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Review

Construction Site Hazard Identification and Worker Adverse Reaction Monitoring Using Electroencephalograms: A Review

Bo'an Wei [1], Bin Yang [1,*], Weiling Zhang [1], Pengju Liu [2], Hanliang Fu [3], Zhihan Lv [4] and Faming Wang [5]

1 School of Energy and Safety Engineering, Tianjin Chengjian University, Tianjin 300384, China; weiboan0115@163.com (B.W.); weiling0879@163.com (W.Z.)
2 Department of Applied Physics and Electronics, Umeå University, 90187 Umeå, Sweden; pengju.liu@umu.se
3 Laboratory of Neuromanagement in Engineering, Xi'an University of Architecture and Technology, Xi'an 710055, China; fuhanliang@xauat.edu.cn
4 Department of Game Design, Faculty of Arts, Uppsala University, 62167 Uppsala, Sweden; zhihan.lyu@speldesign.uu.se
5 Department of Biosystems, KU Leuven, 3001 Leuven, Belgium; faming.wang@kuleuven.be
* Correspondence: binyang@tcu.edu.cn

Abstract: The construction process is a dynamic one, and the complexity of the working conditions and the high level of uncertainty make the construction industry the third most dangerous industry after mining and agriculture. And since the construction industry is vital to the development of a country, safety during construction is of particular importance. A great deal of research, studies and practices have been conducted to reduce potential risks and improve worker efficiency during the construction process. In recent years, with the rapid development of cognitive neuroscience and the integration of medical technology, various wearable monitoring devices have been widely used in the field of building construction for real-time monitoring of workers' physical and mental conditions. Among them, the application of EEG (electroencephalogram) in the building construction process enables researchers to gain insight into the physical and mental state of construction workers while performing construction tasks. This paper introduces EEG technology and portable EEG monitoring equipment and summarizes its application in monitoring workers' adverse reactions (emotion, fatigue, psychological burden, and vigilance) and construction hazard identification during the process of construction in recent years, which provides future EEG research in the field of building construction and construction site safety management.

Keywords: electroencephalogram; construction; hazard identification; worker safety; adverse reaction

Citation: Wei, B.; Yang, B.; Zhang, W.; Liu, P.; Fu, H.; Lv, Z.; Wang, F. Construction Site Hazard Identification and Worker Adverse Reaction Monitoring Using Electroencephalograms: A Review. *Buildings* **2024**, *14*, 180. https://doi.org/10.3390/buildings14010180

Academic Editor: Minkoo Kim

Received: 23 November 2023
Revised: 26 December 2023
Accepted: 8 January 2024
Published: 10 January 2024

1. Introduction

1.1. Research Background

The construction industry plays a critical role in the development of nations and societies. Over 350 million people work in frontline building construction around the world [1]. However, the complexity and high level of uncertainty of working conditions during the construction phase make it the third most hazardous industry after mining and agriculture. Construction accounts for approximately 7% of the total labor force in the United States, but construction workers account for approximately 20% of all industrial fatalities. Based on data published in 2010 by the National Institute for Occupational Safety and Health, the mortality rate among construction workers is 15.2 per 100,000 [2]. Building construction mainly includes work under confined conditions, work at height, physical handling, lifting, and demolition operations. The main potential hazards include hypoxia, falls from height, object strikes, lifting injuries, collapse accidents, and mechanical injuries [1]. According to the statistical results of national housing and municipal engineering safety accidents in 2018 issued by China's Ministry of Housing and Urban–Rural Development, there were a total of 734 construction production safety accidents nationwide, with a total of 840 deaths, and according to the type of accidents, there were 383 accidents of falling from height, which accounted for the largest proportion, accounting for 52.2% of the total number; 112 accidents of object strikes, accounting for 15.2% of the total number; 55 accidents of lifting and demolition accounting for 7.5% of the total; 54 collapse accidents, accounting for 7.3% of the total; 43 mechanical accidents, accounting for 5.9% of the total; and 87 other types of accidents, accounting for 11.9% of the total. Construction is a dynamic process with complex and changing working conditions as well as the possibility of unforeseen circumstances at any time [3,4], necessitating a great deal of effort from frontline workers to ensure that safety incidents do not occur [5]. It is also distinguished by a heavy workload, long continuous working hours, unhealthy working postures, an unsuitable temperature and humidity of the working environment, and easy fatigue [6]. Furthermore, due to a lack of sleep or mood swings [7,8], construction workers may already be fatigued when they begin working [9]. Typically, 20–40% of construction workers exceed recognized physiological thresholds for physical labor [10]. As a result of being unable to concentrate for extended periods of time or frequently experiencing mental fatigue, workers are frequently unable to respond appropriately to potential safety hazards, which can lead to accidents [11]. It has been discovered that adverse reactions such as increased mental fatigue and cognitive decline in construction workers can result in hazards [12]. Recognizing and predicting the occurrence of construction hazards can be accomplished through methods such as the creation of scene graphs with interaction-level scene descriptions [13]. As a result, we can effectively reduce the occurrence of hazards during construction by monitoring both the subjective situation of construction workers and objective identification and prediction of hazards in the construction environment.

However, our research on the impact of environmental personnel is still dominated by subjective evaluation, which is the main technical tool used to study the impact of indoor environmental quality on occupants' indoor comfort [14]. Typically, people assess indoor comfort by completing various evaluation questionnaires, such as thermal comfort [15], visual comfort [16], acoustic comfort [17–19], and perception of indoor air quality [20,21]. The same is true for outdoor building construction environments [22], where we obtain current physiological conditions of construction workers primarily through subjective questionnaires [12], and construction hazard identification primarily through personal inspections by the project manager [23,24], which are overly subjective [25] and closely related to the project manager's personal work status. Subjective evaluation allows us to obtain a large amount of data for research in a short period of time more conveniently, but it also has drawbacks, such as limited topics that can be designed; a wide range of investigations but insufficient depth; variable quality of survey results; and susceptibility to the subjective thoughts of the subjects [9]. As a result, there is an urgent need for effective probes that can monitor the real-time status of building construction personnel in complex building construction environments. EEG, as a noninvasive and noninvasive neuroimaging technique, can provide accurate measurements of brain activity directly [26,27]. The brain can plan and execute autonomous movements, and many purposeful actions and behaviors are accomplished through various computational sequences within the brain [28], and EEG signals can also directly respond to nervous system activity [29]. Currently, physiological monitoring, such as EEG, is widely used in indoor environmental research [30,31]. Hu et al. [30] investigated the effects of various indoor lighting conditions on work efficiency by monitoring subjects' EEG signals. EEG has a variety of applications in the field of sleep monitoring. PSG (polysomnography), for example, is used to determine sleep staging [32,33] and the presence of sleep-related disorders (e.g., OSA (obstructive sleep apnea) [34,35], CSA30 (central sleep apnea) [36], RBD (rapid eye movement sleep behavioral disorder) [37], and so on) in personnel [38].

With the extensive development of cognitive neuroscience technology in recent years, EEG technology can now be used not only for rational monitoring of indoor people, but also for outdoor environments, such as monitoring outdoor people's movement [39,40], observing pedestrians' avoidance behaviors in dangerous situations [41], and exploring outdoor thermal comfort and optimal outdoor environment [42]. People who work outside for long periods of time are exposed to more complex scenarios that consume more energy than those who work indoors, making them more susceptible to physical and psychological fatigue, as is the case in the construction industry. The physical and mental health of construction workers is a source of concern due to their long hours of outdoor work [6]. Many studies have been conducted in recent years on the application of EEG technology to the identification of hazardous behaviors and the monitoring of workers' adverse reactions on construction sites, and the application of EEG in the field of construction is conducive to the in-depth understanding of the physical and mental state of construction workers during construction tasks, as well as the prediction and identification of hazards on construction sites. In order to elucidate, in this paper, we first provide an overview of the EEG technology, then summarize recent applications and research on the monitoring of workers' adverse reactions and the identification of construction hazards in the field of construction, and finally, we look forward to the future development of this field.

1.2. EEG Technology

1.2.1. Four Functional Areas of the Brain

The human brain is the most complex structure known to man, with trillions of organized cells. The human brain is divided into two hemispheres, left and right, each of which controls the response body and receives information from it. Each hemisphere's cerebral cortex is divided into four distinct lobes—frontal, parietal, temporal, and occipital—that are separated by deep sulcal fissures and have distinct functions. We've described the function and location of each lobe in Figure 1. Understanding these will aid us later in understanding the EEG technique.

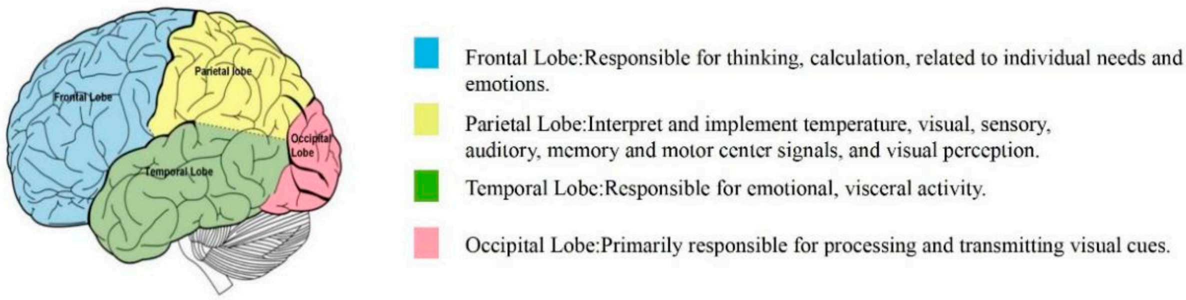

Figure 1. The main functions of the four functional areas of the brain.

1.2.2. Five Brain Wave Frequencies

Hans Berger discovered EEG activity in 1929 and invented a technique for measuring EEG with the goal of providing "a window to the brain." There are five main brain waves in the human brain, as shown in Table 1, ranging in frequency from low to high. These waves are closely related to states such as sleep, thought, cognition, arousal, and increased coordination when the brain is processing tasks. A typical EEG is made up of different frequency bands, and depending on the state of consciousness in which it is located, a specific brain wave will dominate, implying that different frequencies of brain waves correspond to different brain activities [43]. Different EEG frequency bands correspond to different subjective feelings and tasks, and the energy or work power spectral density (PSD) of the EEG waves in each frequency band can indicate that different parts of the brain are activated, reflecting different physiological states [44].

Table 1. The subjective feelings and tasks corresponding to the five brain waves.

Band Name	Frequency Band (Hz)	Subjective Feeling State	Relevant Mandates and Behaviors
Delta (δ)	0.5 Hz–4 Hz	dreamless sleep, non-REM sleep, asleep	Drowsiness, immobility, difficulty concentrating
Theta (θ)	4 Hz–8 Hz	Intuition, recollection, deeply relaxed	Be creative and intuitive; Distraction, lack of concentration
Alpha (α)	8 Hz–13 Hz	relaxed, not irritable, not sleepy	Meditative, no movement
Beta (β)	13 Hz–30 Hz	Alert, excited, focused	Conduct mental activities
Gamma (γ)	30 Hz–Up	High performance	Advanced information processing and information-rich task processing

1.2.3. The International 10–20 Electrode Placement System

The International 10–20 system electrode placement method, as shown in Figure 2, is a standard electrode placement method prescribed by the AASM (American Academy of Sleep Medicine) that is designed to maintain a standardized EEG testing methodology to ensure that the results of a subject's study can be compiled, replicated, and validly analyzed and compared using the scientific method.

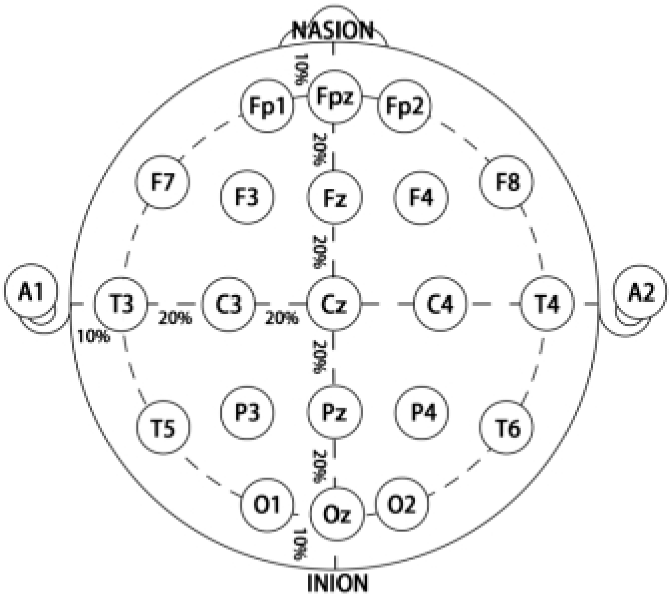

Figure 2. Labels for points according to the International 10–20 electrode placement system.

Electrode placement is primarily cranial in reference and does not differ based on individual differences in head circumference or head shape. The sagittal line is the anterior–posterior line from the root of the nose to the external occipital ridge, and the coronal line is the left–right line between the anterior recesses of the ears. The focal point of the two lines is at the top of the head, where the Cz electrode is located. The sagittal lines were Fpz, Fz, Cz, Pz, and Oz from anterior to posterior, and the spacing between the points was 20% of the sagittal line length except for the distances between Fpz and the root of the nose and Oz and the extra-occipital ramus, which were 10% of the sagittal line length; and along the coronal line, from 10% of the left anterior recess of the left ear, T3, C3 and Cz. The other points' locations are shown above. Arabic numerals were used to represent the electrodes, with the left hemisphere being odd and the right hemisphere being even, A1 and A2 representing the right and left earlobes, respectively, and the numbers decreasing from the lateral to the midline.

1.2.4. Portable EEG Monitoring Devices

Portable monitoring devices, such as smartwatches, have grown in popularity in recent years and can be directly connected to a person's cell phone, making it simple for the user to view various data and understand his or her current physiological state (e.g., heart rate, blood pressure, skin temperature, sleep quality, etc.), to better understand his or her health [45].

In the field of construction, the commonly used portable monitoring equipment is shown in Figure 3. It mainly includes electroencephalogram, eye movement meter, accelerometer, skin temperature sensor, heart rate monitor, inertial measurement unit, and so on. People's physiological signals can be monitored by various portable devices. Electroencephalograms (EEGs) can be used to monitor EEG signals, which are critical for judging construction unsafe behaviors and workers' adverse reactions; construction workers can also wear portable eye-tracking devices to determine risks during the work process [46]; and skin temperature sensors can monitor the skin temperature of construction workers in the moment to obtain the thermal sensation situation at the moment. Millions of people in various industries, including construction workers, use personal portable devices on a daily basis to monitor their heart rate and other health-related physiological parameters to ensure their well-being [47,48]. Nnaji et al. [48] demonstrate, using data from the National Institute for Occupational Safety and Health (NIOSH) fatality data, that the likelihood of accidents can be greatly reduced by the prudent use of intelligent portable monitoring devices.

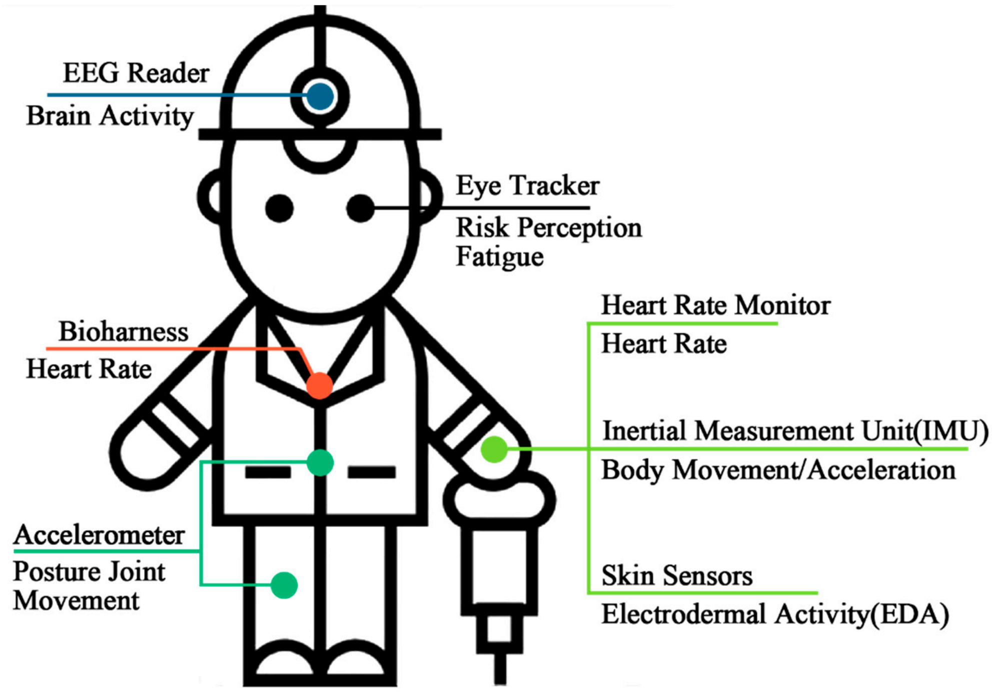

Figure 3. Potential locations and use of portable sensors.

The use of intelligent portable monitoring devices has the potential to improve construction safety and efficiency. Because the healthcare industry has been at the forefront of implementing this type of technology, there are now an increasing number of cases of it being combined with the construction field [49]. Portable EEG monitoring devices that can monitor construction workers' physiological states in real time without causing discomfort to their physiology are novel ideas in current research. Through application examples, this section introduces the portable EEG monitoring device from two perspectives: traditional scalp EEG and ear-EEG.

Traditional Scalp EEG

Wang et al. [50] created a scalp EEG with a set of electrodes and a microprocessor installed in a standard helmet to collect EEG data from eight different parts of the wearer's brain. The mental fatigue of construction workers was objectively monitored using electroencephalography (EEG) signals, and the EEG signals of 16 construction workers were recorded while performing their tasks, and the time-frequency-energy data of the acquired EEG signals were processed using WPT (wavelet packet transform) and CNN (convolutional neural networks) to recognize their current mental fatigue state. The framework provides a cognitive fatigue state classification that matches the self-reported fatigue state with an accuracy of 88.85%, which can be useful in reducing construction risky behaviors and providing assistance in fatigue management for workers.

Chen et al. [51] proposed and tested an EEG-based method for quantifying the mental load of construction workers. PSD (power spectral density) was used to calculate the subjects' post-experimental mental load. The results were consistent with the NASA-TLX (NASA Task Load Index) mental load score. A portable EEG helmet based on the Neurosky ThinkGear module (NeuroSky, San Jose, CA, USA) was also developed to collect four sensing channels at different sensor locations, Fp1, Fp2, Tp9, and Tp10. The location of Fp1 was associated with logical attention; the location of Fp2 was associated with emotional attention. The two frontal EEG channels are compared to Tp9 and Tp10, which can be used as cross-channel references. In addition, an accelerometer was installed on the microcontroller to capture the three-axis motion of the helmet, as shown in Figure 4. In this experiment, each subject was asked to (1) sit in a chair and relax for 5 s; (2) climb a ladder (1 m high, requiring 3–4 s to reach the top); (3) select the appropriate bolt (2–3 s); (4) install the bolt (4–5 min); and (5) climb down the ladder and then rest. The installation task required each subject to select the appropriate nut and then tighten the bolt with a wrench. This task had to be completed three times by each subject. At the end of the experiment, all subjects were asked to complete a questionnaire to assess task load. Subjects wore helmets fitted with instruments which were wirelessly connected to a laptop via Bluetooth during the experiment. Figure 4 depicts a schematic diagram of the experimental subjects and equipment. Figure 4a depicts the subjects with the experimental equipment, Figure 4b depicts the EEG monitoring chip, Figure 4c depicts the nuts and bolts used in the mounting activity, and Figure 4d depicts the ladder that the subjects had to climb.

Figure 4. Experimental apparatus: (**a**) experiment subject; (**b**) EEG hardhat and the EEG monitoring chips; (**c**) nuts and bolts; (**d**) ladder platform [51].

Aryal et al. [52] created a sensing system that used infrared sensors attached to a helmet to monitor skin temperature at four different locations on the face, as well as heart rate and EEG signals. Physiological data from 12 construction workers were collected, and analysis revealed that the combination of skin temperature, heart rate, and EEG signals predicted worker fatigue with an accuracy of up to 82%. Li et al. [53] created a quantitative method for assessing the level of mental fatigue in subjects based on traditional scalp-based EEG measurements by examining and analyzing EEG spectra, such as gravity frequency. By collecting EEG signals from relevant brain regions of the subjects using traditional scalp-type EEG, Xing et al. [54] determined the positive effects of Progressive muscle relaxation and Trigeminal nerve stimulation sessions on the adverse emotions of construction workers at high altitudes.

Ear-EEG

The traditional scalp EEG example was discussed above. Workers are bound to feel uncomfortable when wearing the helmet for an extended period of time due to the extremely limited space inside the helmet and the need to place the electrodes inside the helmet. Furthermore, workers will secrete a lot of sweat when working continuously outdoors, which will affect the electrode impedance and lead to inaccurate monitoring, making continuous EEG monitoring of workers inconvenient. As a result, we summarize another emerging and more popular EEG monitoring device, ear-EEG [55,56].

As shown in Figure 5, Looney et al. [57] developed the world's first ear-EEG in 2012, which drew widespread attention at the time. In general, the benefits of using ear-EEG for monitoring include the fact that it does not obstruct the field of view and that the ear-EEG is usually fixed in the ear canal for measurement, making it securely positioned and less likely to fall off. The ear is also less likely to sweat, avoiding the effects of electrode impedance caused by excessive sweating. While scalp EEG may require the assistance of experienced assistants, the ear-EEG device can be simply placed in the subject's ear, saving labor and improving the stability of continuous monitoring and monitoring efficiency.

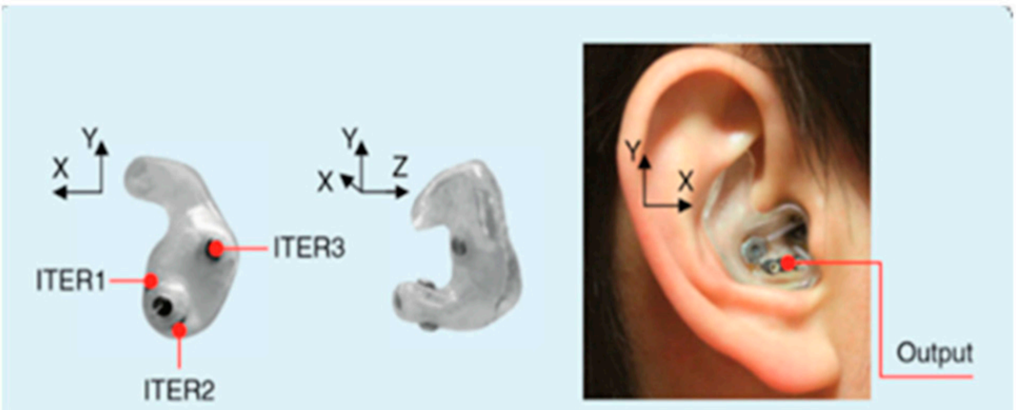

Figure 5. The first in-ear EEG prototype [57].

Ear-EEG can be used to monitor facial expressions and body movements, and this research can aid in emotional recognition and determining the physical and mental states of construction workers. Matthies et al. [55] created an in-ear headset based on Neurosky EEG sensors that can control various cell phone functions using human blinking motions and ear wiggling. In a later study, Matthies et al. [58] used multiple electrodes on a foam earbud to detect 25 facial expressions and gestures using four different sensing techniques. The results showed that five gestures had an accuracy of more than 90% and 14 gestures had an accuracy of more than 50%. Athavipach et al. [56] designed and used an ear-EEG to achieve basic emotion categorization and demonstrated a high level of accuracy. The studies above have shown that ear-EEG has a good performance in monitoring and acquiring EEG signals, which, combined with its headphone-like convenience, confirms that it can be widely used in fields such as medical monitoring [59,60] and sleep monitoring [61].

1.3. EEG Monitoring of Worker Adverse Reactions and Construction Hazard Identification

According to the Occupational Safety and Health Administration, more than 6000 fatalities or injuries of varying severity related to construction projects occur each year, accounting for approximately 20% of all fatalities in the United States. In just one year, 773 housing and municipal safety accidents occurred, resulting in 904 deaths [62]. Approximately 65% of these accidents are caused by falls from great heights, which are frequently caused by non-compliant interactions between workers and other building components. Aside from the enormous loss of life and the impact on injured people, there is also a massive economic loss. To avoid such losses, we must monitor construction workers' adverse reactions and identify construction job site hazards so that they can be reduced or eliminated.

Current researchers have shown a link between brain waves of different frequencies and mental fatigue. Jap et al. [63] found that the energies of EEG signals $(\alpha + \beta)/\theta$, α/β, $(\theta + \alpha)/(\alpha + \beta)$, and θ/β can indicate driver fatigue. The $(\alpha + \theta)/\beta$ energy of EEG signals, in particular, can indicate different degrees of mental fatigue [63–65]. Li et al. [66] used a two-channel EEG model with 92.3% accuracy to monitor driver fatigue.

1.4. Contributions of the Review

Based on the research background presented above, we know that in recent years, EEG research and application have played an important role in the aforementioned fields. With the comprehensive development of cognitive neuroscience technology, it has a greater potential for future development, providing broader ideas for research in various fields both indoors and outdoors, and promoting the advancement of times. This paper examines recent EEG applications in the monitoring of adverse reactions in workers and hazard identification in building construction, providing directions for future research and development.

2. Review Methodology

2.1. Literature Research

The study employed a content-based literature review methodology based on content analysis was used. The exact process of searching for and selecting literature is shown below. Google Scholar, Science Network, and Science Direct were among the databases searched during the review exercise. Journal articles, conference papers, and relevant books were among the target paper types. Finally, a collection of EEG-based literature or books on the monitoring of risky behaviors and workers' adverse reactions in construction was gathered by examining the titles, abstracts, and keywords for human source identification.

To search the literature, Google Scholar, Web of Science, Science Direct, PubMed, and keywords were used. To ensure the relevance and high quality of the selected literature, keywords were used in conjunction with the Boolean operators "AND" and "OR" to conduct a comprehensive search of the literature on EEG in the identification of construction hazards, the use of EEG in adverse reactions in workers, and portable EEG. In addition, the search results were examined, and references in the search results were scrutinized. Although this percentage was small, the review also included highly relevant literature where milestones appeared in the references, despite the fact that it was likely to be outside the search time and English language constraints.

Keyword co-occurrence analysis is a text analysis method for determining co-occurrence relationships between keywords in a given collection of text sets [67] The basic idea behind keyword co-occurrence analysis is that if two keywords appear frequently together in a text, they may be related in some way. This can be accomplished by calculating the co-occurrence frequency of keywords, the co-occurrence matrix, the co-occurrence network, and other factors. The co-occurrence frequency indicates the number of times two keywords appear together in the same text, whereas the co-occurrence matrix and co-occurrence network can visualize the correlation between keywords. Researchers can use keyword co-occurrence analysis to uncover patterns and associations hidden in textual data, which can help them better understand textual content, discover related topics, create concept maps, and so on. This analysis method is useful for processing large amounts of text data, discovering domain knowledge, and assisting decision-making.

In this paper, we also use VOSviewer [68] to analyze the related keywords; the core idea of VOSviewer1.6.18 software is "co-occurrence clustering," which means that two things appearing at the same time are related to each other; there are many types of such correlations, and their strengths and directions differ; different types of groups can be found based on the clustering of measures of the strengths and directions of the relationships. Clustering based on measures of the strength and direction of the relationship can be used to identify different types of groups. The co-occurrence visualization graph, shown in Figure 6, displays scientific terms that appear at least three times in all titles and abstracts. The size of the nodes indicates the frequency of a phrase in the entire literature, the thickness of the line indicates the strength of the association between the phrases, and the color of the same line indicates the proximity between the phrases.

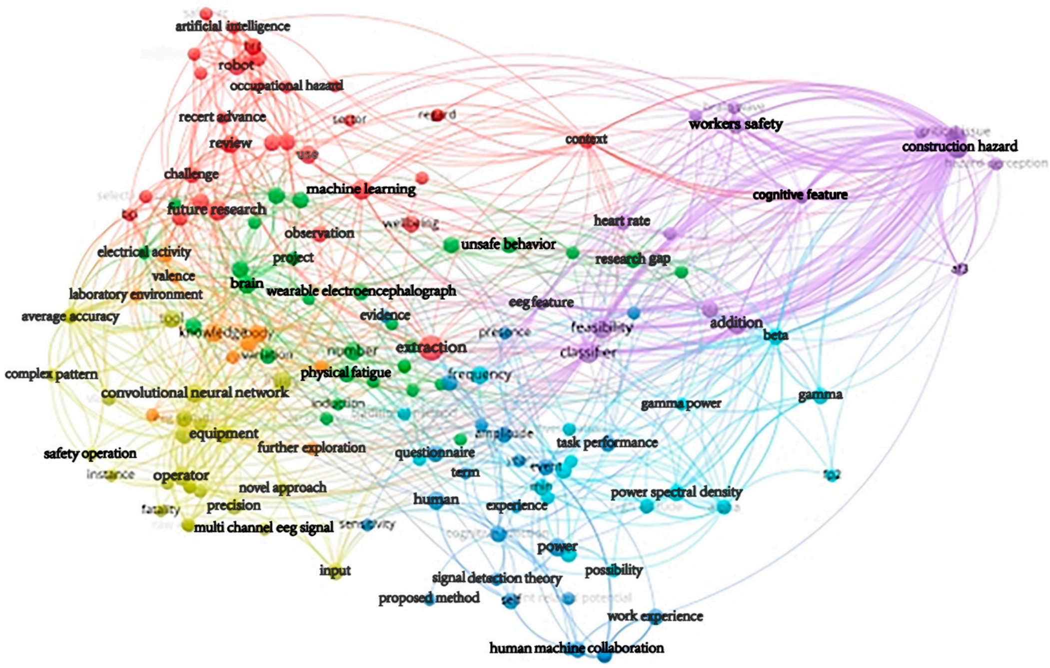

Figure 6. Electroencephalography in construction for hazard identification and monitoring of workers' adverse reactions.

Using these two approaches, this paper reviews a total of 22 articles, primarily focusing on the period between 2019 and 2023, with a small selection of important papers with representative studies prior to 2019.

2.2. Selection Criteria

The process was as follows, as illustrated in Figure 7, which describes the screening and adoption criteria of the literature for this review:

- Consider combining EEG monitoring with subjective monitoring during the monitoring process;
- In terms of monitoring adverse reactions in construction workers through EEG, consider mood monitoring, fatigue monitoring, distraction monitoring, and vigilance monitoring of workers;

- Aspects of the identification of hazardous behavior in construction through EEG include monitoring at the construction site and simulation of the construction site environment in the laboratory through VR technology.

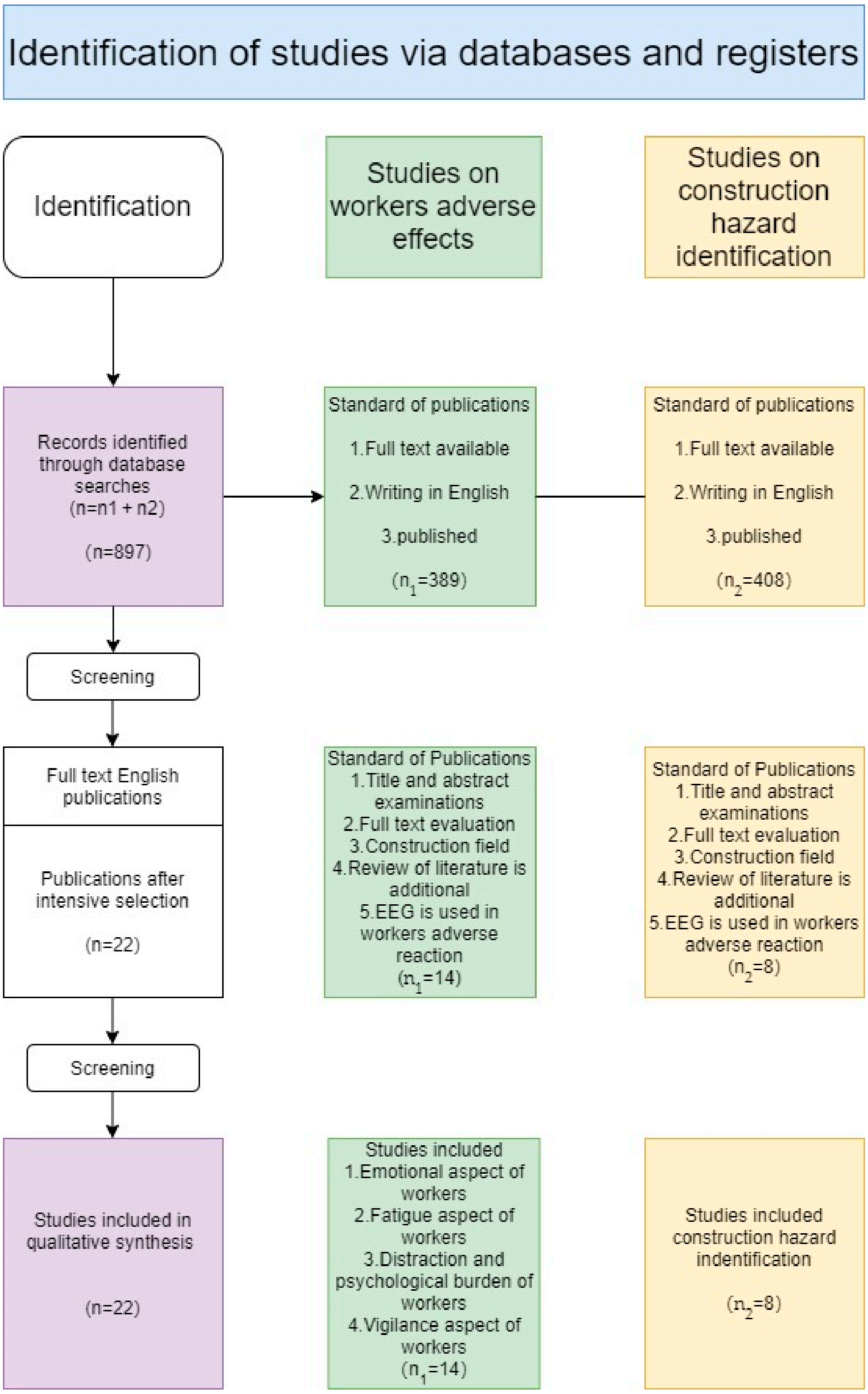

Figure 7. Selection criteria.

3. Worker's Adverse Reaction Monitoring and Construction Hazard Identification

In the process of construction, safety accidents are often caused by the hidden dangers and risks of the construction process itself and the subjective adverse reactions of the construction personnel. The risks in the construction process mainly come from hypoxia caused by long-term operation under closed conditions, accidental falling caused by high-altitude operation, object strike caused by physical handling, lifting injury caused by lifting and dismantling operations, etc. [1]. However, the traditional state recognition is often used to judge the subjective adverse reactions of construction workers. Traditional state identification is heavily reliant on subjective ratings derived from subjects' responses to a series of body and mind-related questions [69,70]. As a result, respondents' assessments of their actual state are frequently biased, and a large sample size is required to compensate for inter-subject variability and difference, preventing real-time state assessment and identification [52]. As a result, a real-time state monitoring method is required to accurately capture the subject's true state in the moment. The recent boom in EEG technology has aided in the realization of such an approach, and EEG technology is increasingly being used to identify construction hazards and monitor construction workers' adverse reactions on the job, providing new ideas for improving construction safety.

3.1. Workers Adverse Effects

EEG-acquired EEG signals have been widely studied in the construction field to analyze construction workers' cognitive state and work status. This includes monitoring workers' moods, fatigue, distraction and mental load, and vigilance in the face of construction hazards. For your convenience, I will describe these aspects in the sections that follow.

3.1.1. Emotional Aspect of Workers

EEG has been shown to monitor and recognize different emotional states in people [71]. Workers' emotional states are especially important during the construction process. The emotional state of construction workers is recognized as a significant factor influencing their performance. Measuring their emotional state should be prioritized to better understand the changes in workers' moods while on the job in order to prevent negative effects on job performance. Among the many methods for measuring mood states, EEG has the greatest potential for quantitative measurement by overcoming the potential bias of subjective mood assessments based on surveys.

Athavipach et al. [56] used ear-EEG to classify basic emotions based on the modeling of valence and arousal emotions. Mir et al. [72] discovered that different types and levels of noise had a significant effect on the amplitude of the EEG signal, which in turn affected the emotional state. The negative emotional impact of noise generated by a saw, lift hammer, and a jackhammer was greatest in the frontal lobe, and the temporal lobe responded differently to noise types with different acoustic characteristics.

Ensuring the safety of construction workers at high altitudes is particularly important because of the year-round characteristics of thin air, low oxygen content and cold climate [54]. Xing et al. [54] proposed a two-time intervention and a neurophysiological intervention in the work gap using on-site scaffolding workers as the research subjects. A sample of 10 subjects was randomly assigned to either the intervention group or the control group. Emotional and psychological inductions were preformed to simulate the status of the stenters under normal work conditions. A 13-min intervention consisting of PMR (progressive muscle relaxation) and TNS (Trigeminal Nerve Stimulation) was then administered to the experimental group in a lounge setting, with the control group using normal resting patterns (i.e., sedentary). During the experiment, wearable EEG sensors were used to collect EEG signals from the relevant brain regions of the subjects, and the collected EEG signals were used to indicate the mood and mental state of the subjects. Through statistical analysis, it was determined that the poor mood and mental state of construction workers at high altitude can be adjusted by combining PMR and TNS, which provide an effective guide to address the poor mood of construction workers at high altitude.

3.1.2. Work Fatigue Monitoring

In terms of monitoring worker fatigue, Aryal et al. [52] used a portable EEG to simulate construction site conditions and concluded that classification accuracy based on features extracted from average skin temperature data was 9% higher than that based on heart rate data, and that combining the two resulted in an optimal accuracy of up to 82%, and also demonstrated that monitoring thermoregulation from the temples was more effective than other methods.

Li et al. [53] developed and experimentally validated a quantitative method to assess the level of mental fatigue of subjects by analyzing and comparing EEG spectral parameters such as gravity frequency and power spectral entropy for the pre-work fatigue of construction workers, and effectively screened the pre-work fatigue of workers by comparing experimental performance and workers' reaction time. Xing et al. [73] designed a variety of manual processing tasks to stimulate the physical fatigue state, arranged the cognitively required risk identification task to induce mental fatigue, and tested this using the EEG integrated analysis method of rhythmic changes, a pilot method for experiments, so that the results of this study provide a reference basis for the management of fatigue in construction workers. Tehrani et al. [74] investigated the effect of working at height on the development of mental fatigue in the context of preventing the risk of falling. Using wavelet transform and sample entropy two methods, the mental fatigue in the VR environment is evaluated, and the conclusion that the high intensity work group reflects a higher level of mental fatigue is reached, and the conclusion can also provide reference for the actual construction environment is reached.

3.1.3. Distraction and Psychological Burden of Workers

Ke et al. [75,76] investigated worker distraction in noise environments in terms of monitoring workers' distraction and mental load. The cognitive performance and ability of workers in various noise environments were studied by having them wear portable EEGs in order to identify the hazards of different noise exposure conditions. The experimental results revealed that the degree of noise exposure had a negative correlation with subject performance, and intrinsic cognitive states such as attention, stress, and mental load were recovered with varying degrees of negative impact on the Big O. Evaluating the effects of noise on cognitive functioning aids in explaining the psychological impact of poor mental performance, whereas neurocognitive monitoring of EEG lays the groundwork for predicting task performance under various noise conditions. Ke et al. [75] used sustained concentration on a response task and a dual-task paradigm to induce distraction and noise interference in workers and discovered that, using feature calculations, the beta frequency of the left temporal lobe and right prefrontal cortex, as well as the frequencies, can distinguish these two states, and that these metrics can be used as an objective evaluation of an individual's sustained focus and inability to sustain focus.

Chen et al. [77] assessed the construction process using mental load in order to develop a hazard assessment measure using neural time and frequency domain analysis. The experimental results demonstrated that EEG signals, particularly those in the low frequency band, were effective in assessing the mental load of construction workers. Then, for the problem of task allocation in construction, an EEG method for task mental load assessment based on the main frequency band PSD was introduced. Experiments were designed and carried out in order to validate the proposed assessment method, and the final statistical results and frequency box model revealed that the assessment results were consistent with the NASA-TLX scale scores and had a high reference value [51].

3.1.4. Vigilance Aspect of Workers

Building construction is a process in which emergencies can happen at any time, and in the face of these emergencies, workers must remain alert at all times to avoid safety accidents, so it is especially important for workers to be alert at work. In an attempt to identify fatigue indicators, Jap et al. [63] studied driving in 52 subjects and evaluated four brain waves (δ, θ, α, β). The results showed that δ and θ activities were stable, α activity decreased slightly, and β activity decreased significantly over time. By further using the four algorithms, (I) $(\theta + \alpha)/\beta$, (II)α/β, (III) $(\theta + \alpha)/(\alpha + \beta)$, and (IV)$\theta/\beta$, it is found that all four algorithms show that the ratio of slow-wave EEG to fast-wave EEG activity increases with time, i.e., the larger the ratio of slow-wave EEG to fast-wave EEG, The less alert the subjects were to danger. The results of this study are particularly important for monitoring the vigilance of workers in the face of hazards during construction.

Chen et al. [78] used some vigilance metrics to quantify construction workers' ability to perceive risk and proposed using wavelet decomposition to study and validate the proposed metrics, as well as field experiments to analyze EEG signal patterns and benchmarking with the results of other existing vigilance assessment methods. Wang et al. [79] proposed a hybrid motor-EEG data type using WPT to calculate vigilance measures, and the agriculture indicators with the highest correlation coefficients were derived from validation experiments and can be used for vigilance detection. These quantitative vigilance indicators can help to improve the safety management capability of construction sites by providing a new perspective on understanding the risk perception process of workers.

3.2. Construction Hazard Identification

The significance of identifying occupational hazards in the building construction industry cannot be overstated; it is the primary component that determines overall safety management [80,81]. In current practice, hazard identification is based only on the inspection of safety managers; their manual inspection of larger building spaces based on relevant legal texts and established risk analysis methods (e.g., job hazard analysis) [23,24] is clearly inadequate. Furthermore, such a solitary hazard identification process is overly subjective and prone to errors and mistakes. Different inspectors frequently perform different tasks and have different standards of judgment, resulting in subjective inconsistency [81,82]. To summarize, we introduced EEG technology to develop a new direction and provide new ideas for hazard identification in the construction field through objective monitoring of physiological information such as EEG in order to effectively reduce human judgment errors.

Because the aforementioned EEG signals have the ability to recognize various adverse reactions of workers during construction work, it is also used to monitor and improve worker safety at work and are particularly useful in the field of hazard recognition in construction to make predictions and judgments about potential hazards during construction and effectively reduce the occurrence of hazardous accidents.

To improve workers' hazard recognition skills, Noghabaei et al. [83] conducted safety training in a virtual reality environment. By wearing VR, the subjects were able to almost recognize the hazards in the building construction environment. Workers in a subsequent study [84] wore both EEG and eye-tracking to navigate a simulated virtual construction site and identify safety hazards, and the 13 best features were chosen from 306 features acquired by EEG and eye-tracking to train a machine learning model. The findings show that EEG and eye tracking can be used to identify construction safety hazards.

Wang et al. [85] used a real-world construction site as a stimulus. Sixty-one construction workers were selected and shown 120 images, and their EEG signals were recorded as they viewed the images. ERP (event-related potential) evoked by safety and dangerous images is extracted from EEG signals, which is a special brain-evoked potential that can reflect the neuroelectrophysiological changes of the brain during the cognitive process [86]. The correlation between EEG prediction and self-reported work experience was calculated by using a nested cross-validation algorithm to train the prediction model to evaluate the performance of the prediction model. Subsequently, predictive values were used to predict participants' behavioral outcomes and casualty experiences to assess the external validity of the model. Finally, the predictive model is tested on an independent data lockbox for out-of-sample validation. The model demonstrates comparable predictive accuracy for workers with different risk propensities and educational backgrounds, eliminates the interference of specific risk types on model performance, and highlights the feasibility of identifying individual characteristics of hazard recognition based on physiological signals. Jeon et al. [87] discovered that the presence of hazards in the built environment could be identified by mood changes using portable EEG sensors in hazardous areas. In a subsequent study, Jeon et al. [88] combined a portable EEG device with immersive virtual reality (VR) to develop an EEG classifier to detect the presence of hazards in building construction. According to the study's findings, the CatBoost classifier performed the best, with an accuracy of 95.1%. Furthermore, three critical channel locations (AF3, F3, and F4) and two frequency bands (Beta and Gamma) were found to be closely related to hazard perception. In 2022, Jeon's team [89] correlated EEG signals with the types of hazards that are likely to occur in construction, as well as conducted experiments in the VR environment, to develop another EEG classifier that simulated construction in the VR environment with different hazardous situations, such as worker falls and circuit tripping. During the experiment, EEG signals from subjects wearing EEG and VR devices were recorded at the same time. For training and testing, two types of EEG features (time/frequency domain features and cognitive features) were extracted, and the EEG classifier was built using 18 advanced machine learning algorithms. Based on a 7-class categorized set of cognitive features, the LightGBM classifier achieves 70.1% accuracy. Jeon et al. [89] relabeled the input data and designed and tested three strategies to improve performance even further. The two-step integrated classification method achieved 82.3% accuracy, according to the results. As a result of the preceding research, we can recognize and distinguish the hazards present in buildings by combining EEG, VR, and ML (machine learning) methods. In the same year, Jeon et al. [90] synthesized previous research and proposed an EEG-based framework for universal hazard identification and active safety management. The framework, as shown in Figure 8, is made up of three parts: (a) the creation of an immersive EEG hazard classifier; (b) multi-sensor, real-time hazard mapping; and (c) behavioral intervention. The framework's feasibility is validated by focusing on the first component (immersive EEG hazard classifier), which is based on an indoor laboratory experiment. The overall framework is depicted in Figure 8. The binary classifier was found to be capable of classifying hazard-related EEG signals with an accuracy of 93.7%, while the multi-class classifier was capable of classifying EEG signals into five different hazard types with an accuracy of 79.3%. It greatly advances the process and development of construction safety management by providing a toolbox that can better identify construction hazards and helps to reduce the occurrence of hazardous events on construction sites.

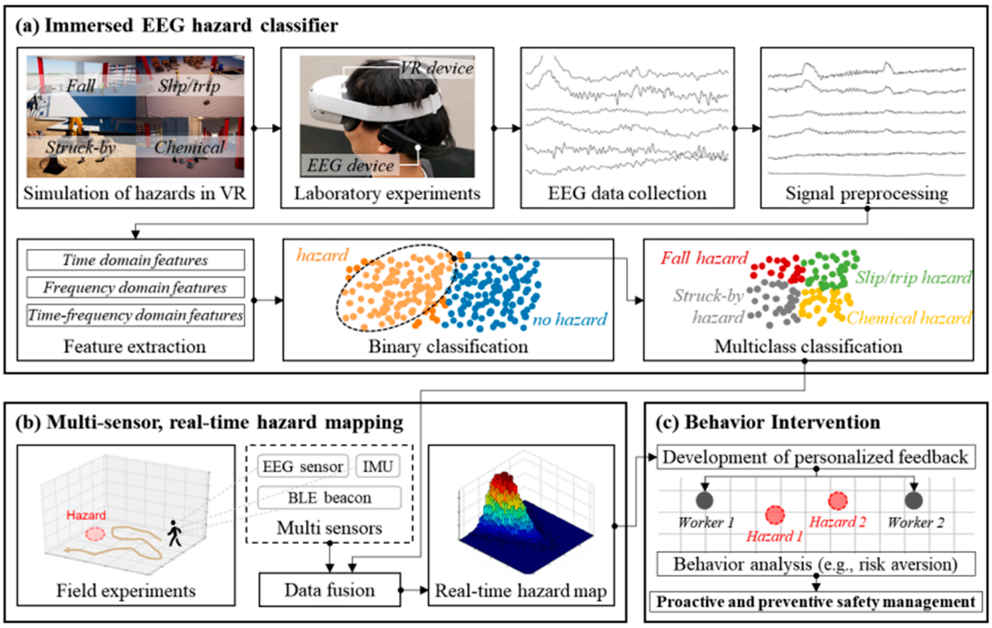

Figure 8. Overall research framework [90].

Liao et al. [91] investigated the directional and time-varying information flow of observed brain activity in a recent study by collecting validated EEG data from 71 construction workers while performing 120-image-based hazard recognition and simulating the directional and time-varying information flow of observed brain activity using adaptive directional transfer functions based on the Granger causal relation test. During hazard recognition, brain connectivity is observed. The findings of this groundbreaking study show that behavioral targets from the dorsal attentional network play a top-down moderating role in hazard localization. The sensory cortex, which primarily serves as an information egress center, collaborates with the frontal lobes and visual cortex to provide an attentional redirection mechanism for the top-down processing of potentially dangerous stimuli.

Efferent information flow was the strongest in the central parietal area (Cz, CP1, CP2, and Pz electrodes) in more than 70% of the subjects, while efferent information flow in the prefrontal lobe was weak. The areas around the Cz, CP1, CP2, and Pz electrodes in the parietal lobe are thought to be “sources” of brain activity related to hazard recognition. Table 2 depicts the information exchange in various brain regions at various times following stimulation.

Table 2. Information exchange in different regions at different times after stimulation.

The Time after Being Stimulated	Information Exchange in Different Regions
200 ms	The parietal lobe has a relatively active exchange of information with the whole brain.
240–300 ms	There is relatively active information outflow from the lateral parietal region.
200–500 ms	Strong information outflow was observed in the left temporal lobe region.
400–600 ms	Strong information outflow was observed in the right parietal lobe region.

From the standpoint of cognitive psychology, the study extends the modules of brain regions to effective brain connections. This is consistent with current research trends in psychophysiology, specifically exploring the relationship between brain neurological indicators and psychological factors while incorporating hazard recognition scenarios during building construction, and is an effective contribution to medical-industrial integration research.

4. Discussion and Limitations

EEG is a method of recording the electrical activity of the brain that can effectively capture how active the brain is at any given time [92]. In recent years, EEG technology has been used in a variety of fields, including medicine, psychology, education, recreation, and sleep health. EEG technology has also begun to be used in the construction field to monitor workers’ physical and mental states and to predict potential hazards, which is critical for improving safety in the construction field. Workers’ safety and physical and mental health are of utmost importance in a construction environment, and EEG technology can be used to assess their current emotional state, cognitive ability, and fatigue level by monitoring their EEG activity in real-time. To prevent occupational accidents, if a worker’s EEG signal shows signs of exertion or cognitive decline, timely measures can be taken to halt the work and allow the worker to take a break. EEG technology can also be used to anticipate potential hazards on construction sites. For example, by monitoring worker EEG activity and combining it with VR equipment [85,86], the working environment of a construction site can be simulated to identify potential safety hazards. It is also possible to predict whether a worker’s error or negligence will occur in the next few seconds or over a period of time, allowing for timely measures to be taken to prevent occupational accidents. In recent years, the use of eye trackers to track the eye movements of construction workers at work to identify potential safety hazards in construction is also gradually rising [93]. In future research, we can also consider the combination of EEG monitoring and eye movement monitoring to further improve the identification of potential safety hazards. Furthermore, EEG classifiers can be developed in conjunction with machine learning algorithms to identify and classify hazards on construction sites [89,90].

Since the application of cognitive neuroscience to outdoor building construction has only recently emerged, the primary limitation of this review is the small number of referable articles and the small number of research directions categorized, with only two directions reviewed: monitoring of adverse reactions in workers and hazard identification during building site construction. Three studies focused on workers' emotional state, four studies focused on workers' fatigue, four studies investigated workers' distraction and mental load, and three studies focused on workers' vigilance. Eight studies focused on hazard identification on construction sites. These studies provide a wide range of perspectives on the use of EEG in the field of building construction, but there are more directions to be explored in future research. The second issue is that there is no categorization of the causes of workers' adverse reactions and building construction hazards, and future work can further analyze the causes of construction hazardous behaviors and workers' adverse reactions, such as the effects of light environment, sound environment, extreme temperature, and extreme dryness or humidity during the construction process. The third flaw is that it does not address the numerous consequences of wearable devices, such as privacy concerns. The application of EEG technology is still in its early stages, and more research and development are needed to improve its accuracy and usefulness. Because of the limitations described above, relevant researchers should proceed with caution when referring to the review's findings.

5. Conclusions and Future Perspectives

EEG is an emerging method for monitoring workers' personal status during building construction, as well as a new way to improve the ability of safety management on construction sites, and has a broad development prospect that merits further research and exploration in the future. Existing studies included in this review have preliminarily confirmed that the use of EEG technology can not only measure the emotional highs and lows, fatigue, distraction, mental load, and vigilance of construction workers but can also be used to identify and judge construction hazards, greatly reducing the dangers in the construction process. Building safety engineers can use current research to develop and refine EEG-based experiments that can help improve safety management in the construction industry. Neuroscientists, on the other hand, can use techniques such as filtering, artifact removal, and signal processing to obtain more high-quality EEG waveform data and improve the accuracy of EEG analysis.

Future research can improve the combination of EEG with other physiological signal monitoring (e.g., EOG (electrooculogram), EMG (electromyogram), ECG (electrocardiogram), and so on) to respond more accurately to the workers' real-time status and understand their health conditions. Simultaneously, we investigated additional machine learning methods for combining physiological monitoring with machine learning to optimize the working environment and improve worker efficiency while preventing and reducing the occurrence of hazards. Meanwhile, as research and technological progress continue, EEG technology is expected to be applied in an increasing number of fields, bringing greater convenience to human life.

Author Contributions: Conceptualization, B.Y. and H.F.; methodology, B.W.; formal analysis, B.W., W.Z., P.L. and B.Y.; investigation, B.W.; resources, Z.L.; data curation, B.W.; writing—original draft preparation, B.W.; writing—review and editing, B.Y. and F.W.; visualization, Z.L.; supervision, B.Y., H.F. and F.W.; project administration, B.Y.; funding acquisition, B.Y. All authors have read and agreed to the published version of the manuscript.

Funding: The authors are grateful for the support of the National Natural Science Foundation of China (No. 52278119).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

EEG	Electroencephalogram
MEG	Magnetoencephalography
EMG	Electromyogram
ECG	Electrocardiogram
EOG	Electro-oculogram
EDA	Electrodermal Activity
TCV	Thermal Comfort Vote
TSV	Thermal Sensation Vote
SVF	Sky View Factor
BCI	Brain-Machine Interface
ERP	Event-related Potential
SVM	Support Vector Machines
IVE	Immersive Virtual Environment
WPT	Wavelet Packet Transform
CSA	Center Sleep Apnea
MSA	Mix Sleep Apnea
PMR	Progressive Muscle Relaxation
TNS	Trigeminal Nerve Stimulation
NASA-TLX	NASA TASK Load Index
ML	Machine Learning
DL	Deep Learning
CNN	Convolutional Neural Networks
MMN	Mismatch Negativity
HMD	Head-mounted Device
RBD	REM Sleep Behavior Disorder
OSA	Obstructive Sleep Apnea
PSG	Polysomnography
TSV	Thermal Sensation Vote
MTSV	Mean TSV
TCV	Thermal Comfort Vote
PSD	Power Spectral Density
VAD	Valence-Arousal-Dominance
α	Alpha
β	Beta
θ	Theta
δ	Delta
γ	Gamma

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