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Review

Applications of electroencephalography in construction

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ABSTRACT

A wearable electroencephalogram (EEG) is considered a means for investigating psychophysiological conditions of individuals in the workplace in order to ameliorate occupational health and safety. Following other sectors, construction scholars have adopted this technology over the past decade to strengthen evidence-based practices to improve the wellbeing of workers. This study presents the state-of-the-art hardware, algorithms, and applications of EEG as a platform that assists in dealing with the risk-prone and complex nature of construction tasks. After summarizing the background of EEG and its research paradigms in different sectors, a comprehensive review of EEG-enabled construction research is provided. First, through a macro-scale review aided by bibliometric analysis a big picture of the research streams is plotted. Second, a micro-scale review is conducted to spot the gaps in the literature. The identified gaps are used to classify the future research directions into theoretical, application, and methodological developments.

1. Introduction

The construction sector has long been regarded as a high-risk industry. In this sector, workers are consistently exposed to unsafe work environments due to, for instance, interactions with machinery and physical hazards [1]. The dynamic workplace and varying nature of construction tasks lead to differing working states and, thus, place the wellbeing of construction workers at exacerbated risks compared to workers of other sectors [2]. According to Safe Work Australia [3], the construction sector accounts for 9% of the total workforce in Australia but recorded 12% of work-related fatalities. This situation is not different in other countries. For instance, in 2016, the construction industry had the highest number of fatal work injuries among all other industries in the United States [4]. Therefore, enhancing health and safety in the construction sector is a top priority for both construction contractors and governmental authorities.

Construction health and safety is multidisciplinary in nature [5–7]. With the emergence of disruptive technologies in recent years, wearable technologies have attracted significant attention to ameliorate occupational health and safety and improve workers' wellbeing in different industries. In this cluster, electroencephalography (EEG) has emerged as one of the fast-growing technologies for measuring individuals' cognitive and mental states under different circumstances in the workplace [8].

EEG is an electrophysiological monitoring system that records the electrical activities generated by cortical neurons [9]. Advancements in computing platforms and sensory technologies have enabled EEG systems to be designed as miniature, lightweight, ultra-low power [10,11], wireless [12], and low cost devices [11,13]. Therefore, deploying portable and mobile EEG has been on the increase in different sectors [14].

The aforementioned developments in EEG and computational neuroscience make it a good choice for scientific and interdisciplinary studies. Thus, EEG has been used not only in clinical and psychiatric [15–17] and psychological and neuroscientific studies [18–23], but also in other fields, such as brain–computer interface (BCI) [24,25], neuromarketing [26–29], gaming [30–33], neuro-ergonomics [34–39], neuroaesthetics [40,41], transportation [42–47], and athlete performance evaluation [48,49]. In the building industry, both neuro-architecture and neuro-urbanism [50–54] use EEG and mobile EEG in their studies to enhance the built environment features.

Based on the theory of behavioral psychology, psychological status

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affects human behavior [55] and external phenomena affect human behavior through mental factors [56,57]. These have perhaps led the construction industry to trial EEG technology in studying the psycho-physiological impacts of the workplace on construction workers. The overall aim has been to improve health and safety in construction projects.

EEG is considered as a strong tool in the construction studies because it directly and cost-effectively measures neural activity with high time resolution, and can be used in mobile format. Mobility is an essential feature for all technologies to be used on the construction sites because of the physical complexities of the workplace or the physical demands of the work. EEG has a great advantage to conduct both laboratory and on-site studies in the construction sector, while other techniques, such as functional Magnetic Resonance Imaging, Positron Emission Tomography, and Magnetoencephalography, can only be used in stationary studies [58–70].

Despite the importance of using EEG in the construction field and its expected contributions, the body of knowledge lacks a structured review on this subject. With a growing number of articles in this field, such a systematic review can organize research areas, methodologies, outcomes, and challenges. A thorough review of the extant literature also assists in spotting the research gaps and, therefore, establishing a readily actionable reference to pathways for future research. Moreover, the review of the scholarly works provides insight into the network of researchers and professionals involved in the implementation of EEG in construction health and safety. This would facilitate future collaborations to share knowledge and expand the adoption of EEG in construction.

The aim of this research is to shed light on the potential applications of mobile EEG on construction sites and investigate the contribution of this technology to workers' wellbeing and safety. This paper paves the way for extended application of mobile EEG to tackle construction challenges relating to workers' mental states. In this regard, reviewing the literature of EEG as a wearable technology to support the construction workforce is the primary concern of this paper. Therefore, the present study summarizes the EEG features and its general research paradigms beyond construction, discusses key EEG applications, research themes and analytical methods in the construction industry, and highlights possible pathways for the future of EEG adoption in the construction industry as a wearable technology to support the workforce. The study adopts both macro-scale and micro-scale approaches in analyzing the literature. While the macro-scale approach is mainly used to identify the overall focus of papers, the micro-scale analysis is employed to systematically classify the research themes and the gaps in the construction literature.

1.1. EEG in practice

1.1.1. Brain electrical activity

The cerebrum is the largest part of the brain anatomy and has four major areas, namely frontal, temporal, parietal, and occipital lobes [71]. These lobes consist of billions of neurons that transfer information, leading to voltage changes in milliseconds across their membranes.

The generated electrical signal is a blend of different frequencies, each of which correlates to a specific state of the brain. These frequencies are classified as delta (0.5–3.5 Hz), theta (4–7 Hz), alpha (8–12 Hz), beta (13–30 Hz), and gamma (> 30 Hz) bands [72]. The delta band frequency appears in deep non-rapid eye movement sleep, which is typically located in the thalamus and is investigated for sleep disorders and alcoholism [9]. The frontal theta band is related to the hardship of mental operations (e.g., memory recall, processing, focused attention, and learning). It becomes more important with the increasing difficulty of a given task. Therefore, mental workload or working memory can be investigated through fluctuations of the theta frequencies, making this band an appropriate candidate to monitor workers, for instance, during construction operations. Beta frequencies appear in the moment of active, busy, or anxious thinking. Typical studies on beta frequencies encompass motor control and simulated-induced alertness [73]. The highest frequencies generated from the human brain are considered gamma band frequencies. Investigations into its origins are still ongoing [74].

1.1.2. EEG electrodes

In EEG, metal sensors (i.e., electrodes) are placed onto the scalp to record the electrical activity of the brain. Since the recorded signals are low voltage, an amplifier is used to strengthen the signals and make the electrical data more tangible [75].

There are different kinds of electrodes that can be selected according to the conditions of the experiment. Mostly, electrodes are categorized based on the conductor between the electrode and the scalp. According to this classification, there are four types of electrodes, including wet, dry, active, and passive [76]. In wet electrodes, a conductive gel, usually made from a compound of silver chloride, is applied to skin; therefore, a better connection is established between the electrode and the scalp [77]. In the absence of a jellied conductor, dry electrodes use a metal piece (usually stainless steel) as a conductor between the electrode and the scalp [78]. Another type of electrode, known as "active", amplifies the signal immediately in between the electrode and the scalp and before transmitting it to the recording system [79]. This can prevent the addition of noise between the electrode and the system. Passive electrodes use a simple approach to ameliorate the signal quality by extending the connection from the conductive material to the equipment [80].

To array the electrodes, the American Electroencephalography Society has presented a 10–20 system in which the electrodes' positions are defined and named across the scalp [68]. In this system, the electrodes are named based on their positions on the scalp, such as Fp (frontal polar), F (Frontal), C (Central), P (parietal), O (occipital), and T (temporal). The number of electrodes may vary based on the experiment; however, the key is to try to distribute the electrodes evenly across the scalp [81].

There are many electrodes and headsets in the market for scientific studies. With recent developments in neuroscience, the number of mobile headsets has also increased. Some headsets are more suitable for construction studies, such as mobile, wireless, and lightweight headsets with a reasonable number of electrodes. Also, electrodes with high-quality signal acquisition without too much preparation are preferred for construction site experiments.

1.1.3. EEG experimental paradigms

The advanced use of EEG requires expertise for signal preprocessing, artifact detection, and feature extraction. EEG signals are prone to artifacts, which can be physiological noises (e.g., lateral eye motions, blinks, and muscle movements), and external ones (e.g., movements of an electrode or the headset, line noise, swaying or swinging) [82]. The complexity of signal processing lies in the fact that an EEG-based dataset is characterized not only by features of the device but also by the respondent population, recording conditions, stimuli, and overall experimental paradigm [83]. Table 1 relates the features and the experimental paradigms by summarizing different EEG signals' analyses, their goals, characteristics, and fields of application.

2. Research method

In this study, a systematic review approach is adopted to avoid any bias and concurrently enhance the quality in mass review of the articles. As shown in Fig. 1, the selected approach for the aim of this review is a hybrid of macro-scale and micro-scale reviews. The study first began at a macro-scale, characterized by an "exhaustive review with selective citation", that is, covering relevant articles from two prominent databases. At this scale, the "focus" of the selected articles was investigated through summarizing their methods, applications, and outcomes [84].

Table 1
EEG experimental paradigms [9].

Metrics and features	Goal	Characteristics	Application fields
Event-related potentials (ERP) analysis	To collect brain electrical signals generated by external stimuli	- Voltage changes in response to stimuli or events - Data selection by epoching or segmentation - The average EEG time-course over different trials is used in the analyses	- General and experimental psychology - Clinical psychology - Biomedical engineering
Frequency-based analysis	To understand the brain processes which direct emotions, feelings, and thoughts	- Analyzing the frequencies that are mainly associated with internal factors, including brain structures and physiological processes - Suitable for studying the general mental state under limited testing time and when the timing precision of stimulus is not the main concern	Investigation of subject response to certain content, product, website, or software interfaces
Frontal asymmetry metrics	To understand states of emotion through high-level frequency-based metrics in which the imbalanced frequencies between the left and right sides of the brain are investigated	- Beta and/or gamma signals are investigated, especially in frontal cortical regions - Positive emotions, engagement, and motivation result in higher band power in the left vs. right frontal cortex and vice versa - Frontal asymmetry can be investigated throughout the frontal electrodes, such as F3 and F4	- Emotion, motivation, and psychopathology - Resting and psychophysiology - Consumer neuroscience, advertisement, and marketing research
Cognitive-affective metrics	To enable understating performance, personality, situation, and interactions	- Associated with functions in the outer layer of the cerebrum related to mental workload or drowsiness - Enables the possibility of monitoring subjects' physiological and mental state (e.g., fatigue and attention level) - Two of the most important metrics are "cognitive state" and "workload"	- Educational technology and educational assessment - Educational psychology - Military psychology - Fatigue, sleep, and psychological assessment

In line with the method stated by Cooper [85], the study was then taken to micro-level by conducting detailed scrutiny of the research outcomes. At the micro-scale, the outcomes were systematically analyzed with a view to identifying the research themes and the gaps in the literature.

2.1. Systematic review

The protocol for searching relevant materials was adopted from Major and Saven-Baden [86]. As depicted in Fig. 1, the process encompassed an exhaustive search into the title, abstract, and keywords of the published research listed on two of the most reputable bibliographic databases, Scopus and Google Scholar. The relevant articles with the required themes and content were identified through screening the abstract and introduction sections. As this review is scoped on the application of mobile EEG in the construction industry, materials that were not fully related were also filtered out from micro-scale review. This means the EEG-related articles must have studied the construction tasks undertaken by construction workers either in a field research (i.e. in real construction sites) or in laboratory settings (i.e. in a pilot study of construction environments) to meet the micro-scale review criterion.

A spreadsheet was then created in order to identify categories of publications for both descriptive and content analysis. The descriptive analysis was to classify the publications based on year, type, title of the publications, and the academic institutions. Furthermore, the focus of the study, EEG channels, software and hardware, signal processing methods, and accuracy of digital signal processing (DSP) were placed into different categories for content, thematic and gap analyses. In this paper, social network analysis (SNA) is adopted as a tool to analyze the categories in both descriptive and content analysis. In order to explore the patterns of the relationships among individuals and groups, SNA provides a wide range of analysis and techniques [87]. There is a plethora of software and tools to perform a network analysis, each of which has its own features and strengths specified for a certain type of network [88]. In this research, Gephi (0.9.2 version) was used as the network analysis tool [89]. It is an open-source software that provides a visualized insight into the structure of the formed networks. The methods used in the present study meets the requirements presented in the previous seminal studies [85,86,90,91] for a methodologically robust and holistic literature review.

2.2. Thematic and gap analysis

Differentiation of themes was based on a classification provided by Fellows and Liu [92]. This method classifies the themes of publications into theoretical and conceptual papers, case studies, and survey articles. Also, the prime model to categorize the outcome of research is presented as a study analysis, framework, and tool/system prototype [90,93,94]. Although gap analysis is usually conducted intuitively in construction research [92], this paper used a structured approach proposed by Sandberg and Alvesson [93] to spot the gaps in the extant literature. Accordingly, the gap spotting encompassed three particular modes, entitled confusion, neglect, and application [93]:

- *Confusion:* The main concern of this approach is to reveal the confusion in previous studies. In other words, the problem has been investigated already in the literature, but the result conflicts with the available evidence. Research questions in this mode seek to highlight and explain contradictions in the existing literature.
- *Neglect:* Pointing out a neglected area in the literature is one of the most prevalent ways to construct a research question. In this mode of gap analysis, the scholar tries to unveil a neglected territory to develop an investigation about it. Papers subject to this kind of gap are categorized in three groups according to their method and result (i.e., over-looked, under-researched, and lack of empirical support).
- *Application*: The last basic mode to identify a gap in the existing body of knowledge is in identifying a new application. Applying this version of gap analysis enables researchers to construct a research question based on the inadequacy of a specific theory or a clear outlook in a particular area of the research. The main idea is to detect the needs of a certain literature for completion or extension.

Although most studies have employed one key approach to construct research questions, applying a combination of different gap analysis modes is not uncommon [93].

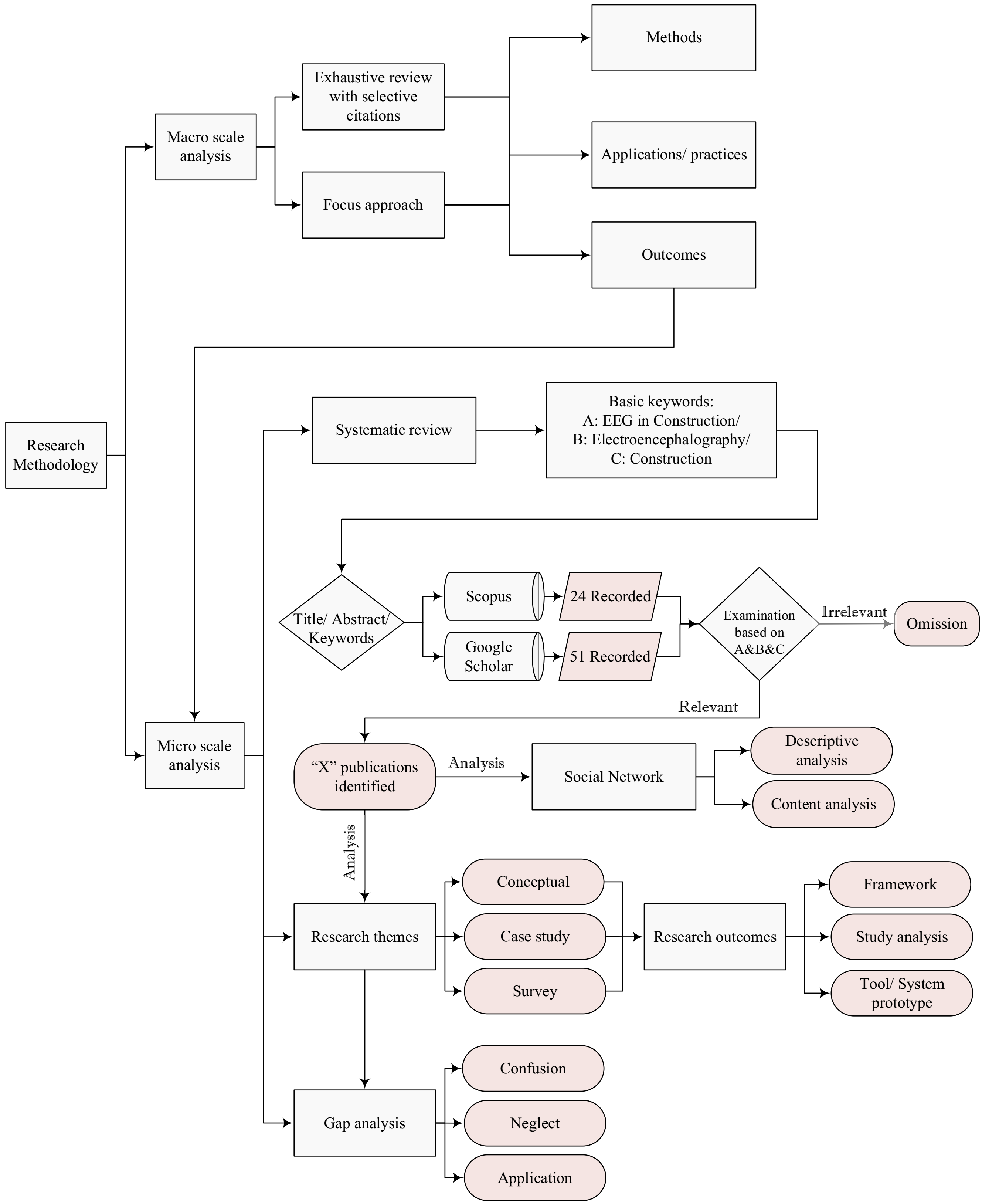

Fig. 1. Methodology flowchart.

3. Results and discussion

3.1. Descriptive analysis

The review of EEG-related construction articles shows that the studies have placed emphasis on demonstrating the potential applications of EEG in the construction industry as a whole rather than narrowing down to any specific construction trade. This has been pursued by experimenting the use of EEG on the tasks that could be performed by most of the trades and in different construction processes. The investigated tasks may involve accident-prone processes, including but not limited to visual concentration or cognitive demand processes in conjunction with a muscular activity under a hazardous situation [95–97]. To exemplify these, some studies have designed a series of tasks, such as climbing a ladder, selecting and picking a tiny material, and fabricating an element, to experiment the usefulness of EEG technology [98]. Nonetheless, there are scenarios in which EEG technology has been used in non-hazardous conditions, for instance, to compare performance of workers with when they are exposed to hazardous conditions.

The first publications related to the application of mobile EEG in the construction industry emerged around 2011 [99]. This was later followed by a slow growth of publications throughout the last decade, as depicted in Fig. 2. By the end of the literature search, a total of 29 purely construction-based EEG studies were found. This may suggest that construction researchers have accepted the concept behind EEG technology and trialed it in the construction sector in recent years. Nonetheless, this concept has been disseminated mostly through the first-tier construction journals (in terms of impact factor), such as *Automation in Construction* (standing for one-third of the publications) and a number of American Society of Civil Engineers' journals. EEG has not yet been ubiquitously used in this sector.

3.2. Content analysis

3.2.1. Keywords

The SNA explores the relationships between entities and how these relationships influence a phenomenon, such as information, through a number of measures. In this study, the most popular individual centrality measures, including degree centrality, weight degree centrality, betweenness centrality and closeness centrality [100], were computed. The use of wearable EEG in construction studies varies according to the nature of the study or research problem. Therefore, a knowledge structure could be mapped by analyzing the keywords' co-occurrence network [101]. In the network of keywords, generated by Gephi (0.9.2 version), the weight assigned to the link between two keywords is computed based on the number of articles in which both of the keywords exist [102]. The initial layout of the network was reformed by applying the force atlas algorithm for further visual clarity [103]. Moreover, nodes with more than two degrees were filtered out for further analysis and this resulted in a more visually accurate network.

To ensure a reliable analysis, similar terms, such as "wearable devices", "wearable EEG", "mobile EEG" and "wearable sensing", were amalgamated. The size of the nodes and their color were adjusted based on the betweenness centrality measures. The betweenness centrality disclosed the importance of location of the nodes and their effect on the whole network. The size of node labels was established in such a way to ensure the flow of information in the network was intelligible. Several analyses were conducted on the network, including the betweenness centrality and weight degree centrality. Eventually, a network consisting of 26 nodes and 95 links, as depicted in Fig. 3, was generated, indicating the keywords of construction EEG-based research.

(In this network, between two particular nodes (keywords), the weight of the edge represents the number of papers in which both keywords existed. The size and color intensity of each node is justified based on the betweenness centrality. Nodes with less than two edges are filtered out from the network.)

In Table 2, analytical results of the network are presented. The relative importance of keywords is based on the values of betweenness centrality. As seen, wearable EEG, brain waves, and safety management are the most frequently used keywords in the research into EEG. "Psychology" and "workers' productivity" are the other two that relate to human factors and placed in the top ten keywords. The only keyword that presents the signal processing territory is "brain signal processing", which appeared in only two publications in the literature [82,104].

3.2.2. Topics

Task workload and cognitive load, fatigue detection, attention, vigilance and hazard awareness, stress recognition, emotional state and valence level, BCI and signal processing were found as the main topics of interest in EEG-based construction research. Fig. 4 demonstrates the percentage of publications in each area of EEG adoption. As seen, the highest percentage of publications belongs to stress recognition. In spite of its top priority, the SNA results (shown in Table 2) does not classify it among the top ten keywords provided by researchers.

Technically, EEG adoption in the construction industry is tied to the advent of suitable signal processing frameworks and their accuracy and effectiveness in practice. The signal processing method has received little attention in EEG-related research in the construction sector and, in particular, for on-site applications. It is noteworthy that the findings of the betweenness centrality of the keywords shows that EEG has been utilized for safety purposes rather than productivity, and referring to workforce productivity in the context of publications does not indicate the focus of the work.

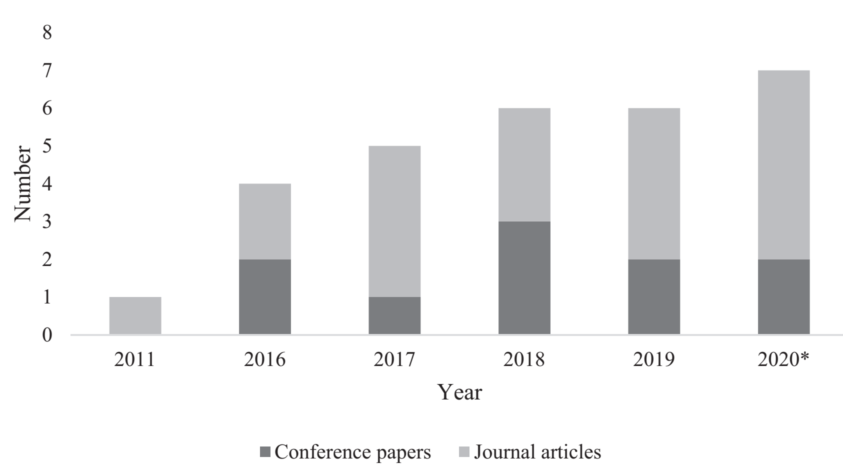

Fig. 2. Annual distribution of the publications, (*: this bar includes publications up until April 2021).

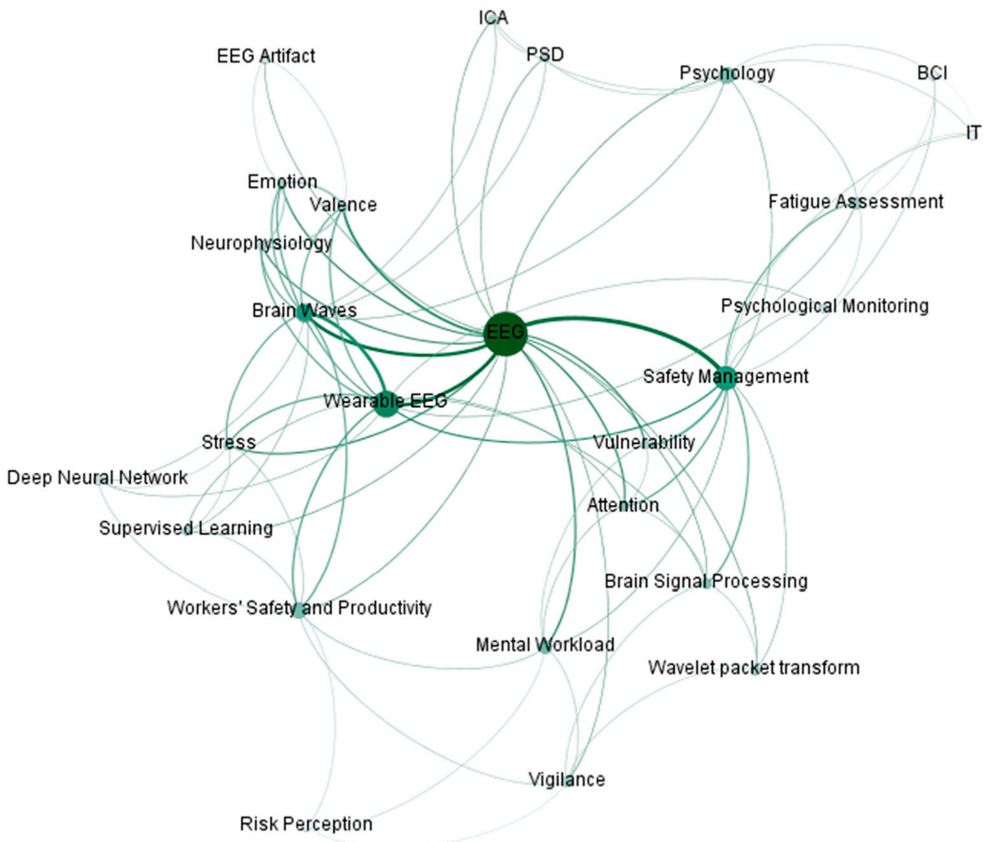

Fig. 3. Relationships and importance of keywords in construction EEG-based studies.

Table 2
Top ten primary keywords of construction EEG-based studies.

Keyword	Betweenness centrality	Weighted degree centrality	Relative importance
Wearable EEG	70	22	1
Brain waves	45	19	2
Safety management	44	14	3
Workers' productivity	28	10	4
Psychology	22	7	5
Mental workload	9	5	6
Brain signal processing	8	6	7
Fatigue assessment	7	7	8
Vigilance	5	5	9
Attention	1	5	10

3.2.2.1. Task workload allocation. Task workload plays a critical role in both the wellbeing and productivity of the workforce. One of the main focuses of EEG research in the construction field is to assess the mental workload of workers. An example is the work of Chen et al., which investigated the potential of applying EEG for evaluating hazards (e.g., workers falling from high places, unsafe behavior) through time-frequency analysis [98]. The mental demands of different construction activities were quantitatively assessed and the signal patterns provided clear distinctions between the studied tasks through their mental loads. In such types of research, the mental workload is correlated to the risk level associated with construction tasks. One approach is to measure EEG signals transmitted from workers' brains as a proxy for assessing their working memory [105]. The ERPs and time-frequency based analysis have been applied to identify vulnerable workers. In line with this, construction scholars have developed a novel framework to assess task workloads using EEG as a quantitative system for monitoring the mental and memory conditions of the workers [106]. A recent research has taken one step further to analyzing EEG signals for assessing task workload with a view to ameliorate poor task allocation [107].

A dominant strategy in using EEG for task workload assessment has been the simplification of the analyses. Simplification approaches include limiting the number of studied tasks, number of electrodes, types of signals, and method of analysis [98,104,105]. The studies have concentrated on three or four tasks to limit the complexity of obtained data. They may also constrain the number of electrodes to one to four channels, mainly from Fp1, Fp2, Tp9, or Tp10 [104,105]. In addition, the focus has been placed on signals from alpha, beta, and gamma bands [98,105]. Also, the data analysis can be limited to recognizing overall patterns, such as statistical variance, and/or sudden spikes in the recorded signals.

3.2.2.2. Fatigue detection. Early detection of fatigue among the construction workforce can reduce the accident rate. EEG has been examined as a means of assessing workers' fatigue levels [108–111]. Fatigue levels have been identified based on variations in a single type of signal or in a metric that combines multiple types of signals. The signals of interest, thus far, have been alpha, beta, and theta. A drop in the signal (s) or a ratio of different signals (for instance (Alpha1 + Theta) / Beta1) can indicate a fatigued worker [108–110]. Compared to the aforementioned approach for task workload analysis, the EEG signal analysis for fatigue detection is more sophisticated. It may require employing data classifiers, such as Support Vector Machine (SVM)-based algorithms, in the signal processing stage [109]. The complexity of fatigue recognition has led to applying EEG in conjunction with devices for measuring physiological states of workers. Skin temperature and heart rate, combined with brainwave signals, can provide an understanding of both

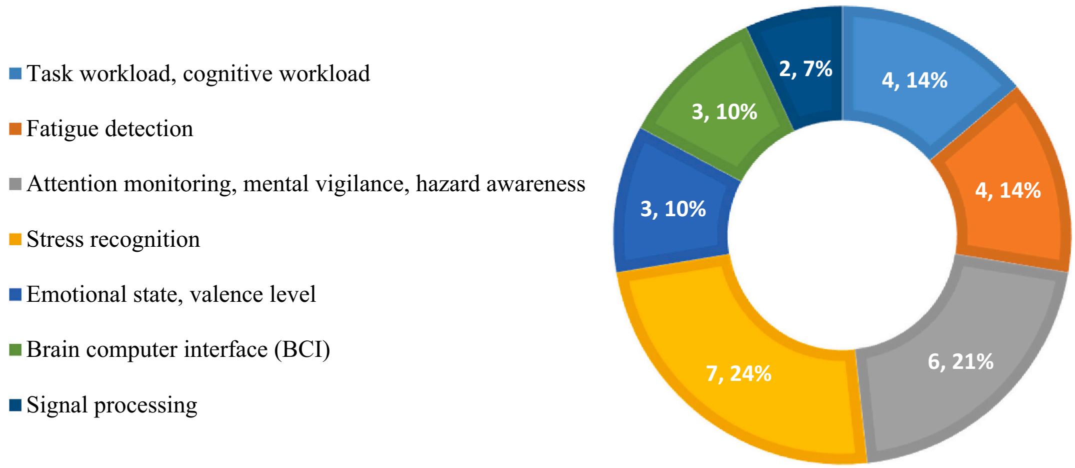

Fig. 4. Topics of interest in the EEG-enabled construction research.

physical and mental fatigue [109]. However, these factors are interrelated and, thus, researchers have begun to investigate such interrelationships [111]. Fatigue is a complex phenomenon and cumulative in nature and, therefore, requires studying construction workers over a longer period of their performance. This exposes practical challenges to using EEG on construction sites [108].

3.2.2.3. Attention and vigilance. EEG-enabled publications attempting to investigate the level of attention and vigilance of construction workers are limited but have been increasing in recent years. The central aim is to measure workers' perceptions and reactions to site risks and hazards [112–115]. Mobile EEG systems are used to identify varying vigilance levels of workers with different demographic backgrounds when they are undertaking tasks in risk-prone scenarios. Such investigations rely on collecting different EEG signals, predominantly from 14 channels [113,114]. However, it is highly likely that a preprocessing stage is required to clean the data sets from artifacts caused by, for instance, eye blinks [114]. In doing so, it is common to use frequency band filters. The paradigm of experiments may set to ERP or frequency-based analyses. In the preprocessing stage, bandpass filter (1-60 Hz), notch filter (50 Hz) and Independent Component Analysis (ICA) may be applied while the signal features may be extracted and classified using Fast Fourier Transform (FFT), Sparse Fast Fourier Transform (SFFT), Wavelet Packet Decomposition (WPD), and SVM algorithms [113,114]. An attempt has recently been made to synchronize the data obtained from eye-tracker and EEG signals with a view to assess visual hazard recognition and its correspondence with brain activity [115].

3.2.2.4. Stress recognition. Several studies have been conducted to assess the stress level of construction workers by mobile EEG. They have all used 14-channel off-the-shelf mobile EEG devices. The effectiveness of stress recognition, however, has significantly been dependent on artifact removal and data classification stages [95–97,116–119]. These require employing sophisticated computational analysis methods to ensure accuracy of the results. An exemplary study proposed an EEG-based stress recognition framework, which employs two deep neural network algorithms (i.e., a fully connected deep neural network (FCDNN) and a deep convolutional neural network (CNN)), to classify the signals and determine the stress level [97]. Data were collected from ten subjects who were performing tasks in both hazardous and non-hazardous conditions, using a 14-channel EEG device and, subsequently, artifact removal methods, such as bandpass filter and ICA, were performed. To classify and measure stress levels, an FCDNN algorithm was applied using Neural Network Toolbox in MATLAB, and its accuracy was 86.5%. In an effort to recognize stress levels in nearly real time, Jebelli et al. used a self-developed algorithm, Online Multitask Learning, and predicted the stress levels with 77.61% accuracy [116]. In another study, researchers applied both linear and nonlinear SVM algorithms to recognize stress levels in the workers with 71.1% accuracy [96]. Principal component analysis (PCA) has been used to reduce the dimension of signal properties. Moreover, fixed and sliding windows have been applied to extract time and frequency domain features. In 2020, Arpaia et al. claimed more than 90% accuracy in recognition of stress using a single differential channel with dry electrodes [95]. Signals were collected according to frontal asymmetry and the collected data were analyzed in MATLAB. PCA was used in the preprocessing stage and the four post-processing algorithms applied included K-Nearest Neighbor (KNN), SVM, Random Forest and Artificial Neural Network (ANN). Although this study was conducted in a non-construction context, the findings show the potential of algorithms in accurate stress recognition. A new stream of research into this domain was introduced in 2020 and found that a correlation between questionnaire-based and EEG-based stress recognition systems exists [118].

3.2.2.5. Emotional state and valence level. Concerning the use of EEG in evaluating emotional state and valence level, two studies were identified in the literature. Jebelli et al. employed a mobile EEG device (Emotiv EPOC+) in safety practice and tried to measure construction workers' valence levels at the workplace [120]. Four EEG channels, including Af4, F4, Af3, and F3 were investigated, and EEG data were obtained from three participants, who performed different kinds of tasks under three scenarios: on the ground, on a ladder, and in a confined space. Hwang et al. applied a bipolar emotional model, valence and arousal, to quantify the workers' emotional states [121]. Data were obtained using a mobile EEG sensor with 14 channels; however, only signals from Af3, F3, Af4, and F4 were investigated. The bandpass filter and ICA were applied to clear out the extrinsic and the intrinsic artifacts, respectively. In the processing stage, mean power spectral density (PSD) of frequency bands (i.e., alpha and beta) were calculated and, based on the power spectrum features, the frontal EEG asymmetry was employed to measure emotional levels. To validate the result, researchers applied the one-way analysis of variance method, and the results of this study shed light on measuring and quantifying on-site workers' emotions and the effects of working conditions on workers' emotions.

3.2.2.6. BCI. There are different views on EEG-based studies of BCI. In this paper, we classify a publication as relating to BCI if construction operators have to interact with computers. A scientific attempt has been made by Rezazadeh et al., who proposed a novel approach to monitoring workers' cognitive load in a virtual environment [99]. In this research, two training environments were developed for crane drivers, in which they were able to control the hoisted loads at a virtual construction site using facial gestures. The results of this paper may lead to improving performance of crane drivers. In 2021, Lui et al. proposed a framework for brainwave-driven human–robot collaboration in which the robot detects the worker's cognitive load and adjusts the robotic performance accordingly [122]. In another research effort, Lui et al. presented a BCI system based on workers' brainwaves to remotely control a robot with 90% accuracy [123].

3.2.2.7. Signal processing. Signal processing is a part of nearly every EEG-based construction research. However, there are only two publications predominantly focused on EEG signal processing of construction activities [82,104]. Since construction sites are dynamic in nature and wearable EEG headsets are prone to noise and artifacts, obtaining high-level EEG signals on construction sites is of high importance. The prominent work by Jebelli et al. proposed a framework to identify and sort out artifacts which originate from body movements [82]. Liu et al. presented a signal processing framework to clear out the ocular artifacts [104]. The researchers compared dependent component analysis with traditional methods, ICA, and PCA. Their proposed methods yielded a promising result in order to obtain high-quality signals on construction sites.

3.2.3. EEG electrodes

To provide a clear illustration of the investigated channels for each state, a zoned scalp is presented in Fig. 5 based on the data presented in the body of knowledge. Previous construction EEG-based research with a focus on stress recognition examined a series of channels that cover almost all the surface of the scalp [95–97,116–119]. These channels include AF3, F3, F7, Fc5, T7, P7, O1, O2, P8, T8, Fc6, F4, F8, and AF4. The EEG-based studies that investigated workers' emotional states have had a focus on AF4, F4, F3, and AF3 channels. The emotional state in the frontal lobe of the brain has been well investigated. The issue of fatigue was investigated in four studies [108–111]. Fp1 is the channel by which the researchers assess workers' fatigue. Compared with fatigue-related channel studies in the transportation sector, both studies emphasized on frontal channels, especially Fp1, as the channels most related to fatigue. The issue of mental workload has also been investigated in frontal lobe studies, especially through Fp1 and Fp2 channels. AF3, F7, and F3 were selected as the most relevant channels for investigating attention levels and mental vigilance of workers. The research findings indicated that EEG signals disseminated from the frontal lobe are highly correlated to the workers' mental and physical state. The aforementioned studies into EEG electrodes provide information about those electrodes on the scalp which have not yet received sufficient attention in construction-based EEG research. For instance, a future study could focus on investigating whether workers' attention, while performing construction tasks, is related to channels F7, F3, and AF3. A positive answer would mean the focus should be on the signals generated from this part of the brain.

3.2.4. EEG analysis software

There are numerous platforms available for processing EEG signals. The most common ones that are being used include R programming language, MATLAB (The Mathworks, Inc., Natick, MA, USA) and its toolboxes (e.g., fieldtrip [124], EEGlab [125]), Python programming language (Python Software Foundation), and brain vision analyzer software (Brain Products GmbH). Among them, MATLAB and its toolboxes are perhaps the most commonly used software suite as four out of five papers published in this domain have used this platform.

3.2.5. Applied hardware in EEG signal acquisition

The two most common devices for data acquisition on construction sites in previous studies are NeuroSky and Emotiv. NeuroSky offers both sensors (TGAM) and headsets (MindWave), and Emotiv products cover a wide range of devices for different purposes (e.g., Epoc+, Insight, Epoc Flex). Nearly 74% of the experiments used Emotiv and 26% employed NeuroSky products (see Table 4). There is no explicit mention of prioritizing one product over another in the scientific literature.

3.2.6. DSP and the level of accuracy

Due to transient and dynamic nature of construction site environments, it is important to develop suitable DSP frameworks for gathering signals. EEG signals are the signatures of neural activities [9], and among these signals there are some signal distortions, or artifacts [72]. Signal processing has three main stages, including image acquisition, preprocessing, and processing, as shown in Table 3. Image acquisition

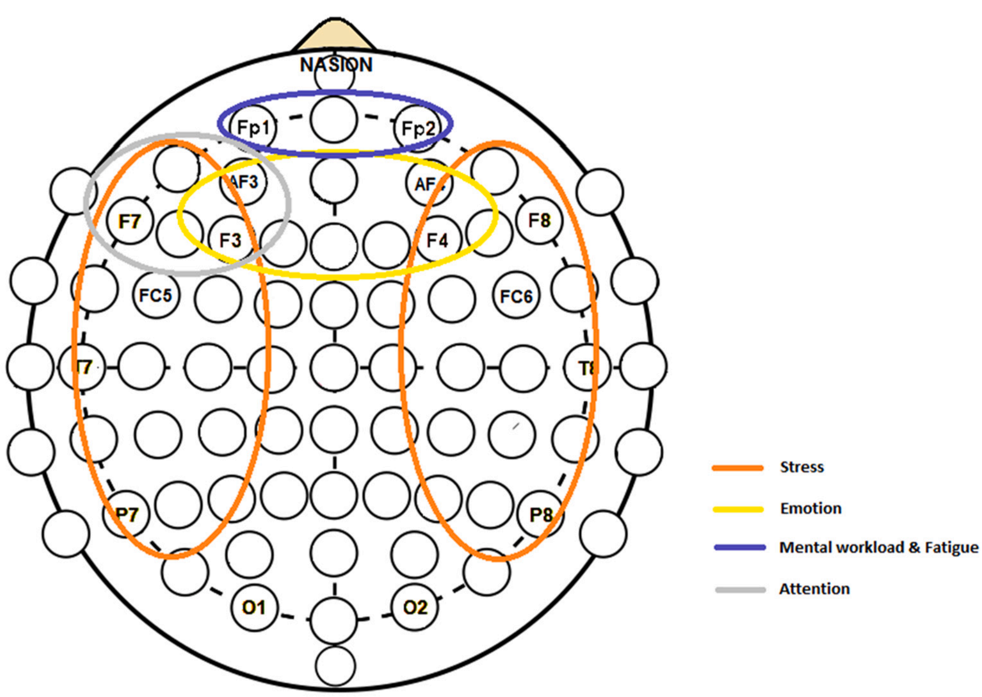

Fig. 5. Electrode position and their cognitive effects used in construction studies.

Table 3
Common methods and techniques for EEG signal processing.

Preprocessing	Processing
Data filtering/Artifact removal	Feature selection and extraction/Classification
• ICA	• Power spectral analysis
• PCA	• Online multitask learning
• DCA	• Machine learning (K-Nearest Neighbors, Gaussian discriminant analysis, SVM with different kernel functions (e.g. linear, nonlinear, quadratic, cubic, Gaussian))
• Multi-nominal logistic regression	• Convolutional neural network
• High pass filter	• Fully connected neural network
• Low pass filter	• PCA
• Notch filter	• Sliding time window
• Third order one-dimensional median filter	• WPD
• Savitzky-Golay filter	• Decision trees
• Moving average filter	• Boosted trees
• Time window (Hanning window, Rectangular window).	• Mathematical method.

refers to the signal to record. Preprocessing consists of two steps, including artifact removal and data filtering. Processing also includes two steps, which are feature selection/extraction and classification [126]. The techniques and approaches adopted in the previous studies for the preprocessing stage include: ICA/high pass filter, low pass filter, and Notch filter (57%), bandpass filter (22%), third order one-dimensional median filter, Savotzky-Golay filter, and moving average filter (7%), time window (7%), and ICA/multi-nominal logistic regression (7%). The preprocessing and processing methods that have been applied are presented in Table 3.

Analyzing the accuracy of the applied DSP methods provides insight into the suitability of the algorithms and techniques, which is valuable to future studies. A DSP approach that yields a high accuracy result has the capacity to be reutilized in future research. As research into EEG in the construction discipline is relatively new, only a very limited number of the papers investigated the accuracy of their algorithms. Thus far, there are five publications that have examined the accuracy of their DSP algorithms. For instance, Aryal et al. applied several algorithms to record and collect EEG signals for scrutinizing workers' fatigue; the boosted trees have yielded the highest accuracy, with 82.6% in the algorithm tested [109]. Other studies have employed various algorithms, such as linear/non-linear SVM, online multitask learning (OMTL), CNN, FCNN, K-Nearest Neighbors, and Gaussian SVM (Table 4). Among these, the FCNN (i.e., Fully Connected Deep Neural Network) has yielded the highest accuracy, with 86.62%, followed by Gaussian SVM, OMTL, and nonlinear SVM for recognizing the stress levels in construction workers (Table 4). One of the latest publications in this field suggests using the combination of four algorithms, including KNN, SVM, Random Forest, and ANN [95]. These methods together yielded an average accuracy above 97% for a non-construction context.

3.3. Thematic and gap analysis

The current research into the EEG applications in the construction discipline was exhaustively reviewed, and their contents were analyzed in three different sections, including the research themes, research outcomes, and the gap analysis. Table 5 presents the outcomes of the analyses.

3.3.1. Research themes

Approximately 80% of the studies that adopted mobile EEG in construction can be categorized as case studies. These studies largely focused on different technical aspects of EEG-based solutions that predominantly contributed to construction safety. The remainder of the studies attempted to discuss a conceptual foundation for the application of EEG in construction. There is a lack of a structured study to survey opinions of experts and practitioners on the potential execution of wearable EEG in construction projects. Moreover, a large-scale survey on the longitudinal study should be conducted to understand the ambiguities pertaining to the applications of EEG in construction.

3.3.2. Research outcomes

More than half of the published studies included some form of statistical/data analysis in deriving their outcomes. These are mainly from the case study themes. These studies provide a scientific ground for the adoption of EEG, its potentials, challenges, and recommendations to overcome the challenges [109,117]. There are four publications aimed at developing prototypes or systems based on the conceptual and case study themes. For instance, Jebelli et al. proposed a stress recognition system to detect workers' stress in a nearly real-time fashion [117]. Of the publications, 30% focused on developing a new conceptual framework, including logics or rules, for enhancing EEG applications in the construction [82,108].

3.3.3. Research gaps

The three types of gaps in the literature, including confusion, neglect, and lack of empirical research, are discussed below:

3.3.3.1. Confusion. While there is extensive potential for using EEG in construction, its practicality may be viewed with skepticism if the experimental studies do not conform to the real-world situations. It is crucially important to assess the conducted methodology with hazardous tasks under real circumstances. Thus, simple tasks and unreal experimental conditions are two issues encountered by the researchers in this particular area. There are a number of works conducted under laboratory settings for examination of their hypotheses (see Table 5). Such works have significant technical merits; however, future studies are required to accommodate real-world settings.

The study conducted by Chen and Song is based on performing one simplified task to evaluate and test their methodology [98]. Compared to the complex and diverse tasks undertaken by an individual worker on a construction site, which require a high level of attention, the selected tasks are usually simpler and require less attention. In addition, the test environment does not simulate the construction site as the studies tend to focus on a short period of performing tasks. This may lead to overlooking the accumulative workload associated with prolonged performance. While the limitations of conducting research are understandable, it is important to focus on pertinent tasks in an environment similar to a real construction site in order to generate a reliable EEG assessment outcome.

3.3.3.2. Neglect. There are a number of issues of neglect in the literature of construction EEG-based research. First, there is a lack of evidence to support the accuracy and reliability of the studies. For instance, the DSP method and its accuracy have great importance in deriving research findings. Therefore, the accuracy yielded from the DSP method should also be studied [105,106]. On the other hand, many of the existing publications have not provided sufficient information about applied DSP algorithms. This impacts the replicability of EEG-related research. With the lack of such information, new studies have to trial multiple algorithms in order to choose the most suitable method for complex and dynamic environment of construction projects.

Moreover, the employment of cutting-edge approaches, such as machine learning algorithms, has yet to be fully applied in EEG-related research. Machine learning approach has proven efficient in dealing with the abundance of data and, thus, the digitalized data generated by EEG devices can potentially be analyzed using such novel algorithms. As virtual reality (VR) and augmented reality (AR) have advanced in the recent years they can provide a more realistic and immersive environment for preliminary experiments to bridge the gap between research and practice.

Table 4
Results of content analysis.

Ref.	Focus of Study	Channels	Frequency bands	Hardware	Software	Preprocessing	Extracting, Classifying	Accuracy (%)
[98]	Mental workload	Fp1, Tp10	theta, alpha, beta, gamma	Neurosky	–	Time window, Lowpass filter	PSD, Engagement index	–
[108]	Fatigue	Fp1	low alpha	Neurosky	–	–	–	–
[105]	Mental workload, vulnerability	Tp10	alpha, beta, gamma	Neurosky	–	Time window	Engagement index, PSD	–
[106]	Mental workload	Fp1	alpha, beta, gamma	Neurosky	–	–	Frequency analysis, PSD	–
[109]	Fatigue	Beta 1 channel	beta	Neurosky	Neuro-Experimenter	Third order one-dimensional median filter, Savitzky-Golay filter, Moving average filter	Boosted trees	82.6
[82]	Signal processing	–	beta	Emotiv Epoc+	–	Low pass filter, High pass filter, Notch filter, ICA	Mean PSD	–
[112]	Attention, Vigilance	AF3, F7, F3	lower gamma frequency	Emotiv Epoc+	EEGlab	Low pass filter, ICA	PSD	–
[120]	Emotional state, Valence level	Af4, F4, Af3, F3	alpha, beta	Emotiv Epoc+	MATLAB	Bandpass filter (0.5 < – < 40 Hz), ICA	Valence value	–
[121]	Emotional state	Af4, F4, Af3, F3	alpha, beta	Emotiv Epoc+	–	Bandpass filter, ICA	Mean PSD, Frontal EEG Asymmetry	–
[95]	Stress	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4	–	Emotiv Epoc+	MATLAB	Low pass filter, High pass filter, Notch filter, ICA	Fully Connected Deep Neural Network	86.62
[96]	Stress	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4	delta, theta, alpha, beta	Emotiv Epoc+	MATLAB, EEGLAB toolbox	Bandpass filter (0.5 < – < 40 Hz), Notch filter, ICA	OMTL-VonNeuman	77.61
[97]	Stress	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4	delta, theta, alpha, beta	Emotiv Epoc+	–	A bandpass filter (0.5 < – < 40 Hz), ICA	Non-linear SVM	71.1
[113]	Mental vigilance	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, AF4	alpha, beta, gamma	Emotiv Epoc+	–	Higher cutoff (>60 Hz), PCA, Event-related potential, Fast Fourier Transform	Wavelet packet transform	–
[116]	Stress	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4	delta, theta, alpha, low beta, beta, high beta, gamma	Emotiv Epoc+	–	PCA, Low pass filter, High pass filter, Notch filter, ICA	Gaussian support vector machine	80.32
[114]	Attention and vigilance	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4	delta, theta, alpha, beta, low gamma	Emotiv Epoc+	–	Fast Fourier Transform, Bandpass filter, PCA	Sliding window, WPD, Vigilance indices	–
[107]	Mental workload	Fp1	gamma	Neurosky	–	ICA	PSD, Three-way analysis of variance	–
[99]	BCI	Frontal, Temporal	alpha	BioPac system	ack100w	Lowpass filter (0.1 Hz)	Root mean square, Fuzzy clustering	96.99%
[110]	Fatigue	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4	alpha, beta, theta	Emotiv Epoc+	–	Notch filter (50 Hz), Bandpass filter (0.5-50 Hz), PCA (Channel selection)	Fourier transform (Time domain to frequency domain), power spectrum	–
[111]	Fatigue	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4	theta, alpha, beta	Emotiv Epoc+	–	Filtering (0.5-40 Hz), ICA	PSD, Mental fatigue index	
[115]	Attention	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4	delta, theta, alpha, beta, low gamma	Emotiv Epoc+	–	Filtering (60 Hz), Clustering	Wavelet packet decomposition, Vigilance index	–
[117]	Stress	–	–	Emotiv Epoc+	–	Filtering, ICA	Fully connected neural network	79.26%
[118]	Stress	Fp1, Fp2	–	EEG-SMT (olimex)	MATLAB	PCA	KNN, SVM, Random forest ANN	>97%
[119]	Stress	Fp1, Fp2	–	Omnifit mindcare headset	–	–	Spectral edge frequency-90	–
[122]	BCI	–	–	Emotiv Epoc+	–	–	–	–
[123]	BCI	–	–	Emotiv Epoc+		–	–	–
[104]			–			DCA	–	–

(continued on next page)

Table 4 (*continued*)

Ref.	Focus of Study	Channels	Frequency bands	Hardware	Software	Preprocessing	Extracting, Classifying	Accuracy (%)
	Signal processing	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4		Emotiv Epoc+				

Table 5
Research themes, outcomes, and research deficiencies of the collected publications.✓

Ref.	Research Design			Research Outcomes			Gap Analysis				
	Conceptual	Case Study	Survey	Study Analysis	Framework	Tool/ System prototype	Confusion	Neglect			Application
								Over-looked	Under-researched	Lack of empirical research	
[98]		✓		✓			✓				
[108]	✓				✓			✓			✓
[121]		✓		✓					✓		
[112]		✓		✓					✓		✓
[105]		✓		✓					✓		
[106]		✓			✓		✓	✓			✓
[109]		✓		✓							
[82]	✓				✓						✓
[120]		✓		✓							
[95]		✓		✓							
[96]	✓					✓					
[113]		✓			✓						
[116]	✓					✓					
[107]	✓					✓					
[99]		✓		✓	✓						✓
[110]		✓		✓	✓						
[111]		✓		✓			✓				
[114]		✓		✓	✓						
[115]		✓		✓			✓			✓	✓
[122]		✓			✓					✓	✓
[123]		✓				✓					✓
[117]		✓		✓							
[118]		✓		✓							
[104]		✓		✓							
[8]			✓	✓					✓		
[97]		✓				✓			✓		
[10]			✓	✓					✓		✓
[14]			✓	✓						✓	
[119]		✓				✓			✓		
Total No.	5	21	3	18	8	6	4	2	7	3	9

3.3.3.3. Application. Vast majority of the published works have explicitly highlighted their contribution to the body of knowledge. There are five publications (shown in Table 5) that require further clarity on how their results contribute to the existing literature. On the other hand, due to insufficient knowledge about the methodical approaches of EEG research in the construction discipline, a number of articles seem to lack a strong underpinning theory [112,119]. This has impeded conclusive validation of the research findings. Employing a theory reinforces the findings and assists in systemic identification and extension of directions for future research in this area.

Lastly, the current applications of EEG predominantly remain at a tactical level of on-site construction management. The investigations on the usefulness of EEG need to be extended to trigger changes in the existing policies for managing construction workforce.

3.4. Future research directions

To fulfill the aims of this research, potential applications and contributions of mobile EEG are outlined below. Based on the analyses and the identified gaps, key future research directions are summarized as follows:

3.4.1. Theoretical developments

Empirical research is required to scrutinize requirements for ubiquitous adoption of EEG in the construction context. Technical viability, economic feasibility, industry perception and acceptance, and legal aspects of applying EEG in construction projects can be key attributes of up-coming studies. The outcomes of such research will assist in designing verifiable EEG case studies. The world of theory is wide; however, the most relevant theories can be borrowed from sectors such as psychology, neuroscience, and management science.

3.4.2. Application/scope development

One new direction is to use EEG for studying the optimal allocation of tasks to construction workers. The extant literature has little or implicit reference to the potential of EEG for such applications. However, this domain deserves a separate pathway to proactively address issues with safety, workload imbalances within a crew, on-the-job skill training and skill promotion on one common platform. Extreme workload is one of the main causes of fatigue in workers [127] and EEG has the potential to provide an evidence basis for a universally adoptable framework for job assignment to construction workers. With growing recognition toward using human-assisted robots on construction sites, it is envisioned that issues associated with human–machine interactions are on rise. This opens a new avenue for EEG-based studies of human–machine interactions in order to optimize the design and utilization of such robots and the design of a convenient environment for human–robot interaction. In future construction research, investigation and comparison of the trades and processes in which wearable EEG has been used is of high importance. To consider real construction trades and demonstrate EEG contribution will contribute to a wider adoption of this technology. Trialing EEG on a wide spectrum of construction tasks with varying levels of complexity and risk can provide a more realistic picture about capabilities and limitations of EEG-based research.

3.4.3. *Methodological developments*

Signal processing has significant potential in improving and expanding the current application of EEG in construction. Future research can further extend the focus on developing hybrid analytical methods for preprocessing (noise and artifacts removal) and post-processing (clustering and pattern recognition) of the collected data from construction sites. Attention can be paid to visualizing the outcomes of analyzed data in order to enable rapid diagnosis of issues with workplace and workers' wellbeing. Future construction studies could also focus on advancing EEG-based research in virtual environments using technologies such as AR and VR. Such platforms enable nearly limitless experimental settings, simulating real-world scenarios in an economic way. More importantly, AR and VR can come into play for assessing the efficacy of signal processing algorithms. Signal processing is an evolutionary and iterative process in most cases relying on data abundance. Hence, existence of cost-effective platforms can facilitate the improvement of this process. Another potential application of VR technology in this field is to investigate the possibility of VR-based construction safety training. Hybridizing EEG devices with other easy-to-use biometric technologies (such as temperature, heart rate, and blood pressure meters) is an area to examine whether and how such technologies can complement or act as a proxy for one another in assessing workers' wellbeing and safety.

4. Conclusions

This paper provided a comprehensive review of the EEG technology and its applications in construction research. The systematic review was founded on three pillars consisting of bibliometric, thematic, and gap analyses. The study characterized the EEG tools and gears, experimental paradigms, topics, keywords, and network of researchers. Moreover, it outlined the major research theme and signal processing approaches. The review highlighted the gaps in EEG-related research through three modes of confusion, neglect and application. Then, it derived various directions for future research.

There are diverse types of EEG devices available in the market. Besides cost factors, selecting a suitable device is mainly based on the movability, number of channels, type of electrodes and amplifying quality of signals. Construction scholars have preferred off-the-shelf wireless EEG devices with up to 14 channels and dry electrodes along with a conventional amplifier. The dominant experimental paradigms include ERP analysis, frequency-based analysis, frontal asymmetry metrics, and cognitive-affective metrics. The US and China are leading the research into EEG-enabled construction and the major topics of interest are stress recognition, attention monitoring, vigilance, and hazard awareness. "Wearable EEG", "brain waves", and "safety management" convey the highest weighted degree of centrality in the extant keywords. Case studies are the main research approach in applying EEG to construction. Some of the construction scholars have pursed a simplification strategy by limiting the number and complexity of studied tasks and trialing in laboratory settings. Moreover, DSP has been limited to the signals from a few channels in some cases, for instance, only Fp1 for workload assessment, due to the high level of artifacts and noise associated with the collected signals. Under such scenarios, a pattern of spikes in the recorded signal is attributed to anomalies of tasks or workplace conditions. Other studies have proven the potential of applying advanced preprocessing filters and post-processing classifiers in drawing accurate conclusions about tasks, workplaces, and workers.

Future research should be directed toward theoretical development, scope expansion, and methodological advancement. Theoretical development can focus on empirical research to scrutinize requirements for ubiquitous adoption of EEG in construction and enhancing the theoretical foundations of EEG-based construction research. Scope expansion can divert attention to studying a wider spectrum of site tasks, optimal job assignments, workers' productivity, and interactions between workers and human-assisted robots. Methodological developments should mainly place emphasis on advancing DSP and trialing EEG in conjunction with other digital technologies.

Declaration of competing interest

None.

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