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Sensores Fisiológicos Vestíveis Aplicados à Segurança e Saúde na Construção Civil: Uma Revisão

Wearable Physiological Sensors Applied to Safety and Health in Civil Construction: A Review

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Abstract

Civil construction is characterized by a high rate of accidents and occupational diseases due to the presence of dynamic, hazardous environments and activities requiring intense physical exertion, which can have a negative impact on workers' health and safety. Several technologies are being implemented in this context to mitigate these effects, such as wearable physiological data devices, which promote continuous and uninterrupted monitoring of various data. The current study aims to investigate the main aspects and metrics addressed in wearable technology applications of physiological data in civil construction. A systematic review of the literature on these devices used in construction to improve occupational health and safety was conducted. As a result, 35 studies followed the review's parameters, which identified five categories of investigation - physical aspect, emotional aspect, risk perception/identification, distraction/attention, and thermal comfort - as well as the major physiological metrics collected, such as heart rate, encephalography, and photoplethysmography data. Wristband devices and heart rate were identified as the most potentially beneficial device and physiological metric for field applications, respectively. This could increase the use of wearable technology in construction environments and pave the way for the use of other devices and physiological data in the field to improve worker health and safety.

Keywords: wearable technology, occupational safety, civil construction.

Resumo

A construção civil é caracterizada por uma alta taxa de acidentes e doenças ocupacionais devido à presença de ambientes dinâmicos e perigosos, além de atividades que exigem esforço físico intenso, o que pode ter um impacto negativo na saúde e segurança dos trabalhadores. Diversas tecnologias estão sendo implementadas nesse contexto para mitigar esses efeitos, como dispositivos vestíveis de monitoramento de dados fisiológicos, que promovem o acompanhamento contínuo e ininterrupto de várias informações. O presente estudo tem como objetivo investigar os principais aspectos e métricas abordados nas aplicações de tecnologia vestível para dados fisiológicos na construção civil. Foi realizada uma revisão sistemática da literatura sobre esses dispositivos usados na construção para melhorar a saúde e a segurança ocupacional. Como resultado, 35 estudos seguiram os parâmetros da revisão, identificando cinco categorias de investigação: aspecto físico, aspecto emocional, percepção/identificação de risco, distração/atenção e conforto térmico, além das principais métricas fisiológicas coletadas, como frequência cardíaca, encefalografia e dados de fotopletismografia. Dispositivos de pulseira e a frequência cardíaca foram identificados como o dispositivo e a métrica fisiológica com maior potencial de benefício para aplicações em campo, respectivamente. Isso pode aumentar o uso de tecnologia vestível em ambientes de construção e abrir caminho para o uso de outros dispositivos e dados fisiológicos no campo para melhorar a saúde e segurança dos trabalhadores.

Palavras-chave: tecnologia vestível, segurança ocupacional, construção civil.

Introduction

Because of the hazardous nature of its activities and the work environment, the construction industry pays special attention to the health and safety of its workers.

Dynamic heavy objects, falling hazards, hazards approaching from all directions, repetitive work, challenging environments, uneven walking surfaces, vehicles, and blind spots are all hazards in the construction environment. (BANERJEE; HEMPEL; SHARIF, 2017). According to OSHA (2021), construction accounted for 20% of all work-related deaths in the private sector in the United States in 2019, accounting for one in every five worker deaths. Furthermore, the construction industry is responsible for 61,000 non-fatal work accidents in the United Kingdom, according to Health and Safety Statistics (2021).

In order to reduce these high rates, minimize worker absenteeism, and make the work environment safer, many methods are used to identify risk factors for workers and/or recognize hazardous activities. These techniques are primarily based on manual approaches, self-reports (questionnaires), and observation and vision, but they are frequently time-consuming, relatively imprecise, intrusive, and prone to errors due to expert judgment (DAVID, 2005; GOLPARVAR-FARD; HEYDARIAN; NIEBLES, 2013; TANEJA et al., 2011). Moreover, safety briefings, training, and organizational monitoring are frequently in place but are inefficient (BANERJEE; HEMPEL; SHARIF, 2017). Another issue is that safety has been measured and managed in a reactive manner, with actions taken in response to negative trends in injuries, which is inefficient in preventing new cases of accidents (HALLOWELL et al., 2013). Wearable technologies have attracted attention in this scenario because they can allow continuous monitoring of vital signs as well as safety performance, promoting the provision of objective data in a non-intrusive and real-time manner, which can be used to make efficient and proactive decisions to solve health and safety problems in construction (AWOLUSI; MARKS; HALLOWELL, 2018).

Among the applications of wearable devices, two major groups stand out: (1) location sensors, which primarily seek to avoid accidents near the equipment and to prevent falls; and (2) physiological data collection sensors (which may be from an organ or organ system) and kinematic sensors (AHN et al., 2019).

Physiological data sensors have been researched in several studies, and the analysis of the collected data allows for application in topics such as physical effort evaluation (GATTI et al., 2012), emotional aspect (HWANG et al., 2018), perceived risk (LEE et al., 2021) and distraction analysis (KE et al., 2021). This demonstrates the wide range of applications of these devices as well as the extensive set of benefits that can be provided by utilizing the captured parameters. As an example of the benefits derived from these investigations, can be mention improvements in construction safety management (CHOI; JEBELLI; LEE, 2019), better productivity and safety performance (GATTI et al., 2012), and early detection and mitigation of stress at construction sites (JEBELLI et al., 2020). In this context, identifying the state of the art in this field is critical in order to demonstrate the challenges and benefits of their development and application.

Thus, the research seeks to answer the following questions: (I) What aspects of construction worker safety and health are being investigated using wearable devices that collect physiological data, and what are the benefits of their use? (II) What data are captured by physiological wearable devices used in the construction industry?

Therefore, the current study seeks to investigate the main aspects and metrics addressed in the use of wearable devices that collect physiological data in construction environments. Furthermore, it seeks to identify the difficulties associated with using these devices on construction sites, as well as their limitations and the benefits derived from their use.

Method

A Systematic Literature Review (SLR) was carried out in order to achieve the study's objectives. The review was carried out in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, a recognized effective method for SLR elaboration. The review process consisted of four steps: (1) protocol definition; (2) article identification; (3) selection steps; and (4) synthesis of selected articles.

Initially, a research protocol was developed to define the parameters used in the SLR, as well as the measures to achieve the review's objectives. The selection criteria, extraction steps, and data analysis strategies were determined in this step. The defined search sources were Engineering Village, Scopus, and Web of Science, which are academic databases recognized by researchers in the investigated field.

Scopus and Web of Science are the most widely used databases in academic research: the former features the largest number of indexed articles and the most recent sources, while the latter also includes a substantial amount of literature published in the past (SEO, 2023). Engineering Village, in turn, is indexed and validated by experts in the field and is recognized as the leading platform for retrieving engineering-related information (Engineering Village Quick Reference Guide, 2015). Thus, the selection of these databases ensures that the search yields relevant articles from a range of publication periods and is closely aligned with the area of interest.

After selecting the databases, it was determined that the articles should be written in English and have fully accessible content. The SLR boundary conditions were determined through exploratory database research.

Through the analysis of the results of these researches, the search language of this review was defined: (*"wearable technology" OR "wearable sensors" OR "wearable devices" OR "wearable electronic devices"*) *AND* (*"construction industry" OR "construction workers" OR "construction safety" OR "construction sites" OR "construction projects" OR "construction activities" OR "construction environment" OR* *"construction hazards" OR "safety engineering" OR "civil engineering"*). It was decided not to limit the search terms to wearable physiological sensors so that works related to the theme would not be overlooked. This was necessary because it was possible to identify, in the initial stages, that not all studies made clear what type of data the sensor used captured in the title, abstract, and keywords fields. Civil construction workers who put in the most effort on construction sites, such as bricklayers, servants, and welders, should make up the study population. The research protocol was entered into the PROSPERO database under the number CRD42022331830.

On 09/10/2021, articles were identified in the three pre-defined databases in the research protocol. At first, 600 articles were obtained. Before beginning the selection process, 290 duplicate articles were eliminated.

The selection stage was divided into two parts: (1) evaluating the article based on its title, abstract, and keywords, and (2) evaluating the article based on its full content. Articles were chosen based on predefined eligibility criteria, ensuring that only relevant literature was included in the review. Adherent studies should meet the following eligibility requirements: (1) be applied to the context of civil construction, particularly with the study's target population; (2) use wearable sensors to collect physiological data in order to promote safety and health; and (3) not be solely a review study. Two authors performed the selection, and any discrepancies were analyzed and discussed with the third author.

Excluded were studies that were related to civil construction and/or the target population but used devices that did not collect physiological data. Case studies were included that used wearable sensors to collect physiological data in controlled environments and simulated tasks, but the results were intended to promote the health and safety of the target population in the field. Because of the topic's topicality, there were no time constraints on the studies' publication. This was later confirmed by the review results, which show that the included articles were published between 2011 and 2021, with roughly 90% of them published between 2016 and 2021. Articles from conferences were not excluded.

The synthesis of the articles included in the review was performed by collecting the following data: (a) devices used; (b) physiological data collected; (c) safety/health aspect of the construction assessed; (d) benefits; (e) investment required to acquire the device; (f) application challenges; (g) population; (h) sample quantity; and (i) type of environment in which the test was performed.

To facilitate better discussions, the studies were divided into six categories based on the safety/health aspect investigated: (1) physical aspect; (2) emotional aspect; (3) risk perception/identification; (4) distraction/attention; (5) thermal comfort; and (6) others.

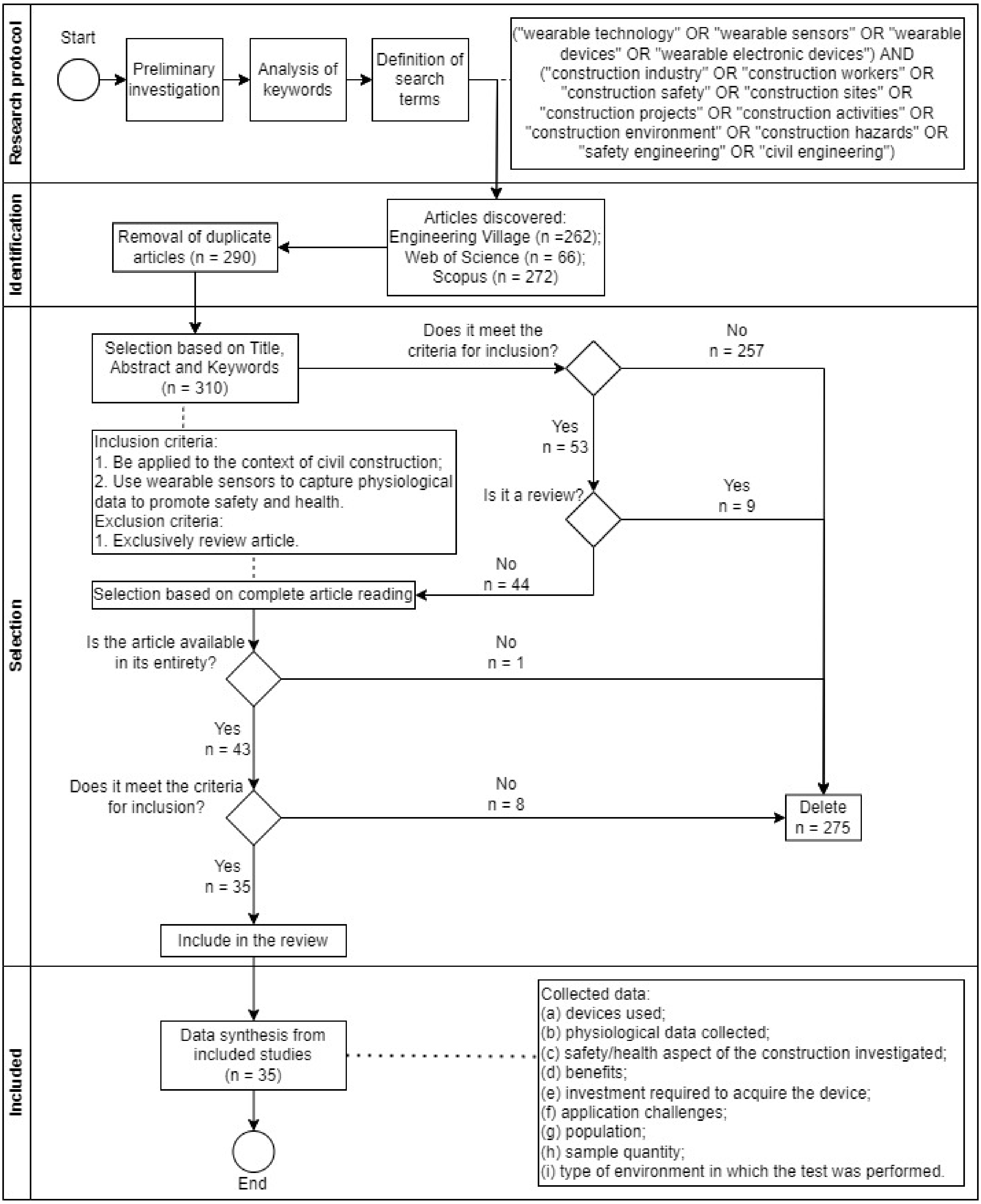
Results and discussions

Analysis of adherent studies

During the identification stage, an initial search yielded 600 articles, 262 of which were retrieved from the Engineering Village database, 66 from Web of Science, and 272 from Scopus. 290 duplicate studies were removed prior to the selection step. 257 articles that did not meet eligibility criteria 1 and 2 and nine review studies were removed during the study selection process based on reading the title, abstract, and keywords. One study was excluded from the selection process because it was unavailable for full reading, and eight studies were excluded because they did not meet the eligibility criteria. This occurred because, although these studies employed wearable sensors in construction environments, their objectives were not related to the promotion of health and safety (for example, they focused exclusively on productivity improvements) or they did not include the analysis of physiological data.

At the end of the selection process, 275 articles were eliminated, leaving 35 for review. Figure 1 illustrates the flowchart of the review steps as well as the results for each step.

Figure 1. Review steps flowchart



Source: Authors.

The journals in which the papers were published, as well as their Impact Factors (IF) and Quartiles (Q), were investigated for the 35 articles. Such data can indicate the quality of the studies. Table 1 summarizes the findings.

Table 1. Journals and conferences

Journals and conferences	IF	ISSN	Q	N	Authors
Automation in Construction	7,700	0926-5805	Q1	10	Hwang et al. (2016); Nwaogu et al. (2021); Ke et al. (2021); Guo et al. (2017); Wang et al. (2017); Jeon et al. (2021); Jebelli, Hwang (2018); Hwang et al. (2017); Lee et al. (2017); Aryal et al. (2017)
Construction Research Congress	-	-	-	5	Jebelli et al. (2020); Jeon et al. (2020); Jebelli, Choi, et al. (2018); Jebelli, Khalili, et al. (2018); Garimella et al. (2020)
Congress on Computing in Civil Engineering, Proceedings	-	-	-	4	Gatti et al. (2012); Li & Gerber (2012); Gatti et al. (2011) e Jebelli et al. (2017)
Journal of Construction Engineering and Management	3,951	0733-9364	Q1	3	Hwang et al. (2018); Jebelli et al. (2019a) e Jebelli et al. (2019b).
Safety Science	4,877	0925-7535	Q1	3	Shakerian et al. (2021); Choi et al. (2019) e Lee et al. (2020).
Annals of Work Exposures and Health	-	-	-	1	Al-Bouwarthan et al. (2020)
Engineering, Construction and Architectural Management	3,531	0969-9988	Q2	1	W. Lee et al. (2021)
IEEE International Conference on Pervasive Computing and Communications, PerCom 2011	-	-	-	1	Forsyth J B et al. (2011)
International Conference on Electronics Packaging, ICEP 2019	-	-	-	1	Kosuda et al. (2019)
Journal of Building Engineering	5,318	2352-7102	Q1	1	B. G. Lee et al. (2021)
Journal of Medical Internet Research	5,428	1438-8871	Q1	1	Brandt et al. (2018)
Proceedings of 1st International Conference on Innovations in Information and Communication Technology, ICIICT 2019	-	-	-	1	Mehata et al. (2019)
Proceedings of the 37th International Symposium on Automation and Robotics in Construction, ISARC 2020: From Demonstration to Practical Use - To New Stage of Construction Robot	-	-	-	1	Hashiguchi, Lim, et al. (2020)
Sensors	3,576	1424-8220	Q2	2	Bangaru et al. (2020); Hashiguchi, Kodama, et al. (2020)

Source: Authors.

Seven journals (n = 21) and seven conferences (n = 14) returned the articles. Of the journals identified, 50% are specifically related to the construction industry, 29% are related to technology, and 14% and 7% are related to health and safety, respectively.

The IF ranged from 3.531 to 7.700, and ten of the 21 studies published in journals are in the journal with the highest IF (7.700), which can be positive for the studies' quality. Only two of the seven journals discovered are not in Q1. This classification is made by comparing the IF of journals with others within their category. The expressive ranking of journals in Q1 is positive, as journals in the first quartile perform better than at least 75% of journals in the same category (FEUP, 2021). Furthermore, journals classified as Q1 are among the highest-rated.

Construction workers made up the research population in 60% of the studies, while students or people with no construction experience made up the research population in 40% of the studies. The experimentation in the second group is significant and mostly justified because they represent the population of workers entering the industry with little or no experience (LEE et al., 2020). However, even those with little experience face different workloads and routines than the population that should represent them. As a result, analyses based on individuals with no construction experience may produce results that are inconsistent with workers' reality.

The average number of participants per study was 14, with 10 people being tested more recurrent, a much lower number than is typically seen on construction sites. This is negative as a more representative sized sample of building environments could provide a wider range of information and analysis that cannot be observed in a limited sample size. That is, a broader range of metrics could be captured with a more expressive population sample. As a result, greater differences in physiological responses between individuals may be visualized, contributing to more reliable analyses and relationships.

The age of the participants was in the range of 21 to 51 years on average, being the most recurrent average age of the population at 25 years. As a result, the test population was primarily composed of young people, which may imply that analyses conducted on an older population are infeasible. This is explained by the fact that, when subjected to the efforts and other factors of construction environments, the physiological responses of a younger worker can differ significantly from those of a more senior worker.

The number or presence of women in the population was not reported in 34% of the studies. However, only the presence of men in the experiment was confirmed by the images in half of these studies. Only eight articles mentioned the presence of women in the tests, and these women made up less than half of the population studied. This is to be expected given that the majority of construction workers are men. On the other hand, it limits our understanding of female physiology.

Only 57% of the studies tested the population in the field. In fact, this indicator limits the analysis because a significant portion of the population was not exposed to typical construction site situations. This would provide a more comprehensive view of the feasibility and accuracy of devices in these environments. The other tests were carried out in controlled environments that included construction task simulations or graphical simulations. Due to the unique characteristics of these environments, which can result in different samples and analyses from tests conducted on construction sites, for example, this last scenario may not be viable or representative of real construction sites.

Research groups

Physical aspect

Fifteen of the 35 studies included looked into workers' Physical Aspect (PA). Workers' PA has been monitored using physiological data to promote, primarily, the reduction of excessive physical effort through workload management on construction sites (BRANDT et al., 2018), as well as the evaluation and reduction of occupational fatigue (LEE et al., 2021b).

Workload management is critical in order to avoid worker fatigue, injuries, errors, or accidents (GATTI et al., 2012; HWANG et al., 2016). Furthermore, excessive physical loads have had significant and, at times, unnoticed negative effects on productivity and safety performance, such as decreased motivation, inability to perform muscle work, and increased unsafe behaviors (GATTI et al., 2012; LI; GERBER, 2012).

In turn, fatigue is viewed as a result of physically demanding workloads, which are common in the construction industry (ABDELHAMID; EVERETT, 2002). Moreover, it is one of the factors that contribute to decreased productivity, poor work quality, and an increased risk of construction accidents, emphasizing the importance of its research in order to improve these rates (ARYAL; GHAHRAMANI; BECERIK-GERBER, 2017). In this context, wearable devices can be used to provide ample opportunity to continuously measure and understand the fatigue and physical demands of construction workers without interfering with their tasks, capturing any significant variations in this aspect (GARIMELLA; SENOUCI; KIM, 2020; HWANG; LEE, 2017). Early detection and mitigation of the fatigue state can significantly reduce the risk of occupational injuries (LEE et al., 2021b).

Emotional aspect

Emotional aspect (EA) analyses were the focus of eight studies. These analyses can primarily help with: (1) recognizing, monitoring, and mitigating high stress on construction sites; and (2) understanding and mitigating construction stressors (GUO et al., 2017; JEBELLI et al., 2018b; JEBELLI; CHOI; LEE, 2019a; JEBELLI; HWANG; LEE, 2018). Besides that, continuous measurement can reveal how workers' emotions change in construction environments (HWANG et al., 2018). Another advantage of this monitoring is the possibility of reducing unsafe workplace behaviors, as existing research shows that construction workers' mental states have a direct influence on their behavior (GUO et al., 2017).

Stress is one of the potentially harmful emotions that can have a negative impact on workers' well-being, safety, and productivity (JEBELLI et al., 2018b; JEBELLI; CHOI; LEE, 2019a). In turn, measuring and characterizing this emotion can lead to a reduction in injuries, accidents, and errors, as well as improve worker satisfaction and promote better working conditions (JEBELLI; CHOI; LEE, 2019a; JEBELLI; HWANG; LEE, 2017). In this context, devices such as the Electroencephalogram (EEG) can aid in the identification of various levels of stress at construction sites, assisting in the early detection and mitigation of high stress in the field (JEBELLI et al., 2020). Furthermore, the EEG can be used to quantitatively measure workers' emotional state in a non-intrusive manner, overcoming a potential bias in the subjective assessment of emotions based on traditional surveys (HWANG et al., 2018).

Risk perception/identification

Four articles were written about risk perception/identification (RP). Because unsafe behaviors are answers to the risk perceived by workers, analyzing unsafe behaviors in the field is critical for safety management (JEON et al., 2020; LEE et al., 2021). These risks, when perceived cause abnormal changes in workers' physiological response patterns (JEON; CAI, 2021). In this way, evaluating RP through physiological data becomes feasible and opens up new avenues for effectively and proactively managing safety in the field (CHOI; JEBELLI; LEE, 2019; JEON; CAI, 2021). Through behavioral interventions, this assessment can help workers adopt safer behaviors (JEON; CAI, 2021).

Another advantage is that if a worker is aware that a risk could endanger their safety, they can proactively adopt appropriate behavior, thus improving safety performance (LEE et al., 2021). Similarly, if a worker disregards a potential hazard, he or she may engage in unsafe behavior (LEE et al., 2021). Further to that, RP investigation is important because construction workers become less sensitive to existing risks after long periods of exposure to them in the field (WANG et al., 2017).

The Electroencephalogram (EEG) has a promising potential among the physiological responses of workers to the perception and identification of risks, as it shows immediate abnormal responses when a danger is perceived (JEON; CAI, 2021), in addition to providing more direct and observable indications of workers' attention status (WANG et al., 2017). The use of this technology has the advantage of assisting in the development of more realistic and rigorous training programs, promoting safer and healthier work behaviors, and assisting in the control and regulation of work errors and inadequate operations (KE et al., 2021; WANG et al., 2017).

Distraction/attention

Monitoring distraction/attention (D/A) is essential so that workers' lack of sensitivity to risks is not further jeopardized by their distraction. Furthermore, distraction is the leading cause of unsafe behavior and potential injuries in the field, as there are scenarios that require a high level of attention to ensure that safety performance is not compromised (KE et al., 2021). In this regard, two studies focused on D/A analyses, with the primary goals of (1) objectively monitoring worker distraction caused by noise and (2) monitoring and quantitative and automatic assessment of levels of attention and surveillance in relation to surrounding hazards (KE et al., 2021; WANG et al., 2017). By investigating the disparity between perceived risk and existing risk and measuring a worker's level of knowledge for hazard recognition, avenues are opened for the development of tailored intervention programs to reduce field accidents (WANG et al., 2017). Another advantage of D/A analysis is that it can help with equipment development and safety monitoring (WANG et al., 2017).

Thermal comfort

Three studies focused on thermal comfort issues (TC). These studies' main goals were to: (1) avoid heat stroke in the field; (2) prevent and recognize heat stress; and (3) assess the impact of workers' exposure to summer heat in Saudi Arabia (AL-BOUWARTHAN et al., 2020; KOSUDA et al., 2019; SHAKERIAN et al., 2021). These investigations are required because, depending on the climatic conditions of the region, workers at construction sites are at high risk of heat exposure, either due to intense physical activities or personal protective clothing (SHAKERIAN et al., 2021). In this regard, Kosuda et al. (2019), created a helmet-like device that demonstrated feasibility for measuring sweat throughout the body, and its use in the field has the potential to prevent heat stroke. Besides that, the heat stress assessment framework proposed by Shakerian et al. (2021) shows promise for improving construction workers' field safety and preventing heat-related illness. Furthermore, TC analyses can aid in the management of guidelines and interventions, such as rest periods, to reduce the effects of heat stress on the workforce (SHAKERIAN et al., 2021).

Others

Two articles were assigned to the category of studies that did not fit into the other groups, which investigated (1) the protection of construction workers against carbon monoxide poisoning through the collection of blood saturation levels and (2) the recognition and classification of construction activities. Moreover, one article fit into more than one category: Physical Aspect and Emotional Aspect, as it aimed to assess workers' physical and mental health. Electrodermal Activity (EDA) signals were used for mental analysis, and Photoplethysmography (FPG) and Temperature signals were used for physical analysis in this case.

Physiological data analyzed in the studies

The main metrics captured for the evaluation of each aspect, which are presented in Table 2, were visualized based on the grouping of studies. The most common data is Heart Rate (HR), which was collected in 17 studies and was more common in the analysis of the PA group. However, Photoplethysmography (PPG) analyses are present in most groups, with the exception of the D/A group, indicating the viability of this metric for a broader range of applications.

Other data examined included Electroencephalogram data (EEG), Temperature (TP), Sleep Data (SD), Energy Consumption (EC), Electrodermal Activity (EDA), Transpiration (TNP), and Electromyography (EMG).

Table 2. Types of data captured in each investigation group

Groups	N[1]	Metrics								
		HR[2]	**EEG[3]**	**TP[4]**	**PPG[5]**	**SD[6]**	**EC[7]**	**EDA[8]**	**TNP[9]**	**EMG[10]**
PA	16	14	1	5	2	4	3	1	-	-
EA	9	2	5	2	1	1	1	2	-	-
RP	4	-	2	1	1	-	-	2	-	-
D/A	2	-	2	-	-	-	-	-	-	-
TC	3	1	-	2	1	-	1	1	1	-
Others	2	-	-	-	1	-	-	-	-	1
Total	36[11]	17	10	10	6	5	5	6	1	1

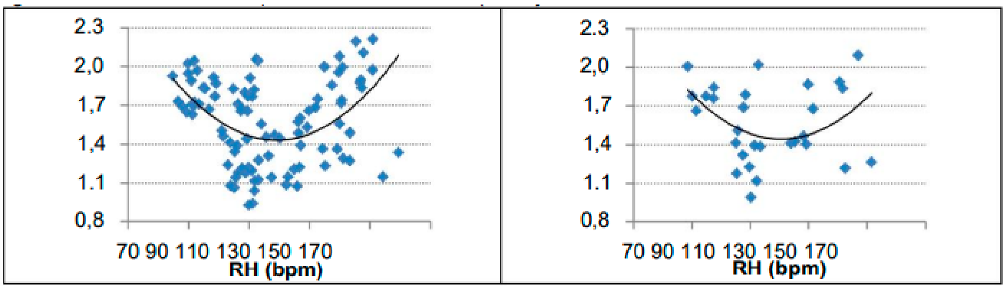
OBS[1]: Number of articles. OBS[2]: Heart rate. OBS[3]: Electroencephalogram data. OBS[4]: Temperature. OBS[5]: Photoplethysmography. OBS[6]: Sleep data. OBS[7]: Energy consumption. OBS[8]: Electrodermal activity. OBS[9]: Transpiration. OBS[10]: Electromyography. OBS[11]: Total has one more article, as one of the studies was included in PA and EA.

Source: Authors.

Heart rate

When HR is monitored in real-time, it has the potential to assess a worker's physical demands in various construction tasks, as well as provide information about workers' personal health status (HWANG et al., 2016). Gatti et al. (2012) confirmed that HR is a predictor of workers' physical strain and demonstrated that a parabolic relationship between HR and productivity can be established using analyses of eight regression models (Figure 2). Their findings indicate that workers who deviate from this relationship may face excessive physical strain. Therefore, this aspect's continuous measurement ensures that significant physical demands can be monitored and alerted to (HWANG; LEE, 2017).

Figure 2. Parabolic relationships established between HR and productivity



Source: Adapted from Gatti et al. (2012).

These findings may pave the way for active intervention in the execution of tasks in the field. Workers can be reallocated to less demanding activities or scheduled for strategic breaks if excessive physical demands are identified in real time. Furthermore, with long-term monitoring, patterns of each worker's level of physical demand related to various construction tasks can be identified, allowing for the creation of individualized and integrated activity plans that take each worker's physical capacity into account.

In addition, HR is also used as an objective measure of physical workload, while heart rate variability (HRV) is used as an objective measure of exhaustion, physiological fatigue, and stress. Furthermore, the HRV it has been found to be a more useful physiological indicator for prediction and fatigue measurement than other HR measurement variables (LEE et al., 2017, 2020).

In the Emotional Aspect (EA) domain, HRV was identified as a stress biomarker (NWAOGU; CHAN, 2021). In turn, in the Physical Aspect (PA) domain, W. Lee et al. (2017) demonstrated that a lower HRV can make people more susceptible to physical fatigue. Besides that, W. Lee et al. (2020) discovered that HRV can be used to measure exhaustion. Such findings demonstrate the utility of measuring HRV for PA and EA analysis. The most stressful and exhausting activities can be identified by integrating the results of this data analysis, which contributes to better task management while taking the physical and mental state of the workers into account.

As for Resting HR and HR recovery (recovery from peak HR to resting HR) were used as indicators of each individual's personal resources because the speed of HR recovery can indicate an individual's personal physical capacity worker (BROUHA, 1967; LEE et al., 2020). Meantime, W. Lee et al. (2021) discovered that resting HR was not a significant predictor of fatigue prevalence, but this was justified by the fact that resting HR depends on the age of the subjects and the analyses were conducted in a young population. Thus, to reassess resting HR as a possible predictor of fatigue, an analysis in a population with a greater age range diversity is required. This fact supports the hypothesis that the limitations of the studies' application in individuals with an average age of 25 years may imply the infeasibility of analyses conducted on an older population.

Another indicator studied was the HR Reserve Percentage (%HRR), which is a relative measure of physical demands that is useful for normalizing HR differences in each individual and can also be used to predict occupational fatigue (HWANG; LEE, 2017; LEE et al., 2022). The %HRR is calculated as a percentage between (1) the difference between work HR (captured during task performance) and resting HR (a level without physical intensity and demand) and (2) the difference between maximum HR and resting HR (HASHIGUCHI et al., 2020; HWANG; LEE, 2017; LEE et al., 2022). Based an analysis of the %HRR, Hwang and Lee (2017) showed that workers who perform physically demanding tasks – such as carpenters and bricklayers – are more likely to face excessive physical demands with more than 30% of the average %HRR (when the value moderate physical demands would be below 30%HRR). Furthermore, their findings indicated that outdoor work, the effects of age on elderly workers, and performing activities cleaning, transport, and removal of heavy materials can result in excessive physical demands. Thus, identifying the factors and activities that significantly increase physical demand can then lead to personalized construction task management. For example, in order to avoid excessive physical demands when performing cleaning services (a task with higher physical demand), workers with higher physical conditioning could be assigned and strategic work periods could be established.

Additionally, Hashiguchi et al. (2020), developed a model to estimate the impact of workload risk using the HR Reserve Percentage (%HRR) of the worker, which proved the hypothesis about the impact of physical workload on the %HRR of the workers. Moreover, their findings revealed that a large portion of the test population was working with more than 40%HRR, emphasizing the importance of developing techniques to reduce workers' physical demands. Corroborating these findings, Jebelli, Choi, et al. (2018) demonstrated that individuals have a higher %HRR when working in conditions requiring more physical demand than when working in conditions requiring less physical demand. Further to that, a positive correlation was found between the stress index and %HRR, demonstrating the utility of this data for Emotional Aspect (EA) analyses (NWAOGU; CHAN, 2021).

Despite the success of HR, its use in physical analysis can be hampered by other factors. This is explained because, regardless of the workloads employed, several factors can influence HR, such as environmental conditions, health conditions, stress, hydration, digestion, stimulant substances, and depressive substances, compromising the relationship between the HR and physical analysis (GATTI et al., 2012; GATTI; MIGLIACCIO; SCHNEIDER, 2011).

Several studies have implemented procedures to control these factors, such as: (1) instructing participants not to ingest digestive, stimulant, or depressant substances before the experiments (GATTI et al., 2012); (2) providing unlimited and easily accessible water to participants, as hydration is directly related to workers' physical responses during the workday (GATTI et al., 2012; LEE et al., 2017) ; (3) use of health history questionnaires to exclude subjects with pathologies that could affect HR (HASHIGUCHI et al., 2020; HWANG; LEE, 2017); (4) control of environmental conditions to keep them stable throughout the experiment (GATTI et al., 2012); and (5) guidance to ensure that participants do not deviate from their usual work patterns (HASHIGUCHI et al., 2020).

Some of these procedures, however, may be impractical in the field. For example, in the case of the instruction not to consume stimulant or depressant drinks, there is no way to control this factor outside of the construction site, in addition to having a significant impact on workers' personal lives. Controlling environmental conditions in the field is also nearly impossible due to the dynamic nature of construction environments. Such findings highlight the need for studies that take these indicators into account and demonstrate how these factors can be treated in the analysis of physiological data, so that the studies are more consistent with workers' and the work environment's reality.

Encefalogram data

Electroencephalogram data (EEG) were most commonly used in Emotional Aspect (EA) analyses. EEG devices record brain waves and have the potential to measure emotional states in a continuous and quantitative manner (HWANG et al., 2018). This data can be used for emotional analysis because it reflects patterns like relaxation, attention, evaluation, vigilance, and alertness (WANG et al., 2017).

When analyzing EEG data, Hwang et al. (2018) discovered that emotions such as happiness and excitement are more prevalent in less stressful situations (such as working on the ground), whereas nervousness and irritation are more prevalent in confined space work and stair work. The identification and relationship of construction activities with the emotions provided to workers can then be used to improve management and task distribution. This strikes a balance between the demands of more stressful activities and, as a result, provides less recurrence of negative emotions, which can benefit workers and, by extension, organizations.

In addition, EEG data are the most commonly used in Risk Perception/ Identification (RP) analyses and have proven to be viable for this analysis in construction environments by monitoring workers' emotional states, as emotions change when individuals are exposed to hazards (JEON et al., 2020; JEON; CAI, 2021). In this sense, it was discovered that negative valences (such as fear and nervousness) are associated with high-risk situations, whereas positive valences (associated with positive emotions) are associated with low-risk situations (JEON et al., 2020). By monitoring these valences in the field, it is possible to identify vulnerable workers in real-time and make efficient interventions to prevent accidents and mitigate stressors, thereby improving workers' emotional states, which can have a direct impact on task performance.

Moreover, it was discovered in Distraction/Attention (D/A) analyses that EEG indicators in the frequency domain are critical for distinguishing a distracted from a focused state (KE et al., 2021). Ke et al. (2021), demonstrated the feasibility of determining whether a worker is focused or distracted, as well as monitoring attention using EEG data based on frequency range indicators. Based on the analysis of these frequency, it was also possible to assess cognitive load concentration levels and identify vulnerable individuals in the field (WANG et al., 2017).

Another advantage of using EEG for these analyses is that it can provide faster responses to changes in workers' attention states than preventive measures like safety training or occupational risk analysis (KE et al., 2021). Furthermore, EEG signals provide a good indication of the use of working memory in the brain, which is directly related to concentration (WANG et al., 2017).

Temperature

Temperature (TP) is typically measured with a wristband sensor equipped with a thermal cell that detects skin temperature via infrared energy This measure has shown promise in Thermal Comfort (TC) research for assessing thermal stress (SHAKERIAN et al., 2021). However, Jebelli, Choi, Lee (2019a) demonstrated that TP is not an adequate physiological signal for stress recognition in the field of Emotional Aspect (EA). TP proved to be efficient for the physical assessment of workers in the field of Physical Aspect (PA) analysis, as it significantly increased the accuracy of forecasting physical demand (JEBELLI; CHOI; LEE, 2019b). As a result, despite being the second most investigated metric in the included studies, TP is restricted to investigations of only two groups (PA and TC), making capturing this metric less appealing for field application.

Photoplethysmography

Photoplethysmography (PPG) detects changes in volemia (the amount of blood circulating in the body) caused by cardiac activity and is commonly used to extract responses such as HR and HRV, which can be linked to a person's stress levels (JEBELLI; CHOI; LEE, 2019a; SHAKERIAN et al., 2021). In the PA field, Jebelli et al. (2019b) demonstrated that the PPG significantly improves the accuracy of the proposed model of automatic prediction of workers' levels of physical demand, demonstrating the efficacy of this metric in this evaluation. PPG was found to differ significantly between normal, cold, and hot weather conditions in TP analyses, but these signals are not as predictive as other physiological signals for assessing heat stress during physical activities (SHAKERIAN et al., 2021). PPG could also be used to measure workers' blood saturation levels, which was successful in carbon monoxide poisoning analyses (FORSYTH et al., 2011). As can be seen, the PPG is effective for both extracting HR measurements and direct analysis of this signal. Furthermore, this measure showed promise for the investigation of a wide range of investigation groups, being present in all investigations except Distraction/Attention (D/A). This may indicate the potential of collecting this metric in the field.

Sleep data

Sleep Data (SD) were also collected for PA analysis. This monitoring is possible because the degree of influence of workload on workers' physiological fatigue and stress varies depending on each individual's sleep quality, which can be monitored through wearable technology (LEE et al., 2017). Moreover, W. Lee et al. (2017) demonstrated that a person with good sleep quality and off-duty physical activity expended less energy on tasks with a higher workload (related to higher mean HR). This demonstrates the significance of the effect of sleep on construction worker performance (GARIMELLA; SENOUCI; KIM, 2020). Furthermore, it demonstrates the feasibility of collecting this data to promote load management while taking each worker's sleep state into account. Despite these results, sleep measurements were not useful for the fatigue prediction model proposed by W. Lee et al. (2021). Besides that, collecting this data is difficult because it is done out of the field by wristband-type devices. Thus, continuous monitoring is dependent on the worker's own efforts to use the device while sleeping and may be met with skepticism due to the potential for intrusion into their personal lives.

Energy Consumption

Energy Consumption (EC) has been used in studies to estimate workload (LEE et al., 2020), monitor occupational fatigue (LEE et al., 2021b), and label workers' physical demands JEBELLI; CHOI; LEE, 2019b). Li and Gerber (2012) calculated the average and maximum energy expenditure (in calories) from the output of the sensors used and demonstrated that the change in magnitude of energy expenditure is much greater than the change in magnitude of Heart Rate (HR) when the subject is under physical load. Furthermore, W. Lee et al. (2017) used it to demonstrate that sleep efficiency may be related to EC, as individuals with low sleep efficiency demonstrated high energy expenditure during task performance. However, this relationship should be investigated further in future research, due to the small sample size (population = 6). This finding lends support to the theory that a small population may be unrepresentative for efficient analyzes of physiological metrics.

Electrodermal activity

Electrodermal Activity (EDA) is the change in electrical properties of the skin caused by sweat secretion (BENEDEK; KAERNBACH, 2010). It can be decomposed into (1) electrodermal response (EDR) – which refers to short-term changes and (2) electrodermal level (EDL) – a slowly changing tonic component (EDL) (CHOI; JEBELLI; LEE, 2019). EDR has been demonstrated to represent the ability to distinguish between low and moderately high-risk activities, and thus can distinguish more dangerous activities in the field (CHOI; JEBELLI; LEE, 2019).

EDA is a useful tool for measuring worker stress; however, when analyzed alone, it may be insufficient for identifying physical demands (JEBELLI; CHOI; LEE, 2019a, 2019b). Moreover, when individuals perceive a significant risk, this physiological response undergoes significant changes, and thus the EDA is a potential evaluator of risk as a feeling (CHOI; JEBELLI; LEE, 2019). Shakerian et al. (2021) demonstrated that EDA is promising for the evaluation of thermal stress in addition to its potential for Risk Perception/Identification (RP) analyses.

Because EDA was successfully used for EA, RP, and Thermal Comfort (TC) analyses, it can be concluded that this measure would be economically beneficial for construction employment. This is explained by the fact that by monitoring a single physiological signal, at least three investigation groups can be studied, and treatments and data analysis are limited to a single physiological measure.

Transpiration and Electromyography

Transpiration (TNP) and Electromyography (EMG) Sweating and Electromyography (EMG) were used in one study each, from the TC and "Others" groups. Sweat has been shown to be an effective heat stroke monitoring tool (KOSUDA et al., 2019). In turn, EMG has been used successfully to recognize construction activities (BANGARU; WANG; AGHAZADEH, 2020). This recognition, in turn, can be used for individual monitoring and management, as well as safety training. However, due to the small number of studies conducted, these metrics must be refined before being used in construction safety and health management.

Physiological data combination

The integration of physiological data and other contextual information has the potential to significantly improve construction safety management practices (CHOI; JEBELLI; LEE, 2019). For example, while HR, skin temperature, and %HRR confirm the potential of physiological signals to determine individual physical demands, they are insufficient for continuous identification of the physical demand of workers with varying characteristics during the execution of various tasks in short time intervals in the field JEBELLI; CHOI; LEE, 2019b). As a result, a variety of physiological signals are required to determine workers' physical demands JEBELLI; CHOI; LEE, 2019b). Jebelli et al. (2019b) captured HR, EDA, and TP and developed a framework for distinguishing levels of physical demand that achieves 90% accuracy in distinguishing low and high levels and 87% accuracy in distinguishing low, moderate, and tall levels.

The fatigue classification also performed well when multiple parameters were used. The classification accuracy based solely on features extracted from the mean of the skin TP data was 9% higher than that based solely on the HR data, and the combination of the two data produced the best accuracy of 82% (ARYAL; GHAHRAMANI; BECERIK-GERBER, 2017). Garimella et al. (2020) demonstrated that using only HR data, the accuracy of their fatigue prediction model - Support Vector Machines (SVM) - was 69,23%, with a significant improvement when the model began to rely on HR and sleep quality data. As a consequence, the accuracy increased to 76,92%.

Among the difficulties in using physiological data, the highlights are the removal of extrinsic signal artifacts (such as environmental noise and electrode burst) and intrinsic (generated by internal changes in the body, such as eye movements), which can negatively affect the analysis of these data (JEON et al., 2020; JEON; CAI, 2021). However, several filtering methods, such as bandpass filter, notch filter, bandpass filters, rolling, notch, hampel, and independent component analysis, were used to reduce these artifacts (JEBELLI; CHOI; LEE, 2019b; JEON et al., 2020) . As a result, it is clear that, in addition to purchasing devices, investment in technical manpower for data analysis and treatment is required in order to obtain efficient results from physiological signals, and for the use of these technologies to actually improve health and occupational safety.

Devices which collect physiological data

Wristbands, headset-type EEG devices, chest straps, armbands, smart clothing, adhesive devices, and smaller sensors attached to helmets were used to collect data. In total, seven different types of wristbands, three different types of headset-type EEG, eight different types of chest straps, one armband, two adhesive devices, and three smaller devices attached to helmets were used. Furthermore, four studies did not specify the type of device used, with an unidentified chest strap, a device placed on the workers' arm, a headset, and a wristband being used. Table 3 shows the devices used, as well as the measured data for each application group.

The EMOTIV EPOC+ 14 Channel Mobile Brainwear® headset was the most commonly used device in the studies, appearing in eight studies from three different groups. The E4 Bracelet by Empatica was the second most frequently used device in five studies involving three groups. The Fitbit bracelet was used in three studies involving three different groups. These findings show that these equipments can be used to analyze a broader range of construction safety aspects. In this case, because a single piece of equipment may be sufficient for multiple aspects analysis, studies can be more comprehensive while requiring less investment Another advantage of using this equipment is that by using only one device for investigations, the handling and configuration issues are reduced to a single device and the investigation of different groups is maintained.

The Zephyr BioHarness 3 chest straps was also used in three studies, but only in the PA Group. The other devices identified were only used in two studies.

Table 3. Devices used

Category	Device	N	Groups	Analyzed Data
Adhesive (n = 2)	FREEEMG (BTS Bioengineering Corp., Quincy, MA, EUA)	1	TC	EMG
	Electrodes	1	PA	HR
Armbands (n = 1)	Myo armband	1	TC	EMG
Chest straps (n = 8)	Hidalgo EQ-01	1	PA	HR – TP
	Polar H10® by Polar Electro Inc.	1	EA	HR
	Polar H7® by Polar Electro Inc.	1	PA	HR
	Polar® RCX3	1	Others	HR
	Zephyr BioHarness (BH) – BT by Medtronic	2	PA	HR – TP
	Zephyr BioHarness 3 by Medtronic	3	PA	HR – SD
	Zephyr HxM by Medtronic	1	PA	HR
	Not identified	1	PA	HR
Smaller sensors attached to helmets (n = 3)	Xpod by Nonin integrated with an oximetry sensor	1	TC	PPG
	HSHCAL 101B - ALPS COMPANY	1	Others	TNP – TP
	Infrared temperature sensor - MLX90614	1	AF	TP
Headset (n = 3)	Neurosky Mindwave	1	PA	EEG
	Emotiv Epoc+ 14 Channel Mobile Brainwear®	8	EA-RP-D/A	EEG
	Not identified	1	EA	EEG

Category	Device	N	Groups	Analyzed Data
Wristbands (n =7)	ActiGraph GT9X Link	1	PA	EC - SD
	Authorial (feasibility study)	1	PA	HR - TP
	Basis Peak	2	PA-EA-Others	PPG – EDA – HR – TP – EC
	E4 by Empatica	5	PA-EA-RP	EDA – PPG – TP
	Fitbit	3	PA-EA-Others	HR – SD – EC
	Garmin vivofit	1	PA	HR – SD
	Not identified	2	PA-EA	EDA – HR – PPG – TP
Smart clothing (n = 1)	Cocomi	2	PA	HR
Not identified (n = 1)	Device positioned on the arm	1	PA	EC

N = Number of studies where it was used

Source: Authors.

Chest straps and wristband devices are ideal for capturing Heart Rate (HR). Chest straps are Electrocardiogram (ECG) sensors that are worn around the chest. They provide a continuous HR reading and have already been validated for providing consistent and reliable HR readings at rest and during physical exertion (HWANG; LEE, 2017; LEE; GORELICK; MENDOZA, 2011). Wristband devices, on the other hand, monitor HR via a built-in PPG sensor, which can have its signals affected by signal noise and motion artifacts, making Photoplethysmography (PPG)-based HR extraction insufficiently accurate during construction tasks (BOLOURSAZ MASHHADI et al., 2016; HWANG et al., 2016; KOCK, 2018).

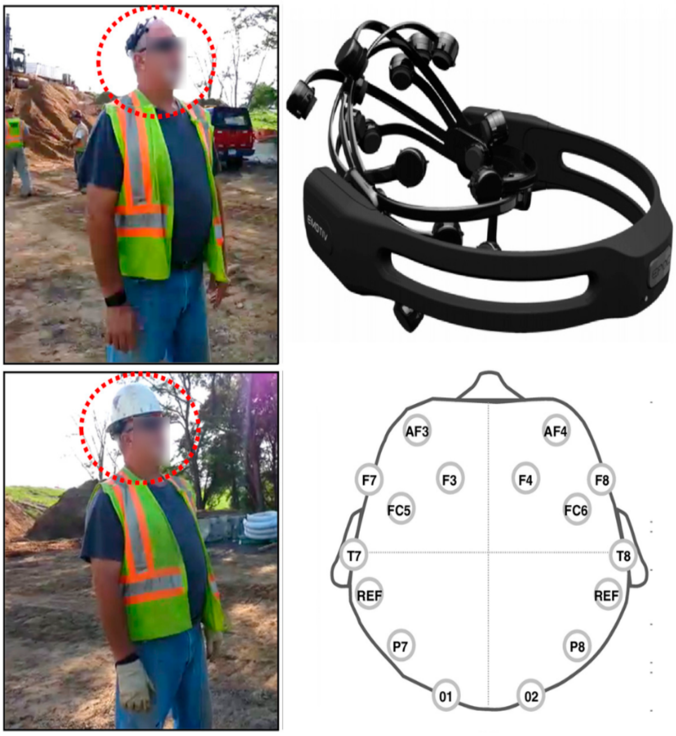
Figure 3. Wristband and chest strap device

Source: Adapted from Gatti; Migliaccio; Schneider (2011), Hwang et al. (2016) and Jebelli et al. (2018b)

Because of this distinction between the two devices, studies have examined the various methods of capturing HR between chest straps and wristbands (HWANG et al., 2018; HWANG; LEE, 2017). The potential of PPG-based HR monitoring of wristband-type devices was validated through these analyses. Furthermore, signal processing techniques have been used in several studies to improve the accuracy of using the PPG in wristbands to obtain the HR (HWANG; LEE, 2017). In this context, Hwang et al. (2016) demonstrated, through a comparative analysis of HR between a PPG sensor and an ECG sensor in a chest strap used as the truth, that HR measurement via PPG has 4.79% mean percentage error and 0.85 correlation coefficient for entire data sets, implying that PPG sensors could be used for HR monitoring in the field. Concerning the difference in comfort and acceptability, W. Lee et al. (2017) reported that workers preferred the wristband device used in the study (ActiGraph GT9X) over the Zephyr BioharnessTM 3 strap, which received criticism from workers due to discomfort, weight, and use. Besides that, data from wristband devices (specifically, Empatica's E4 Wristband) has been shown to have the potential to measure workers' stress while performing tasks, allowing for reasonable accuracy in stress recognition (JEBELLI; CHOI; LEE, 2019a). These findings suggest that the use of these devices may be more advantageous than the use of straps because, in addition to being lighter and more comfortable for workers, they are viable for PA, EA, and RP analysis.

The headsets device are Electroencephalogram (EEG) sensors that capture brain waves. These devices monitor central nervous system activity and are typically attached or fitted to personal protective helmets for use in the field (HWANG et al., 2018). It was discovered that, despite the noise of the signals, and with the correct methods of filtering and data analysis, they are useful for analysis of the Physical Aspect (PA), Emotional Aspect (EA), Risk Perception/Identification (RP), and Distraction/Attention (D/A). Despite this, the efficiency of using this device on construction sites is dependent on a conscientious workforce that stays with the helmet during the performance of their tasks - not adjusting it in a way that compromises the device's position - so that critical data is not overlooked. As a result, continuous monitoring of the workforce is required with regard to the correct and permanent use of the helmet, so that the device remains correctly adjusted and data collection is not interrupted.

Figure 4. Headset device



Source: Adapted from Hwang et al. (2018) and Jebelli; Hwang; Lee (2018).

Despite the positive results of using the devices, factors such as fatigue cannot be accurately predicted using only metrics collected by wearable sensors, necessitating additional information such as perceived workload, physical health status of workers, and physical ability to work (LEE et al., 2021b).

As a result, several studies used, in addition to the collection of physiological metrics, questionnaires on perceived workload, condition tests, and physical resistance and fatigue scales, such as: (1) providing verbal expressions about subjective feelings about the physiological load and the fatigue condition; (2) investigation of perceived exertion using Borg, Ottoson (1986) CR-10 scale; (3) 12-item Form Health Survey by Ware et al. (1996) for fatigue prediction; (4) six-minute walk test and (5) Checklist Individual Strength. The use of these questionnaires in the field can impair worker concentration and productivity. These mechanisms, however, were mainly used to validate the efficacy of the treatment and the interpretation of the physiological metrics. Once the method used in the studies is validated, the use of wearable technology in the field may occur without the use of these questionnaires. However, more research is required before this can happen due to population size limitations and a significant amount of testing in controlled environments, which can produce results that differ from the reality of construction environments.

Conclusions

The current study looked into the main aspects and metrics addressed in the use of wearable devices that collect physiological data in construction settings. In addition to reporting the benefits of each investigation, the review identified five research groups using these devices: Physical Aspect (PA), Emotional Aspect (EA), Risk Perception/identification (RP), Distraction/Attention (D/A), and Thermal Comfort (TC). Among the primary advantages of investigating these aspects is the possibility of lowering the risk of occupational injuries, lowering the incidence of errors and stress, and increasing worker satisfaction.

The review identified the captured data - Heart Rate (HR), Electroencephalogram data (EEG), Temperature (TP), Sleep Data (SD), Energy Consumption (EC), Electrodermal Activity (EDA), Transpiration (TNP) and Electromyography (EMG) - as well as its benefits and relationships with each aspect group in which they were used. The investigation of multiple physiological parameters resulted in significant positive changes in the analyses of several PA group studies, specifically in the investigations into worker physical demand and fatigue. HR data was the most commonly collected and showed promise for PA and EA analyses. This, combined with the fact that there is robust literature on the application of HR, makes this measure promising to be the gateway to more frequent and even permanent analyses of physiological data in the field.

Wristband devices, chest straps, and EEG headsets devices stood out among the equipment. There are differences in HR capture between chest straps and wristbands; however, there are advantages to using the latter over the straps because they are more comfortable, have higher acceptability among workers, and produce good results, particularly when applied to PA and EA groups. EEG headsets are also promising, particularly for EA analysis. Although its data for brainwave analysis are limited, analyzing workers' EA it is possible to carry out investigations in other groups, such as RP and D/A, because these can be analyzed through the workers' mental state.

As a consequence, the current review concludes that wristband devices and EEG headsets are promising for the growing use of wearable technologies in the field. Wristbands may be even more prominent in this context, as they were well accepted by workers and do not require monitoring in their continuous use by workers, as EEG headsets do. This is explained by the fact that data collection can be interrupted if the worker removes or changes the helmet position (where the EEG headset is attached or adjusted), which is less likely with the wristband because it is most efficiently caught on the workers' wrists. Besides that, wristbands also collect HR, which is regarded as one of the most promising measures for collecting physiological data in the field.

Despite the positive findings, the analysis has limitations, primarily due to the small number of participants in several studies, as well as the lack of diversity in the age group of the population tested, which is primarily comprised of young people. Signal artifacts were identified as the main challenges for analyzing physiological signals; however, several signal filtering solutions are available and have been used successfully in studies. Despite this, several aspects remain to be investigated in order to effectively implement physiological data capture in the field. For example, it is necessary: (1) studies that make the investigation of these metrics appealing to organizations, such as demonstrating how the use of these technologies affects accident rates and productivity, and (2) investigations into the acceptance and satisfaction of workers when using these devices, as well as the assessment of the impact of cultural factors on the use of the devices.

In this way, the current study's objectives were met, demonstrating the applicability of the method used in SLR, which, in turn, can pave the way for greater implementation of physiological wearable devices in the context of health and safety in civil construction. Future work is required for this, primarily to reassess the analyses that were compromised due to age and population size. As a result, more accurate and reliable results can be obtained, paving the way for a promising path for health and safety management in the field that is based on technologies rather than subjective, counter-productive, and inaccurate methods.

Authors' contributions

Juliana de Jesus da Silva: Data curation, Conceptualization, Methodology, Writing – original draft, Formal Analysis, Investigation. **Felipe de Sá Moreira:** Writing - review & editing, Formal Analysis, Validation, Supervision. **Luiz Maurício Furtado Maués:** Writing - review & editing, Formal analysis, Validation. **Wylliam Santana:** Writing - review & editing, Formal analysis, Validation.

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