INTERNATIONAL JOURNAL OF INTEGRATED ENGINEERING
ISSN: 2229-838X e-ISSN: 2600-7916

IJIE

Vol. 16 No. 5 (2024) 324-340
https://publisher.uthm.edu.my/ojs/index.php/ijie

A Review of HRV and EEG Technology Applications in Industry 5.0: Emphasising Manufacturing Efficiency and Worker Well-Being

Saranjuu Chulakit[1], Amirul Syafiq Sadun[1*], Nor Anija Jalaludin[1], Hairulazwan Hashim[1], Hasliza Hassan[1], Salwa Mahmood[2], Noraini Marsi[2] Muhammad Ashraf Fauzi[3]

[1] *Department of Electrical Engineering Technology, Faculty of Engineering Technology, Universiti Tun Hussein Onn Malaysia Pagoh Campus, 84600 Panchor, Johor, MALAYSIA*

[2] *Department of Mechanical Engineering Technology, Faculty of Engineering Technology, Universiti Tun Hussein Onn Malaysia Pagoh Campus, 84600 Panchor, Johor, MALAYSIA*

[3] *Faculty of Industrial Management, Universiti Malaysia Pahang Al-Sultan Abdullah, 26300 Gambang, Kuantan, Pahang, MALAYSIA*

*Corresponding Author: amirul@uthm.edu.my
DOI: https://doi.org/10.30880/ijie.2024.16.05.025

Article Info

Received: 15 February 2024
Accepted: 21 June 2024
Available online: 12 August 2024

Keywords

Heart Rate Variability (HRV), Electroencephalography (EEG) in Manufacturing, Industry 5.0

Abstract

This review paper examines the role of physiological monitoring techniques in the manufacturing industry, particularly through the use of Heart Rate Variability (HRV) and Electroencephalography (EEG), aligning with the human-centric approach of Industry 5.0. Delving into the current applications and potential of these biometric tools, the paper highlights their significance in enhancing worker well-being, safety, cognitive workload management, and the optimisation of human-machine interactions. A systematic literature search employing the PRISMA framework was conducted, revealing a marked preference for HRV over EEG in current research, although both have been shown to offer substantial benefits. The review underscores the precision of ECG-based HRV measurements as pivotal for assessing autonomic nervous system activity, with implications for employee health outcomes. The analysis of EEG studies reflects its utility in mapping psychological states and fostering advanced Brain-Computer Interface technologies, contributing to safer and more efficient manufacturing processes. As the review concludes, the integration of HRV and EEG monitoring is poised to become a standard practice within the industry, signalling a shift towards manufacturing operations that prioritize the health and satisfaction of the workforce while maintaining operational excellence. The findings advocate for the adoption of these monitoring techniques as part of a larger strategy to ensure a responsive, adaptive, and worker-centric manufacturing environment. This paper paves the way for future research to explore the full spectrum of possibilities that HRV and EEG monitoring hold for the evolution of the manufacturing sector.

1. Introduction

The term 'Industry 4.0', first introduced in 2011 as part of the German government's high-tech strategy, quickly became a significant topic of discussion, especially after its debut at that year's at Hannover Fair [1]. This concept marked a paradigm shift in manufacturing methodologies, representing a move towards the full automation of the industry by integrating cutting-edge technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and Cyber-Physical Systems (CPS). The implementation of interconnected sensors and devices via the internet led to the creation of fully autonomous self-monitoring systems, capable of real-time analysis and problem-solving, thereby significantly reducing the need for human intervention [2], [3].

However, the move towards Industry 4.0, which raised concerns about social fairness and long-term sustainability due to its strong focus on automation and technological efficiency, led to the introduction of Industry 5.0 in 2021 [4]. This shift refocused attention to include the human element in the manufacturing landscape, emphasising a human-centric approach [5]. This evolution seeks not only to maintain efficiency but also aiming to improve the quality of human life and experience in the industrial context [6], [7], [8].

Building on the transformative narrative from Industry 4.0 to Industry 5.0, this paper delves into the potential integration of physiological monitoring tools, specifically HRV and EEG, within the realm of manufacturing. These tools are pivotal in gauging worker well-being and cognitive load, aligning seamlessly with the human-centric vision of Industry 5.0. This investigation seeks to explore how current studies of HRV and EEG have been applied in the manufacturing sector and their application in enhancing worker well-being and operational efficiency.

Guided by the imperative to explore how HRV and EEG monitoring can be integrated within Industry 5.0 manufacturing settings, this paper assesses its current and future applications. By systematically reviewing the use of these technologies, the study contributes novel insights into their role in promoting a human-centric manufacturing model. It underscores the significance of HRV and EEG technologies in enhancing both operational efficiency and worker well-being, thus offering a framework for future research aimed at leveraging physiological data to advance manufacturing practices towards a more adaptive, responsive, and inclusive model.

2. Methodology

The systematic search for relevant literature in this review was conducted using Google Scholar and SCOPUS, which are comprehensive repositories of academic publications. Keywords played a crucial role in this process, steering the research towards relevant studies. As depicted in Figure 1, the search strategy utilised the keywords "Heart Rate Variability" or "HRV" and "Electroencephalogram" or "EEG," combined with the term "Manufacturing."

Keyword 1		Keyword 2		Domain
"Heart Rate Variability" OR "HRV"	OR	"Electroencephalogram" OR "EEG"	AND	Manufacturing

Fig. 1 *Keyword search strategy*

The review used the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram, as illustrated in Figure 2, to systematically guide the selection and evaluation of studies. This diagram outlines a structured approach for selecting and evaluating research literature, starting from the initial identification of records through screening, eligibility assessment, and ultimately, the inclusion of studies in the review.

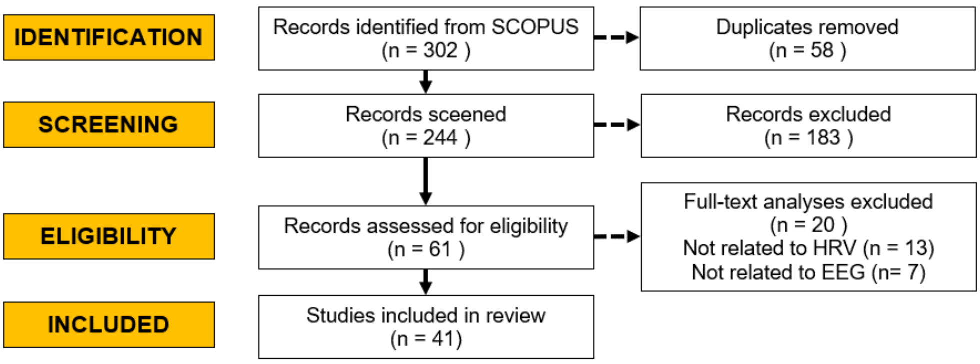

Fig. 2 *PRISMA flow diagram*

As outlined in Figure 2, the initial search in SCOPUS yielded 302 records. After the removal of duplicates, 244 records remained and were subsequently screened. This screening process led to the exclusion of 183 records for various reasons. Following this, 61 records were thoroughly evaluated for their relevance and eligibility. During this phase, 20 full-text analyses were excluded because they did not relate to HRV (13 studies) or EEG (7 studies). After this rigorous selection process, 41 studies were deemed suitable for inclusion in the final review. To ensure comprehensive coverage and access to the full texts of these studies, Google Scholar was utilised as a supplementary tool for retrieving each of the research papers. This approach not only facilitated access to the papers but also ensured that the review encompassed a broad spectrum of relevant literature.

The review then categorized these 41 papers based on their specific focus which are HRV, EEG, or a combination of both HRV and EEG methodologies. Figure 3 illustrates the distribution of these studies across different publication years, offering valuable insights into the evolving research trends within these scientific domains.

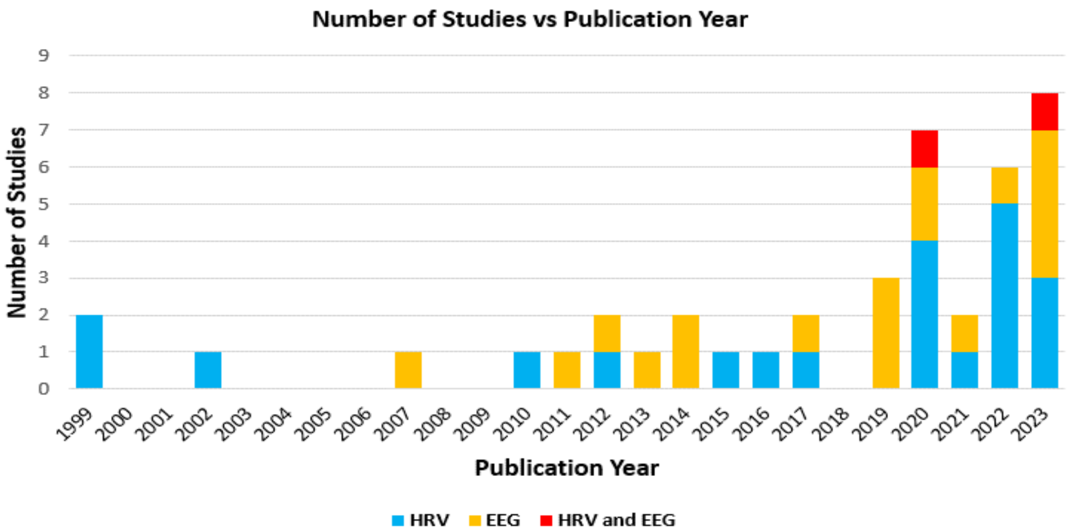

Fig. 3 *Distribution of reviewed studies across publication years*

Further examination of Figure 3, along with the data presented in Table 1, reveals that 21 studies focused on HRV, 18 on EEG, and 2 on both HRV and EEG. This distribution mirrors the current trends and focal areas in physiological monitoring within the manufacturing sector.

Table 1 *Categorization of studies based on focus area*

Category	Number of studies	References
HRV	21	[9]-[29]
EEG	18	[30]-[47]
HRV and EEG	2	[48][49]

The analysis indicates a slight predominance of HRV-related studies compared to those focusing on EEG. However, both fields are well-represented in the literature. The inclusion of studies that integrate HRV and EEG is occasional but significant, highlighting a growing interest in these methodologies within the manufacturing sector for various applications. This review emphasizes the diverse applications of HRV and EEG in enhancing safety, productivity, efficiency, and worker well-being in manufacturing environments.

3. Research Utilising HRV Approaches in Manufacturing

3.1 HRV Research Focus Areas and Trends

The intersection of HRV research and manufacturing has garnered attention for its potential to enhance worker wellbeing and efficiency. An overview of current literature reveals diverse applications of HRV within this context, as depicted in Figure 4.

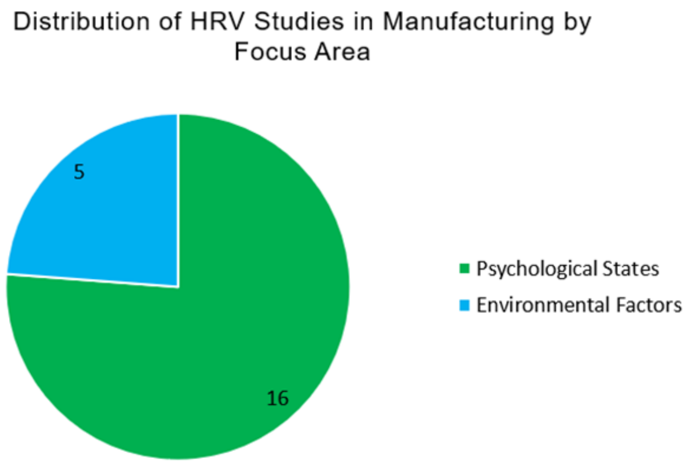

Fig. 4 *Distribution of HRV studies in manufacturing by focus area*

The pie chart in Figure 4 elucidates the distribution of research foci within the realm of HRV studies in manufacturing. It is evident from the chart that the majority of studies, 16 in total, are concentrated on psychological states. This indicates a robust interest in understanding how the psychological well-being of manufacturing workers is influenced by their work and environment. Psychological states, such as stress, fatigue, and cognitive load, can be discerned from HRV measurements, which provide objective data to gauge worker well-being.

Conversely, a smaller fraction of the studies, represented by 5 in the chart, focuses on environmental factors. These studies delve into how various elements of the manufacturing environment, such as noise, temperature, and air quality, might affect the HRV and, consequently, the health and performance of the workers. The findings suggest that while environmental factors are acknowledged, there is a predominant emphasis on the psychological aspects of worker health in manufacturing settings.

3.2 Recent Approach of HRV Applications in Manufacturing

The application of HRV in the manufacturing sector serves as a pivotal gauge for workers' health across various domains, namely stress, fatigue, mental workload, and environmental impacts.

The assessment of stress utilising HRV has been central to numerous studies. In 2023, research employing the PRISMA methodology critically reviewed stress indicators within intelligent manufacturing systems. This study illuminated HRV's crucial role in gauging stress, marking a significant step forward compatible with the principle of Industry 4.0 and 5.0 developments [9], [10]. A study conducted in 2022 explored the effects of forest therapy on reducing work-related stress among manufacturing employees, with HRV serving as a crucial biomarker for quantifying stress levels [11]. This study involved employees from a manufacturing plant who were experiencing high levels of occupational stress. Participants were divided into two groups that are one participated in a structured forest therapy program, while the control group continued their regular routines. The findings revealed that participants in the forest therapy group exhibited significant improvements in HRV metrics, indicative of reduced stress levels, and reported enhanced mood states and quality of life. Moreover, studies from 2020 have showcased the effectiveness of HRV biofeedback monitoring to evaluate the impact of stress management interventions on assembly line workers' cognitive workload and productivity [12]. This multifaceted approach aimed to correlate subjective stress levels with objective physiological measures, providing a comprehensive overview of the workers' stress and cognitive states. The study's outcomes suggested that incorporating EEG monitoring into daily operations can significantly contribute to optimising human-machine interactions and elevating manufacturing efficiency. Earlier research from 2012, 2010, and 2002 further explored the relationship between job stress and HRV [13], [14], [15], [16].

Fatigue detection and analysis via HRV have also been a significant area of focus. A 2022 study applied machine learning and sensor technology to explore demographic factors affecting fatigue detection [17]. In a 2020 study, an advanced collaboration model between humans and machines was tested on an injection moulding line, utilising machine learning to adapt task sharing based on real-time monitoring of workers' fatigue through wearable devices (Polar H10 chest strap & Huawei Watch 2) [18]. This approach dynamically adjusted tasks between employees and collaborative robots (cobots), aiming to optimize workload and enhance productivity. Results demonstrated significant improvements in worker well-being and operational efficiency, exemplifying a successful integration of technology into manufacturing to create a more responsive and human-centred production environment. Next, a 2017 study further explored HRV's role during assembly tasks, demonstrating its effectiveness in detecting and managing fatigue among a wide range of worker demographics. This research highlights how HRV analysis can be a powerful tool for enhancing both the health and productivity of the workforce, contributing to a more supportive and efficient manufacturing environment [19].

The mental workload has been another key area studied through HRV. The 2022 study investigates human mental workload in collaborative environments with robots by capturing and analysing HRV physiological signals through wearable sensors (NeXus-4 and Smartwatch DTA-S50). Utilising a machine learning approach, particularly a random forest algorithm, this research classified mental workload levels with a high degree of accuracy (94%). The study highlights the potential for these methodologies to improve human-robot interaction by tailoring tasks to human operators' current mental states, thus supporting the development of more human-centric manufacturing systems in line with Industry 5.0 principles [20]. A 2021 study highlighted how task complexity and informational assistance systems (using devices like iPad Air 2 and Vuzix M300 for AR) impact mental workload, suggesting that optimized assistance systems can significantly reduce mental strain [21]. Furthermore, a 2020 study employed HRV and the NASA-TLX test to assess cognitive workload, supporting the development of tasks that align with operators' cognitive capacities, enhancing both performance and safety in smart manufacturing settings [22].

HRV has also been used to examine the health impact of environmental factors. A 2022 study examined the physiological effects of noise exposure, using HRV as an indicator of autonomic response to environmental stressors [23]. The 2015 study assessed cardiovascular impacts of shift work in South Korea's automobile factories through 24-hour ambulatory ECG recordings, showing reduced HRV variability in night-shift workers, which indicates impaired autonomic response to circadian disruptions, posing potential cardiovascular risks [24]. Moreover, studies from 2016, examining the cardiovascular effects of titanium dioxide particle exposure [25], and from 1999, investigating the effects of working hours on cardiovascular functions [26], [27], have contributed to understanding environmental influences on worker health through HRV analysis.

This compilation of HRV research underscores the method's value in assessing and improving worker health across diverse facets of the manufacturing environment. The systematic categorisation of research into distinct areas such as stress, fatigue, mental workload, and environmental factors enables a targeted approach to tackling the challenges faced by the manufacturing workforce. The inclusion of specific case studies and recent findings not only showcases HRV's practical applications but also aligns with the evolving focus on human-centric manufacturing practices, reinforcing HRV's significance as a pivotal tool in promoting workplace well-being in line with Industry 5.0 ideals.

3.3 HRV Measurement Devices

The assessment of HRV within the manufacturing context relies heavily on the accuracy and reliability of the hardware used to capture physiological data. The selection of HRV devices is crucial as it directly impacts the quality of the measurements and the subsequent analyses derived from them. In recent studies, a variety of HRV device brands have been employed to gather data necessary for evaluating worker health and stress levels. These devices, as summarized in Table 2, vary in terms of brand and sensor type, indicating a range of methodologies and preferences in the measurement of HRV across different research contexts.

Table 2 *HRV device brands and sensor types utilised in recent research*

Reference	HRV Device Brand	Sensor Type
[12], [13], [28]	emWave Pro	PPG
[11]	T-REX® (Monitor and Care Taewoong Medical)	ECG
[20]	Smartwatch DTA-S50	ECG
[21]	Faros eMotion 180° Holter ECG	ECG
[22]	BITalino®Plugged Kit BLE	ECG
[15], [16], [26], [27]	LRR-03 (GMS Co. Ltd., Japan)	ECG
[19]	Polar Heart Rate Monitor	ECG
[24]	Marquette Medical Systems	ECG
[14]	I-330 C2 (J & J Engineering)	ECG

The emWave Pro, utilising photoplethysmography (PPG) technology, has been used in studies [12], [13], [28]. PPG sensors operate by detecting blood volume changes in the microvascular bed of tissue, offering a non-invasive measure of HRV. This method is particularly user-friendly and is often praised for its convenience and comfort, making it suitable for workplace settings where ease of use is a priority.

Several other studies have opted for devices equipped with electrocardiography (ECG) sensors, such as the T-REX® used in study [11], the Smartwatch DTA-S50 referenced in study [20], and the Faros eMotion 180° Holter ECG from study [21]. These devices, including the BITalino Plugged Kit BLE [22], LRR-03 [15], [16], [26], [27], Polar Heart Rate Monitor [19], Marquette Medical Systems [24], and I-330 C2 [14], all harness the ECG method for HRV data collection. ECG sensors, recognised for their clinical accuracy, measure the electrical activity of the heart to provide precise readings of HRV. They are commonly used in research due to their high level of sensitivity and accuracy.

Analysing the distribution of sensor types used in HRV research, as depicted in Figure 5, there is a clear preference for ECG sensors over PPG in the current literature. This preference is likely due to the precision offered by ECG measurements, which is critical when assessing the subtle changes in HRV associated with stress, fatigue, and other psychological states.

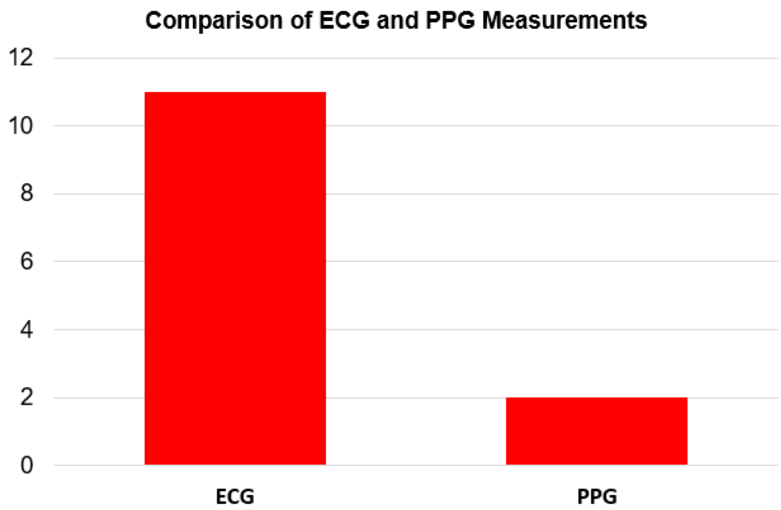

Fig. 5 *Proportion of HRV studies using ECG and PPG sensors*

In detail, Figure 5 showcases a bar graph comparing the usage frequency of ECG and PPG sensors in HRV studies. It is evident that the ECG method significantly outweighs PPG in its application. The graph indicates that ECG, being the more traditional approach, is favoured for its robustness and detailed data acquisition capabilities, essential for capturing the nuanced aspects of HRV.

In summary, the selection of HRV devices in recent studies primarily reflects a reliance on ECG technology due to its accuracy and detailed data provision. While PPG sensors offer a non-invasive and user-friendly alternative, they are less frequently employed, possibly due to the higher precision required for HRV analysis in the context of occupational health research. The preference for ECG devices indicates a research trend towards methodologies that ensure high fidelity in HRV data, which is paramount for the effective assessment of autonomic nervous system activity and related health outcomes in the manufacturing workforce. The careful consideration of hardware in HRV studies underlines the importance of measurement precision in the pursuit of reliable and actionable health insights within the industrial environment.

3.4 HRV Parameters and Key Findings

In the realm of manufacturing, HRV has been a focal point to gauge various health-related concerns. The measured parameters and their correlated findings provide critical insights into employees' well-being. Table 3 below summarises the parameters measured, and its key findings related to influence of HRV with various research focus.

Table 3 *HRV research summarised findings*

References	Research Focus	Parameter Measured	Key Findings
[22]	Cognitive Workload	Heart Rate (HR), RMSSD	Higher HR and lower RMSSD indicate increased cognitive load.
[25]	Exposure to Particles	HRV	Titanium dioxide particles may affect HRV, especially parasympathetic activity.

[17], [18], [19]	Fatigue	Mean RR, SDNN, RMSSD, LF, HF, LF/HF Ratio	An initial increase then decrease in LF/HF ratio suggests rising fatigue.
[28]	Life Satisfaction	HRV Coherence	Resonant breathing improves HRV coherence, enhancing life satisfaction.
[20], [21]	Mental Workload	HR, rrHRV, RMSSD	Lower HRV parameters signal reduced stress
[23]	Noise Exposure	HRV, HR	HR is impacted by peak noise levels and rises over time during exposure.
[24]	Shift Work	Mean RR, SDNN, RMSSD, pNN50, TP, LF, HF, LF/HF Ratio	Night-shift workers show less variation in HRV metrics, possibly increasing cardiovascular disease risk due to disrupted circadian rhythms
[9], [10], [11], [12], [13], [14], [15], [16], [29]	Stress	HR, SDNN, RMSSD, TP, LF, HF, HRV Coherence	- Forest therapy boosts HRV and reduces stress. - Multimodal stress management improves HRV and lessens negative emotions. - Workers under high stress show lower HRV coherence. - Higher low-frequency HRV activity is linked to reduced depression, anxiety, and stress. - Short-term employees under high strain exhibit higher LF HRV.
[26], [27]	Working Hours	HF and LF Power, LF/HF Ratio, Urinary Noradrenaline (NA)	Longer working hours are associated with reduced sympathetic activity, indicated by lower urinary noradrenaline and a lower LF/HF ratio in HRV.

Recent studies have delved into different aspects of occupational health by measuring various HRV parameters. Study [22] focused on cognitive workload, measuring heart rate and RMSSD—a measure of heart rate variability. It found that a higher heart rate coupled with a lower RMSSD could indicate increased mental demand on workers. The influence of environmental factors was examined in study [25], which investigated the effects of titanium dioxide particles on HRV. The study suggested these particles might impact the heart's variability, particularly affecting the parasympathetic (rest-and-digest) activities of the nervous system.

Fatigue has been another significant research area, with studies [17], [18], [19] investigating various HRV metrics such as the mean RR intervals, SDNN, RMSSD, and the LF/HF ratio. These studies generally found that an increase followed by a decrease in the LF/HF ratio could be indicative of rising fatigue levels. The impact of life satisfaction on HRV was explored in study [28]. It was found that resonant breathing could improve HRV coherence, which may contribute to an increase in life satisfaction among individuals. Studies [20], [21] addressed mental workload by measuring heart rate and various HRV parameters. The key takeaway was that lower variability in these HRV parameters could be associated with reduced stress levels.

The effects of noise exposure on heart health were explored in study [23]. The research concluded that heart rate tends to rise over time when exposed to peak noise levels, indicating stress response. Shift work, a common practice in manufacturing, was examined in study [24]. The findings indicated that night-shift workers might have less variation in HRV metrics, which could increase the risk of cardiovascular disease due to disrupted sleep patterns and circadian rhythms.

A broad range of studies [9], [10], [11], [12], [13], [14], [15], [16], [29] investigated stress and its physiological markers. Some of these studies highlighted the benefits of forest therapy and multimodal stress management on HRV, suggesting that such interventions can enhance HRV and reduce stress. They also found that workers under high stress often show lower HRV coherence, and higher low-frequency HRV activity can be linked to reduced depression, anxiety, and stress. Interestingly, short-term employees experiencing high stress might exhibit higher low-frequency HRV, which could be an adaptive response to acute stressors. Lastly, studies [26], [27] focused on the association between working hours and HRV. Long working hours were associated with reduced sympathetic activity, as evidenced by lower urinary noradrenaline levels and a lower LF/HF ratio, suggesting that overwork could dampen the body's stress response over time.

In synthesizing these findings, it's clear that HRV parameters serve as a mirror reflecting various states of worker health and well-being. Elevated heart rates and changes in HRV metrics like RMSSD, LF, HF, and the LF/HF ratio provide a quantifiable picture of the effects of cognitive demands, environmental factors, fatigue, life satisfaction, mental workload, noise exposure, shift work, stress, and long working hours on employees. This body of evidence underscores the importance of monitoring HRV as a practical tool for identifying health risks and the efficacy of well-being interventions in the manufacturing industry. As research continues to expand, HRV could become a standard metric for safeguarding worker health and enhancing productivity.

3.5 HRV Contributions to Manufacturing

In the quest to enhance the manufacturing environment, HRV research has proven to be a vital tool. It has shed light on various facets of the workplace, revealing how the well-being, safety, efficiency, and productivity of workers are interconnected. HRV research contributions, as chronicled in Table 4, have led to significant improvements in several core areas within manufacturing settings.

Table 4 *HRV research contributions to manufacturing*

References	HRV Research Contribution to Manufacturing
[11], [12], [13], [14], [20], [28]	Worker Well-being
[18], [24], [25]	Safety
[15], [22]	Efficiency
[12], [16], [17], [21], [26], [27], [29]	Productivity

Studies that focus on worker well-being, such as [11], [12], [13], [14], [20], [28] have underscored the importance of monitoring physiological indicators to ensure that workers are not only physically fit but also mentally poised. For instance, by adopting stress reduction techniques that influence HRV positively, workers have shown improved well-being and lower stress levels. In terms of safety, the insights from HRV research, particularly from studies [18], [24], [25], have been instrumental. These studies have helped identify workplace conditions that may pose health risks, allowing for interventions that create safer working environments. For instance, by understanding the HRV changes due to night shifts, manufacturers can better assess the potential health risks and adapt work schedules accordingly.

Efficiency in manufacturing is another area that has benefited from HRV research. Studies such as [15], [22] have utilised HRV metrics to assess the workload and its impact on workers. This line of inquiry has led to more informed decisions about task assignments and work pacing, ensuring that employees are working at optimal levels without undue stress, thereby maintaining efficiency. Productivity, a key objective in manufacturing, has also been closely examined through the lens of HRV. The collective findings from studies [12], [16], [17], [21], [26], [27], [29] indicate that factors affecting HRV, such as stress levels and working hours, can influence how effectively employee's work. These insights have prompted changes in workplace practices to better align with the health and capabilities of workers, ultimately driving productivity.

The integration of HRV research in the manufacturing sector has been transformative. It has provided a deeper understanding of how worker health impacts overall workplace dynamics. By acknowledging and addressing the various stressors that employees face, manufacturing environments can be tailored to support not only the health and safety of workers but also the overall productivity and efficiency of operations. As this body of research continues to grow, it is likely that HRV will become an even more integral part of the continuous improvement strategies within the manufacturing industry, ensuring that the human aspect of industrial operations is not only preserved but optimised.

4. Research Utilising EEG Approaches in Manufacturing

4.1 EEG Research Focus Areas and Trends

EEG as a research tool in manufacturing environments has garnered significant interest due to its potential to enhance understanding of cognitive dynamics and human-machine interaction. In examining the deployment of EEG in this sector, the focus areas predominantly revolve around two critical applications, as depicted in Figure 6.

Int. Journal of Integrated Engineering Vol. 16 No. 5 (2024) p. 324-340

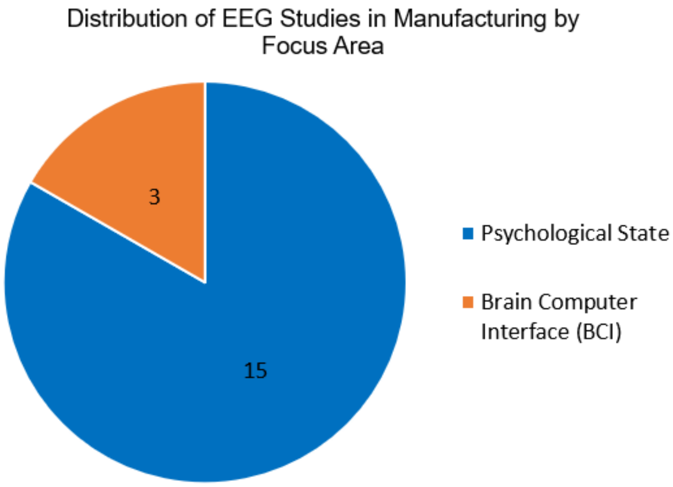

Fig. 6 *Distribution of EEG studies in manufacturing by focus area*

The predominant area of EEG application within the manufacturing context, as shown in Figure 6, is the monitoring of employees' psychological states. The majority of studies in this category aim to investigate mental workload, stress, cognitive strain, mental fatigue, and attentional focus. The driving force behind such research is to enhance the interplay between worker well-being and operational efficiency, ultimately contributing to heightened safety and productivity in the manufacturing environment.

In contrast, a smaller yet significant portion of research, highlighted by a distinct segment in Figure 6, is dedicated to the application of Brain-Computer Interface (BCI) technologies. These cutting-edge studies strive to create direct communication channels between the human brain and robotic systems. The adoption of BCI within the manufacturing sector has the potential to radically alter the way humans interact with machines, offering a more intuitive and natural engagement with complex machinery and robotic systems.

4.2 Recent Approach of EEG Applications in Manufacturing

The recent introduction of EEG into the manufacturing field signifies a transition toward a deeper understanding and improvement of cognitive and operational aspects of industrial labour. This shift has given rise to two principal areas of research that are the analysis of psychological states and the advancement of BCI technology.

EEG has been instrumental in psychological state research for quantifying mental workload, stress, fatigue, and other cognitive processes critical to ensuring safety and enhancing worker productivity. Notably, in 2023, a researcher developed a novel method to measure visual mental workload in assembly tasks without relying on specific task types [30]. By using a gel-based wireless EEG device, they gathered data on different levels of mental workload while operators followed visual instructions. This approach marks a significant step toward creating a universal tool for assessing mental workload in various manufacturing scenarios. Another 2023 study introduced a neuroergonomic assessment to evaluate mental workload in industrial human-robot interaction assembly tasks [31]. Employing the SMARTING wireless EEG system, this research demonstrated significant reductions in mental workload when incorporating robots, suggesting avenues for cognitive load optimisation in manufacturing settings.

Similarly, [32] has employed literature review methodologies to elucidate the role of neuroergonomics in addressing psychosocial risks and enhancing safety. This insight underscores the pivotal role of EEG in fostering ergonomic innovations within the manufacturing. Meanwhile, a 2022 study has explored the detection of mental fatigue through AI-augmented EEG analysis employing non-invasive EEG technology [33]. The research proposed a prototype interface to signal fatigue onset, thereby mitigating accident risks and enhancing operational safety in safeguarding worker health.

Subsequent EEG research in manufacturing has delved into cognitive assessment, focusing on assessing cognitive states such as problem-solving, attention, and memory. For example, studies in 2020 and 2019 analysed Lean Shopfloor Management in Industry 4.0 using EEG sensors and deep learning, focusing on problem-solving behaviours and the management system's impacts on process owners and leaders [34], [37]. The 2020 research achieved a 96.5% accuracy in classifying behaviours through neurological activity patterns under different management systems, while the 2019 study highlighted the prefrontal cortex's role in different problem-solving strategies. This combined approach showcases the potential of EEG data in enhancing manufacturing by aligning operations with the cognitive styles of management personnel.

In 2019, a researcher has aimed to identify EEG features capable of predicting cognitive overload, particularly in memory tasks among assembly workers [35]. They utilised the Biosemi ActiveTwo system to monitor EEG data, focusing on the correlation between alpha power activity and cognitive load levels during tasks of varying complexity. Another noteworthy study related to EEG and cognitive assessment in the workplace was conducted in 2019, focusing on worker attention [36]. This study aimed to develop cognition-aware computing within industrial environments, utilising wearable EEG and Kinect motion sensors to monitor and analyse the interaction between brain dynamics and physical movement among workers performing repetitive tasks.

Furthermore, in 2020, a study investigated how different standard times for assembling a product with Legos affected participants' brainwave behaviours, utilising the Emotiv Epoc wireless device for EEG monitoring [38]. This research aimed to explore the impact of mental workload variations induced by changing assembly speeds (100%, 80%, and 70% standard times). Findings revealed significant differences in brainwave intensity across various standard times, suggesting that adjusting task pacing can influence cognitive strain. Next in a 2017 study, researchers used the SMARTING system and Kinect sensors to record EEG and movement data from workers performing repetitive tasks, aiming to detect changes in attention and engagement [39]. The study demonstrated a decline in cognitive alertness over time, evidenced by decreases in P300 amplitude and Engagement Index, along with increases in unrelated movements. Similarly, in a 2014 study, researchers utilised the SMARTING wireless EEG system to monitor operators' vigilance levels in real work environments, focusing on reducing errors and improving safety [40]. The study aimed to measure and maintain vigilance through psychophysiological metrics, using EEG signals and ERPs like P300 to track cognitive processing and attention. This approach demonstrates the potential for real-time monitoring systems to enhance workplace safety by providing operators with alerts on their alertness levels, aiming to minimize accidents and boost efficiency in industrial settings.

The exploration of BCI systems for applications in a manufacturing context received a comprehensive review in a 2023 study, which focused on integrating EEG-based BCI systems in the Industrial Internet of Things (IIoT) for enhancing human-machine interaction and improving industrial processes [41]. The researchers analysed existing literature and performed lab-scale experiments using a single-channel EEG headset, comparing it with multi-channel EEG systems in various industrial scenarios. The finding suggests that single-channel EEG headsets can facilitate complex applications with reasonable accuracy. Further, in 2021, a study focused on BCI aimed to develop an innovative framework that leverages an individual's EEG signals to facilitate direct control over an industrial robot by the shop-floor operator [42]. This approach is designed to allow operators to command robots using their brain signals, thereby enhancing the interaction between humans and robots in manufacturing environments. Lastly, in 2007, a researcher critically reviewed the use of EEG-based BCI systems in manufacturing, aiming to show how EEG signals can control robots and enhance efficiency and interaction between humans and machines [43].

In conclusion, the investigation of EEG applications within manufacturing highlights a significant shift towards enhancing cognitive assessments and BCI technologies in industrial settings. However, the translation of these advancements from controlled laboratory studies to actual manufacturing environments has been limited. This gap is primarily attributed to the ergonomic challenges posed by current EEG systems, which are often impractical for daily use in manufacturing due to discomfort and the intrusive nature of continuous monitoring, alongside ethical concerns regarding worker privacy and consent. To realise the full potential of EEG technologies in improving manufacturing processes and worker well-being, future research must focus on the development of user-friendly, ergonomic EEG devices and the establishment of comprehensive ethical guidelines.

4.3 EEG Measurement Devices

In the field of BCI systems and psychological state evaluation, the choice of hardware is of paramount importance. The studies under review have utilised a wide range of EEG devices, along with various electrode channel configurations, to monitor brainwave activities for research objectives. Figures 7 and 8 provide an overview of the EEG devices and electrode channels that have been documented in studies pertinent to the application of EEG within the manufacturing sector.

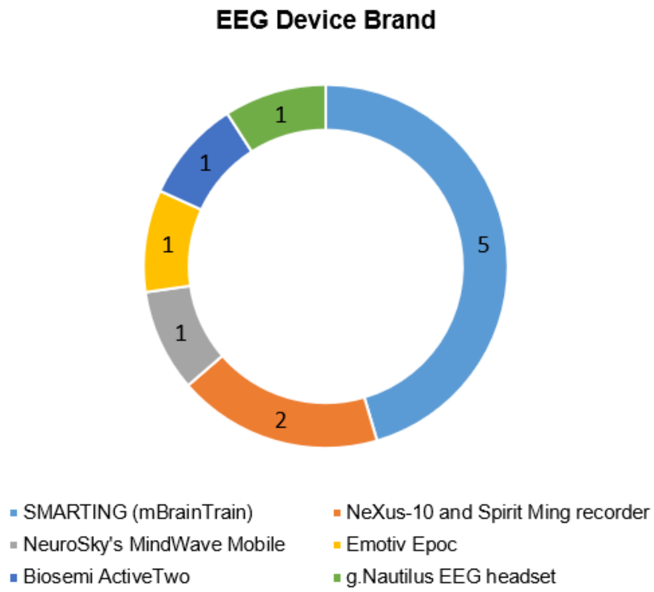

Fig. 7 *EEG device brands utilised*

Based on Figure 7, the SMARTING device by mBrainTrain emerges as the preferred EEG apparatus, having been selected for use in five distinct investigations [30], [31], [36], [39], [40]. The predilection for this device may be ascribed to its reputed dependability and the particular attributes that resonate with the research requisites. Alternately, the NeXus-10 and Spirit Ming recorder were employed in a couple of studies [44], [45], whereas NeuroSky's MindWave Mobile [46], Emotiv Epoc [38], Biosemi ActiveTwo [35], and the g.Nautilus EEG headset [42]were each featured once within the array of studies examined.

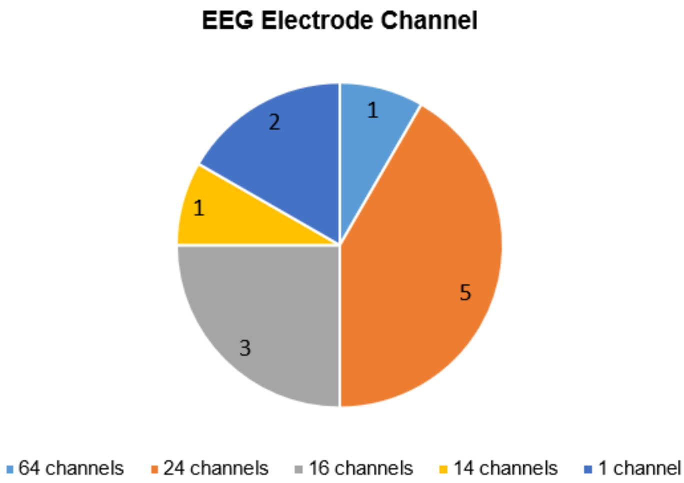

Fig. 8 *Variation in EEG electrode channels*

Moving on to the electrode channels, Figure 8 displays a clear preference for 24-channel configurations, which were utilised in five studies [30], [31], [36], [39], [40]. This preference may indicate a balance between spatial resolution and practical considerations such as setup complexity and data management. Three studies selected a 16-channel setup [34], [38], [42], one study implemented a 14-channel system [37], and a single-channel EEG was employed in two instances [41], [44].

In particular, study [41] provides a persuasive argument for the utility of a single-channel EEG headset in applications related to manufacturing processes. The researchers conducted a comparative analysis, measuring the performance of their single-channel EEG data against that from multi-channel datasets, namely those with 64, 32, and 25 channels, derived from various studies accessible online. The core finding of the study is the demonstrated viability of a streamlined, single-channel setup. Despite its simplicity, this configuration was shown to be adept at facilitating complex tasks, such as job inspection within manufacturing environments, achieving an impressive accuracy rate of 70%. This degree of accuracy, attained with a single-channel EEG, suggests that such devices can provide an equilibrium between functionality and simplicity, proving to be appropriate for certain industrial applications where comprehensive EEG monitoring might be unwarranted or not feasible.

In summary, the choice of hardware appears to be significantly influenced by the specific objectives and limitations inherent to each study. For example, a more extensive channel array may be required for a nuanced neural depiction crucial for intricate cognitive evaluations, whereas a single-channel EEG could be sufficient for concentrated studies or preliminary testing where extensive neural mapping is not essential.

4.4 EEG Parameters and Key Findings

EEG has emerged as a pivotal tool in understanding various psychological states in the manufacturing context. This section synthesizes key findings from studies [30], [31], [33], [35], [36], [38], [39], [40], [44], [45], [46], [47] that have utilised EEG to evaluate psychological states such as mental workload, mental fatigue, and cognitive processes. The Table 5 summarises the findings related to psychological states and their associated EEG parameters.

Table 5 *Correlation of EEG parameters with psychological states and findings*

References	Psychological State	Key EEG Parameters	Key Findings
[30], [31], [38], [44], [45]	Mental Workload	- Theta (θ) wave - Alpha (α) wave - Beta (β) wave - Gamma (γ) waves - Sensory Motor Rhythm (SMR) wave	Increases in mental workload lead to an increase in θ/α and β/α power ratios. There is also an increase in θ, β, γ, and SMR wave activities.
[33], [46], [47]	Mental Fatigue	- Theta (θ) wave - Alpha (α) wave - Beta (β) wave	An increase in mental fatigue is associated with an increase in θ power.
[36], [39], [40], [47]	Cognitive Process (Attention)	- Theta (θ) wave - Alpha (α) wave - Beta (β) wave - P300 - Sensory Motor Rhythm (SMR) wave	A decrease in attention is associated with a decrease in P300 amplitude, and an increase in attention is linked with an increase in SMR wave activity.
[35]	Cognitive Process (Memory)	- α (Alpha) wave	An increase in cognitive load leads to a decrease in α wave power.

Table 5 provides a comprehensive overview of the correlations between EEG parameters and various psychological states in the manufacturing context, as demonstrated by numerous studies. In the area of mental workload, a wide range of EEG parameters, including Theta (θ), Alpha (α), Beta (β), Gamma (γ), and Sensory Motor Rhythm (SMR) waves, have been shown to have significant correlations. It is noted that an increase in mental workload typically results in higher θ/α and β/α power ratios, along with increased activities in θ, β, γ, and SMR waves, as indicated in studies [30], [31], [38], [44], [45].

Regarding mental fatigue, a crucial factor in manufacturing settings, a significant relationship has been found with changes in θ wave power. Specifically, an increase in mental fatigue is reflected by a rise in θ power, suggesting a reduction in cognitive efficiency, as pointed out in [33], [46], [47].

Furthermore, regarding cognitive processes, especially attention, which is essential for task performance, distinct EEG markers have been identified. A decrease in attention is linked with a reduction in P300 amplitude, while an increase in attention is associated with an increase in SMR wave activity. This relationship is key for detecting lapses in attention in real-time, as indicated in studies [36], [39], [40], [47].

Finally, memory processing, an important cognitive function in the manufacturing sector, is primarily associated with α (Alpha) wave activity. Notably, an increase in cognitive load tends to result in a decrease in α wave power, a finding uniquely reported in [35]. However, there are no significant findings related to correlation of EEG parameter and it finding for the cognitive process for problem solving and BCI studies.

In conclusion, the analysis in Table 5 emphasizes the crucial role of key EEG parameters in mapping psychological states in the manufacturing sector. Theta (θ), Alpha (α), Beta (β), Gamma (γ), and Sensory Motor Rhythm (SMR) waves have been identified as significant indicators of mental workload, with increases in these parameters correlating with heightened mental demands. Mental fatigue is specifically associated with an increase in θ wave power, indicating a decline in cognitive performance. For cognitive processes like attention and memory, distinct EEG markers such as changes in P300 amplitude and α wave power provide valuable insights. This understanding of the relationship between EEG parameters and psychological states can inform strategies to enhance cognitive well-being and productivity in manufacturing environments.

4.5 EEG Contributions to Manufacturing

From the studies, the use of EEG within the manufacturing sector has contributed to various aspects of the work environment, aiming to improve both human factors and operational outcomes. Table 6 summarizes the EEG studies that contributions to the manufacturing sector across four different aspects that are worker well-being, safety, efficiency, and productivity. Each aspect is frequently emphasized in the manufacturing sector to minimize waste and increase profits.

Table 6 *EEG research contributions to manufacturing*

References	EEG Research Contribution to Manufacturing
[31], [32], [34], [40], [44]	Worker Well-being
[32], [33], [46]	Safety
[30], [31], [41], [42]	Efficiency
[34], [45]	Productivity

Table 6 showed the key areas where EEG research has impacted manufacturing, showcasing how EEG technology contributes to four main outcomes that are worker well-being, safety, efficiency, and productivity. Each of these outcomes is crucial for a successful manufacturing process. Focusing on worker well-being, studies demonstrate that EEG can help reduce mental workload. For instance, [31] details how robots can alleviate some of the strain on workers, while [32] discusses the benefits of neuroergonomics for a safer and healthier workplace. Additionally, [34] investigates how a deeper understanding of brain functions can enhance worker well-being, [40] emphasizes the development of systems for real-time issue alerting, and [44] explores the design of equipment tailored to our natural physiological processes.

In terms of safety, EEG has been instrumental in detecting when workers are becoming mentally fatigued, a key factor in accident prevention, as outlined in [33], [46]. Furthermore, [32] illustrates how the application of neuroergonomic principles can bolster safety measures. Regarding efficiency, EEG contributes to optimizing job designs to align with how people work most effectively, as seen in [30]. [31] highlights how robots can assist workers, simplifying tasks and streamlining the manufacturing process. [41], [42] showcase the advantages of EEG-based BCIs for tasks such as job inspection and facilitating human-robot collaboration, enhancing operational smoothness.

Lastly, productivity benefits from EEG research by offering insights into how brain function influences work performance, as discussed in [34]. [45] further demonstrates the potential of EEG-based BCIs to leverage people's skills and increase production capabilities. In summary, EEG research is proving to be an invaluable asset in manufacturing, enhancing worker satisfaction and performance, ensuring a safer work environment, improving process efficiency, and boosting production output.

5. Research Utilising Integration HRV and EEG Approaches in Manufacturing

In recent years, the application of Electroencephalography (EEG) and Heart Rate Variability (HRV) in the manufacturing industry has become increasingly prominent. This trend aligns with the principles of Industry 5.0, which emphasizes a human-centric approach in the workplace. Despite the growing interest, there remain relatively few studies that explore the integration of HRV and EEG within the manufacturing context. Two notable studies stand out in this field are a [48] study focusing on stress measurement in manufacturing environments, and a [49] study aimed at enhancing the safety of epileptic patients in industrial settings.

The [48] study aimed to measure stress comprehensively by analysing physiological signals, including HRV and EEG, alongside performance indicators and workers' perceptions of stress. This approach sought to understand the impact of stress on both worker well-being and performance. The method involved a combination of performance evaluation, physiological monitoring, and stress perception questionnaires. The study used various devices to measure heart rate, electrodermal activity, brain activity, and muscle activity. The findings emphasized the need to consider a wide range of physiological and psychological parameters to accurately assess stress levels in a manufacturing context.

Meanwhile, the [49] study was designed to improve the safety of epileptic workers. It focused on developing a system to predict epileptic seizures, reducing risks to both employees and machinery. This system, integrating with industrial IoT applications, monitored vital signs using EEG and other sensors. Notably, it employed accelerometers to analyse employee movements, helping to predict seizures and allow for timely intervention.

Both studies contribute valuable insights to the manufacturing sector. The [48] study lays the groundwork for interventions to enhance worker well-being and productivity, while the [49] research offers a novel solution for the safety of workers with specific medical needs. Although neither study directly links HRV and EEG, their combined use underscores their importance in managing worker health and safety. In conclusion, the integration of HRV and EEG in manufacturing represents a significant step forward in occupational health and safety. These technologies offer a pathway to more personalized and proactive health measures, greatly enhancing workplace safety and efficiency.

6. Discussion

In the context of integrating HRV and EEG technologies within the manufacturing industry, several challenges and opportunities emerge, particularly when considering the advancement towards Industry 5.0. The real-time application of HRV is increasingly recognised for its potential to enhance manufacturing efficiency and worker well-being. However, the application of EEG in a similar real-time context faces difficulty due to the complexity and cost of the equipment, as well as ethical concerns surrounding continuous monitoring of workers. Despite these challenges, the integration of these technologies offers a promising approach for creating a more responsive, adaptive, and human-centric manufacturing environment. In the event of establishing a correlation between HRV and EEG, it becomes possible to utilise wearable devices, such as smartwatches, to approximate EEG metrics. This advancement could significantly mitigate the challenges associated with the real-time implementation of physiological monitoring, thereby rendering such monitoring more practical in manufacturing environments.

The contribution of HRV and EEG monitoring to the Industry 5.0 paradigm extends beyond technological integration, touching on the human-centric manufacturing. By facilitating a deeper understanding of worker physiological states, these technologies pave the way for policies and practices that prioritize worker safety, well-being, and efficiency. Challenges such as the non-invasiveness of devices and noise interference in data collection require innovative solutions that balance technological feasibility with ethical considerations. As manufacturing environments evolve, the potential for these technologies to inform policymaking and leadership decisions grows, emphasising the need for a strategic approach that aligns technological advancements with the welfare of the workforce.

Moreover, ethical considerations surrounding the monitoring of physiological data in the workplace highlight the needed to be clarify, participatory practices that respect worker privacy and autonomy. Establishing clear guidelines and gaining informed consent are crucial to promote trust and acceptance among workers. The discussion on integrating HRV and EEG monitoring into manufacturing practices brings to light the broader conversation about the role of technology in enhancing human work conditions. As society moves towards the increasing adoption of such integrations, it becomes crucial to address the complex technological and ethical challenges while maintaining a reliable commitment to enhancing both individual and collective well-being.

7. Conclusion

In conclusion, the review has systematically unpacked the integration of physiological monitoring in the manufacturing sector, underscoring its alignment with Industry 5.0's human centric paradigm. The exploration of HRV and EEG methodologies has illuminated their potential to enhance not only the well-being and safety of workers but also the overall productivity and efficiency of manufacturing processes. The research indicates a growing trend towards the adoption of such biometric monitoring tools, with an emphasis on their application for stress management, cognitive workload assessment, and the optimisation of human-machine interfaces. Building upon the insights gained from the integration of HRV and EEG in the manufacturing sector, this review further emphasizes the need for technological advancements to be ethically aligned with the principles of Industry 5.0. Recognising this, the paper proposes a forward-looking research agenda centred around the development of an ethical framework for the application of HRV and EEG technologies. This framework aims to balance operational efficiency with the privacy and autonomy of workers, recommending the use of non-invasive, wearable devices such as smartwatches that not only respect the individual's comfort but also integrate seamlessly with existing IIoT systems. Such an approach is designed to provide immediate insights into the physiological states of workers, enabling adjustments that prioritize well-being and efficiency in real-time.

The path forward includes conducting a pilot study in a real manufacturing environment to evaluate the practical impact of HRV and EEG monitoring on worker well-being, safety, and productivity. This critical step will involve closely examining workers' responses to these technologies, particularly their views on privacy and technology acceptance. By analysing the outcomes of this study, the research aims to shed light on the practicalities of implementing physiological monitoring technologies in the workplace, contributing valuable insights to the ongoing discussion about ethical technology use. Ultimately, this seeks to establish a set of guidelines and best practices that could inform future implementations across the manufacturing industry, ensuring that innovation in worker monitoring remains ethically grounded and human centric. This approach not only aligns with the foundational values of Industry 5.0 but also ensures that technological progress enhances the manufacturing landscape in an ethical, inclusive, and productive manner.

Funding

This research was supported by Ministry of Higher Education (MOHE) through Fundamental Research Grant Scheme (FRGS/1/2023/ICT06/UTHM/02/2).

Acknowledgement

We would like to extend our sincere gratitude and appreciation to MOHE for financially supporting this work.

Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm their contributions to the paper as follows: ***conceptualization:*** *Amirul Syafiq Sadun, Hairulazwan Hashim, Hasliza Hassan, Salwa Mahmood, Noraini Marsi, Muhammad Ashraf Fauzi;* ***literature search and review:*** *Saranjuu Chulakit, Amirul Syafiq Sadun, Nor Anija Jalaludin;* ***draft manuscript preparation:*** *Saranjuu Chulakit;* ***review and editing:*** *Amirul Syafiq Sadun, Hairulazwan Hashim, Nor Anija Jalaludin, Hasliza Hassan, Salwa Mahmood, Noraini Marsi, Muhammad Ashraf Fauzi. All authors reviewed and approved the final version of the manuscript.*

References

[1] X. Xu, Y. Lu, B. Vogel-Heuser, and L. Wang, “Industry 4.0 and Industry 5.0—Inception, conception and perception,” *Journal of Manufacturing Systems*, vol. 61, pp. 530–535, 2021, doi: https://doi.org/10.1016/j.jmsy.2021.10.006.

[2] P. K. R. Maddikunta *et al.*, “Industry 5.0: A survey on enabling technologies and potential applications,” *Journal of Industrial Information Integration*, vol. 26, p. 100257, 2022, doi: https://doi.org/10.1016/j.jii.2021.100257.

[3] O. Ayasrah and F. M. Turan, “A Review of Multi-criteria Decision-Making Methods Using Application of Variable Weight Theory and IF-TOPSIS-EF,” in *Recent Trends in Manufacturing and Materials Towards Industry 4.0*, M. N. Osman Zahid, A. S. Abdul Sani, M. R. Mohamad Yasin, Z. Ismail, N. A. Che Lah, and F. Mohd Turan, Eds., in Lecture Notes in Mechanical Engineering. , Singapore: Springer Singapore, 2021, pp. 13–24. doi: 10.1007/978-981-15-9505-9_2.

[4] N. Q. A. Adanan, F. M. Turan, and K. Johan, “Industrial Sustainability Policy and Standards-Related on Management Discipline of SMEs Industry in Malaysia: A Conceptual Framework,” in *Recent Trends in Manufacturing and Materials Towards Industry 4.0*, M. N. Osman Zahid, A. S. Abdul Sani, M. R. Mohamad Yasin, Z. Ismail, N. A. Che Lah, and F. Mohd Turan, Eds., in Lecture Notes in Mechanical Engineering. , Singapore: Springer Singapore, 2021, pp. 25–32. doi: 10.1007/978-981-15-9505-9_3.

[5] N. S. Sahimi, F. M. Turan, and K. Johan, “Framework of Sustainability Assessment (FSA) method for manufacturing industry in Malaysia,” *IOP Conf. Ser.: Mater. Sci. Eng.*, vol. 342, p. 012079, Apr. 2018, doi: 10.1088/1757-899X/342/1/012079.

[6] S. Huang, B. Wang, X. Li, P. Zheng, D. Mourtzis, and L. Wang, “Industry 5.0 and Society 5.0—Comparison, complementation and co-evolution,” *Journal of Manufacturing Systems*, vol. 64, pp. 424–428, 2022, doi: https://doi.org/10.1016/j.jmsy.2022.07.010.

[7] W. N. S. W. Lanang, F. M. Turan, and K. Johan, “Incorporating attitudinal parameter in assessing sustainability of Malaysia manufacturing industry,” *IOP Conf. Ser.: Mater. Sci. Eng.*, vol. 342, p. 012076, Apr. 2018, doi: 10.1088/1757-899X/342/1/012076.

[8] N. Q. A. Adanan, F. M. Turan, and K. Johan, “Sustainable Finished Product Optimization on Quality Response and Attitudinal Parameters,” in *Advances in Mechatronics, Manufacturing, and Mechanical Engineering*, M. A. Zakaria, A. P. P. Abdul Majeed, and M. H. A. Hassan, Eds., in Lecture Notes in Mechanical Engineering. , Singapore: Springer Singapore, 2021, pp. 261–268. doi: 10.1007/978-981-15-7309-5_25.

[9] G. Blandino, “How to Measure Stress in Smart and Intelligent Manufacturing Systems: A Systematic Review,” *Systems*, vol. 11, no. 4, 2023, doi: 10.3390/systems11040167.

[10] T. A. Tran *et al.*, “Heart Rate Variability Measurement to Assess Acute Work-Content-Related Stress of Workers in Industrial Manufacturing Environment - A Systematic Scoping Review,” *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 53, no. 11, pp. 6685–6692, 2023, doi: 10.1109/TSMC.2023.3282141.

[11] H. Choi, Y. H. Jeon, J. W. Han, J. Moon, S. Y. Kim, and J. M. Woo, “The Effects of a Forest Therapy on Work-Related Stress for Employees in the Manufacturing Industry: Randomized Control Study,” *Global Advances In Health and Medicine*, vol. 11, pp. 1–10, 2022, doi: 10.1177/2164957X221100468.
[12] A. P. Sutarto, K. M. Khairai, and M. N. Abdul Wahab, “Multimodal stress-management intervention improves physiological, psychological, and productivity of assembly-line workers,” *Industrial Engineering and Management Systems*, vol. 19, no. 4, pp. 812–824, 2020, doi: 10.7232/iems.2020.19.4.812.
[13] A. P. Sutarto, K. M. Khairai, and M. N. A. Wahab, “Assessment of stress among assembly-line workers: Correlation between subjective and objective physiological measures,” *International Journal of Human Factors and Ergonomics*, vol. 7, no. 3, pp. 207–224, 2020, doi: 10.1504/IJHFE.2020.110094.
[14] A. Purwandini Sutarto, M. N. Abdul Wahab, and N. Mat Zin, “Resonant breathing biofeedback training for stress reduction among manufacturing operators,” *International Journal of Occupational Safety and Ergonomics*, vol. 18, no. 4, pp. 549–561, 2012, doi: 10.1080/10803548.2012.11076959.
[15] K. H. Lee, K. Yoon, M. Ha, J. Park, S. H. Cho, and D. Kang, “Heart rate variability and urinary catecholamines from job stress in Korean male manufacturing workers according to work seniority,” *Industrial Health*, vol. 48, no. 3, pp. 331–338, 2010, doi: 10.2486/indhealth.48.331.
[16] A. Shin, S. S. Hwang, J. S. Kim, D. Kang, and S. Cho, “제조업 근로자에서 직무 스트레스가 자율 신경계 활성도에 미치는 영향,” vol. 14, no. 3, pp. 280–287, 2002.
[17] A. Lambay, Y. Liu, Z. Ji, and P. Morgan, “Effects of Demographic Factors for Fatigue Detection in Manufacturing,” *IFAC-PapersOnLine*, vol. 55, no. 2, pp. 528–533, 2022, doi: 10.1016/j.ifacol.2022.04.248.
[18] A. Bettoni *et al.*, “Mutualistic and adaptive human-machine collaboration based on machine learning in an injection moulding manufacturing line,” *Procedia CIRP*, vol. 93, pp. 395–400, 2020, doi: 10.1016/j.procir.2020.04.119.
[19] A. M. Nardolillo, A. Baghdadi, and L. A. Cavuoto, “Heart rate variability during a simulated assembly task; influence of age and gender,” *Proceedings of the Human Factors and Ergonomics Society*, vol. 2017-Octob, pp. 1853–1857, 2017, doi: 10.1177/1541931213601943.
[20] C. J. Lin and R. P. Lukodono, “Classification of mental workload in Human-robot collaboration using machine learning based on physiological feedback,” *Journal of Manufacturing Systems*, vol. 65, no. 43, pp. 673–685, 2022, doi: 10.1016/j.jmsy.2022.10.017.
[21] D. Bläsing and M. Bornewasser, “Influence of increasing task complexity and use of informational assistance systems on mental workload,” *Brain Sciences*, vol. 11, no. 1, pp. 1–19, 2021, doi: 10.3390/brainsci11010102.
[22] S. Digiesi, V. M. Manghisi, F. Facchini, E. M. Klose, M. M. Foglia, and C. Mummolo, “Heart rate variability based assessment of cognitive workload in smart operators,” *Management and Production Engineering Review*, vol. 11, no. 3, pp. 56–64, 2020, doi: 10.24425/mper.2020.134932.
[23] M. A. M. Said, Z. Wellun, and N. K. Khamis, “Effects of Noise Hazards towards Physiology Especially Heart Rate Performance among Worker in Manufacturing Industry and Their Prevention Strategies: A Systematic Review,” *Iranian Journal of Public Health*, vol. 51, no. 8. pp. 1706–1717, 2022. doi: 10.18502/ijph.v51i8.10251.
[24] S. Lee, H. Kim, D. H. Kim, M. Yum, and M. Son, “Heart rate variability in male shift workers in automobile manufacturing factories in South Korea,” *International Archives of Occupational and Environmental Health*, vol. 88, no. 7, pp. 895–902, 2015, doi: 10.1007/s00420-014-1016-8.
[25] S. Ichihara *et al.*, “Exposure assessment and heart rate variability monitoring in workers handling titanium dioxide particles: a pilot study,” *Journal of Nanoparticle Research*, vol. 18, no. 3, pp. 1–14, 2016, doi: 10.1007/s11051-016-3340-2.
[26] T. Sasaki *et al.*, “Effect of working hours on cardiovascular-autonomic nervous functions in engineers in an electronics manufacturing company,” *Industrial Health*, vol. 37, no. 1, pp. 55–61, 1999, doi: 10.2486/indhealth.37.55.
[27] T. Sasaki, K. Iwasaki, T. Oka, and N. Hisanaga, “Association of working hours with biological indices related to the cardiovascular system among engineers in a machinery manufacturing company,” *Industrial Health*, vol. 37, no. 4, pp. 457–463, 1999, doi: 10.2486/indhealth.37.457.
[28] M. Nubli *et al.*, “Correlation Between Life Satisfaction and Heart Rate Variability Coherence Among Blue-Collar Workers – Case Study In A Malaysian Electronic Manufacturing Company,” vol. 2, 2023, doi: https://doi.org/10.56943/jsh.v2i2.297.
[29] T. A. Tran, J. Abonyi, L. Kovacs, G. Eigner, and T. Ruppert, “Heart Rate Variability Measurement to Assess Work-Related Stress of Physical Workers in Manufacturing Industries-Protocol for a Systematic Literature Review,” *SISY 2022 - IEEE 20th Jubilee International Symposium on Intelligent Systems and Informatics, Proceedings*, pp. 313–318, 2022, doi: 10.1109/SISY56759.2022.10036300.
[30] M. P. Brito *et al.*, “Visual Mental Workload Assessment from EEG in Manual Assembly Task,” 2023, doi: 10.3850/981-973-0000-00-0.

[31] C. Caiazzo, M. Savkovic, M. Pusica, D. Milojevic, M. C. Leva, and M. Djapan, “Development of a Neuroergonomic Assessment for the Evaluation of Mental Workload in an Industrial Human–Robot Interaction Assembly Task: A Comparative Case Study,” *Machines*, vol. 11, no. 11, Nov. 2023, doi: 10.3390/machines11110995.
[32] I. Lombardi, V. Fernando Muñoz Martínez, V. Paolo Senese, and S. Capece, “Design, Human Factors and Neuroergonomics for safety in manufacturing,” in *Human Factors in Accessibility and Assistive Technology*, AHFE International, 2023. doi: 10.54941/ahfe1003653.
[33] M. M. Rivera, L. Martinez, A. O. Zezzatti, A. Navarro, J. Rodarte, and N. López, “Prototype interface for detecting mental fatigue with EEG and XAI frameworks in Industry 4.0,” in *Explainable Artificial Intelligence in Medical Decision Support Systems*, Institution of Engineering and Technology, 2022, pp. 117–136. doi: 10.1049/pbhe050e_ch4.
[34] D. Schmidt, J. V. Diez, J. Ordieres-Meré, R. Gevers, J. Schwiep, and M. Molina, “Industry 4.0 lean shopfloor management characterization using EEG sensors and deep learning,” *Sensors (Switzerland)*, vol. 20, no. 10, May 2020, doi: 10.3390/s20102860.
[35] J. Morton *et al.*, “Identifying predictive EEG features for cognitive overload detection in assembly workers in Industry 4.0,” 2019.
[36] P. Mijović *et al.*, “Communicating the user state: Introducing cognition-aware computing in industrial settings,” *Safety Science*, vol. 119, pp. 375–384, Nov. 2019, doi: 10.1016/j.ssci.2017.12.024.
[37] J. Villalba-Diez, X. Zheng, D. Schmidt, and M. Molina, “Characterization of industry 4.0 lean management problem-solving behavioral patterns using EEG sensors and deep learning,” *Sensors (Switzerland)*, vol. 19, no. 13, Jul. 2019, doi: 10.3390/s19132841.
[38] A. I. García Acosta, J. de la Riva Rodríguez, J. Sánchez Leal, and R. M. Reyes Martínez, “Analysis of brainwaves behavior, employing different standard times during the assembly of a product with legos for manufacturing applications,” in *Intelligent Systems Reference Library*, vol. 166, Springer Science and Business Media Deutschland GmbH, 2020, pp. 411–427. doi: 10.1007/978-3-030-26488-8_18.
[39] P. Mijović, M. Milovanović, I. Gligorijević, V. Ković, I. Živanović-Mačužić, and B. Mijović, “Investigating Brain Dynamics in Industrial Environment – Integrating Mobile EEG and Kinect for Cognitive State Detection of a Worker,” 2017, pp. 66–78. doi: 10.1007/978-3-319-58628-1_6.
[40] P. Mijović, I. Gligorijević, E. Giagloglou, I. Mačužićand, and B. Jeremić, “Psychophysiological Measurements in Real Working Environments Wireless EEG Study of the Operators’ Vigilance,” 2014. [Online]. Available: http://www.innhf.eu
[41] R. Ajmeria *et al.*, “A Critical Survey of EEG-Based BCI Systems for Applications in Industrial Internet of Things,” *IEEE Communications Surveys and Tutorials*, vol. 25, no. 1, pp. 184–212, 2023, doi: 10.1109/COMST.2022.3232576.
[42] A. Mohammed and L. Wang, “Intelligent human-robot assembly enabled by brain EEG,” in *Advanced Human-Robot Collaboration in Manufacturing*, Springer, 2021, pp. 351–371. doi: 10.1007/978-3-030-69178-3_14.
[43] T. Shanmugapriya and S. Senthilkumar, “Robotics and the Brain-Computer Interface System: Critical Review for Manufacturing Application,” *International Journal of Innovative Research in Computer and Communication Engineering (An ISO*, vol. 3297, no. 2, 2007, [Online]. Available: www.ijircce.com
[44] Q. G. Ma, X. L. Sun, H. J. Fu, D. C. Zhao, and J. F. Guo, “Manufacturing process design based on mental and physical workload analysis,” in *Applied Mechanics and Materials*, 2013, pp. 482–485. doi: 10.4028/www.scientific.net/AMM.345.482.
[45] Q. Ma, Q. Shang, H. Fu, and F. Chen, “Mental workload analysis during the production process: EEG and GSR activity,” in *Applied Mechanics and Materials*, 2012, pp. 193–197. doi: 10.4028/www.scientific.net/AMM.220-223.193.
[46] I. Arieshanti, Annual IEEE Computer Conference, C. T. International Conference on Information, S. 8 2014 09 24 Surabaya, and ICTS 8 2014.09.24 Surabaya, “Analyzing Brainwave Using Single Electroencephalographic Channel To Identify Manufacturing Supervisor Fatigue,” 2014.
[47] Q. Ma, Q. Shang, J. Bian, and H. Fu, “A Research on the Application of Physiological Status Information to Productivity Enhancement,” 2011.
[48] A. Apraiz, G. Lasa, F. Montagna, G. Blandino, E. Triviño-Tonato, and A. Dacal-Nieto, “An Experimental Protocol for Human Stress Investigation in Manufacturing Contexts: Its Application in the NO-STRESS Project,” *Systems*, vol. 11, no. 9, Sep. 2023, doi: 10.3390/systems11090448.
[49] A. Hayek, S. Telawi, J. Börcsök, R. Abi Zeid Daou, and N. Halabi, “Smart wearable system for safety-related medical IoT application: case of epileptic patient working in industrial environment,” *Health and Technology*, vol. 10, no. 1, pp. 363–372, Jan. 2020, doi: 10.1007/s12553-019-00335-2.