques
Brain	Brain laterality *	EEG
Cardiovascular	Increased heart rate Increased blood pressure	ECG PPG SPH
Electrodermal	Increased arousal Increased skin temperature	GSR ST
Muscular	Changes in facial expression	MEG CV
Respiratory	Increased respiration rate Variations in chest wall movement	RMM Spirometry Capnography
Ocular	Increased pupil diameter Gaze patterns	VOG IOG

* Increased brain activity on the right hemisphere for negative emotions. Increased left hemisphere activity for positive emotions.

TABLE 7. Key companies in the market and their most representative products for measuring activity in the CNS.

Company	Devices	Observations
Emotiv	Epoc Flex Epoc X Insight2 MN8	32-channel - Gel or saline electrodes 14-channel - Saline-based electrodes 5-channel - Semi-dry polymer sensors 2-channel EEG earbuds + audio + microphone
brain.space	brain.space	460 sensors for full-head coverage - Dry electrodes
Bitbrain	Diadem Air Hero Versatile EEG	12-channel - Dry electrodes 8-channel - Dry electrodes 9-channel - Dry electrodes 8, 16, 32, and 64 channels cap
CGX	Quick-20m Quick-20r v2 Quick-32r Mobile-128 Mobile-72 Dev Kit	20-Channel - Dry Electrodes 21-channel + 2 channels (EEG/EOG/EMG/ECG) - Dry electrodes 32-channel - Dry electrodes 128-channel - Wet electrodes 72-channel - Wet electrodes 8-channel - Dry electrodes
Brain Products	actiCAP slim actiCAP snap actiCAP Xpress Twist BrainCap R-Net	8 to 160 channel - Gel electrodes - Fixed electrodes 8 to 160 channel - Gel electrodes - Removable electrodes 8, 16, or 32 channels - Dry electrodes 8 to 256 channels - Gel electrodes 32 to 160 channels sizes - Sponge-based electrodes
OpenBCI	EEG Electrode Cap Kit Ultracortex "Mark IV" EEG Headset Gelfree BCI Electrode Cap Headband kit	21-channel - Gel electrodes 16-channel - Dry electrodes - 3D Printed EEG headset 16-channel - Saline electrodes 8-channel - Dry electrodes
Galea	Galea	Headset integrates EEG + VR + EMG + EOG + EDA + PPG
Biosemi	Biosemi caps	16 to 256 channels
g.tec	g.Nautilus Pro g.Nautilus Pro Flexible g.Nautilus Multi-Purpose g.Nautilus Research	8, 16, or 32 channels - Dry or wet electrodes 8, 16, 19 or 32 channels - Hybrid or wet electrodes 8, 16, 32, 64 channels - Hybryd or wet electrodes - ECG/EOG/EMG 8, 16, 32, 64 channels - Hybryd or gel electrodes
Neuroelectrics	Enobio	8, 20 and 32 channels -Dry and wet electrodes

understand key aspects of each factor and guide future research and practice in this area.

Further, a summary of the technologies used to measure the alterations in psychophysiological signals is presented. For readability issues, the information is divided into two different tables. The first table (Table 7) focuses on technologies that measure brain activity related to the central nervous system (CNS), while the second table (Table 8) covers devices that measure the physiological signals affecting the peripheral nervous system (PNS). Both tables include the most notable currently available commercial solutions for each technology in the list. As this paper's objective is to investigate the measurement of human factors in the workplace to improve worker well-being and industrial results, only technologies that are compatible with working environments are covered in these tables. In this sense, technologies that are incompatible with the working activities (such as magnetoencephalography and sphygmomanometry among others) are not listed.

VII. DISCUSSION AND CONCLUSION

Controlling human factors in industrial workplaces is crucial for improving worker well-being and productivity. The six human factors discussed in this article – physical fatigue, attention, mental workload, stress, trust, and emotional state – have a significant impact on workers' performance and well-being, and thus they should be monitored and controlled. Understanding the effects of each human factor on psycho-physiological signals is essential to develop effective control strategies.

Different human factors can affect several psycho-physiological signals, and it can be challenging to distinguish one from another. For instance, stress can cause an increase in heart rate, breathing rate, and electrodermal activity. However, cognitive workload provokes very similar reactions, including also an increase in heart rate and electrodermal activity. Therefore, it is essential to consider multiple signals to identify the specific human factor that needs to be addressed.

Furthermore, measuring psycho-physiological alterations can be difficult, as some equipment, such as magnetoencephalograms and sphygmomanometers among others, may not be compatible with the industrial environment, rendering them impossible to use for industrial implementation. However, by combining different techniques and devices, it is possible to achieve full coverage of the main variables needed

TABLE 8. Key companies in the market and their most representative products for measuring activity in the PNS.

Techniques	Company	Devices	Observations
ECG	plux	cardioBAN Kit	
	Bittium	Bittium Faros 360 Bittium Faros 180 Bittium Faros 180L	1-3 Channels for Demanding Ambulatory ECG Monitoring 1 Channel recording for Ambulatory ECG Monitoring for 7 days 1 Channel recording for Ambulatory ECG Monitoring for 14 days
	Shimmer	Shimmer3 ECG	
	Polar	Polar H10	
GSR	plux	Biosignalplux EDA Sensor	
	Shimmer	Shimmer3 GSR+	
	Empatica	embracePLUS	EDA + SpO2 + HR + Temperature + Respiratory rate + Others
EMG EOG	plux	muscleBAN Kit	
	TMSi	Textile HD-EMG grids Flex PCB HD-EMG grids Micro eletrode multi cable Snap eletrode multi cable	32 or 64 channel - Grids with various sizes and topologies 64-channel - 8 by 8 HD-EMG grid 32 channels for small surface electrodes in customizable topology 32 channels and snaps for standard disposable surface electrode
	Shimmer	Shimmer3 EMG Unit	
RMM	Spes Medica	Reusable Respiratory Effort Sensors	
	ADInstruments	Equivital Sensor Belt Repiratory Belt Sensor Respiratory Belt Transducer	Belt with shoulder straps for better adjustment
	Vernier	Go Direct Respiration Belt	
	Smartex	Wearabale Wellness System	Respiratory signals + ECG + Posture + Energy expenditure
VOG IOG	Tobii Pro	Tobii Pro Glasses Tobii Pro Spectrum Tobii Pro Fusion Tobii Pro Spark Tobii Pro Nano	Mobile eye tracker - 50 Hz or 100 Hz sampling frequency Screen-based - max. screen 24" - 60 to 1200 Hz sampling frequency Screen-based - max. screen 24" - 30 to 250 Hz sampling frequency Screen-based - max. screen 27" - 60 Hz sampling frequency Screen-based - max. screen 24" - 60 Hz sampling frequency
	Pupil Labs	Neon Invisible Core	Mobile eye tracker - 200 Hz sampling frequency Mobile eye tracker - 200 Hz sampling frequency Mobile eye tracker - 200 Hz sampling frequency
	Smart Eye	AI-X XO Aurora Smart Eye Pro	Screen-based - max. screen 24" - 60 Hz sampling frequency Remote eye tracker - 30 Hz to 120 Hz sampling frequency Remote eye tracker - 60 Hz to 250 Hz sampling frequency Remote eye tracker - 2 to 8 cameras - 360-degree head and eye tracking - 60 Hz and 120 Hz sampling frequency
	View Point System	VPS 19	Mobile eye tracker - 60 Hz sampling frequency
	Argus Science	ETVision System	Mobile eye tracker - 180 Hz sampling frequency
	Gazepoint	GP3 HD	Screen-based eye tracker - 150 Hz sampling frequency
	Ergoneers	DIKABLIS Glasses 3 DIKABLIS HDK Eye Tracker	Mobile eye tracker - 60 Hz sampling frequency Mobile eye tracker - 60 Hz sampling frequency

to assess and utilize human factors. For example, using a portable electroencephalogram (EEG) to measure brain activity and an electromyogram (EMG) to measure muscle activity can provide a comprehensive understanding of how physical fatigue impacts worker performance.

Industry 5.0 emphasizes a human-centric perspective in industrial environments. Monitoring human factors is one way to achieve this, as it can lead to numerous benefits, such as a healthier environment, increased worker satisfaction, and improved safety and well-being. Additionally, it can also result in improved productivity, as it can help to identify the root cause of poor performance and implement strategies to improve it.

While the literature on this topic is extensive, there is still room for deeper theoretical and experimental analysis of the influence of human factors in industrial environments. Also, further research is necessary to develop new techniques and devices that enable the inclusion of newer and more accurate metrics to evaluate human factors. For instance, new developments in wearable technology and sensor fusion can offer a more integrated and holistic approach to measuring human factors. To illustrate some potential research beyond the scope of this paper, computer vision has been identified as a valuable technique to assess certain human factors like physical fatigue, trust and emotional state. The complexity of these techniques demands a specific review to assess the potential impact in this area.

In conclusion, controlling human factors in industrial workplaces is essential for achieving both human and productivity benefits. By prioritizing the well-being of workers and utilizing technological advancements, industrial environments can become more human-centric and efficient. More research and development are needed to expand our understanding of human factors and to improve the techniques and devices used to monitor them. This will enable the development of more effective and tailored strategies to enhance worker well-being and boost productivity in industrial settings.

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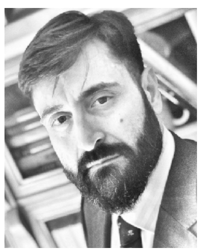

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