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Review

Understanding the Unexplored: A Review on the Gap in Human Factors Characterization for Industry 5.0

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Abstract: The integration of neurophysiological techniques into Industry 5.0 represents a transformative approach to assessing human factors in real-world operational settings. This study presents a systematic review of existing literature to evaluate the application of neurophysiological methods in assessing cognitive and emotional states, such as workload, stress, attention, and trust, within industrial environments. A total of X peer-reviewed articles published between 2018 and 2024 were analyzed following a structured methodology. The findings reveal that EEG (45%), eye-tracking (30%), EDA (20%), and ECG (15%) are the most frequently adopted techniques for monitoring cognitive and emotional responses. Additionally, 60% of the studies focused on stress and workload assessment, while only 25% examined trust and collaboration in human–robot interaction, highlighting a gap in comprehensive teamwork analysis. Furthermore, only 35% of the studies validated their approaches in real-world industrial settings, emphasizing a significant limitation in ecological validity. The review also identifies that multimodal integration remains underexplored, with just 15% of studies combining multiple neurophysiological signals for a more holistic assessment. These results indicate a growing but still fragmented research landscape, with clear opportunities for expanding real-world applications, improving methodological standardization, and fostering interdisciplinary collaboration. Future research should prioritize validation in dynamic, real-life work environments and explore the synergistic potential of multimodal neurophysiological approaches to enhance human-centred industrial systems.

Keywords: Industry 5.0; EEG; human factors; mental states; neurophysiological signals

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1. Introduction

The advent of Industry 5.0 marks a new phase in the industrial transformation process. According to the European Commission (EC) this paradigm provides a transformative vision for industry as a driver of sustainability, resilience, and human-centricity [1]. In contrast to the focus of Industry 4.0, which was to ensure that all industrial sectors make

optimal use of new technologies and manage their transition towards higher value digitized products and processes [2], Industry 5.0 emphasizes a more human-centric approach, even if specific concepts related to the human–machine interaction, as the Digital Twin approaches, are still included in the concept of Industry 4.0. In this regard, it has to be underlined that the focus of Industry 5.0 concept is based on the rising of the human-centric approach. This not only aims at production efficiency but also at the creation of safer, more inclusive and cognitively optimized working environments through collaboration between humans and machines. This shift in perspective represents a significant challenge for modern industry, which must reorient its processes to integrate advanced technologies with the psychophysical needs of workers.

A crucial element of this transformation is the optimization of human factors, which encompass the physical, cognitive, and emotional dimensions that influence workers' capacity to interact effectively with complex systems. The aim of Industry 5.0 is to create work environments where human decision-making, experience, and creativity are enhanced rather than replaced, through the use of emerging technologies such as artificial intelligence (AI), collaborative robotics and cyber-physical systems. However, the introduction of cobots, semi-automated interfaces and adaptive systems entails new cognitive and psychological responsibilities for workers [3], who must adapt rapidly to evolving technologies, process real-time information and operate in highly interconnected environments. Consequently, there is a need for a comprehensive understanding of the dynamics governing human–machine interaction (HMI). In response to these challenges, neurophysiological methodologies offer a valuable perspective for analyzing and improving this type of collaboration. Techniques such as electroencephalography (EEG), eye movement monitoring (eye-tracking), electrodermal activity (EDA), photoplethysmography (PPG) and electrocardiogram (ECG) facilitate objective measurement of cognitive and emotional states, thereby providing valuable data for the design of ergonomic interfaces, adaptive support systems and customized training programmes. These measures are distinguished from subjective evaluation questionnaires, e.g., NASA Task Load Index [4] for the detection of perceived mental workload, and behavioural parameters by their objectivity, high temporal resolution and ability to reveal implicit mechanisms of the human body.

Previous reviews have explored related aspects of human factors and Industry 5.0, but none have specifically focused on the comprehensive analysis of neurophysiological methodologies and their ability to address the identified gaps. For example, Loizaga and colleagues [5] conducted a comprehensive study of human factors, sensory principles, and commercial solutions for human-centred working operations in Industry 5.0 but did not delve into the detailed analysis of neurophysiological methods. Similarly, Panagou and collaborators [6] presented a scoping review of human–robot interaction research towards Industry 5.0 human-centric workplaces but did not focus on the specific contribution of neurophysiological methodologies.

This review addresses the gap in the existing literature by providing a detailed overview of the applications of neurophysiological methodologies in the evaluation and optimization of human factors in Industry 5.0. In detail, the dynamics related to the main human factors will be analyzed, with particular attention paid to the contribution of neurophysiological techniques in the measurement of stress, mental workload, attention, trust and learning. Furthermore, the opportunities and challenges associated with the use of these tools in industrial contexts will be discussed. Finally, the main gaps in the current literature will be identified, and future directions will be suggested to promote an effective transition to a more human-centred, sustainable, and technologically advanced industrial model.

2. Methods

Material Selection

The present review follows an accurate and rigorous methodology to ensure comprehensive coverage of the research topic and transparency in the selection process. Specifically, the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework was adopted to structure the review process comprehensively and consistently. The application of the PRISMA methodology allows for clear documentation of the stages of literature selection, inclusion, and exclusion criteria, ensuring the replicability and reliability of the findings. This ensured that only the papers assumed to be relevant, up-to-date, and of high quality were included, as shown in Figure 1. The literature search was conducted using major scientific databases, including Scopus, Web of Science, and PubMed, with the objective of identifying studies utilizing neurophysiological methods for human factors analysis in the context of Industry 5.0. Therefore, the literature research was focused on previous works based on neurophysiological signals, such as the one representing the brain activity and the autonomous nervous system activations (e.g., electrodermal and cardiac activities). More specifically, the present work aimed at identifying (i) how have neurophysiological methods been used to assess human factors in industrial environments, and (ii) what are the existing gaps and limitations in current research on neurophysiological methods in Industry 5.0. In order to achieve this, a review was performed by focusing on the neurophysiological signal-based works (i.e., brain activity, electrodermal and cardiac activities, and eye-tracking).

In this context, the search strategy was based on the use of specific keywords and the application of exclusion criteria. The query used on both search engines was as follows: ('neurophysiological measures' OR 'EEG' OR 'GSR' OR 'EDA' OR 'eye-tracking' OR 'ECG') AND ('human factors' OR 'worker training' OR 'operator training' OR 'human-machine interaction') AND ('Industry 5.0' OR 'semi-automated machines' OR 'automation'). The Boolean AND and OR operators were employed in order to obtain a combination of terms that would encompass the widest possible range of research pertinent to the utilization of neurophysiological measures for the evaluation of human factors in human–machine interaction and in an industrial context. The inclusion criteria were defined as follows:

- Studies focusing on the characterization of human factors in industrial or workplace settings.
- Research employing neurophysiological methods (e.g., EEG, EDA, PPG) to evaluate human factors.
- Articles providing empirical data, theoretical insights, or methodological advancements related to Industry 5.0.

Similarly, the exclusion criteria were defined as it follows:

- Studies not directly related to the context of Industry 5.0.
- Research focusing exclusively on clinical or non-industrial applications.
- Articles without accessible full text or with incomplete datasets.

The analysis included peer-reviewed articles published in English between 2018 and 2024. This ensured that the review was based on the most recent findings and thus, related to Industry 5.0, which has its theoretical origins less than a decade ago. The initial search yielded a total of 56 articles, of which 36 were excluded due to thematic irrelevance, as they focused on the study of human factors in automotive or air traffic control. The final sample comprised 20 articles, which were included in the review to provide a comprehensive and up-to-date overview of the applications of neurophysiological methods in Industry 5.0. In summary, the 45% of the selected works rely exclusively on the HFs characterization through the EEG features, while the 25% rely on the multimodal approach (i.e., considering the combination of different neurophysiological signals). Table 1 presents an

overview of the articles included in the present review and the relevant neurophysiological methods employed.

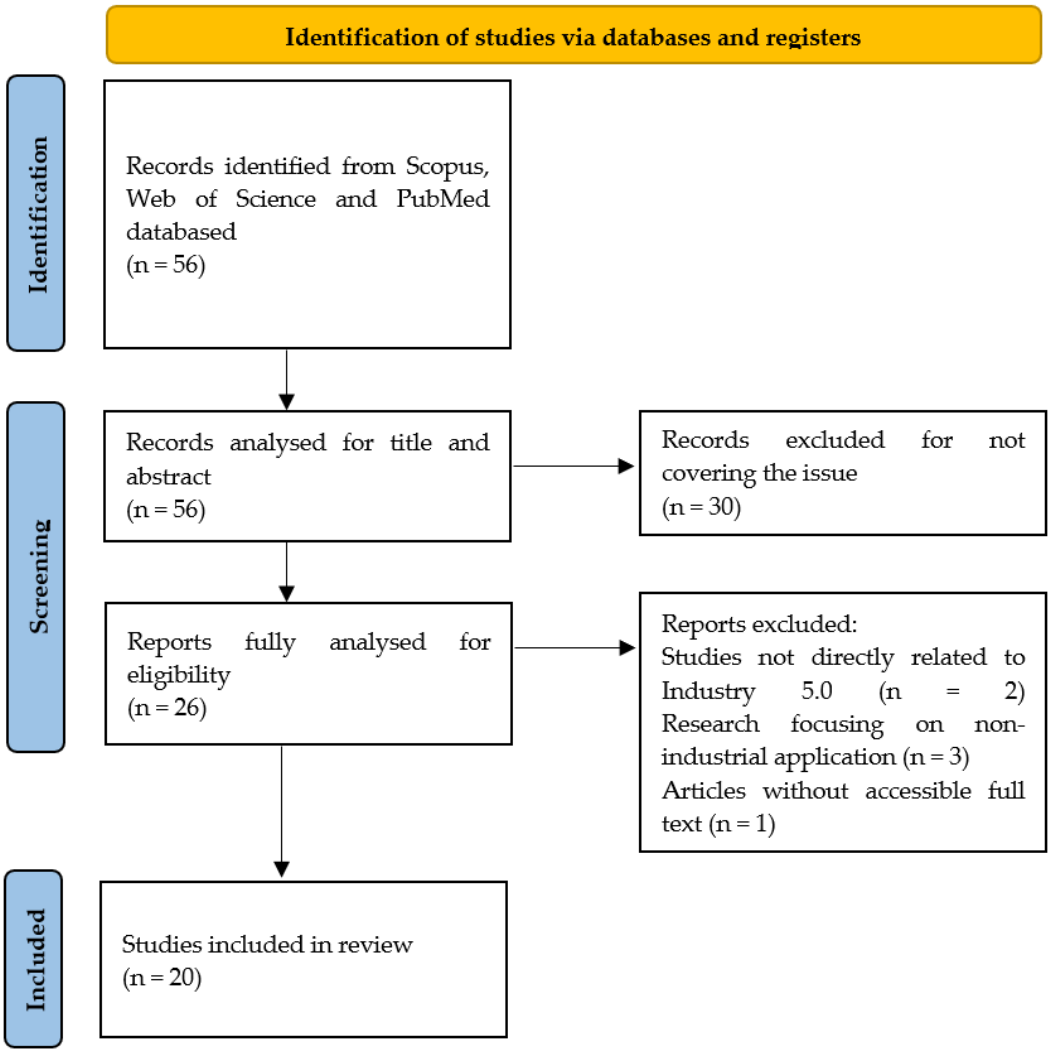

Figure 1. Articles selection flowchart for integrative literature review performed according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework.

Table 1. List of articles included in the review and relevant neurophysiological methods applied.

Title	Year	Author	Neurophysiological Methods	Nature of Research
A Novel Measurement Method for Performance Assessment of Hands-Free, XR-Based Human–Machine Interfaces	2024	[7]	EEG, Eye-tracking	Quantitative study
Assessing Trust in Collaborative Robotics with Different Human–Robot Interfaces	2024	[8]	EDA	Quantitative study
Integrating Mental Workload Management in advanced Human–Machine Interaction: the development process of the Proof-Of-Concept to refine the concept	2024	[9]	EEG	Qualitative study
Eye-tracking support for analyzing human factors in human–robot collaboration during repetitive long-duration assembly processes	2024	[10]	Eye-tracking	Quantitative study

Table 1. *Cont.*

Title	Year	Author	Neurophysiological Methods	Nature of Research
Multimodal Assessment of Cognitive Workload Using Neural, Subjective and Behavioural Measures in Smart Factory Settings	2023	[11]	EEG, fNIRS	Quantitative study
An Experimental Protocol for Human Stress Investigation in Manufacturing Contexts: Its Application in the NO-STRESS Project	2023	[12]	EEG, ECG, EDA, EMG	Qualitative study
Advanced workstations and collaborative robots: exploiting eye-tracking and cardiac activity indices to unveil senior workers' mental workload in assembly tasks	2023	[13]	Eye-tracking, PPG	Quantitative study
Digital Identification of the Human Condition as a Prerequisite for the Effectiveness of the Organizational Automation (Biocybernetic) Systems Operation	2022	[14]	ECG	Qualitative study
Assessing attentive monitoring levels in dynamic environments through visual neuro-assisted approach	2022	[15]	EEG, Eye-tracking	Quantitative study
Effect of Cognitive Fatigue, Operator Sex, and Robot Assistance on Task Performance Metrics, Workload, and Situation Awareness in Human–Robot Collaboration	2021	[16]	ECG	Quantitative study
Neural Correlates of Variations in Human Trust in Human-like Machines during Non-reciprocal Interactions	2019	[17]	EEG	Quantitative study
Human or not human? Performance monitoring ERPs during human agent and machine supervision	2019	[18]	EEG	Quantitative study
Cognitive work protection—A new approach for occupational safety in human–machine interaction	2019	[19]	EEG	Qualitative study
A classification model for sensing human trust in machines using EEG and GSR	2018	[20]	EEG, EDA	Quantitative study
EEG-Based Neural Correlates of Trust in Human–Autonomy Interaction	2018	[21]	EEG	Quantitative study
Eye tracking: A promising method for inferring trust in real time	2018	[22]	Eye-tracking	Quantitative study
Toward Industry 5.0: A Neuroergonomic Workstation for a Human-Centred, Collaborative Robot-Supported Manual Assembly Process	2024	[23]	EEG	Quantitative study
A Comprehensive Study of Human Factors, Sensory Principles, and Commercial Solutions for Future Human-Centred Working Operations in Industry 5.0	2023	[5]	/	Review
Human-in-the-loop configurations in process and energy industries: a systematic review	2022	[24]	/	Review
Interface for Human Machine Interaction for assistant devices: A Review	2020	[25]	/	Review

Table 1. *Cont.*

Title	Year	Author	Neurophysiological Methods	Nature of Research
Human–machine interaction towards Industry 5.0: Human-centric smart manufacturing	2024	[26]	/	Review
A scoping review of human robot interaction research towards Industry 5.0 human-centric workplaces	2023	[6]	/	Review
Neuroergonomics on the Go: An Evaluation of the Potential of Mobile EEG for Workplace Assessment and Design	2023	[27]	/	Review
Evaluating quality in human–robot interaction: A systematic search and classification of performance and human-centred factors, measures and metrics towards an Industry 5.0	2022	[28]	/	Review

3. Relevant Human Factors in Industry 5.0

The concept of Industry 5.0 is defined by an increasing collaboration between advanced technologies and human beings, with the objective of fostering the well-being, safety, and productivity of workers. This objective can be pursued by optimizing human factors. Despite the absence, due to their close interdependence, of a definitive list of human factors for describing human–machine interaction in this novel context [6], five states between physical, cognitive and psychological have been identified as being particularly pertinent: mental stress, mental workload, attention, trust, and learning.

3.1. Stress

In one classic interpretation, stress is defined by Lazarus and colleagues as "a particular relationship between the person and the environment that is appraised by the person as taxing or exceeding their resources and endangering their well-being" [29]. In the context of the workplace, stress can be defined as a reaction to organizational pressures, complex tasks and interaction with technological environments. It has been demonstrated that work-related stress has a significant correlation with burnout and other mental disorders [30], resulting in reduced performance or the intention to leave one's position. The principal causes of stress in contemporary industrial contexts include information overload resulting from the concurrent processing of multiple data streams in real time, the adaptation to novel technologies and human–machine interactions. Indeed, the study by Korner and colleagues identified several stress factors related to the introduction of modern systems in the manufacturing industry [31]. These included technical problems, poor usability, low situation awareness, and increased requirements for employees' qualifications. When these factors are combined, they can cause a disruption to the workflow and a slowdown of the work process, which in turn leads to additional time pressure and perceived stress. Therefore, stress management needs to be approached in a multidimensional manner, encompassing ergonomic interface design, the implementation of support systems for the real-time monitoring of critical stress conditions, and the provision of training programmes designed to equip workers with the skills necessary to effectively manage stress.

3.2. Mental Workload

The mental workload is used to describe the amount of mental resources required by an individual to complete a task at a given time. This intricate measure has been delineated by Sweller in Cognitive Load Theory as comprising three principal components: cognitive load,

intrinsic load, and germinal load [32]. These are, respectively, associated with the nature and complexity of the task, the manner of information presentation, and the processes of learning new information. In the industrial context, mental workload represents a crucial indicator for the assessment of the level of mental effort required by workers, particularly in situations of high human–machine interaction. The advent of Industry 5.0 has resulted in a shift towards workers having to make rapid decisions based on real-time information, while simultaneously supervising systems such as collaborative robots (cobots) and semi-automated machinery. This has led to an increase in the cognitive demands placed upon workers, who are required to adapt to evolving technologies on a continuous basis. It has been demonstrated that an excessive cognitive load for manufacturing workers can result in a decline in the quality of their work, with an increase in human error being a direct consequence [33,34]. The implementation of adaptive systems and collaborative robots that reduce the cognitive load through automation, in conjunction with appropriate staff training, can lead to an optimization of human–robot collaboration.

3.3. Attention

Attention can be defined as a selective process that determines which items are selected for subsequent processing [35]. This factor is examined in terms of situation awareness (SA), which can be defined as "perception of those elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future" [36]. Attention is fundamental to forming and maintaining situational awareness, and the ability to correctly allocate attentional resources helps workers detect and perceive hazards, thus reducing the risk of accidents [37,38].

3.4. Trust

The psychological concept of trust refers to the attitude of security and positive expectation towards an entity (e.g., a machine or system), based on the perception of its reliability, predictability, and transparency. According to Lee and See [39], trust in automation can be defined as "the belief that a system will operate effectively, reliably and safely in a given situation".

The concept of trust is not static and can be subject to change based on direct experience, observed performance, and user characteristics. In the context of human–machine interactions, trust is of paramount importance to ensure the effective and safe use of semi-automated machines and collaborative robots (cobots). In a human-centred context, trust in machines is contingent upon the clarity, simplicity, and consistency of interaction.

It is important to note that an excess of trust may induce negligent behaviour, such as a lack of supervision, while an insufficient level of trust may result in the ineffective use of machines, leading to a reduction in productivity. Therefore, it is crucial to identify a balanced level of trust, which may vary from one subject to another [40].

3.5. Learning

The term learning is used to describe the process by which an individual acquires, organizes and applies new knowledge or skills. In Industry 5.0, the training phase is not a one-time event; rather, it is a continuous and adaptive process. This is necessary to adapt to changing processes and interact with emerging technologies such as artificial intelligence. Individual differences pose limits to learning, e.g., not all workers learn at the same pace or in the same way, some workers resist change, and the complexity of the systems may result in a high cognitive load. Continuous or lifelong learning is seen as the best way to meet the dynamic challenges of the working environment [1,41].

4. Results

4.1. Equipment for Neurophysiological Signals Collection

The monitoring of human factors through the use of neurophysiological measurements can only contribute to the enhancement of health and working conditions for users if the equipment employed for the collection of biosignals is ergonomically designed and does not impact the performance of activities. Given its significance in an operational context, this section will offer a comprehensive overview of the devices used in the scientific literature in order to obtain information on the primary human factors under consideration.

The primary methodology employed in the studies included in this review is electroencephalography (EEG) (percentage on the total selected studies corresponding to 55% [7,9,11,12,15,17–21,23]), which, as a representative measure of brain dynamics, namely the central nervous system (CNS), enables the monitoring of psychological states such as the mental workload, trust, and attention. In order to investigate the neural correlates of trust in human–machine interaction, Wang and colleagues [21] used the Cognionics HD72 high-density wireless dry EEG system (Cognionics, Inc., San Diego, CA, USA), collecting data from 46 electrodes positioned according to the international 10-5 System [42]. Despite the large number of electrodes in the specific experiment, the instrumentation did not particularly interfere with the performance of the tasks. However, low- to medium-density recording devices are predominantly used in experimental protocols. Jung and colleagues [17] employed the BrainCap EEG system (Brain Products GmbH, Gilching, Germany), which has 32 integrated electrodes (Ag/AgCl and passive) located at standard positions given by the International 10–20 system. Although these systems can reach up to 256 channels, this configuration represents a compromise between wearability and spatial resolution of brain activity.

The majority of studies were carried out with low spatial density devices (percentage on the total number of selected EEG studies corresponding to 64% [7,11,12,15,19,20,23]) in order to ensure minimal invasiveness and compatibility with other acquisition devices. The first example is the BrainWatch device, a portable system with wireless data transfer (Smarting MOBI), intended for online estimation of a user's mental workload during manual assembly tasks. This headphone-shaped device was custom-developed for the specific experimental scenario and was equipped with 11 semidry electrodes [23]. Moreover, the 14-channel Emotiv Epoc+ neuro-headset (Emotiv Inc., San Francisco, CA, USA) was used to provide a baseline measure of cognitive activity in conjunction with an eye-tracking system [15].

Zakeri and colleagues [11] implemented a simultaneous acquisition of signals, EEG and fNIRS, to obtain the brain's electrical signals and hemodynamic activity, respectively. EEG was recorded using TMSi Mobita wireless data acquisition system with 19 electrodes (Twente Medical Systems International B.V., Oldenzaal, The Netherlands), while an eight-channel system, Artinis Octamon (Artinis Medical Systems BV, Elst, The Netherlands), was adopted for fNIRS. Akash and colleagues [20] opted for the B-Alert X-10 nine-channel EEG device (Advance Brain Monitoring, Carlsbad, CA, USA), with electrode placement according to the 10–20 system. The use of iMotions (iMotions, Inc., Boston, MA, USA) facilitated synchronization with another biosignal, electrodermal activity (EDA), which was recorded using the Shimmer3 GSR+ Unit (Shimmer, Boston, MA, USA).

Regarding the autonomic nervous system activity monitoring, the EDA signal provides a measure of the continuous changes in skin conductance in response to sweat secretion by the sweat glands. This is why it is used for the assessment of mental states that are reflected in the activation of the sympathetic nervous system, such as stress [43]. For this purpose, Menolotto and colleagues [8] adopted the same device to infer stress conditions of operators while performing assembly tasks with a cobot. Frequently, biosignals describing cardiac activity (e.g., ECG and PPG) are analyzed for the same human factors characterized

by the EDA signal. Both of these autonomic correlates of emotion arousal can be acquired nowadays through minimally invasive devices such as bracelets or chest bands. In their work, Hopko and colleagues [16] employed a two-lead chest affixed device (Actiheart 5, Camntech, Fenstanton, UK) to record electrocardiogram (ECG) signals.

Moreover, in the context of human–robot collaboration, eye-tracking represents a significant neurophysiological signal [44,45], offering a non-invasive means of evaluating human factors in studies. The Tobii Pro Glasses 2 and Tobii Pro Glasses 3 (Tobii AB, Danderyd, Sweden) are the primary devices used in research [10,15,46,47], with collected eye movement data analyzed using the Tobii Pro Lab software (version 2.0). In comparison with alternative psychophysiological methodologies, it is distinguished by its particular value in the domains of ergonomics [48], the study of operator-machine interactions [49], the identification of inefficiencies [50], and the training of workers to understand their learning processes [51]. The method affords the acquisition of numerous metrics, thereby providing a comprehensive array of information regarding the cognitive processes (e.g., mental workload) of the user, even during protracted tasks, due to its minimally invasive nature. Additionally, it can be integrated with AR or VR devices [52], which are typically employed to assist operators in communicating within the HRC [53].

4.2. Neurophysiological Assessment of Human Factors

The analysis of human factors in Industry 5.0 is based on the application of a combination of neurophysiological methods, each with specific capabilities to detect signals associated with stress, workload, attention and other cognitive and emotional dimensions, as shown in Table 2. The strength of this approach is that it provides an objective assessment, which is a significant advantage over other techniques such as subjective questionnaires and behavioural parameters. However, both methods are often acquired together in order to validate and strengthen the evidence obtained during studies.

Table 2. Overview of mental states in the considered literature for user monitoring in Industry 5.0.

Human Factor	Neurophysiological Signal	Evaluation Method	Relevance to Industry 5.0
Stress	EEG [11]	Increased theta- and beta-band power and decreased alpha-band power during tasks with high complexity or cobot speed	Work safety, errors' reduction, task efficiency enhancement in HRI
	EDA [12,20]	Phasic component analysis captures fast responses linked to emotional arousal	
	IMU [8]	Log Dimensionless Jerk (LDLJ) metric, where smoother movements indicate lower stress levels	
Mental workload	EEG [11,23]	Ratios such as TAR (Theta/Alpha), TBR (Theta/Beta) for real-time workload estimation	Overload prevention, training performance monitoring
	fNIRS [11]	Monitoring hemodynamic responses in the prefrontal cortex to assess workload variations	
	ECG/PPG [9,13,14,16]	Heart Rate Variability (HRV), particularly LF/HF ratio, to distinguish between high and low workload states. Increased HF occurred under high assistance and fatigue conditions	

Table 2. *Cont.*

Human Factor	Neurophysiological Signal	Evaluation Method	Relevance to Industry 5.0
Attention	Eye-tracking [15]	Fixation duration, saccade patterns, and blink frequency used to derive metrics like the Task Engagement Index (TEI) to classify attentiveness	Situational awareness, accident prevention
Trust	Eye-tracking [22]	Fixation count and duration indicate trust levels during HRI	Safety, collaboration, over/undertrust prevention
	EEG [17,20,21]	Decreased theta band power in the fronto-central region correlates with higher trust associated with cobot's correct actions	
	EDA [8,20]	Maximum and Net phasic components combined with EEG features provide real-time trust estimation through a classification model	
Learning	Eye-tracking [10]	Pupillary dilation, fixation number and duration and saccade frequency assess cognitive effort during learning phases	Fast adaptation, productivity maintenance

4.3. Neurophysiological Characterization of Stress in Industry 5.0

As previously mentioned, this factor is primarily detected by examining EDA signal parameters, as it is capable of capturing physiological arousal, which is associated with stress, anxiety and cognitive load. The EDA signal is decomposed into two components: the tonic (slow-varying) and the phasic (fast-varying). The analysis is primarily focused on the phasic component, as it is considered more indicative of fast cognitive activities and stress-related emotional responses [20]. The assessment of mental stress in the context of Industry 5.0 was carried out by means of experimental protocols involving the performance of assembly tasks in cooperation with a collaborative robot [8,10,11,20].

Menolotto and colleagues [8] employed an integrated methodology that combined subjective data (self-assessment questionnaires) and objective data (collected via wearable sensors). A series of neurophysiological measures were collected during two collaborative tasks with the robot (puzzle assembly and construction of a 3D structure). Each of these tasks was performed with three different human–robot interfaces (HRIs): hand control, touchscreen, and data glove. The objective of this study was to correlate perceived stress and confidence with interface and task characteristics. The objective metrics included Inertial Measurement Units (IMUs) and Electrodermal Activity. IMUs were employed for the purpose of assessing the fluidity of movement, which was correlated with hesitation or insecurity, using the log dimensionless jerk (LDLJ) metric: values closer to 0 indicate more fluid movements and a lower level of stress or muscle tension; on the other hand, high negative values suggest more irregular movements and a potential increase in stress. The level of stress exhibited by the participants varied significantly in accordance with the specific HRI and the nature of the task being performed. In terms of the ergonomics of the tools employed, it was demonstrated that the keyboard and touchscreen engendered greater confidence than the data glove, which was less intuitive and more stressful. Indeed, interaction with data gloves gave rise to more hesitation and less fluidity of movement, indicating less confidence.

In their study, Zakeri and colleagues [11] adapted the Stroop task, which is a standard task for assessing a person's control of their cognitive behaviour [54]. A pick-and-place task

was selected for analysis, as it involves the decision-making processes of a human worker. The environment is constructed such that the human worker is required to collaborate with a collaborative robot (cobot) and adjust their performance speed to align with that of the cobot. The objective of this study is to identify and analyze the effects of task complexity, speed and load capacity of the cobot on human mental stress using electroencephalogram (EEG) and fNIRS measurements. Subsequent analysis focused on the delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–28 Hz), and gamma (28–50 Hz) frequency bands power. The results indicated activation in the prefrontal cortex (FP1-F3-F7), a region critical for cognitive control and stress regulation. A reduction in relative alpha-band power, which is associated with increased cognitive activation and stress, occurred with increasing task complexity. Task complexity was the most significant factor in the induction of cognitive stress, while the load capacity of the cobot showed no significant differences in perceived stress. Despite the evidence, stress is treated more indirectly in these studies, mainly as a secondary effect of the mental load and fatigue factor. Consequently, a substantial proportion of the evidence pertaining to stress is more appropriately associated with changes in mental load, which is investigated as the primary human factor in the studies under consideration.

4.4. Neurophysiological Characterization of Mental Workload in Industry 5.0

Mental load has been monitored in most studies carried out in an operational context [10,11,13,16,23], so there are several neurophysiological metrics describing it in the literature. Pluchino and colleagues [13] employed eye-tracking and heart rate measurement to analyze the mental load of senior workers during assembly tasks with collaborative robots (cobots) within ergonomically advanced workstations. The metrics extracted from eye-tracking (duration and frequency of fixations) permitted the cognitive engagement and mental load of the participants to be evaluated. The duration and frequency of blinks were employed as indicators of fatigue and mental effort. When a dual task (comprising the main task and a secondary mathematical task) was performed, a notable increase in blink frequency was observed, indicating an elevated cognitive load. Moreover, these metrics were capable of predicting the number of errors made, suggesting that an augmented mental load has a detrimental impact on performance. Cardiac activity was employed as an indicator of the level of physical and mental effort. Heart rate confirmed a general engagement during the tasks but was not sensitive enough to detect more subtle variations in cognitive load, i.e., between the single-task and dual-task conditions. Ultimately, eye-tracking proved to be a more effective method for detecting changes in cognitive load during complex tasks, providing an in-depth under-standing of workers' mental load. Similar eye-tracking metrics were used by Gervasi and colleagues [10] in a study aimed at the simultaneous determination of mental load and learning during collaborative assembly processes.

A different parameter of cardiac activity, namely the heart rate variability (HRV) was employed for the purpose of monitoring continuous, non-intrusive physiological responses, with the objective of assessing participants' cognitive states, particularly in relation to mental fatigue and workload [16]. The participants were required to complete a task of polishing metal surfaces in collaboration with a joystick-controlled UR10 robot, with the assistance provided varying between low and high levels. The task required the participant to follow a predefined 'S'-shaped trajectory, delineated on the metal surface, comprising three lateral movements and two 'U'-shaped curves. The HRV and indices HF, LF, and HF/LF ratio, indicative of sympathetic and parasympathetic activity, were employed as a mean of classifying the participants' levels of mental fatigue and workload. It was observed that an increase in mental fatigue resulted in a predominant reduction in para-sympathetic activity or an increase in the LF/HF ratio. Moreover, the HRV data were correlated with

a number of experimental variables, including the level of robotic assistance, the gender of the operator and the fatigue status of the participants. Concerning mental fatigue, during robot-assisted sessions, increased parasympathetic activity was detected in the final blocks, suggesting potential recovery from fatigue levels. Concerning sex effects, women showed significant differences in LF/HF parameters compared to men, suggesting different sensitivity to fatigue states.

Another widely used neurophysiological method for characterizing mental load is the EEG [55]. Spectral analysis was found to be more frequent. In a recent study, Knežević and colleagues [23] employed electroencephalography (EEG) to validate a neuroergonomic workstation for a human-centred, collaborative robot-supported manual assembly process. A BrainWatch module, comprising a commercial EEG device (Smarting MOBI) and a custom-developed algorithm for the calculation of workload indices in real time, was employed to measure three indices related to the Cz channel: theta-alpha ratio (TAR), theta-beta ratio (TBR), and engagement index (EI). These were calculated according to the following equations:

$$\mathrm{TAR} = \frac{P_\theta}{P_\alpha},$$

$$\mathrm{TBR} = \frac{P_\theta}{P_\beta},$$

$$\mathrm{EI} = \frac{P_\beta}{P_\alpha + P_\theta}$$

where P_ϑ, P_α, and P_β represent the spectral powers in theta, alpha, and beta frequency bands, respectively. TAR is an index of workload and mental effort, based on the assumption that an increase in mental load is associated with a decrease in alpha power and an increase in theta power. TBR is associated with working memory, attention, and drowsiness and assumes that an increase in alertness and task engagement results in an increase in beta power and a decrease in theta power, while EI reflects mental effort, vigilance, attention, alertness, and task engagement [55,56]. Concurrently, a subjective assessment was conducted utilizing a subjective questionnaire, namely the NASA Task Load Index, with the objective of establishing a correlation between the scores obtained by the latter and the EEG indices. The intention was to ascertain which EEG indices are responsive to alterations in specific workload components as measured by the NASA-TLX. The correlation analysis revealed a significant positive correlation between the TAR and the mental demand score, a significant positive correlation between the TBR and the mental demand score, a significant negative correlation between the TAR and the overall performance score and a significant negative correlation between the EI and the effort score.

EEG and fNIRS features collected during an examination of the mental workload of workers in an intelligent factory environment were used in a machine learning approach to predict traditional measures (subjective and behavioural) [11]. Two methods were employed: the first one was linear regression, which was used to identify correlations between variables. The second method was artificial neural networks (ANN), which were used to capture any non-linear relationships. Models were constructed using a variety of predictor variables (EEG only, fNIRS only, or a combination of EEG and fNIRS) and target variables (subjective measures (NASA-TLX score), behavioural measures (missed beeps and reaction times). Finally, the KNN (K-Nearest Neighbours) classification was also implemented to assess the accuracy of the predictions. For NASA-TLX as the target, the highest accuracy, where 69.4% was achieved using all EEG frequency band powers as features while leaving one subject out for testing (first cross-validation method), whereas the second cross-validation method resulted in the highest accuracy of 58.3% when only fNIRS features are used.

4.5. Neurophysiological Characterization of Attention in Industry 5.0

Visual attention in dynamic environments was analyzed by eye-tracking [15] and with the aid of EEG merely to corroborate the occurrence of cerebral activity throughout the experimental phases. The presence of positive EEG signals was indicative of the participants' cognitive engagement during the monitoring period. Eye-tracking is capable of measuring eye movements to gain insight into where an individual is directing their gaze, the objects or events that capture their attention. In their experiment, Li and colleagues investigated dynamic monitoring in animated environments, with a specific focus on air traffic control (ATC). Participants were engaged in simulated radar monitoring tasks designed to assess attention levels in realistic and complex scenarios. The device measured several eye parameters, including the number of fixations (Fix-C), which refers to the number of fixation points on objects in the radar; the fix duration of fixations (Fix-D), which indicates the time spent in fixation on an object; the observed objects (Fix-AS), which represents the number of aircraft detected; the landing fixations (Fix-Land), which are specific fixations on an aircraft or on the label of a flight; and the zero fixation count (Fix-Zero), which refers to the frames with no fixations detected. The data were normalized against the number of objects on the screen and were employed to differentiate between attentional and inattentive behaviour. The results demonstrated that more attentive participants exhibited higher values in Fix-C, Fix-D, and Fix-AS, whereas less attentive participants demonstrated higher values in Fix-Zero. The integration of EEG and eye-tracking data enabled the development of a Task Engagement Index (TEI), a quantitative measure of attention levels. The TEI consists of two main categories: General Attentive Monitoring (GAM), which measures general attention towards the entire monitored environment; Object of Interest Focused Attention (OIFA), which measures specific attention towards objects of interest. The final TEI score is obtained by normalizing each parameter against the total number of objects or frames to ensure comparability, converting the values of each parameter into scores on a scale of 0 to 3 (or 4.5 for OIFA parameters) and finally summing them up (maximum: 18 points). This is used to classify participants into four attention bands: Highly Attentive (Score between 13.5 and 18); Attentive (Score between 9 and 13.5); Inattentive (Score between 4.5 and 9); Highly Inattentive (Score between 0 and 4.5).

4.6. Neurophysiological Characterization of Trust in Industry 5.0

A promising means of measuring trust in a continuous, real-time, and nonintrusive way is represented by eye tracking [57,58]. Lu and colleagues [22] employed eye tracking to measure and track real-time variations in operators' level of trust in automation as a function of system reliability and priming. The principal objective was to identify pertinent eye-tracking metrics for the detection of these variations in trust, with a view to supporting the design of adaptive technologies capable of detecting and correcting potential errors in trust calibration. The participants were required to monitor six video feeds from drones (UAVs) in a military identification simulation. During the experiment, the reliability of the automation was manipulated at two levels (high: 95%, low: 50%), and half of the participants received prior information on reliability (priming). A number of eye-tracking metrics were acquired and categorized into three distinct groups: temporal metrics such as the total fixation duration and average fixation duration; spatial metrics, i.e., mean saccade amplitude, backtrack rate, rate of transitions and scan path length per second; counting metrics such as the number of fixations and the number of transitions between areas of interest (AOI). The results demonstrated that system reliability had a significant impact on tracking behaviour. In particular, low reliability systems were associated with a higher frequency and duration of fixations, as well as a less efficient and systematic visual path, characterized by a higher backtrack rate and scan path length. Moreover, it

resulted that priming had an impact on certain eye-tracking metrics, including average fixation duration (which was longer in primed participants) and the efficiency of saccades and visual transitions (which were reduced in non-primed participants). A correlation test between eye-tracking metrics and subjective ratings of confidence revealed a negative correlation, confirming that a lower level of trust is associated with more frequent and in-depth visual monitoring.

A further study on human trust [20], conducted by means of electroencephalogram (EEG) analysis, also exploits data from the EDA signal to develop a classification model capable of estimating the level of trust in intelligent systems in real time. The participants were required to interact with a simulator that represented a car equipped with obstacle detection sensors. They had to determine whether to place trust in the sensors based on their accuracy. From the EEG data a total of 63 features were extracted in the temporal domain, comprising mean, variance, peak-to-peak value, mean frequency, RMS, and energy. Additionally, 84 features were extracted in the spectral domain, encompassing mean, variance, and energy for delta, theta, alpha, and beta bands. From the EDA signal, the tonic and phasic components were isolated, respectively, corresponding to slow and fast changes in autonomic nervous system responses. However, in the classification process only the phasic component was employed. Subsequently, two models were obtained based on a Quadratic Discriminant Analysis (QDA) classifier, selected for its minimal training time and capacity to provide valuable posterior probabilities for real-time applications. The general model, based on a common set of characteristics for all participants, demonstrated an average accuracy of 71.22%. In comparison, the customized model, based on an optimized set of characteristics for each participant, exhibited an average accuracy of 78.55%. However, despite better performance of the former, it requires a greater investment of time for training. The less accurate general model is faster and more readily generalizable to a large population. These results demonstrate that EEG and EDA can be used for the real-time detection of trust, with potential applications in intelligent interactive systems.

Another study on human trust was conducted by Jung and colleagues [17]. They aimed at identifying neural correlations of trust in humanoid robotic agents in non-reciprocal interactions, wherein only humans could intervene in the decisions of artificial partners. EEG was used to monitor brain signals during a decision-making task in which participants were required to choose between two colour options with different risk and reward profiles. Agents were characterized by external and internal humanity, with the former differentiating them as human or robotic in appearance and the latter distinguishing them by their risk levels in decision-making (high, medium, low). The analysis was focused on the theta band (4–8 Hz) in the fronto-central region. A change in trust was observed in response to the agent's decision, resulting in an increase after a correct decision and a decrease after an incorrect decision. Significant differences emerged 0.4 s after the onset of the agent's decision, showing a decrease in theta power after a correct decision and an increase after an incorrect decision. The EEG response was more pronounced in the interaction with human-looking agents than robotic ones, especially when confidence was higher, indicating a greater cognitive sensitivity to anthropomorphism.

The findings of Wang and colleagues [21] substantiate the selection of the fronto-central region as a suitable area of focus for the investigation of trust during interactions with autonomous systems. The evocation of trust during decisions made in an investment game with artificial agents of varying reliability was analyzed using electroencephalogram (EEG) signals acquired via EEG. Power spectral features were calculated, namely the average power of the following frequency bands: Delta (1–4 Hz), Theta (4–8 Hz), Alpha (8–13 Hz), Beta (13–30 Hz), and Gamma (30–42 Hz). This was achieved by extracting the aforementioned bands from a 5 s signal with a moving step of 1 s using a sliding

window. The results demonstrated that all five frequency bands exhibited significant correlations with trust. Since, the theta band was associated with decision-making and memory retrieval [59,60], the alpha and beta bands reflected cognitive engagement and mental load [61,62] and the gamma band was linked to positive and negative emotions [63], it can be inferred that the aforementioned factors play a fundamental role in determining and reflecting human trust in human–autonomy interaction.

4.7. Neurophysiological Characterization of Learning in Industry 5.0

The existing literature on learning in the context of Industry 5.0 is limited, partly due to the difficulty of isolating individual factor information. The study conducted by Gervasi and colleagues [10] evaluated various human factors, including mental load and learning, in human–robot collaboration (HRC) during repetitive assembly processes of extended duration. The present study utilized eye-tracking metrics to analyze learning in a repetitive assembly process in human–robot collaboration (HRC). The evaluation of learning was made possible due to the participants' lack of prior experience with cobots, and the participants performed 8 h shifts, divided into two 4 h sessions, thus allowing the learning effects to be observed over time. The utilization of eye-tracking metrics enabled the highlighting of the learning process and the distinction of the initial phases of skill acquisition from those of consolidation, thereby providing an objective and continuous assessment of cognitive adaptation during work. The metrics encompassed mean pupil dilation, number of fixations, and number of saccades. A significant increase in pupillary dilation was observed at the commencement of the shifts, indicative of an increased use of mental resources to learn the process steps. As the trials progressed, pupillary dilation decreased, signalling a reduction in cognitive load due to the acquisition of the required skills. A high number of fixations was found in the early stages, indicative of an active process of learning and visual orientation. This value gradually decreased with repetition, suggesting greater familiarity with the task. Saccades were frequent in early trials, indicating intense visual exploration and high use of cognitive resources to acquire new information. The subsequent reduction in saccades indicates a transition to a more automatic and less cognitively demanding performance. The results of the study demonstrated that cognitive effort increased during morning shifts, which were predominantly associated with the learning process, while afternoon shifts were characterized by the prevalence of mental fatigue.

Figure 2 and Table 2 summarize the key points emerged from the scientific review in terms of neurophysiological modelling of the relevant mental states in the context of Industry 5.0.

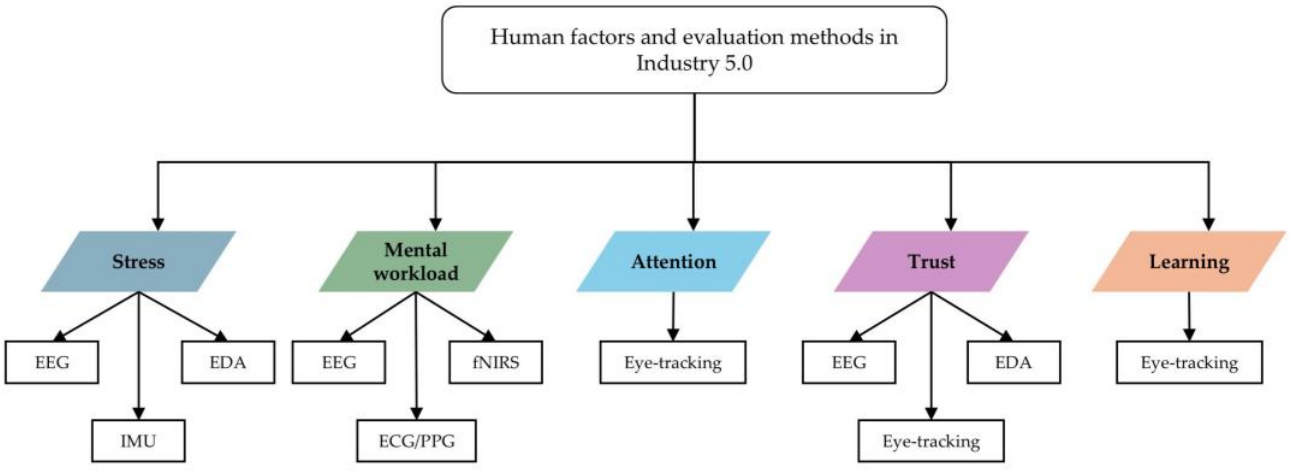

Figure 2. Scheme of the key points emerged from the scientific review in terms of neurophysiological characterization of mental states relevant for Industry 5.0.

5. Discussion

This review emphasized the critical importance of neurophysiological methodologies, in contemporary scientific research, for the characterization of human factors in Industry 5.0. Human factors assume considerable importance in a context that aspires to a human-centric, sustainable, and resilient vision of workplaces where human–machine interaction is implemented to enhance productivity and efficiency. The continuous monitoring of workers' well-being through the analysis of these human factors is fundamental in addressing individual needs, thereby fostering a more human and inclusive work environment. Furthermore, the assessment of workers' mental states and responses facilitates the development of more intuitive interfaces and intelligent systems that facilitate mutual adaptation. In this regard, it must be underlined that incorporating Human factors evaluations during the operational phase not only ensures a safer and more efficient working environment but also fosters resilience by enabling systems to adapt dynamically to human limitations and capacities. This approach ultimately enhances the overall decision-making process, reducing errors and improving outcomes in complex operational settings Consequently, this approach has the potential to generate economic, social, and environmental value. The objective of this study was to identify the predominant neurophysiological methods employed in the analysis of mental states, such as stress, mental workload, attention, trust and learning, in the recent literature. The followings provide a summary of the key points emerged from the presented review:

- Even if the sensitivity of neurophysiological signals to environmental factors, such as movement artefacts or electrical interference, might limit the applicability of these methods in highly dynamic settings, the advent of miniaturized and wireless sensors provides an avenue for more user-friendly solutions, enabling seamless integration into wearable devices without compromising data quality.
- The use of advanced signal processing and machine learning algorithms offers the potential to enhance artefact removal, feature extraction, and real-time interpretation of neurophysiological data. This could also address the current limitations characterizing the neurophysiological signal quality when collected by the actual wearable technologies.

Regarding the principal objective of the presented review, these were the key gaps identified in scientific literature:

- Limitation in the context of the real-world validation, since many studies were confined to laboratory environments, which do not fully replicate the complexities of real-life workplaces. More field studies are needed to validate these techniques in diverse occupational settings.
- As of now, few studies effectively integrate EEG, EDA, and PPG data in real-world applications. It emerged that the multimodal approaches should be furtherly developed and applied in real-world contexts.
- Current research often overlooks the broader organizational and teamwork dynamics. Expanding the focus to include group-level metrics, such as collective stress or shared workload, could provide valuable insights for optimizing team performance.

The analysis revealed that the mental states under investigation are often interconnected, sometimes by a cause–effect mechanism, such as workload and stress, so that several factors are analyzed within the same study. Correlation tests with behavioural parameters or the results of questionnaires used for single-factor assessment (e.g., the NASA Task Load Index for assessing mental load) can be used for their discernment.

The predominant methodologies employed in the articles under consideration are electroencephalography and eye-tracking. A significant body of research has demonstrated

that the spectral characteristics of the EEG signal, particularly in the prefrontal region, exhibit notable sensitivity to variations in stress and mental load. In this context, a decline in relative alpha band power, commonly associated with an escalation in cognitive activation, has been observed as the complexity of an assembly task intensifies. Statistically significant alterations have been documented in the bands power of the fronto-central area during human–robot collaborative tasks. Of particular interest is the finding that a decrease in theta band occurred subsequent to correct decisions by the robotic agent, coinciding with an increase in confidence. EEG spectral features were demonstrated to be a valid means to predict mental load and replace subjective evaluations. An alternative classification approach, incorporating spectral and temporal characteristics of the EEG signal and the phasic component of electrodermal activity, was adopted to predict the level of confidence in real-time, exhibiting a satisfactory level of accuracy.

Also, eye tracking shows promise in providing information with respect to a greater number of mental states. Through the analysis of temporal metrics (e.g., fixation duration, blinks), spatial metrics (e.g., saccade amplitude), and counting metrics (e.g., number of fixations), it is possible to assess various aspects of cognitive function, including mental workload, attention, trust, and learning. A notable increase in the frequency of blinks, for instance, can be indicative of an elevated mental workload. In relation to trust, lower levels were associated with higher frequencies and durations of fixations. The integration of various eye-tracking metrics has enabled the development of a TEI engagement index, which serves as a quantitative metric for the level of visual attention. Conversely, pupillary dilation has facilitated the assessment of the learning phases of workers during extended work shifts. A decrease in pupillary response has been shown to be indicative of reduced cognitive load associated with learning. Concurrently, a high number of fixations and saccades were recorded in the initial phase, decreasing over time.

In the extant literature, correlates of cardiac and electrodermal activity have been used to a lesser extent, often in a multimodal human factors analysis. The phasic component (SCR) of the electrodermal activity (EDA) signal has been employed for the assessment of workers' stress, as it is known in the literature to be correlated with emotional arousal, anxiety, and stress. During HRC in assembly tasks, heart rate variability demonstrated a correlation with mental workload, such that increased mental fatigue is reflected in a reduction in parasympathetic activity and, consequently, an increase in the LF/HF ratio. Furthermore, LF/HF was capable of detecting significant differences in mental workload between men and women; however, it proved less sensitive than eye-tracking in registering minor fluctuations in mental states.

The advantage of the methods employed lies in their good wearability and minimal invasiveness in experimental scenarios, which extends their use to out-of-the-lab application. Specifically, eye-tracking, cardiac, and electrodermal activities are acquired by means of mobile devices such as glasses and bracelets that can also be adapted for use in real-world contexts. With regard to electroencephalography (EEG), the majority of devices under consideration are wireless systems with a low electrode density, easily transferable to real operating contexts.

The previous findings emphasize the efficacy and potential of evaluating human factors in Industry 5.0 through the use of neurophysiological measures. Nevertheless, the intricate interconnection among disparate mental states, which has led researchers to prefer a multidimensional approach, complicates the isolation of distinct components, as these are not readily discernible without subsequent correlation with subjective assessments. Consequently, there is an absence of a consistent characterization of factors such as learning and mental stress, which are directly associated with mental workload and fatigue.

Furthermore, given the wide applicability of neurophysiological measures, to date, there is a lack of standardization in the methodologies adopted, which limits comparability between studies and the practical applicability of results. Hence, future research could be based on the precise identification of mental states that affect workers' well-being and that can be precisely determined by means of a standardized experimental protocol. This would make it possible to obtain an objective estimate of human factors even in working environments, enabling better management of human–machine interaction, as well as the development of more intuitive and intelligent technologies that help the user to manage stress, fatigue and errors.

6. Conclusions

The advent of Industry 5.0 has shifted the focus of industrial systems toward human-centricity, emphasizing collaboration between humans and advanced technologies. This study critically reviewed the current state of human factors characterization in Industry 5.0, exploring the applications of neurophysiological methodologies, such as EEG, EDA, and eye tracking, in assessing mental states like stress, workload, attention, trust, and learning. By performing so, we identified key gaps in the existing literature and proposed pathways for future research.

One major finding of this review is the lack of standardized methodologies for evaluating human factors across diverse industrial contexts. While neurophysiological techniques provide objective and real-time insights into workers' mental states, since they were adopted by the 90% of the selected scientific studies, their practical implementation is limited by challenges related to wearability, invasiveness, and compatibility with real-world operations. This limitation hinders the comparability of results and the development of universally applicable solutions. Addressing this gap requires a concerted effort toward developing standardized protocols, integrating multimodal systems, and advancing wearable technologies to enhance applicability in operational settings.

The study also highlights the intertwined nature of human factors, such as the correlation between workload and stress, which complicates their independent assessment. A multidimensional approach, supported by advanced computational methods like machine learning (by considering approximately the 25% of the selected scientific works), is essential to disentangle these interdependencies and create robust models for human factors evaluation.

Looking ahead, future research should prioritize the development of adaptive systems that leverage neurophysiological data to personalize human–machine interactions, enhance training programmes, and optimize workplace ergonomics. Furthermore, a deeper exploration of underrepresented factors, such as trust and learning, could unveil novel strategies for improving collaboration between humans and machines.

This paper calls for a paradigm shift in Human Factors research, urging the scientific community to address these gaps and explore innovative methodologies that align with the human-centric vision of Industry 5.0. By bridging these gaps, we can pave the way for safer, more inclusive, and technologically advanced workplaces, ultimately contributing to the sustainability and resilience of industrial systems.

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References

1. Industrial Technologies Roadmap on Human-Centric Research and Innovation for the Manufacturing Sector ERA Research and Innovation. Available online: https://op.europa.eu/en/publication-detail/-/publication/4a5594d1-4ee3-11ef-acbc-01aa75ed71a1/language-en (accessed on 18 November 2024).
2. European Commission. *Directorate-General for Research and Innovation Industry 5.0 Towards a Sustainable, Human-Centric and Resilient European Industry*; Publications Office of the European Union: Luxembourg, 2023; ISBN 978-92-76-25308-2. [CrossRef]
3. Sgarbossa, F.; Grosse, E.H.; Neumann, W.P.; Battini, D.; Glock, C.H. Human Factors in Production and Logistics Systems of the Future. *Annu. Rev. Control* **2020**, *49*, 295–305. [CrossRef]
4. Hart, S.G.; Staveland, L.E. Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research. *Adv. Psychol.* **1988**, *52*, 139–183. [CrossRef]
5. Loizaga, E.; Eyam, A.T.; Bastida, L.; Lastra, J.L.M. A Comprehensive Study of Human Factors, Sensory Principles, and Commercial Solutions for Future Human-Centered Working Operations in Industry 5.0. *IEEE Access* **2023**, *11*, 53806–53829. [CrossRef]
6. Panagou, S.; Neumann, W.P.; Fruggiero, F. A Scoping Review of Human Robot Interaction Research towards Industry 5.0 Human-Centric Workplaces. *Int. J. Prod. Res.* **2024**, *62*, 974–990. [CrossRef]
7. Angrisani, L.; D'Arco, M.; De Benedetto, E.; Duraccio, L.; Regio, F.L.; Tedesco, A. A Novel Measurement Method for Performance Assessment of Hands-Free, XR-Based Human-Machine Interfaces. *IEEE Sens. J.* **2024**, *24*, 31054–31061. [CrossRef]
8. Menolotto, M.; Komaris, D.S.; O'Sullivan, P.; O'Flynn, B. Assessing Trust in Collaborative Robotics with Different Human-Robot Interfaces. In Proceedings of the Conference Record—IEEE Instrumentation and Measurement Technology Conference; Institute of Electrical and Electronics Engineers Inc.: Istanbul, Turkey, 2024.
9. Nenni, M.E. Integrating Mental Workload Management in Advanced Human-Machine Interaction: The Development Process of the Proof-Of-Concept to Refine the Concept. In Proceedings of the HORA 2024—6th International Congress on Human-Computer Interaction, Optimization and Robotic Applications, Proceedings; Institute of Electrical and Electronics Engineers Inc.: Istanbul, Turkey, 2024.
10. Gervasi, R.; Capponi, M.; Mastrogiacomo, L.; Franceschini, F. Eye-Tracking Support for Analyzing Human Factors in Human-Robot Collaboration during Repetitive Long-Duration Assembly Processes. *Prod. Eng.* **2024**, *19*, 47–64. [CrossRef]

11. Zakeri, Z.; Arif, A.; Omurtag, A.; Breedon, P.; Khalid, A. Multimodal Assessment of Cognitive Workload Using Neural, Subjective and Behavioural Measures in Smart Factory Settings. *Sensors* **2023**, *23*, 8926. [CrossRef] [PubMed]
12. Apraiz, A.; Lasa, G.; Montagna, F.; Blandino, G.; Triviño-Tonato, E.; Dacal-Nieto, A. An Experimental Protocol for Human Stress Investigation in Manufacturing Contexts: Its Application in the NO-STRESS Project. *Systems* **2023**, *11*, 448. [CrossRef]
13. Pluchino, P.; Pernice, G.F.A.; Nenna, F.; Mingardi, M.; Bettelli, A.; Bacchin, D.; Spagnolli, A.; Jacucci, G.; Ragazzon, A.; Miglioranzi, L.; et al. Advanced Workstations and Collaborative Robots: Exploiting Eye-Tracking and Cardiac Activity Indices to Unveil Senior Workers' Mental Workload in Assembly Tasks. *Front. Robot. AI* **2023**, *10*, 1275572. [CrossRef]
14. Kodkin, V.L.; Artem'eva, E.V. Digital Identification of the Human Condition as a Prerequisite for the Effectiveness of the Organizational Automation (Biocybernetic) Systems Operation. *Sensors* **2022**, *22*, 3649. [CrossRef]
15. Li, Y.F.; Lye, S.W.; Rajamanickam, Y. Assessing Attentive Monitoring Levels in Dynamic Environments through Visual Neuro-Assisted Approach. *Heliyon* **2022**, *8*, e09067. [CrossRef]
16. Hopko, S.K.; Khurana, R.; Mehta, R.K.; Pagilla, P.R. Effect of Cognitive Fatigue, Operator Sex, and Robot Assistance on Task Performance Metrics, Workload, and Situation Awareness in Human-Robot Collaboration. *IEEE Robot. Autom. Lett.* **2021**, *6*, 3049–3056. [CrossRef]
17. Jung, E.S.; Dong, S.Y.; Lee, S.Y. Neural Correlates of Variations in Human Trust in Human-like Machines during Non-Reciprocal Interactions. *Sci. Rep.* **2019**, *9*, 9975. [CrossRef] [PubMed]
18. Somon, B.; Campagne, A.; Delorme, A.; Berberian, B. Human or Not Human? Performance Monitoring ERPs during Human Agent and Machine Supervision. *Neuroimage* **2019**, *186*, 266–277. [CrossRef]
19. Neu, C.; Kirchner, E.A.; Kim, S.K.; Tabie, M.; Linn, C.; Werth, D. Cognitive Work Protection—A New Approach for Occupational Safety in Human-Machine Interaction. In *Lecture Notes in Information Systems and Organisation*; Springer: Berlin/Heidelberg, Germany, 2019; Volume 29, pp. 211–220.
20. Akash, K.; Hu, W.L.; Jain, N.; Reid, T. A Classification Model for Sensing Human Trust in Machines Using EEG and GSR. *ACM Trans. Interact. Intell. Syst.* **2018**, *8*, 1–20. [CrossRef]
21. Wang, M.; Hussein, A.; Rojas, R.F.; Shafi, K.; Abbass, H.A. EEG-Based Neural Correlates of Trust in Human-Autonomy Interaction. In Proceedings of the 2018 IEEE Symposium Series on Computational Intelligence, SSCI 2018, Bengaluru, India, 18–21 November 2018.
22. Lu, Y.; Sarter, N. Eye Tracking: A Process-Oriented Method for Inferring Trust in Automation as a Function of Priming and System Reliability. *IEEE Trans. Hum. Mach. Syst.* **2019**, *49*, 560–568. [CrossRef]
23. Kneževic, N.; Savic, A.; Gordic, Z.; Ajoudani, A.; Jovanovic, K. Toward Industry 5.0: A Neuroergonomic Workstation for a Human-Centered, Collaborative Robot-Supported Manual Assembly Process. *IEEE Robot. Autom. Mag.* **2024**, *1*, 2–13. [CrossRef]
24. Amazu, C.W.; Demichela, M.; Fissore, D. *Human-in-the-Loop Configurations in Process and Energy Industries: A Systematic Review*; Research Publishing Services: Dublin, Ireland, 2023; pp. 3234–3241.
25. Roopak, M.; Tian, G.Y.; Chambers, J. An Intrusion Detection System Against DDoS Attacks in IoT Networks. In Proceedings of the 2020 10th Annual Computing and Communication Workshop and Conference (CCWC), Las Vegas, USA, 6–8 January 2020; ISBN 9781728137834.
26. Yang, J.; Liu, Y.; Morgan, P.L. Human–Machine Interaction towards Industry 5.0: Human-Centric Smart Manufacturing. *Digit. Eng.* **2024**, *2*, 100013. [CrossRef]
27. Wascher, E.; Reiser, J.; Rinkenauer, G.; Larrá, M.; Dreger, F.A.; Schneider, D.; Karthaus, M.; Getzmann, S.; Gutberlet, M.; Arnau, S. Neuroergonomics on the Go: An Evaluation of the Potential of Mobile EEG for Workplace Assessment and Design. *Hum. Factors* **2023**, *65*, 86–106. [CrossRef] [PubMed]
28. Coronado, E.; Kiyokawa, T.; Ricardez, G.A.G.; Ramirez-Alpizar, I.G.; Venture, G.; Yamanobe, N. Evaluating Quality in Human-Robot Interaction: A Systematic Search and Classification of Performance and Human-Centered Factors, Measures and Metrics towards an Industry 5.0. *J. Manuf. Syst.* **2022**, *63*, 392–410. [CrossRef]
29. Lazarus, R.S.; Folkman, S. *Stress, Appraisal, and Coping*; Springer Publishing Company: Berlin/Heidelberg, Germany, 1984.
30. Zhou, S.; Chen, H.; Liu, M.; Wang, T.; Xu, H.; Li, R.; Su, S. The Relationship between Occupational Stress and Job Burnout among Female Manufacturing Workers in Guangdong, China: A Cross-Sectional Study. *Sci. Rep.* **2022**, *12*, 20208. [CrossRef] [PubMed]
31. Körner, U.; Müller-Thur, K.; Lunau, T.; Dragano, N.; Angerer, P.; Buchner, A. Perceived Stress in Human–Machine Interaction in Modern Manufacturing Environments—Results of a Qualitative Interview Study. *Stress. Health* **2019**, *35*, 187–199. [CrossRef] [PubMed]
32. Sweller, J. Cognitive Load during Problem Solving: Effects on Learning. *Cogn. Sci.* **1988**, *12*, 257–285. [CrossRef]
33. Realyvásquez-Vargas, A.; García-Alcaraz, J.L.; Arredondo-Soto, K.C.; Hernández-Escobedo, G.; Báez-López, Y.A. Effects of Mental Workload on Manufacturing Systems Employees: A Mediation Causal Model. *Work* **2023**, *76*, 323–341. [CrossRef] [PubMed]
34. Giorgi, A.; Ronca, V.; Vozzi, A.; Aricò, P.; Borghini, G.; Capotorto, R.; Tamborra, L.; Simonetti, I.; Sportiello, S.; Petrelli, M.; et al. Neurophysiological Mental Fatigue Assessment for Developing User-Centered Artificial Intelligence as a Solution for Autonomous Driving. *Front. Neurorobot* **2023**, *17*, 1240933. [CrossRef] [PubMed]

35. Wickens, C.D.; Hollands, J.G.; Banbury, S.; Parasuraman, R. *Engineering Psychology and Human Performance*, 4th ed.; Psychology Press: New York, NY, USA, 2015. [CrossRef]
36. Endsley, M.R. Design and Evaluation for Situation Awareness Enhancement. In *Proceedings of the Human Factors Society Annual Meeting*; Sage Publications: Los Angeles, CA, USA, 1988; Volume 32, pp. 97–101. [CrossRef]
37. Hasanzadeh, S.; Esmaeili, B.; Dodd, M.D. Examining the Relationship between Construction Workers' Visual Attention and Situation Awareness under Fall and Tripping Hazard Conditions: Using Mobile Eye Tracking. *J. Constr. Eng. Manag.* **2018**, *144*, 04018060. [CrossRef]
38. Ronca, V.; Brambati, F.; Napoletano, L.; Marx, C.; Trösterer, S.; Vozzi, A.; Aricò, P.; Giorgi, A.; Capotorto, R.; Borghini, G.; et al. A Novel EEG-Based Assessment of Distraction in Simulated Driving under Different Road and Traffic Conditions. *Brain Sci.* **2024**, *14*, 193. [CrossRef] [PubMed]
39. Lee, J.D.; See, K.A. Trust in Automation: Designing for Appropriate Reliance. *Hum. Factors* **2004**, *46*, 50–80. [CrossRef] [PubMed]
40. Merritt, S.M.; Heimbaugh, H.; Lachapell, J.; Lee, D. I Trust It, but i Don't Know Why: Effects of Implicit Attitudes toward Automation on Trust in an Automated System. *Hum. Factors* **2013**, *55*, 520–534. [CrossRef] [PubMed]
41. Rial-Gonzalez, P.; Sarceda-Gorgoso, M.C.; Queiruga, O.S. Lifelong Learning as a Response to the Challenges of Industry 5.0 within the Context of Horizon 2030. *Educar* **2024**, *60*, 305–319. [CrossRef]
42. Jurcak, V.; Tsuzuki, D.; Dan, I. 10/20, 10/10, and 10/5 Systems Revisited: Their Validity as Relative Head-Surface-Based Positioning Systems. *Neuroimage* **2007**, *34*, 1600–1611. [CrossRef] [PubMed]
43. Jacobs, S.C.; Friedman, R.; Parker, J.D.; Tofler, G.H.; Jimenez, A.H.; Muller, J.E.; Benson, H.; Stone, P.H. Use of Skin Conductance Changes during Mental Stress Testing as an Index of Autonomic Arousal in Cardiovascular Research. *Am. Heart J.* **1994**, *128*, 1170–1177. [CrossRef] [PubMed]
44. Gervasi, R.; Mastrogiacomo, L.; Franceschini, F. A Conceptual Framework to Evaluate Human-Robot Collaboration. *Int. J. Adv. Manuf. Technol.* **2020**, *108*, 841–865. [CrossRef]
45. Arkouli, Z.; Michalos, G.; Makris, S. On the Selection of Ergonomics Evaluation Methods for Human Centric Manufacturing Tasks. *Procedia CIRP* **2022**, *107*, 89–94. [CrossRef]
46. Lu, Y.; Saner, N. Eye Tracking: A Promising Method for Inferring Trust in Real Time. In *Proceedings of the Human Factors and Ergonomics Society*; Human Factors and Ergonomics Society Inc.: Philadelphia, PA, USA, 2018; Volume 1, pp. 175–176.
47. Giorgi, A.; Ronca, V.; Vozzi, A.; Sciaraffa, N.; di Florio, A.; Tamborra, L.; Simonetti, I.; Aricò, P.; Di Flumeri, G.; Rossi, D.; et al. Wearable Technologies for Mental Workload, Stress, and Emotional State Assessment during Working-Like Tasks: A Comparison with Laboratory Technologies. *Sensors* **2021**, *21*, 2332. [CrossRef]
48. Zheng, T.; Glock, C.H.; Grosse, E.H. Opportunities for Using Eye Tracking Technology in Manufacturing and Logistics: Systematic Literature Review and Research Agenda. *Comput. Ind. Eng.* **2022**, *171*, 108444. [CrossRef]
49. Renner, P.; Pfeiffer, T. Attention Guiding Techniques Using Peripheral Vision and Eye Tracking for Feedback in Augmented-Reality-Based Assistance Systems. In Proceedings of the 2017 IEEE Symposium on 3D User Interfaces, 3DUI, Los Angeles, CA, USA, 18–19 March 2017.
50. Bhatia, N.; Sen, D.; Pathak, A.V. Visual Behavior Analysis of Human Performance in Precision Tasks. In Proceedings of the Engineering Psychology and Cognitive Ergonomics: 12th International Conference, EPCE 2015, Held as Part of HCI International 2015, Los Angeles, CA, USA, 2–7 August 2015; Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). Springer: Cham, Switzerland, 2015; Volume 9174.
51. Sausman, J.; Samoylov, A.; Regli, S.H.; Hopps, M. Effect of Eye and Body Movement on Augmented Reality in the Manufacturing Domain. In Proceedings of the ISMAR 2012—11th IEEE International Symposium on Mixed and Augmented Reality, Atlanta, GA, USA, 5–8 November 2012.
52. Chu, C.H.; Liu, Y.L. Augmented Reality User Interface Design and Experimental Evaluation for Human-Robot Collaborative Assembly. *J. Manuf. Syst.* **2023**, *68*, 313–324. [CrossRef]
53. Ronca, V.; Ricci, A.; Capotorto, R.; Di Donato, L.; Freda, D.; Pirozzi, M.; Palermo, E.; Mattioli, L.; Di Gironimo, G.; Coccorese, D.; et al. How Immersed Are You? State of the Art of the Neurophysiological Characterization of Embodiment in Mixed Reality for Out-of-the-Lab Applications. *Appl. Sci.* **2024**, *14*, 8192. [CrossRef]
54. Bugg, J.M.; Jacoby, L.L.; Toth, J.P. Multiple Levels of Control in the Stroop Task. *Mem. Cogn.* **2008**, *36*, 1484–1494. [CrossRef] [PubMed]
55. Fernandez Rojas, R.; Debie, E.; Fidock, J.; Barlow, M.; Kasmarik, K.; Anavatti, S.; Garratt, M.; Abbass, H. Electroencephalographic Workload Indicators During Teleoperation of an Unmanned Aerial Vehicle Shepherding a Swarm of Unmanned Ground Vehicles in Contested Environments. *Front. Neurosci.* **2020**, *14*, 40. [CrossRef] [PubMed]
56. Ronca, V.; Di Flumeri, G.; Vozzi, A.; Giorgi, A.; Arico, P.; Sciaraffa, N.; Babiloni, F.; Borghini, G. Validation of an EEG-Based Neurometric for Online Monitoring and Detection of Mental Drowsiness While Driving. *Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.* **2022**, *2022*, 3714–3717. [CrossRef]

57. Duchowski, A.T. A Breadth-First Survey of Eye-Tracking Applications. *Behav. Res. Methods Instrum. Comput.* **2002**, *34*, 455–470. [CrossRef] [PubMed]
58. Sharafi, Z.; Soh, Z.; Guéhéneuc, Y.G. A Systematic Literature Review on the Usage of Eye-Tracking in Software Engineering. *Inf. Softw. Technol.* **2015**, *67*, 79–107. [CrossRef]
59. Jacobs, J.; Hwang, G.; Curran, T.; Kahana, M.J. EEG Oscillations and Recognition Memory: Theta Correlates of Memory Retrieval and Decision Making. *Neuroimage* **2006**, *32*, 978–987. [CrossRef] [PubMed]
60. Ratcliff, R.; Philiastides, M.G.; Sajda, P. Quality of Evidence for Perceptual Decision Making Is Indexed by Trial-to-Trial Variability of the EEG. *Proc. Natl. Acad. Sci. USA* **2009**, *106*, 6539–6544. [CrossRef] [PubMed]
61. Berka, C.; Levendowski, D.J.; Lumicao, M.N.; Yau, A.; Davis, G.; Zivkovic, V.T.; Olmstead, R.E.; Tremoulet, P.D.; Craven, P.L. EEG Correlates of Task Engagement and Mental Workload in Vigilance, Learning, and Memory Tasks. *Aviat. Space Env. Med.* **2007**, *78*, B231–B244.
62. Dimitriadis, S.I.; Sun, Y.; Kwok, K.; Laskaris, N.A.; Thakor, N.; Bezerianos, A. Cognitive Workload Assessment Based on the Tensorial Treatment of EEG Estimates of Cross-Frequency Phase Interactions. *Ann. Biomed. Eng.* **2015**, *43*, 977–989. [CrossRef] [PubMed]
63. Massar, S.A.A.; Rossi, V.; Schutter, D.J.L.G.; Kenemans, J.L. Baseline EEG Theta/Beta Ratio and Punishment Sensitivity as Biomarkers for Feedback-Related Negativity (FRN) and Risk-Taking. *Clin. Neurophysiol.* **2012**, *123*, 1958–1965. [CrossRef] [PubMed]

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