Automation in Construction 177 (2025) 106346

Contents lists available at ScienceDirect

Automation in Construction

journal homepage: www.elsevier.com/locate/autcon

Electroencephalography (EEG) for psychological hazards and mental health in construction safety automation: Algorithmic Systematic Review (ASR)

Haytham Elmousalami [a,b,*], Felix Kin Peng Hui [a,*], Lu Aye [a]

[a] Department of Infrastructure Engineering, Faculty of Engineering and Information Technology, The University of Melbourne, Vic 3010, Australia
[b] Projects Section head and project management professional (PMP) at General Petroleum Company (GPC), Egypt

ARTICLE INFO

Keywords:
Electroencephalography (EEG)
Sustainable construction safety
Psychological hazards recognition
Safety automation
Algorithmic systematic review (ASR)
Search paper algorithm (SPA)

ABSTRACT

This algorithmic systematic review investigates the applications of electroencephalography (EEG) for recognizing psychological hazards and monitoring mental health in construction safety. As automation and wearable technologies gain traction, EEG systems provide real-time insights into workers' cognitive and emotional states, helping to identify stress, fatigue, and safety risks. Utilizing a structured search algorithm, literature from Scopus and Web of Science was filtered and analysed to create a comprehensive framework for EEG deployment in five key domains: automated psychological and cognitive assessment, hazard recognition and safety decision-making, advanced technology integration, situational awareness enhancement, and sustainability contributions. The review underscores the synergy of EEG with robotics, virtual reality, and wearable devices, enhancing safety management in construction. Challenges such as data privacy and scalability are thoroughly examined. This paper significantly advances the understanding of EEG's role in construction automation, offering future research directions to optimize EEG-based systems for a safer, more sustainable construction industry.

1. Introduction

The Introduction section presents a structured overview of four key areas central to this study. 1.1 explores construction safety with a focus on psychological hazards such as stress, fatigue, and cognitive overload. 1.2 introduces electroencephalography (EEG) as a promising tool for real-time cognitive monitoring in high-risk environments. 1.3 highlights the existing knowledge gaps in the integration of EEG within construction safety practices. Finally, 1.4 outlines the research objectives and methodology adopted to address these gaps and guide the investigation.

1.1. Construction safety and psychological hazards

The construction sector represents approximately 13 % of the global gross domestic product and has been linked to a significant proportion of workplace injuries [1–3]. In 2023, the construction industry accounted for 27 % of all reported fatal and serious injuries [4,5]. In the United States, construction-related occupational fatalities made up 28 % of the total workplace fatalities in 2018. Meanwhile, in the United Kingdom, the 2019 fatality rate in construction was three times higher than the average across all industries. Similarly, Singapore experienced 14 fatal accidents in its construction sector in 2022 [2,6]. A large portion of the construction industry faces mental health challenges, with high stress levels being prevalent. In 2021, 16.5 % of construction workers reported heavy alcohol use [7,8]. In 2015, construction and extraction workers accounted for 20 % of male suicides, while in 2012, the industry had the second-highest rate of heavy alcohol consumption [7,9]. These alarming statistics highlight the critical importance of addressing both physical and psychological hazards to improve overall worker well-being and safety in the construction sector.

Psychological hazards are elements or aspects of the work environment that pose a risk to an individual's mental health and well-being,

Abbreviation: AI, Artificial Intelligence; ANN, Artificial Neural Networks; APCA, Automated Psychological and Cognitive Assessment; AR, Augmented Reality; ASR, Algorithmic Systematic Review; ATI, Advanced Technology Integration; BCI, Brain-Computer Interface; BMI, Brain-Machine Interaction; CNN, Convolutional Neural Network; EEG, Electroencephalography; fNIRS, Functional Near-Infrared Spectroscopy; HFE, Human Factors and Ergonomics; HRSDM, Hazard Recognition and Safety Decision-Making; ML, Machine Learning; NLP, Natural Language Processing; qEEG, Quantitative Electroencephalography; RQs, Research Questions; SDGs, Sustainable Development Goals; SPA, Search Paper Algorithm; SWE, Situational Awareness Enhancement; UPnP, Universal Plug and Play; VR, Virtual Reality.

* Corresponding authors at: Department of Infrastructure Engineering, Faculty of Engineering and Information Technology, The University of Melbourne, Vic 3010, Australia.

E-mail addresses: helmousalami@student.unimelb.edu.au (H. Elmousalami), kin.hui@unimelb.edu.au (F.K.P. Hui), lua@unimelb.edu.au (L. Aye).

https://doi.org/10.1016/j.autcon.2025.106346
Received 16 January 2025; Received in revised form 10 June 2025; Accepted 12 June 2025
Available online 27 June 2025

such as workplace stress, harassment, emotional demands, lack of social support, job insecurity, and organizational factors that can contribute to mental health issues such mental fatigue, psychological stress, anxiety, depression, and burnout [10,11]. Psychological hazards, such as mental fatigue, are prevalent in construction projects because of high-pressure environments and demanding workloads. Workers, including labourers, employees, and engineers, face long shifts, tight deadlines, complex tasks, and stringent safety regulations, all of which heighten psychological stress [12,13]. These stressors reduce cognitive function, focus, and decision-making abilities, increasing the risk of accidents and compromised safety. The mental workload in such high-risk settings emphasises the need to recognize, assess, and mitigate psychological hazards [14,15]. Addressing these issues is essential to improve worker well-being, enhance performance, and ensure the safe and efficient completion of construction projects [14]. Neurophysiological hazards pertain to how the brain and nervous system respond to physical or environmental stressors [16,17]. Neurophysiological hazards include excessive noise, vibrations, or extreme temperatures that can impair cognitive and motor functions, leading to decreased reaction times, focus, and overall physical performance, increasing the likelihood of accidents. While psychological hazards affect mental well-being, neurophysiological hazards directly impact the brain's functioning and physical motor coordination [18].

1.2. Electroencephalography (EEG)

EEG is a non-invasive neuroimaging method that captures and evaluates brain electrical activity [19]. It has been demonstrated that the bio-signals collected by EEG correspond to the postsynaptic potentials of pyramidal neurons in the cerebral cortex [20,21]. The cerebral cortex represents the human brain's external layer of neural tissue and is crucial for cognitive functions. As the primary centre for neural integration in the central nervous system, it is essential to manage attention, perception, awareness, thinking, memory, language, and consciousness [20,21]. Voltage fluctuations recorded by an EEG bio-amplifier and electrodes enable the assessment of typical brain activity. In a healthy individual, EEG patterns reflect different states of wakefulness. The observed frequency range is between 1 and 30 Hz, while the amplitudes vary from 20 to 100 μVolt [22,23].

EEG electrodes, typically worn on the scalp, capture brainwaves across various frequency bands, including Delta (0.3–4 Hz), Theta (4–8 Hz), Alpha (8–13 Hz), and Beta (13–30 Hz) as in Fig. 1. These signals are analysed in multiple domains: frequency, time, time-frequency, and nonlinear analysis, utilizing advanced techniques such as AI, as well as quantitative EEG (qEEG) [24,25]. The insights derived from EEG analysis find applications across a diverse set of fields such as safety monitoring, brain-computer interfaces (BCI), control systems for robots and machines, medical neuroscience, neuromarketing, education and training, and other sectors, including military and gaming. This comprehensive integration of EEG data acquisition through electrodes, sophisticated analysis, and broad application spectrum emphasises its significance in both research and practical deployments [26,27].

Artificial Intelligence (AI) plays a transformative role in construction engineering and management, with applications ranging from digital twin modelling [28–31] and cost prediction [31–35] to the development of smart cities [36,37]. These technologies enhance decision-making, optimize resource allocation, and improve project lifecycle efficiency. In parallel, AI contributes significantly to the field of construction safety by enabling the classification and interpretation of electroencephalography (EEG) signals. By applying advanced machine learning algorithms such as deep neural networks, support vector machines, and recurrent architectures. Accordingly, AI systems can detect and analyse cognitive states, including mental fatigue, stress, and attention levels among construction workers. This capability supports the early identification of psychological hazards, facilitating proactive safety interventions. The integration of AI with EEG analysis thus represents a novel approach in enhancing occupational health monitoring and promoting a data-driven safety culture within the construction industry.

1.3. Knowledge gaps and objectives

Several past related works reviewed the impact and benefits of EEG on smart construction safety. As outlined in Table.1, some studies share a focus on hazard recognition and safety decision-making [38,39]. Other studies focus on the technological integration of EEG in the construction of psychological assessment [40–42]. However, there are several gaps:

- A few papers, such [39,41] require an update to 2024 papers and knowledge.
- Numerous publications are surveys rather than systematic literature reviews (SLR), and most papers do not include a systematic literature review.
- While the studies listed explore various aspects of EEG application from hazard recognition and cognitive decision-making to worker adversities, none of them address the intersection with sustainability. This gap suggests a potential area for exploring how EEG technologies can contribute to sustainable construction practices, potentially

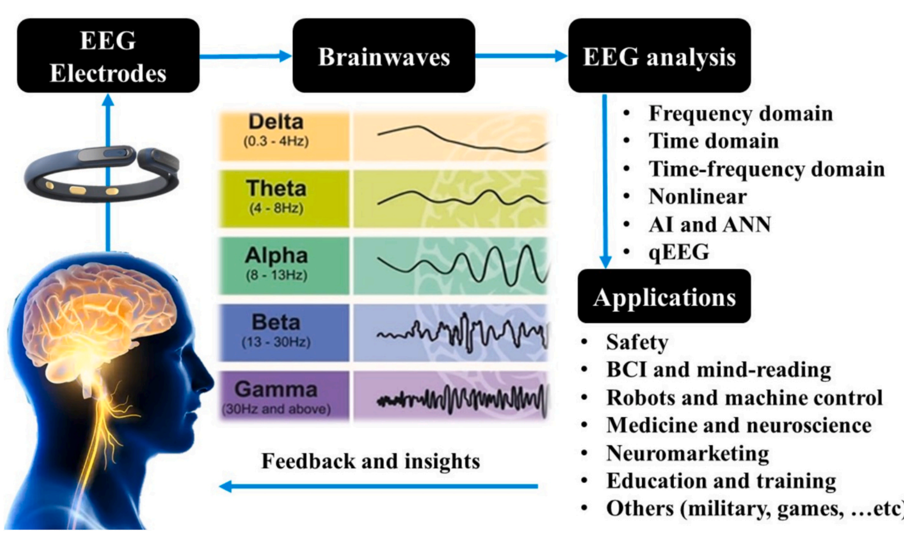

Fig. 1. Integrative framework of EEG technology from electrode placement to diverse applications [22,23].

Table 1
Comparison of past review papers and this work.

Reference	Main Objective	Year	Research Pillars					SLR
			Hazard recognition and safety decision-making	Psychological and cognitive assessment	Technology integration	Sustainability	Future perspectives and limitations	
[39]	EEG in Construction Safety Review	2019	✓	✓	×	×	✓	✓
[41]	Review of Human Fall Detection Technology	2020	✓	✓	✓	×	✓	×
[42]	SLR for Wearable Sensors and AI for Safety and Ergonomics	2022	✓	×	✓	×	×	×
[40]	Physiological computing for construction safety	2022	✓	×	✓	×	✓	×
[43]	EEG and Computing Neuroscience of Construction Workers	2022	×	✓	×	×	✓	×
[44]	Applications of EEG in construction	2022	✓	×	✓	×	✓	✓
[45]	Cognitive Statuses Tools in Construction Health and Safety	2023	×	×	✓	×	✓	✓
[38]	EEG for Construction Site Hazard Identification	2024	×	×	✓	×	×	✓
This work	EEG applications in construction safety	–	✓	✓	✓	✓	✓	✓

by optimizing safety protocols to improve long-term worker health outcomes.

- Some studies' inclusion and exclusion criteria, research questions, and paper selection procedures were not entirely apparent.
- Some studies conducted research based on only one database. As a result, many articles have been neglected, and the results will not be dependable.
- Some papers did not consider limitations and future perspectives, while others did not focus on construction engineering and management.
- Scarcity of studies combining EEG technology with psychological and cognitive assessments in the construction sector.

Therefore, there is a need for comprehensive research examining how EEG can monitor and enhance the cognitive and psychological well-being of workers simultaneously. This represents an opportunity to develop multi-dimensional EEG applications that can contribute significantly to improving occupational health and safety protocols in the construction industry. Therefore, this study aims to dissect the current landscape of research, identify gaps, and propose future directions for integrating EEG solutions. By analysing trends, network collaborations, and thematic focuses within the existing literature, the research objective is to explore the impact of EEG on the following:

1) Hazard recognition and safety decision-making,
2) Psychological and cognitive assessment,
3) Technology integration,
4) Sustainable Construction,
5) Future Perspectives and Limitations.

1.4. Research methods

This work explores the application of EEG technology in enhancing psychological and mental health within sustainable construction safety. As the construction industry faces unique challenges related to mental health risks and safety concerns, leveraging EEG offers a novel approach to monitoring and managing these issues effectively. As in Fig. 2, the structure of a study on EEG applications in sustainable construction safety. Section 2 describes the Algorithmic Systematic Review (ASR) methodology used to gather and analyse relevant EEG studies, highlighting the use of the Search Papers Algorithm (SPA). Section 3 presents the Results and Discussion of Scientometric Research, focusing on trends, networks, and key analyses, including the contributions of researchers and countries. Section 4 details the EEG Applications for

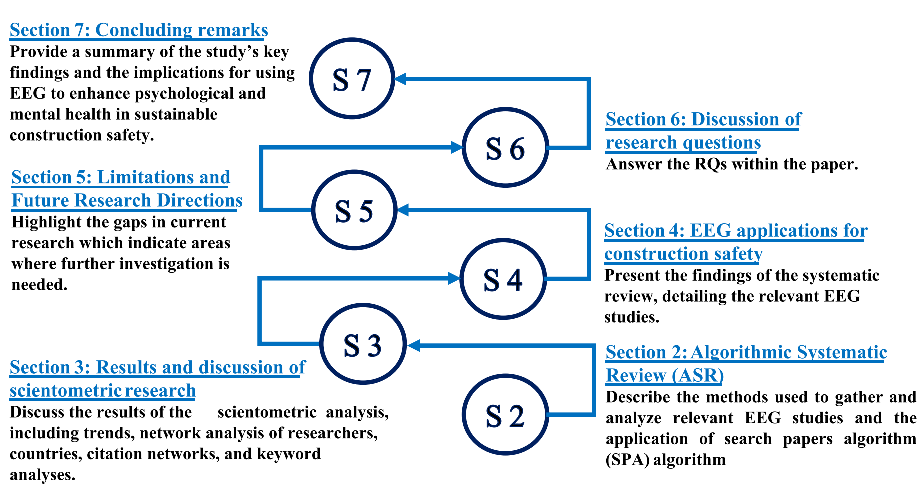

Fig. 2. Research structure.

Construction Safety, presenting the findings from the systematic review of EEG-related studies. Section 5 addresses Limitations and Future Research Directions, identifying knowledge gaps that need further exploration. Section 6 answers the Research Questions (RQs) posed in this article, while Section 7 completes with Conclusions, summarising key findings, and discussing the implications of using EEG to enhance psychological and mental health in construction safety.

2. Algorithmic Systematic Review (ASR)

Algorithmic Systematic Review (ASR) is a literature review approach to reviewing academic literature that employs algorithms to systematically filter, select, and evaluate relevant papers. This method begins with the identification of a broad set of studies using predefined keywords, followed by the application of specific inclusion and exclusion criteria across multiple databases, such as Scopus and Web of Science [46–48]. The algorithm merges and removes duplicates of the resulting papers, creating a refined pool for deeper analysis. Each paper undergoes further scrutiny, such as through full-text reviews, to assess its relevance based on established research questions or hypotheses. By using algorithmic techniques, ALR enhances the efficiency, consistency, and transparency of the review process, especially in handling large volumes of literature, and reduces human bias while ensuring a rigorous and replicable synthesis of knowledge.

ASR begins with the curiosity of research questions (RQs) and developing search algorithms to systematic the literature review research. The screening papers algorithm (SPA) is an algorithm that is designed to systematically filter and select relevant academic papers from large databases for ALR as in Fig. 3. Initially, papers are retrieved using predefined basic keywords depending on RQs. The algorithm applies inclusion and exclusion criteria for each database to filter the initial set of papers, resulting in two subsets: N_{sc} from Scopus and N_w from Web of Science. These subsets are then merged to create a combined set of papers, N_m. The algorithm removes duplicate entries to ensure uniqueness, generating a screened set of N_s, where N_s is the final, non-redundant set of papers. A deeper evaluation is performed on each paper within N_s through a full-text review, applying further specific criteria to discard irrelevant papers. This results in a final set of screened papers, N_f, representing the most relevant studies meeting the research objectives. Therefore, SPA ensures efficiency and consistency in large-scale literature reviews. The steps of the SPA algorithm are in Algorithm 1 as follows:

Algorithm 1

Screening papers algorithm (SPA).

```
Inputs: Basic Keywords, Inclusion/Exclusion Criteria, Database (Scopus, Web
of Science)
Definitions:
Nsc: Number of filtered papers from Scopus database
Nw: Number of filtered from the Web of Science (WoS) database
Nm: Number of merged papers
Ns: Number of screened papers
Nf: Number of final screened papers
1. Initialise: Retrieve initial sets of papers using basic keywords
2. For each database (Scopus and WoS):
     Apply inclusion/exclusion criteria to filter papers
   End For
Return [Nsc, Nw]
3. Merge results from both databases:
     Nm = Nsc + Nw
Return [Nm]
4. Remove duplicates to ensure unique papers:
     Nm ≥ Ns ≥ Max (Nsc + Nw)
Return [Ns]
5. For each paper in Ns
     Perform deeper evaluation (e.g., full-text review)
     Discard papers not meeting further specific criteria
     Update Nf where Nf ≤ Ns
   End For
Return [Nf]
End
```

The SPA is crucial for conducting ALR as it organises and streamlines the process of identifying and evaluating relevant academic papers. By integrating databases such as Scopus and Web of Science, SPA efficiently filters, and merges search results based on predefined inclusion and exclusion criteria. The SPA paves the way for the automation of SLR and ASR, which significantly reduces the time and effort involved in manual searches. This automation ensures a consistent and unbiased selection of literature, enhances the reproducibility of the review, and allows researchers to focus on analysing the content rather than on the logistics of paper retrieval. The algorithm's ability to remove duplicates systematically and conduct in-depth evaluations ensures that only the most pertinent and high-quality papers are considered, leading to more reliable and comprehensive outcomes in academic research.

ALR's philosophy depends on combining both scientometric and systematic review approaches as a mixed review method to provide a comprehensive analysis. The resulting final sample (N_F) is divided into two primary analytical pathways: scientometric analysis and identifying research pillars. The scientometric analysis includes examining the annual research trend, and constructing a network of countries, researchers, citations, and keywords, mapping the intellectual landscape and collaboration patterns within the field. Concurrently, the research pillars focus on classifying the literature into different application-based and sustainability-based categories and identifying existing knowledge gaps and future trends. This dual approach provides a comprehensive overview of the field, integrating quantitative metrics and thematic insights to inform subsequent research efforts.

2.1. Formulation of Research Questions (RQs)

The research questions (RQs) are the first step in the ALR for investigating the use of EEG technology in assessing psychological and mental health within the context of sustainable construction safety. In Section 1.3, a few knowledge gaps were highlighted. To fill these gaps, the following RQs were developed to explore how EEG can be leveraged to monitor mental health, enhance worker well-being, and prevent safety risks associated with cognitive impairments. RQs aim to explore how EEG can be leveraged to monitor mental health, enhance worker well-being, and prevent safety risks associated with cognitive impairments. As the methods outlines, the RQs guide the ASR of EEG applications in detecting psychological stressors and their impact on the specific area of construction safety. The following discussion addresses each research question, thoroughly analysing EEG's role in promoting mental health and safety in sustainable construction.

RQ1: What is the trend of annual research publications and citations?

RQ2: What are the influential keywords and recurrence relations?

RQ3: What are the current research avenues in EEG for Psychological and Mental Health in Sustainable Construction Safety?

RQ4: How does EEG-based real-time monitoring of brain activity correlate with improvements in worker performance and safety in construction?

RQ5: What role can EEG technology play in promoting sustainable construction safety through the early detection of cognitive impairments?

RQ6: How effective are current machine learning algorithms in analysing EEG data for predicting mental health issues in high-risk construction settings?

RQ7: What are the primary challenges in integrating EEG technology with existing safety protocols in construction practices?

RQ8: To what extent can EEG analysis contribute to sustainable construction by improving long-term mental health outcomes for workers?

RQ9: What is the impact of EEG-based situational awareness evaluation on team coordination, communication, and decision quality in dynamic construction tasks?

RQ10: To what extent does EEG contribute to sustainable development goals (SDGs), particularly in promoting long-term mental health, decent work conditions, and innovation in construction safety practices?

RQ11: What are the ethical, legal, and organizational implications of widespread EEG adoption for continuous worker monitoring in construction?

RQ12: How can EEG data support the development of adaptive, individualized safety protocols that respond to real-time cognitive states?

2.2. *Screening Papers Algorithm (SPA) execution*

After formulating RQs, the bibliometric data extraction process starts with a searching phase using specific keywords: "EEG" OR "electroencephalography" combined with "construction safety" OR "construction sustainability". The search is conducted across two major databases: Scopus and Web of Science (WoS). A total of 364 papers from Scopus (N_{sc}) and 187 papers from WoS (N_w) were identified in this identification phase.

In the screening phase, the identified papers are filtered based on inclusion criteria, such as publication years (2014–2024), document type (articles and review papers only), and language (English only). This results in 117 included papers from Scopus and 128 from WoS, which are then merged into a combined set ($N_m = 245$ papers). After removing 66 duplicate entries, 179 unique papers (N_s) were considered for further eligibility assessment. In the eligibility phase, titles, abstracts, and full texts of these 179 papers were scanned, resulting in the exclusion of 87 papers. The final included sample (Step 5) comprises 92 papers (N_f), which are deemed relevant and are included in the systematic review.

In other words, the inclusion and exclusion criteria for the literature selection process were systematically applied to ensure the relevance and quality of the screened studies. The inclusion criteria required that papers be published between 2014 and 2024, classified as either research articles or review papers, and written in English. These criteria were uniformly applied across both Scopus and Web of Science (WoS)

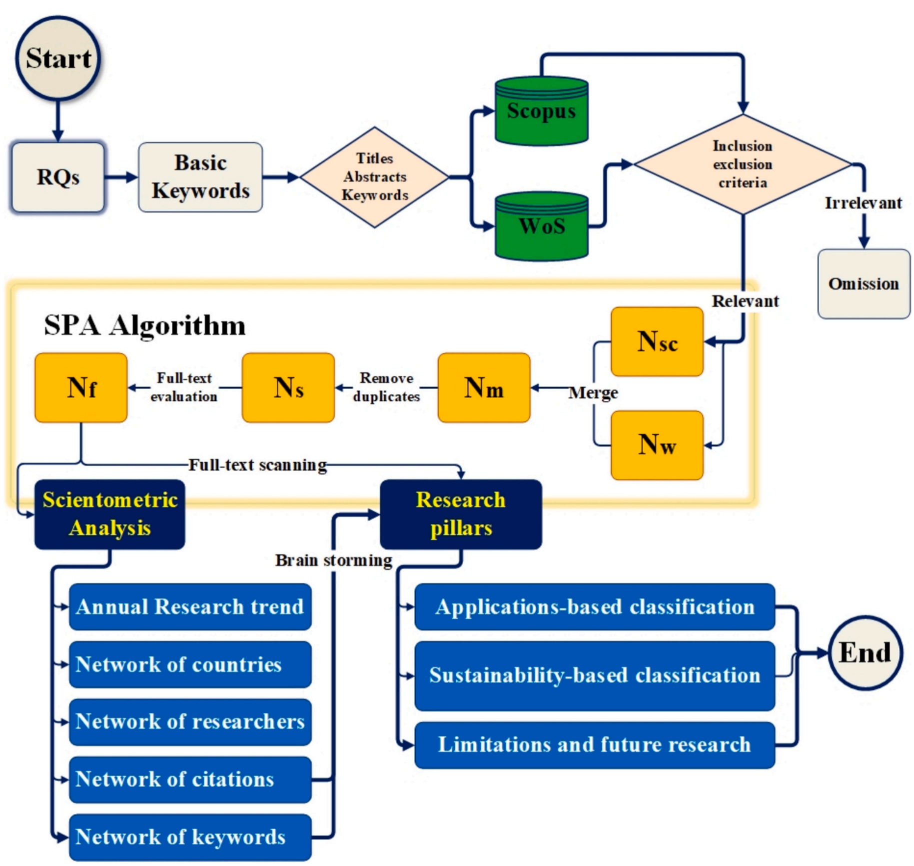

Fig. 3. Algorithmic literature review (ALR) including the screening papers algorithm (SPA).

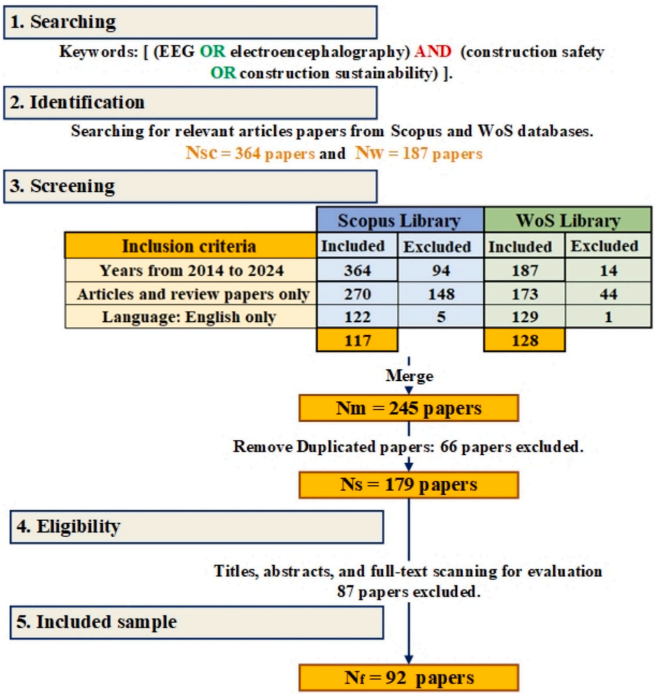

Fig. 4. Application of SPA algorithm.

databases. Initially, 364 papers were retrieved from Scopus and 187 from WoS. After applying the inclusion criteria, the number of eligible papers was reduced to 117 from Scopus and 128 from WoS. Duplicate entries were then removed, resulting in a non-redundant set of 179 papers. A deeper evaluation through title, abstract, and full-text reviews led to the final inclusion of 92 papers that fully met the research objectives as in Fig. 4.

3. Results and discussion of the scientometric review

The Results and Discussion section of the scientometric review presents a comprehensive analysis across several key dimensions. It begins with an examination of the annual research trends in EEG applications for construction safety (3.1), followed by an analysis of the countries actively contributing to this field (3.2) and the leading researchers involved (3.3). The section also includes a network analysis of active institutions (3.4), citation patterns of published articles (3.5), interdisciplinary research interactions (3.6), and a keyword co-occurrence network analysis (3.7) to identify emerging themes and research hotspots.

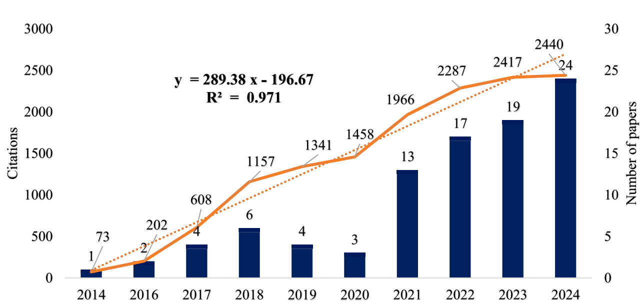

Fig. 5. Annual research publications and citations.

3.1. Annual EEG for construction safety studies trend

The analysis of the final sample (N_f) shows that the screened papers were divided into 84 articles (89 %) and 9 reviews (11 %), with a total of 2265 citations for articles (93 %) and 175 citations for reviews (7 %). As a result, there are a few review papers (9 articles) with little citation impact (7 % of citations). Fig. 5 shows a clear upward trend in the number of citations for EEG studies in construction safety from 2014 to 2024. After a relatively low number of papers, with only 6 papers published in 2018 and 3 in 2020, the cumulative number of citations increased from 73 citations in 2014 to 2440 citations in 2024, with a significant jump between 2021 and 2022 (from 13 to 17 articles). The number of papers published in 2024 peaked at 24 papers. This suggests a growing trend and exploration in EEG research for construction safety.

3.2. Analysis of engaged countries

While developed countries have made significant contributions to the safety and human well-being field, there is a clear need for greater research efforts in developing regions to ensure that construction workers worldwide benefit from the advancements in EEG technology. Fig. 6 illustrates the global distribution of EEG studies related to construction safety. The colour of each country represents the number of papers published in that region, ranging from 0 to 24. The majority of EEG studies in construction safety have been conducted in developed countries, particularly in North America, Europe, and Asia. Countries with the highest number of papers include China, the United States, and the United Kingdom, suggesting that these regions have been at the forefront of research in this area. However, the map reveals a significant gap in research coverage for developing countries. Various regions in Africa, South America, and Oceania have limited or no published EEG studies on construction safety. This suggests that there is a need for increased research efforts in these areas to address the unique challenges faced by construction workers in developing countries and to promote safer working conditions.

There is a strong network of collaborations between countries, suggesting a shared interest in advancing EEG applications for construction safety. Fig. 7 illustrates the relationships between countries based on the number of co-authored EEG studies on construction safety. The size of each circle represents the number of papers published by that country, while the lines connecting the circles indicate collaborative research efforts. As the largest circle, the United States appears to be the dominant player in EEG research for construction safety. It has collaborated with a wide range of countries, including China, Hong Kong, Germany, Australia, and the United Kingdom. China also plays a significant role in the field, with numerous published papers and collaborations with the United States, Hong Kong, and other countries. Australia has collaborated with the United States and Germany, suggesting a growing interest in this field in the region.

The collaborative landscape of EEG research for construction safety among various countries is shown in Fig. 8. Based on the total link strength, which represents the intensity of collaboration, the United States and China emerge as the central hub, connecting with a wide range of countries. South Korea and the United Kingdom have established substantial collaborations with the United States, indicating their active participation in this field. While Australia, Belgium, Canada, Germany, Hong Kong, Italy, Pakistan, and Singapore have fewer collaborative links, their contributions to the research are still valuable, demonstrating a global interest in advancing EEG technology for construction safety.

3.3. Analysis of engaged researchers

The productivity and impact of researchers engaged in EEG applications for construction safety are illustrated in Fig. 9. Based on the number of published papers and citations, Jebelli H emerges as the most

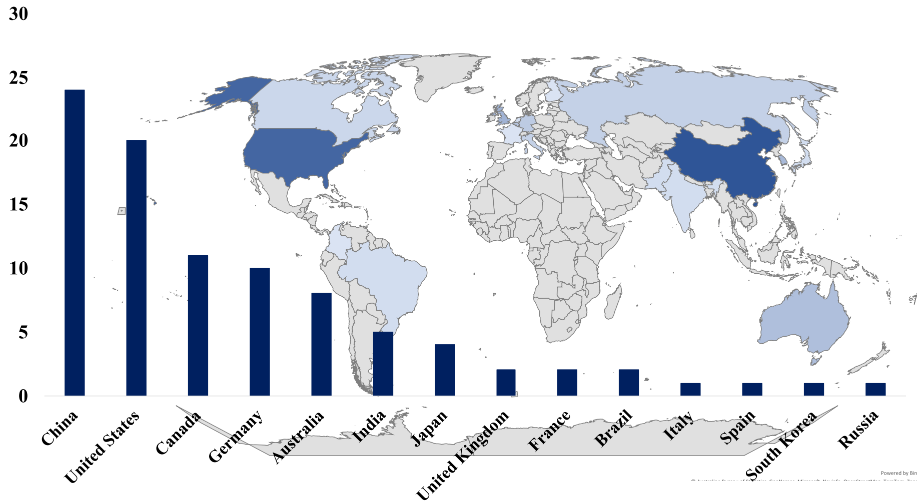

Fig. 6. Research's most influential countries based on the number of publications.

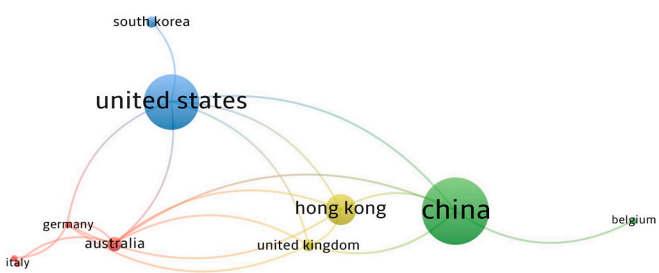

Fig. 7. Network of the research's most influential countries.

prolific researcher, with a considerable number of documents and a high citation count. Liu Yz and Hwang S. also demonstrate significant contributions to the field, with a strong balance of publications and citations. While the number of papers and citations decreases for subsequent researchers, it is crucial to note that each researcher has made valuable contributions to the advancement of EEG technology in construction safety.

3.4. Network analysis of active institutes

The collaborative landscape of EEG research for construction safety among various institutions is displayed in Fig. 10. Based on the total link strength, which represents the intensity of collaboration. City University of Hong Kong and the University of Michigan demonstrate significant research output and impact, with a combined total of 17 documents and 1085 citations. Shenzhen Research Institute and Pennsylvania State

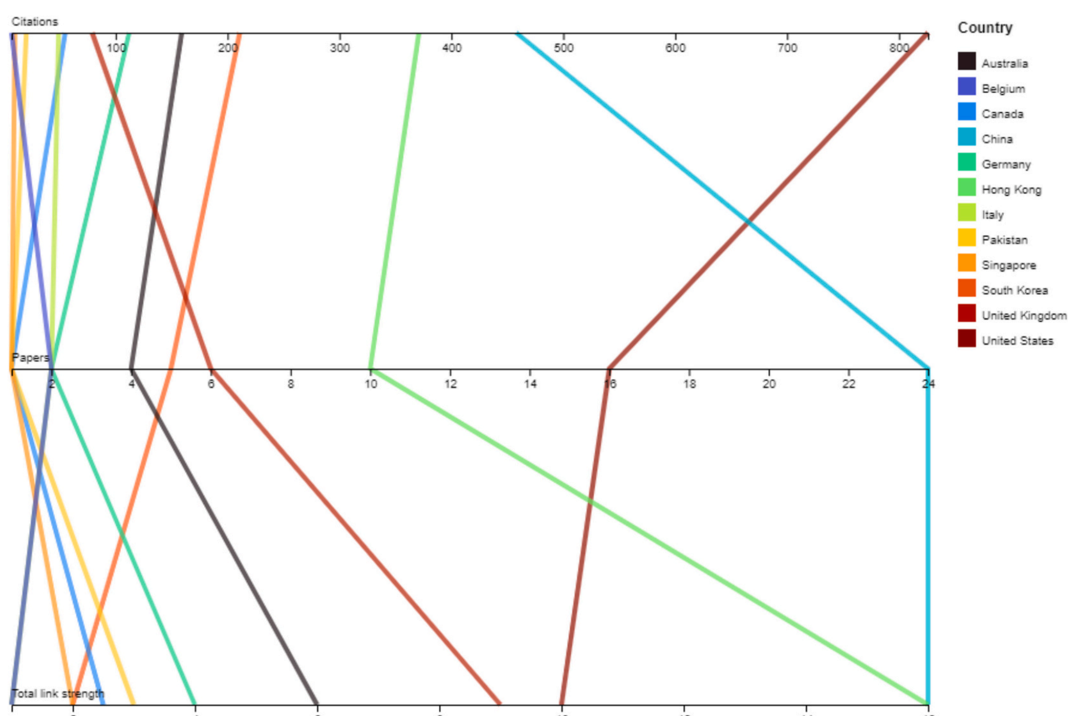

Fig. 8. Top collaborating countries.

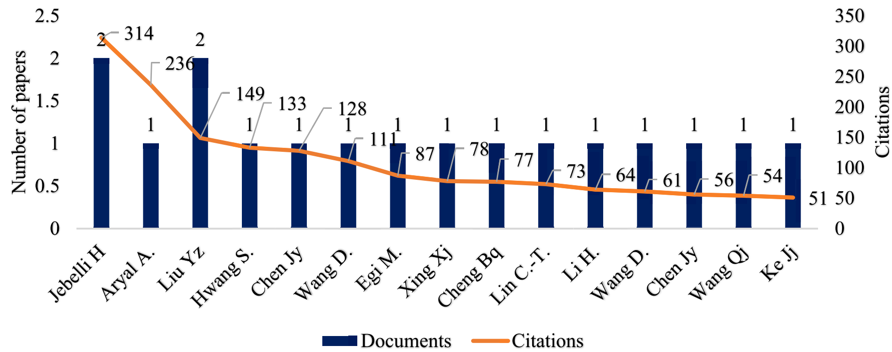

Fig. 9. Most influential authors.

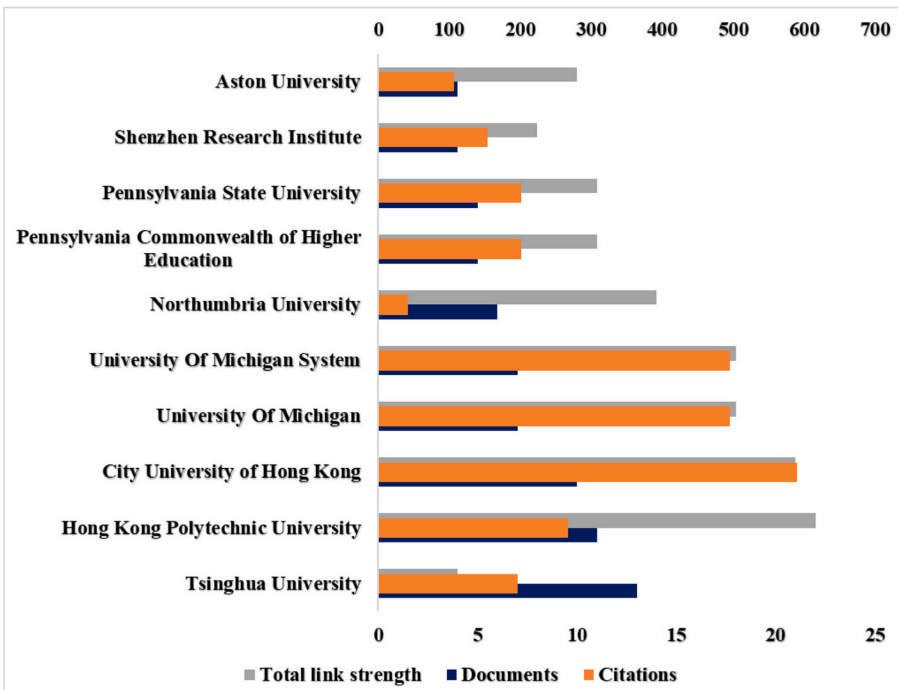

Fig. 10. Analysis of engaged institutes.

University demonstrate strong collaborative networks, with total link strengths of 23 and 18, respectively. While Northumbria University and the University of Michigan system have fewer collaborative links, their contributions to the field are still valuable.

3.5. Analysis of article citations

The analysis presented in Table 2 reveals that EEG research in construction safety is acquiring traction, with 1480 citations (61 % of total citations) stemming from only 13 key papers. The highest-cited articles are concentrated in leading journals such as Automation in Construction and the Journal of Construction Engineering and Management, reflecting the interdisciplinary nature of this research. Studies with the most citations, such as those by [49](236 citations) and [50] (210 citations), focus on monitoring fatigue and stress in construction workers using EEG, indicating the critical importance of physiological and psychological hazard detection in the construction industry. Several studies emphasise the development of wearable EEG systems for real-time monitoring, such as [51,52], which demonstrates the technological advancements in EEG applications for safety.

A noticeable trend in the articles is the focus on mental workload and cognitive monitoring, exemplified by the works of [54,55,60]. These studies explore the cognitive demands placed on workers and their impact on safety and performance, reinforcing the importance of mental health alongside physical safety in construction. The relatively recent articles, such as [55] (2020) and [55](2022), focus on integrating EEG with advanced neurophysiological approaches and cognitive computing, showcasing the growing sophistication of EEG applications in construction safety.

The distribution of citations among the top-cited journals in the research field is displayed in Fig. 11. The dominant journal is Automation in Construction, accounting for a substantial 70 % of the total citations (1480). This suggests that research published in this journal has had a significant impact on the EEG for construction safety. Following Automation in Construction, the Journal of Construction Engineering and Management, Journal of Computing in Civil Engineering, IEEE Systems Journal, and IEEE Transactions on Computational Social Systems receive 13 %, 7 %, 5 %, and 5 % of the citations, respectively. These findings indicate that while Automation in Construction is the leading journal, research published in the other journals also contributes valuable insights.

Table 2
Top-cited articles in EEG for construction safety research with 1480 citations (61 %) of 2440 total citations based on the final sample (N_f).

Reference	Citations	Journal	Year	Key findings
[49]	236	Automation in Construction	2017	Physiological measures for tracking construction worker tiredness.
[50]	210	Automation in Construction	2018	Construction site stress recognition by EEG-based personnel.
[53]	133	Journal of Construction Engineering and Management	2018	Utilizing EEG to Monitor Construction Workers' Emotional States.
[54]	128	Automation in Construction	2016	Determining Construction Safety via Mental Workload Evaluation.
[51]	111	Automation in Construction	2017	Monitoring construction workers' attentiveness and alertness with a wearable, wireless EEG.
[52]	104	Journal of Computing in Civil Engineering	2018	High-quality brain waves obtained from a wearable EEG device using the signal-processing framework.
[55]	78	Automation in Construction	2020	Construction workers' physical exhaustion and the production of mental exhaustion: A pilot research using a neurophysiological method.
[43]	77	IEEE Transactions on Computational Social Systems	2022	Critical Review on Assessing Construction Workers' Cognitive Statuses Using EEG.
[43]	76	Automation in Construction	2021	Brainwave-driven cooperative human-robot work in the building.
[56]	73	Automation in Construction	2021	Brain-computer interface enables construction robots to operate hands-free.
[57]	73	IEEE Systems Journal	2014	Universal Plug and Play (UPnP) home networking smart living environmental auto-adjustment management system based on brain-computer interface.
[58]	64	Automation in Construction	2019	Construction workers' pre-service tiredness detection using wearable EEG-based signal spectral analysis.
[59]	61	Automation in Construction	2019	Monitoring and assessing the attentiveness of construction workers using hybrid kinematic-EEG data
[60]	56	Journal of Construction Engineering and Management	2017	Evaluating Cognitive Task Stress in Construction Projects by An Innovative EEG Method.

3.6. Research discipline interactions

The bar chart on the left-hand side of Fig. 12 categorizes various disciplines based on the frequency of papers analysed in the study. The chart spans multiple disciplines, with 'Engineering' appearing as the most frequent, indicating a strong emphasis on technical aspects in the study. Other prominently featured disciplines include 'Computer Science' and 'Neuroscience,' reflecting the integration of technological and neural analysis in the EEG research for construction safety.

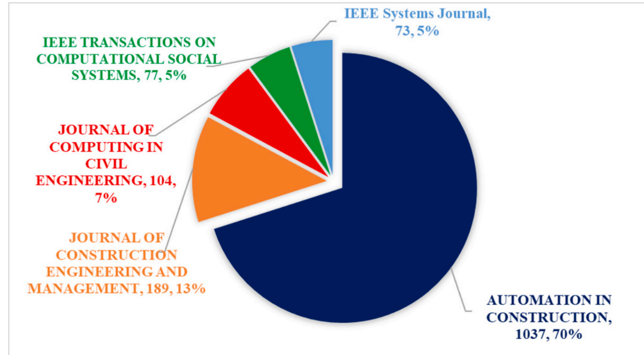

Fig. 11. Top-cited Journals in the research (1480 citations).

'Construction Safety' and 'Psychology' also stand out, highlighting the focus on safety and mental health aspects within the construction safety practices. Other significant frequencies are observed in related fields such as 'VR and brain-machine interface (BMI) Technology', 'Environmental Science', 'Automation Control', and 'Behavioural Sciences', showcasing a multidisciplinary approach to understanding and improving mental health and safety in construction settings through EEG applications for sustainable construction safety.

The Venn diagram on the right side of Fig. 12 visualises the intersections of Engineering, Medicine, and Computer Science research disciplines. Key focal areas include "EEG for Safety," which lies at the convergence of all three fields, demonstrating its multidisciplinary relevance in areas such as biomedical engineering and safety protocols. Virtual reality and augmented reality "VR/AR" and "Robots" are shared between Engineering and Computer Science, highlighting their technological and automation aspects. The overlap between Engineering and Medicine emphasises integrations in "Biomedical Engineering" and "BMI" (Brain-Machine Interfaces), pointing to advancements in medical devices and technologies. Finally, the shared space between Medicine and Computer Science features "Computational Neuroscience" and "Biosignals processing," underscoring the role of data science and algorithms in analysing neurological and physiological data. This diagram suggests a dynamic interplay of disciplines aimed at enhancing EEG technology for safety.

3.7. Network of keywords analysis

The interrelationships among various keywords related to EEG applications in construction safety are displayed in Fig. 13. Several key clusters of keywords emerge from the network. Cluster 1, highlighted in red, primarily focuses on the cognitive and physiological aspects of construction worker safety. Keywords such as attention, vigilance, fatigue, and mental workload are central to this cluster, emphasizing the importance of monitoring these factors to assess worker performance and identify potential risks. Cluster 2, depicted in green, centres around the technological advancements in EEG research. Keywords like machine learning, deep learning, risk, and construction highlight the role of these technologies in developing innovative EEG-based solutions for construction safety. Cluster 3, coloured blue, is concerned with the broader context of construction safety, including concepts such as recognition, safety, mental fatigue, and workload. This cluster emphasises the importance of addressing these factors to improve overall worker safety. Finally, Cluster 4, represented in yellow, focuses on the methodological aspects of EEG research. The identified cluster of keywords, such as 'classification' and 'management,' emphasises key methodological aspects in EEG research. 'Classification' relates to the processing and categorisation of EEG data, while 'management' refers to the techniques and strategies required for effectively managing and implementing data analysis processes in EEG applications.

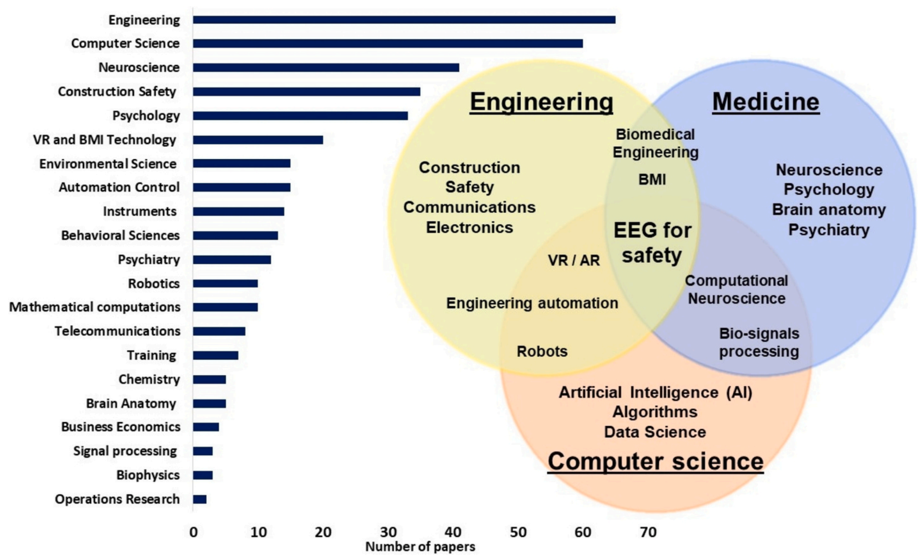

Fig. 12. Venn diagram of research disciplines interactions based on a bar chart of disciplines frequencies in the studied papers (N_f).

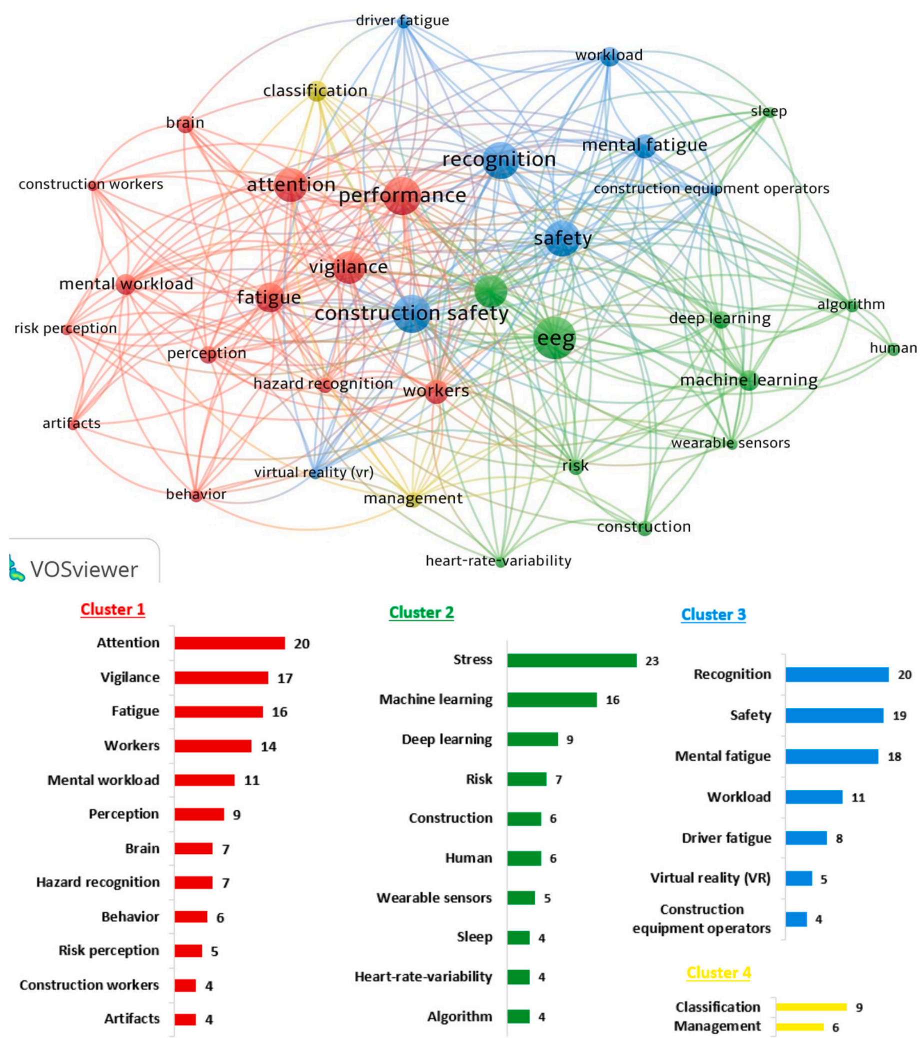

Fig. 13. Keywords clusters and interrelations.

4. EEG applications for construction safety

The scientometric review offers a broad perspective on EEG's impact on construction safety. However, it overlooks detailed applications and gaps. Therefore, an algorithmic systematic review was conducted on the final sample ($N_f = 92$) papers included in the scientometric review to address this shortcoming. This process involved analysing these papers' introduction, methodology, and discussion sections. To categorise and arrange the 92 papers, a combination of literature review, systematic sorting, and synthesis methodologies was conducted. The primary aim was to categorise these articles based on the type of EEG applications and the sustainability impact on construction safety practices. As a result, the final sample (Nf = 92) was synthesised into five main categories: Automated Psychological and Cognitive Assessment, Hazard Recognition and Safety Decision-Making, Advanced Technology Integration, Situational awareness enhancement, and Sustainability contribution, as in Fig. 14.

Recent advancements in EEG and physiological sensing have significantly enhanced research on construction safety, with notable contributions from leading institutions. Researchers at the University of Illinois Urbana-Champaign (UIUC), led by H. Jebelli, have pioneered EEG-based brain-computer interfaces (BCIs) to monitor workers' cognitive states, enabling real-time detection of attention lapses and mental fatigue to improve safety outcomes [50,53,61]. At Pennsylvania State University (Penn State), studies have explored EEG-driven human-robot collaboration, where brainwave signals are used to optimize robotic assistance, thereby reducing cognitive workload and enhancing operational safety [62]. The University of Michigan (UMICH) has further expanded EEG applications by investigating the impact of emotional states on hazard perception, demonstrating that stress and anxiety impair risk assessment capabilities in construction workers [52,53].

Recent advancements have enabled the practical implementation of electroencephalography (EEG) in real-world construction scenarios to monitor workers' cognitive states and enhance safety protocols. Jiang et al. (2024) provided a comprehensive review of EEG applications for understanding cognitive processes under risky scenarios, shedding light on how safety performance can be improved using brain activity data [19]. Jeon and Cai (2023) conducted a comparative study that utilized EEG-based hazard identification in both virtual and real environments, emphasizing the dynamic nature of construction sites [26]. Their earlier work (Jeon & Cai, 2022) further demonstrated the use of wearable EEG devices to classify construction hazards through cognitive state assessment, using thousands of real project cases to validate their classifier [63]. Complementing these findings, Cheng et al. (2022) critically reviewed methods for measuring and computing construction workers' cognitive status using EEG, highlighting its growing reliability in practical field settings [43].

4.1. Automated Psychological and Cognitive Assessment (APCA)

EEG offers significant potential to enhance construction safety by providing automated psychological and cognitive assessments (APCA) of workers in real time. By monitoring brain activity, EEG can detect mental states such as fatigue, stress, and cognitive overload. These are key factors that compromise decision-making and attention on construction sites. This data can be integrated into safety management systems to trigger timely interventions, such as task reallocation or rest breaks, to minimize the likelihood of accidents. Moreover, EEG-driven insights can be used to personalize safety training and optimize work schedules, ensuring that workers are cognitively fit for high-risk tasks and contributing to a safer and more efficient construction ecosystem.

Of the 92 papers (N_f), 50 specifically addressed APCA where each paper of the 92 papers may be categorized into one or more categories or sub-categories of the EEG applications based on its research scope and contribution. APCA can be sub-categorized into four methodological categories: (1) Mental Fatigue Detection and Monitoring, (2) Cognitive Load Assessment, (3) Workload Assessment, and (4) Stress Recognition and Management, as in Fig. 15.

4.1.1. Mental fatigue detection and monitoring

The largest share of APCA is allocated to the Mental Fatigue Detection and Monitoring category, comprising 36 % of APCA (18 papers of

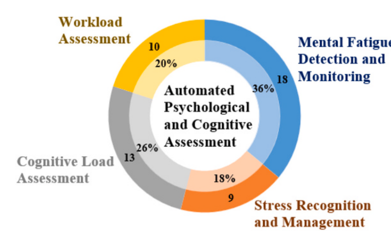

Fig. 15. Subcategories and applications of APCA.

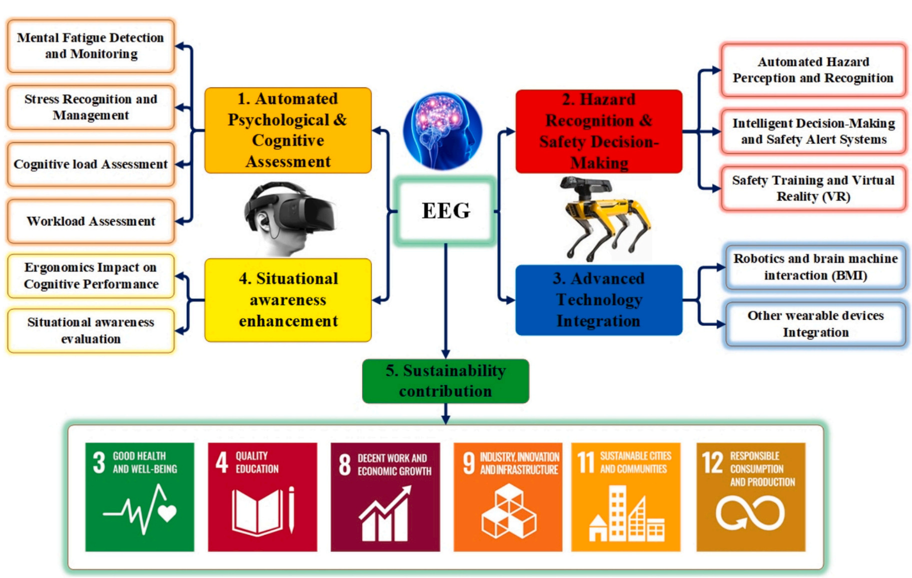

Fig. 14. A framework of EEG applications for sustainable construction safety.

N_f), highlighting its prominence in current research. Mental fatigue detection and monitoring are crucial in psychological and cognitive assessment, especially in high-risk environments such as construction sites, offshore operations, or oil and gas-related projects [49]. Utilizing technologies such as EEG, this area focuses on identifying signs of tiredness and decreased alertness among workers [14,64]. By continuously monitoring brain wave patterns, researchers can pinpoint changes that indicate fatigue, potentially preventing accidents caused by lapses in concentration or slow reaction times. Early detection of mental fatigue enables timely interventions, such as suggesting breaks or rotating tasks, thereby maintaining safety and productivity [3,65].

The research on mental and cognitive fatigue explores various methods for assessing and mitigating fatigue in construction tasks using EEG and other physiological signals. Key studies include the validation of facial feature measurements for real-time fatigue assessment and the impact of physical fatigue on cognitive performance [66]. Advanced techniques such as deep learning algorithms for detecting mental fatigue and the development of wearable EEG-based systems for fatigue screening are prominent in this body of work, reflecting the ongoing efforts to enhance safety through better fatigue management [66,67].

In pilot research using a neurophysiological methodology, the effects of physical exhaustion on the induction of mental weariness in construction workers were investigated. [55]. The impact of cognitive fatigue on attention and the implications for construction safety were examined from a neuroscientific perspective [3]. The mental fatigue of construction equipment operators was monitored using a smart cushion-based method with deep-learning algorithms [64]. To classify mental fatigue during construction equipment operations based on data, multimodal integration was carried out, combining visual signals, electrodermal activity, and electroencephalography. [68]. Mental fatigue in construction equipment operators was detected non-invasively through geometric measurements of facial features [69]. Construction workers' pre-service tiredness assessment was carried out using wearable EEG-based signal spectral analysis [58]. Enhanced sequential learning and timeliness were used to measure construction workers' mental exhaustion in real-time. [70].

4.1.2. Cognitive load assessment

Cognitive load assessment is the second largest portion of APCA, which accounts for 26 % of APCA (13 papers of N_f). Cognitive load assessment examines the amount of mental demand placed on an individual during task performance [43,71]. By assessing cognitive load, researchers can determine how much information a person is processing and whether it is within their capacity to manage safely and effectively. EEG provides real-time insights into brain activity, helping to adjust tasks to avoid overwhelming construction workers, which leads to mistakes and injuries. Therefore, the cognitive load assessment area is fundamental in designing tasks and work schedules that optimize human cognitive capabilities and safety [51,72].

On the other hand, investigating cognitive processes and visual attention in hazard recognition focuses on understanding the neural mechanisms underlying hazard perception in construction ecosystem [73]. Research in this subcategory examines fixation-related potentials to gauge visual attention and how individual differences, such as personality traits and prior experience, influence cognitive responses to hazards [71]. Studies address the impact of multi-dimensional unsafe psychology on cognitive states and the real-time monitoring of mental fatigue, providing insights into how cognitive factors affect hazard recognition [43,74,75].

A brain-inspired perception feature and cognition model was applied to a safety patrol robot [71]. The impact of cognitive fatigue on attention and the implications for construction safety were examined from a neuroscientific perspective [3]. The cognitive statuses of construction workers based on electroencephalograms were measured and computed, with a critical review conducted [43]. Workers' emotional state during construction tasks was measured using a wearable EEG device [53]. With the use of a wearable EEG device, construction workers' noise-induced distractions were observed. [76]. The attentiveness and focus of laborers engaged in building tasks were observed using wearable, wireless electroencephalography equipment. [51]. Using wearable EEG, a cognitive state evaluation was used to classify construction dangers into many classes. [63].

4.1.3. Workload assessment

Workload Assessment research holds a smaller share of APCA with 20 % (10 papers). Research on fatigue and workload measurement emphasises the neurophysiological approaches used to assess these factors in construction tasks. Workload assessment focuses on quantifying the physical and mental effort required by tasks to ensure that the work tasks are aligned with workers' capabilities [60,77]. This assessment helps in balancing task demands with worker skills and capacities to prevent overburdening. Techniques such as EEG-physiological monitoring and task analysis are used to gauge how workload impacts worker performance and health. Optimizing workload is essential for preventing burnout and ensuring that operational efficiency is maintained without compromising safety [39,51,75].

This subcategory focuses on interventions designed to alleviate fatigue and cognitive load in construction ecosystem. The research includes innovative approaches such as human-centric robotic manipulation, which leverages physiological computing mechanisms to perceive and respond to workers' cognitive load [40]. A novel electroencephalography approach was proposed for assessing task mental workload in construction projects to minimize accidents [60]. The attention and concentration of software developers were investigated to improve the workers' productivity and performance [78]. Cross-task mental workload recognition was performed based on EEG tensor representation and deep transfer learning [77]. Using hybrid kinematic-EEG data, construction workers' attentiveness was identified and measured to assess the worker's workload and mental status [59]. A wearable, wireless electroencephalography device was used to monitor the attentiveness and attentiveness of construction workers [51]. Additionally, the development of transcutaneous acupoint electrical stimulation gloves aims to relieve mental fatigue in crane drivers, demonstrating practical applications of physiological interventions to improve worker well-being and performance [79].

4.1.4. Stress recognition and management

Only nine papers (18 %) discuss stress recognition and management. Stress recognition and management involves identifying physiological and psychological stressors to help mitigate their negative impacts on workers. This process utilizes sensors to monitor indicators such as EEG patterns, heart rate variability, and cortisol levels, which reflect stress levels [50,80]. The objective is to understand how stress affects worker performance and productivity to develop strategies that help manage or reduce stress in the workplace. Effective stress management ensures that workers remain focused and efficient, reducing the likelihood of errors that could lead to accidents, fatalities, or decreased productivity [53].

This subcategory investigates the monitoring of stress and emotional states in construction workers using EEG technology. Research focuses on the impact of environmental factors such as oxygen content, safety equipment, and auditory warnings on workers' stress levels and emotional responses [66,81]. Studies highlight the application of EEG-based methods to measure emotional states and habituation to safety signals, providing insights into how these factors influence overall well-being and performance in construction settings [77]. On building sites, EEG-based worker stress recognition was carried out. [50]. Wearable EEG was used to evaluate the emotional state of construction workers throughout their jobs [53]. Stress levels were determined by physiological signals correlated with the rework of engineering drawing jobs [80]. An EEG-based circumplex model of effect was developed to identify interindividual differences in thermal comfort [81].

4.2. Hazard Recognition and Safety Decision-Making (HRSDM)

Hazard Recognition and Safety Decision-Making (HRSDM) is a critical approach in construction safety that utilizes EEG to enhance the ability of workers to recognize potential hazards and make informed safety decisions in real-time [82]. This methodology leverages the brain's electrical activity to detect cognitive states that signal awareness or recognition of danger, enabling pre-emptive actions to mitigate risks [63,83,84]. By integrating EEG, HRSDM aids in identifying when workers are under cognitive stress or distraction, conditions that significantly increase the probability of accidents on construction sites. This approach enhances overall project efficiency by ensuring that workers remain alert and aware of their surroundings [85–87]. Therefore, HRSDM is an essential component in the broader field of construction safety management, offering a technologically advanced method to protect workers and promote high safety standards on construction sites. Of the 92 papers (N_f), 38 specifically addressed HRSDM. These studies can be subcategorized into three methodological categories: (1) Automated Hazard Perception and Recognition, (2) Intelligent Decision-Making and Safety Alert Systems, and (3) Safety Training and Virtual Reality (VR), as in Fig. 16.

The integration of EEG and wearable technology into construction safety protocols offers an intelligent pathway to developing personalized safety systems that enhance worker participation, improve safety behaviours, and reduce accident rates. By continuously monitoring individual workers' cognitive and emotional states, such as fatigue, stress, and attention levels. Accordingly, EEG systems can provide real-time feedback tailored to each worker's unique physiological responses [19,38]. This personalized approach enables the identification of workers who can be at higher risk of accidents due to cognitive overload or diminished vigilance. Implementing adaptive interventions, such as customized rest breaks or targeted safety training, can address these risks proactively. Moreover, involving workers in the process by providing them with insights into their cognitive states fosters a culture of safety awareness and personal responsibility. Such individualized safety measures enhance the effectiveness of safety protocols and contribute to a reduction in workplace accidents, promoting a safer and more efficient construction environment [88,89].

4.2.1. Automated hazard perception and recognition

Automated Hazard Perception and Recognition comprises the largest portion of the HRSDM category, accounting for 42 % (16 papers), underscoring the critical role of EEG in detecting and responding to potential hazards in real-time. Automated Hazard Perception and Recognition refers to the use of EEG technology to detect and identify potential safety hazards in laborers' behaviour on construction sites [84,90]. This approach typically involves sophisticated electrodes and AI algorithms to analyse brain waves and environmental data to predict risks before they lead to accidents. Integrating EEG into the safety management framework enhances the system's capabilities by monitoring workers' brain activity to identify cognitive states that impair hazard perception [91].

EEG can be utilized to detect signs of cognitive overload or fatigue in real-time, which are critical factors that reduce a worker's ability to recognize hazards promptly [92]. Artificial intelligence and deep learning can analyse EEG data, where the system can alert safety managers or workers when there is a diminished capacity for safe decision-making, thereby enabling proactive measures to mitigate risks [63]. This integration of EEG with automated hazard perception technologies helps maintain high safety standards and supports continuous monitoring and improvement of occupational health practices, leading to a safer working environment [93,94].

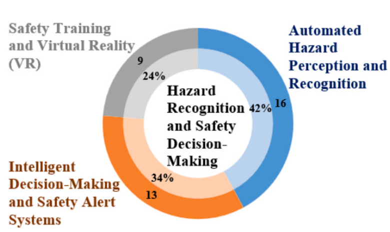

Fig. 16. Subcategories of HRSDM.

4.2.2. Intelligent decision-making and safety alert systems

Intelligent Decision-Making and Safety Alert Systems represent 34 % (13 papers of N_f) of the HRSDM category, highlighting the use of EEG to enhance cognitive decision-making processes and trigger safety alerts effectively [44,66,79]. For instance, if EEG data indicates that a worker is experiencing cognitive fatigue or stress, the system can automatically trigger alerts or recommend breaks, effectively minimizing the likelihood of accidents. In high-risk sectors like construction, where prompt and informed decision-making may considerably decrease hazards and increase overall safety, these solutions are essential to fostering a responsive and adaptable safety culture [1,40,95,96].

Recognizing and classifying awkward working postures in construction was crucial for improving worker safety and ergonomics [82]. Automated identification of alcoholic EEG signals was introduced in the brain-computer interfaces (BCIs), contributing to the development of reliable BCI systems [93]. Brain-regulated learning techniques for classifying on-site hazards using small datasets were explored [3Using a multilevel logistic regression technique, the mediating role of brain activity between dispositional characteristics and hazard detection was re-examined [87]. The fixation-related potential was used to explore visual attention and cognitive processes in construction danger detection [85].

4.2.3. Safety training and virtual reality (VR)

The Safety Training and Virtual Reality (VR) category covers 24 % (9 papers) and demonstrates the integration of EEG with VR technologies to train workers in recognizing hazards and making safer decisions in a controlled, immersive environment. This subcategory explores the application of EEG-based hazard recognition in both virtual and real construction environments. Comparative studies evaluate the effectiveness of wearable EEG systems in identifying hazards across different settings, including immersive virtual environments. Safety training in construction is increasingly incorporating Virtual Reality (VR) and EEG technologies to enhance effectiveness and engagement [60,65,97]. By utilizing VR, trainees can immerse themselves in realistic construction environments, experiencing potential hazards without real-world risks. The integration of EEG allows for the monitoring of trainees' cognitive and emotional responses during these simulations, providing insights into their levels of stress, attention, and engagement. This combination enables trainers to tailor training programs to individual needs, optimize learning outcomes, and ultimately improve safety performance on construction sites by fostering better awareness and quicker response to hazardous situations [98–100].

An EEG-based mental workload evaluation was conducted for AR head-mounted display use in construction assembly tasks [97]. Trust dynamics in human-robot collaboration were analysed through psychophysiological responses in an immersive virtual construction environment [97]. Mental fatigue was assessed using electroencephalography (EEG) and virtual reality (VR) for construction fall hazard prevention [65]. Biometric responses were used to predict the individual's learning success in virtual reality-based construction safety instruction [100]. To perform virtual reality safety instruction, deep EEG-net, and physiological data were used [101].]. The use of wearable electroencephalogram (EEG) and virtual reality (VR) technologies for classifying construction hazard-related perceptions was investigated, demonstrating the potential of immersive technologies in safety training [94].

4.3. Advanced Technology Integration (ATI)

Advanced Technology Integration (ATI) in construction safety refers to incorporating cutting-edge technologies, such as EEG, to enhance hazard identification, decision-making, and overall safety performance on construction sites [97,102]. Integrating EEG with other advanced systems such as wearable sensors, AI-driven analytics, smart wearables such as smartwatches, smart air pods, smart rings, and smart footwear that monitor workers' vital signs, bio-signals, movements, and environmental exposure [45,82]. Eye-tracking devices and accelerometers measure attention and physical exertion, while construction robotics assist in repetitive or dangerous tasks, reducing the likelihood of fatalities. Smart cushions and biosensors provide real-time feedback on posture and physical strain, while integrated systems analyse fatigue, stress, and focus data [42,102]. By linking these devices, ATI allows for continuous, real-time assessment of cognitive and physical states, enabling proactive interventions and tailored safety protocols, improving safety outcomes by minimizing human error and enhancing worker well-being on construction sites. Of the 92 papers (N_f), 23 specifically addressed ATI. These studies can be subcategorized into two methodological categories: (1) Robotics and brain-machine interaction (BMI) and, (2) Other Wearable Devices Integration as in Fig. 17.

Integrating EEG and wearable technology with immersive technologies such as virtual reality (VR) and augmented reality (AR) offers significant advancements in construction safety by enabling real-time monitoring of workers' cognitive states. For instance, studies have demonstrated that EEG-VR systems can assess mental fatigue and attention levels in high-risk scenarios, such as working at heights, allowing for proactive interventions to prevent accidents. Similarly, EEG-AR integrations have been shown to enhance situational awareness by providing real-time feedback on cognitive load, thereby improving hazard recognition and decision-making processes [94,98].

Moreover, the application of machine learning algorithms to EEG data facilitates the development of predictive models that can identify patterns associated with fatigue, stress, or decreased attention. These models enable automated safety systems to anticipate and mitigate potential risks before they manifest. The convergence of EEG with VR, AR, and machine learning thus represents a transformative approach to enhancing safety protocols in the construction industry, promoting a proactive and data-driven safety culture [26,65].

4.3.1. Robotics and brain-machine interaction (BMI)

Robotics and brain-machine interaction (BMI) accounts for 52 % (12 papers) of the ATI focus. In construction safety, the integration of robotics with BMI presents a transformative approach to reducing hazards and enhancing worker performance [57,103]. By using EEG-based systems to monitor brainwave activity, BMI enables real-time communication between a worker's cognitive state and robotic systems [104,105]. For instance, construction robots can be designed to respond to changes in a worker's mental state, such as detecting fatigue or stress, and adjust their operations accordingly either slowing down tasks or providing assistance [97,102]. This symbiosis between human cognition and robotics enhances task precision and safety in high-risk environments and reduces the physical strain on workers by enabling robots to take over dangerous or repetitive tasks. The combination of EEG data and BMI can improve decision-making processes on the site and prevent accidents, paving the way for safer, semi-autonomous construction practices [74].

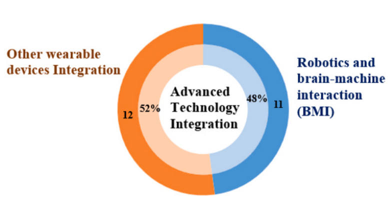

Fig. 17. Subcategories of ATI.

Trust dynamics in human-robot collaboration were analysed through psychophysiological responses in an immersive virtual construction environment [97]. In UPnP home networking, a brain-computer interface-based smart living environmental auto-adjustment control system was created [57]. It was suggested to use a brain-computer interface to control construction robots with their hands-free [56]. A brain-inspired perception feature and cognition model was applied to a safety patrol robot [71]. Brainwave-driven human-robot collaboration in construction was investigated [103]. To assist in building predictive models of human-agent interactions in smart settings, electrophysiological characteristics were investigated [106].

On the other hand, the integration of EEG in human-machine collaboration holds immense potential for revolutionizing construction safety, particularly in high-risk tasks. Future EEG-based systems could enable workers to control construction robots directly through neural signals, allowing for hands-free operation in hazardous environments such as confined spaces, heights, or demolition zones [86,107]. This reduces direct exposure to risks and enhances task precision, as robots can be guided by real-time cognitive input. Additionally, EEG can help assess a worker's mental workload or stress level, allowing collaborative robots to adjust their behaviour, for example, by offering support when cognitive fatigue is detected or pausing tasks during moments of mental overload. Such adaptive systems, driven by brain-computer interfaces, promise a new era of smart, responsive construction environments where safety, productivity, and human-machine synergy are optimized [19,84].

4.3.2. Other wearable devices integration

Other Wearable Devices Integration accounts for 48 % (11 papers) of the ATI focus. Wearable devices integrated with EEG significantly elevate construction safety by providing real-time monitoring and feedback on both cognitive and physical conditions [38,108]. Smartwatches, smart rings, and smart air pods track vital signs such as heart rate, blood oxygen levels, and physical movements, while smart footwear monitors gait and balance, preventing slips and falls [45,82]. EEG headbands detect mental states such as fatigue, stress, or attention lapses, allowing for proactive interventions. Additionally, eye-tracking devices assess focus and engagement, while accelerometers provide insights into physical strain and potential overexertion [52,109]. When these devices are interconnected through ATI, the devices generate a comprehensive safety profile of workers, offering data-driven insights into both cognitive and physical well-being. This holistic monitoring approach enables real-time adjustments, improving both individual safety and overall site performance by minimizing risks related to human error, mental distraction, or physical exhaustion.

The literature on wearable sensors and artificial intelligence for physical ergonomics was thoroughly reviewed [42]. Wearable sensing technologies with EEG for personalized construction safety monitoring were explored [61,110]. A review was performed on human fall detection technology as a possible lifesaver [41]. A feasibility study employing consumer-grade wearables in an immersive virtual world was conducted to determine eye-tracking and brain activity characteristics for danger recognition assessment [99]. With the use of hybrid kinematic-EEG signals, construction workers' attentiveness was identified and measured [59]. An EEG signal-processing framework was developed to obtain high-quality brain waves from an off-the-shelf wearable EEG device [52]. An analysis was carried out on the use of electroencephalograms to monitor workers unfavourable reactions and identify hazards on construction sites [38].

4.4. Situational awareness enhancement (SWE)

Situational awareness enhancement (SWE) in construction safety through EEG focuses on using brainwave monitoring to assess and improve workers' cognitive focus, attention, and mental workload. EEG devices, such as headbands, detect brain activity associated with different mental states, allowing for real-time monitoring of workers' situational awareness. By analysing brainwave patterns, EEG can identify moments of mental fatigue, distraction, or cognitive overload, which are key factors that compromise situational awareness in high-risk construction environments. This data can then be used to provide immediate feedback or alerts, prompting workers to refocus or take breaks before lapses in awareness lead to accidents. By improving real-time understanding of a worker's mental state, EEG helps enhance decision-making and reaction times, leading to safer, more responsive behaviour on construction sites. Of the 92 papers (N_f), 28 specifically addressed SWE. These studies can be subcategorized into two methodological categories: (1) Ergonomics Impact on Cognitive Performance, and (2) Situational awareness evaluation, as in Fig. 18.

4.4.1. *Ergonomics impact on cognitive performance*

Ergonomics' Impact on Cognitive Performance accounts for 54 % (15 papers) of the SWE category. Ergonomics is the study of human-machine interaction, focusing on designing environments and tools that are safe, comfortable, and efficient for users. In the context of construction safety, ergonomics has a crucial role in preventing injuries and enhancing worker performance. By optimizing physical workspaces, equipment, and task demands, ergonomics can reduce physical strain, fatigue, and cognitive overload. As a result, Ergonomics can positively impact situational awareness, which is the ability to perceive, understand, and anticipate changes in the environment. EEG can be used to measure brain activity and assess cognitive workload, providing valuable insights into how ergonomic interventions affect situational awareness. By identifying factors that contribute to cognitive fatigue or distraction, EEG can help researchers and practitioners develop more effective ergonomic strategies to improve safety and productivity in construction ecosystem.

EEG-based detection of adverse mental states under multi-dimensional unsafe psychology was conducted for construction workers at height [15]. The impact of cognitive fatigue on attention and the implications for construction safety were examined from a neuro-scientific perspective [3]. Monitoring of distraction of construction workers caused by noise was performed using a wearable EEG device [76]. The impact of noise intensity and content on EEG-measured cognitive function was examined [67]. Simulated high-altitude helium-oxygen diving was studied [111]. An integrated approach was employed to evaluate the effect of indoor CO_2 concentration on human cognitive performance and neural responses in an office environment [112]. The emotional and mental conditions of high-altitude construction workers were addressed with a multi-component, neurophysiological intervention [113].

4.4.2. *Situational awareness evaluation*

Situational awareness evaluation accounts for 46 % (13 papers) of the SWE category. Situational awareness is the ability to perceive, understand, and anticipate changes in the environment. In the context of construction safety, it refers to a worker's ability to be aware of their surroundings, potential hazards, and the actions of others on the job site. This awareness is essential for preventing accidents and ensuring safe working conditions [114,115]. EEG can be used to measure brain activity and assess cognitive workload, providing valuable insights into a worker's situational awareness. By studying patterns of brain activity, researchers can identify factors that may impair a worker's ability to perceive, understand, and respond to potential hazards [116,117]. This information can be used to develop training programs, safety interventions, and ergonomic improvements to enhance situational awareness and reduce the risk of accidents in construction ecosystem [115].

Measuring the habituation of auditory warnings was performed using behavioural and physiological data [117]. An investigation was conducted on the importance of human factors and ergonomics (HFE) in mediating the relationship between Industry 4.0 deployment and operational excellence [116]. Trust dynamics in human-robot collaboration were analysed through psychophysiological responses in an immersive virtual construction environment [97]. Identification of driver emotions was set using multimodal inputs, such as electrophysiological response, nasal-tip temperature, and vehicle behaviour [118]. A comparative study was conducted between safety signs and safety comics in construction workplaces for the design of safety warnings and risk perception inducement [114]. A multimodal analysis based on feature-level fusion was conducted to identify and categorise difficult working postures in the construction industry [82].

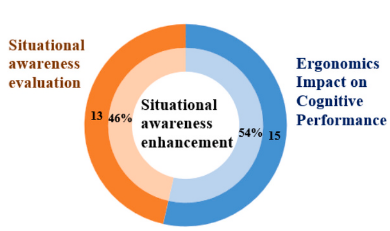

Fig. 18. Subcategories of SWE.

4.5. *Sustainability contribution*

The application of EEG for construction safety can significantly contribute to sustainability by enhancing worker well-being and reducing accidents, which minimizes project delays and resource waste [39,43]. By proactively addressing these workers' cognitive states, and identifying signs of fatigue, stress, or distraction, construction projects can operate more efficiently, reduce the need for costly rework, and lower material wastage. Moreover, improving safety through EEG monitoring aligns with the broader goals of sustainable development by promoting a safer, healthier working environment and fostering a culture of safety that ensures the longevity and resilience of the workforce and infrastructure [39,41,43]. Of the 92 papers (N_f), all papers addressed SDGs whereas most of the papers contributed to more than

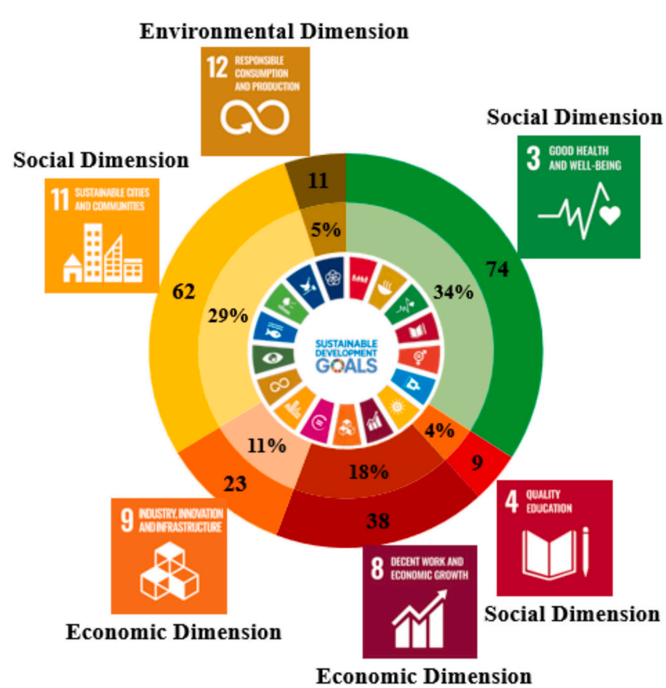

Fig. 19. Number and percentage of papers used to address the sustainability cluster.

one goal of SDGs on its research scope and contribution. These studies can be subcategorized into six goals: (1) Goal 3: Good Health and Well-being, (2) Goal 4: Quality Education, (3) Goal 8: Decent Work and Economic Growth, and (4) Goal 9: Industry, Innovation, and Infrastructure (5) Goal 11: Sustainable Cities and Communities, and (6) Goal 12: Responsible Consumption and Production as in Fig. 19.

SDGs are meticulously crafted to address the multifaceted nature of sustainability, which encompasses environmental, social, and economic dimensions. Each SDG targets specific aspects while often overlapping in their broader impacts. For instance, SDG 12 (Responsible Consumption and Production) is pivotal for environmental sustainability, as it advocates for resource efficiency and waste reduction. In the social sphere, SDGs such as Good Health and Well-being (SDG 3) and Quality Education (SDG 4) focus on improving health outcomes and educational accessibility, respectively, thus fostering a robust and educated society [43,80]. Meanwhile, SDG 11 enhances social sustainability by making urban environments more liveable and resilient. On the economic front, SDG 8 and SDG 9 are crucial, with the former enhancing economic growth through decent work opportunities and the latter bolstering infrastructure and innovation [43,80]. Together, these goals interlink to form a comprehensive framework aimed at achieving a balanced and sustainable future, highlighting the need for integrated approaches that consider all facets of sustainability [27,119].

4.5.1. Goal 3: Good health and well-being

The Good Health and Well-being goal represents 34 % of SDGs and exists in 74 of 92 papers where one paper final screened sample ($N_f = 92$ papers) can be classified for more than one SDG. EEG in construction safety directly contributes to SDG 3 by monitoring workers' mental health states, such as stress and fatigue, to ensure their well-being [14,50,53,76]. By detecting cognitive impairments or mental fatigue early, EEG can help implement timely interventions, reducing the risk of accidents and promoting a safer working environment [3,15,49,55]. By proactively addressing mental health and safety, this strategy helps construction workers' total well-being and works to guarantee healthy lifestyles and promote well-being for people of all ages.

Several studies have explored the application of EEG in monitoring construction workers' mental states and implementing interventions for their well-being. A suggested method for identifying unfavourable mental states under multi-dimensional hazardous psychology in construction workers at heights uses EEG. [15]. An EEG-based system for workers' stress recognition at construction sites was developed [50], while mental fatigue in construction workers was identified using EEG and deep learning [14]. These studies demonstrate the potential of EEG technology in promoting the well-being of construction workers by detecting and mitigating mental health issues, contributing to SDG 3.

4.5.2. Goal 4: Quality education

Quality Education represents 4 % of SDGs and exists in nine papers. EEG technology in construction safety can enhance training programs by integrating neurofeedback into educational tools and simulations [98,100,101]. This application aids in developing more effective safety training sessions that adapt to the cognitive load and learning paces of individual workers, improving learning outcomes [97,99,102]. By fostering a better understanding of safety protocols through tailored educational content, EEG contributes to achieving quality education in the construction industry.

Numerous researchers have investigated the integration of neurofeedback and EEG in construction safety education. To evaluate mental effort while using AR head-mounted displays for building assembly jobs, an EEG-based assessment was created [98], enabling tailored training experiences. VR safety training using deep EEG-net and physiology data was proposed [100,101], using neural impulses to enable adaptive learning. Employing biometric responses to predict individual learning outcomes in virtual reality-based construction safety instruction showed [100,102]. These studies highlight the role of EEG technology in enhancing the quality of construction safety education by adapting training content and methods to the individual cognitive states and learning patterns of workers.

4.5.3. Goal 8: Decent work and economic growth

Decent Work and Economic Growth represent 18 % of SDGs in 38 papers. The utilization of EEG for construction safety was aligned with SDG 8 by promoting safer and more secure working conditions [51,59,76]. EEG monitoring can lead to fewer work-related injuries, a healthier workforce, and reduced downtime due to accidents [14,49,55]. This enhancement in workplace safety and health can improve productivity and economic growth, as well-protected workers are more efficient and contribute positively to their companies and the broader economy.

Numerous studies have shown how EEG may enhance construction site safety and foster respectable working conditions. Construction workers' mental exhaustion was detected using EEG and deep learning [14], enabling interventions to prevent fatigue-related accidents. Following a neurophysiological methodology, the effects of physical exhaustion on the induction of mental exhaustion in construction workers were investigated [120]. Fatigue in construction workers was monitored using physiological measurements, including EEG [49]. By detecting and mitigating fatigue and other cognitive impairments, EEG technology contributes to creating a safer and more productive working environment, supporting economic growth in the construction industry.

4.5.4. Goal 9: Industry, innovation, and infrastructure

Goal 9 represents 29 % of SDGs in 62 papers. Incorporating EEG into construction safety practices represents an innovative approach to enhancing industry safety standards and infrastructure development [56,71,102]. By using cutting-edge neurological monitoring technologies, the construction industry can automate and pioneer safety improvements that minimize the risk of accidents, showcasing innovation in deploying new technologies for critical safety enhancements [104,105].

Novel applications of EEG and brain-computer interfaces (BCI) in construction safety have been explored in several studies. A suggested method for security surveillance assistance that is performance-driven, adaptable, and automated to detect hazards is an EEG-based system [121]. Investigations were conducted into the multi-class categorisation of construction dangers by wearable EEG-based cognitive state evaluation [63]. Wearable EEG and VR were utilized [94] for classifying construction hazard-related perceptions. Brain-regulated learning for classifying on-site hazards with small datasets was explored [52]. These innovative approaches demonstrate the adoption of advanced neurological technologies by the construction industry to enhance safety monitoring, hazard detection, and risk mitigation, contributing to improved infrastructure and safer working environments.

4.5.5. Goal 11: Sustainable cities and communities

Goal 11 represent 11 % of SDGs in 23 papers. A contribution to SDG 11 was made by EEG technologies by ensuring that the construction workforce, integral to building sustainable cities and communities, operates safely and efficiently [59,76]. Monitoring brain activity to enhance safety protocols helps in maintaining a resilient and capable workforce that can contribute to the sustainable development of urban areas, fostering community well-being and resilience [3,15,50].

Several studies have demonstrated the application of EEG for monitoring brain activity and enhancing safety protocols in the construction workforce. The impact of cognitive fatigue on attention and the implications for construction safety were examined from a neuroscientific perspective [3]. An EEG-based approach for detecting adverse mental states under multi-dimensional unsafe psychology for construction workers at height was proposed [15]. An EEG-based system was developed for workers' stress recognition at construction sites [50,112]. By detecting and mitigating cognitive impairments, fatigue, and adverse mental states, these EEG-based approaches contribute to maintaining a resilient and capable construction workforce, supporting the sustainable development of urban areas, and fostering community well-being.

4.5.6. Goal 12: Responsible consumption and production

Goal 12 represents 5 % of SDGs in 11 papers. The waste associated with workplace accidents and injuries can be reduced in the construction industry by improving safety measures through EEG [75,102]. More efficient use of human resources and materials, minimizing losses, and promoting responsible production practices, leads to better safety management [102,104]. This application of EEG in ensuring efficient and safe work processes aids in achieving more sustainable consumption and production patterns.

Several studies have explored the use of EEG for improving safety and reducing waste in construction. Mental fatigue of construction workers was identified using EEG and deep learning, enabling interventions to prevent fatigue-related accidents and associated losses [113,122]. A neurophysiological method was used to investigate how physical exhaustion affects the development of mental exhaustion in construction workers [3,55]. Fatigue in construction workers was monitored using measurements, including EEG [75,102]. By detecting and mitigating factors like fatigue that can lead to accidents and inefficiencies, these EEG-based approaches contribute to responsible consumption and production practices in the construction industry [43,80].

5. Limitations of the work and future research avenues

Many systematic review papers rely solely on a single database, such as Scopus or Web of Science. Therefore, there is a growing need to establish algorithmic steps for conducting a comprehensive and replicable systematic literature review. The Screening Papers Algorithm (SPA) does not serve as a replacement for traditional systematic review methodologies; rather, it represents a formalization of the established stages of these methodologies. Specifically, SPA codifies key elements of the conventional review process, such as keyword-driven literature searches, application of predefined inclusion and exclusion criteria, removal of duplicate records, and full-text screening, into a structured, algorithmic workflow. This formalization enhances the transparency, reproducibility, and operational efficiency of the review process, particularly when dealing with multiple and large datasets. By automating and systematizing these steps, SPA contributes to methodological rigor and consistency while maintaining alignment with the fundamental principles of traditional systematic reviews. Its contribution, therefore, lies methodological innovation and in reinforcing existing practices through algorithmic precision and scalability. However, future research is needed to empirically test and validate the effectiveness of the SPA algorithm in comparison to traditional manual review methods. A key limitation of the current study is the absence of such validation, which restricts the ability to generalize the algorithm's performance or confirm its superiority in terms of accuracy, reliability, or efficiency.

Following a comprehensive review of 92 research papers, several prominent gaps have been identified as especially critical. The authors have highlighted important avenues for exploration stemming from these gaps and have outlined multiple strategies for implementation to address them, as showed in Table 3 and Fig. 20. Studies exploring the use of EEG in construction safety encounter several limitations that affect both their findings and practical implementation. A common challenge is the limited sample size, which restricts the generalizability of results, particularly when studies are conducted in controlled laboratory environments that do not accurately reflect the complexity and dynamic nature of real construction sites. Participant selection bias poses a problem, as workers who volunteer for these studies differ significantly in characteristics or motivations from the broader workforce [65,97–101].

EEG signals are susceptible to noise and artifacts caused by muscle activity, eye movements, or electrical interference, which can reduce

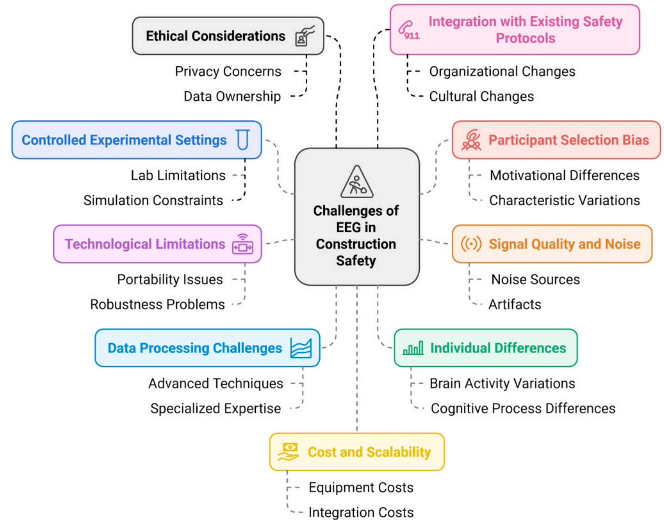

Fig. 20. Knowledge gaps and challenges of EEG for construction safety.

Table 3
Knowledge gaps of the screened sample.

Gaps	Definitions	References
Limited sample size	A small sample size of participants limits the generalizability of findings.	[63,66,83,84,121,124,125]
Controlled experimental settings	Laboratory or simulated environments cannot fully replicate real-world conditions.	[65,97–101]
Participant selection bias	Participants have different characteristics or motivations compared to the general population of construction workers.	[55,63,66,67,83,84,121,124,125]
Signal quality and noise	EEG signals can be affected by noise and artifacts such as muscle activity, eye movements, and electrical interference, reducing data accuracy.	[15,58,67,77,81,123]
Technological limitations	Some EEG devices with few electrodes are not suitable in terms of portability, robustness, and ease of use in harsh construction environments.	[15,58,67,74,77,81,103,119,123,126]
Data processing challenges	Analysing and interpreting EEG data can be complex, requiring advanced signal processing techniques and specialized expertise.	[3,15,42,43,57,112,115,127]
Individual differences	Variations in brain activity, sleep patterns, and cognitive processes make it difficult to develop generalized models.	[45,63,66,73,83,84,121,124,125]
Ethical considerations	Privacy, data ownership, and misuse concerns arise from EEG use in the workplace.	[3,14,49,55,58,64,68,69]
Integration with existing safety protocols	Incorporating EEG-based systems into established safety practices and procedures requires significant organizational and cultural changes, which can be challenging to implement.	[3,14,49,55,58,64,68,69,71,84,128,129]
Cost and scalability	EEG equipment and integration with other technologies such as robots can be expensive, limiting widespread adoption.	[15,58,67,74,77,81,103,105,106,119,123,126]

data accuracy [15,58,67,77,81,123]. Technological limitations, such as issues with portability, robustness, and ease of use, make deploying EEG systems in harsh construction environments even more difficult. Data processing and interpretation further complicate the use of EEG, as advanced signal processing techniques and specialized expertise are required. Individual differences in brain activity and cognitive processes challenge the development of generalized models or approaches. Ethical concerns related to privacy, data ownership, and the potential misuse of neuroimaging technologies in the workplace also arise [3,14,49,55,58,64,68,69]. Integrating EEG systems into current safety protocols requires significant organizational and cultural shifts, while the high cost of equipment and data processing creates barriers to widespread adoption, especially for smaller companies or projects with constrained budgets.

Implementing EEG and bio-signal wearable technologies in the construction sector involves substantial initial investments in hardware, software, and infrastructure to support real-time data acquisition and analysis. For many organizations, particularly those in developing regions, the high cost of integrating such advanced systems can be prohibitive in the absence of clear evidence demonstrating return on investment. Furthermore, ongoing requirements for maintenance and system upgrades, coupled with concerns around data security and privacy, add additional layers of complexity that hinder widespread adoption [43,64].

Equally important are the human factors that influence the successful deployment of such technologies. Change management and Worker acceptance play a central role, as the use of wearable EEG devices can raise concerns about surveillance, comfort, and personal data privacy. Without proper engagement, training, and clear communication of benefits, workers may resist adoption or use the devices improperly, undermining their effectiveness [19,43]. Training programs tailored to both technical and non-technical users are essential to build trust and ensure accurate data handling. Therefore, future research should explore strategies for enhancing user acceptance, minimizing training barriers, and proposing scalable, cost-effective solutions to facilitate integration across diverse construction settings [14,101].

On the other hand, the integration of EEG technology into construction safety systems introduces significant ethical considerations, particularly concerning data privacy and the potential for misuse. EEG data can reveal sensitive information about an individual's cognitive and emotional states, making it imperative to establish robust ethical and regulatory frameworks to protect workers' mental privacy [19,130]. Concerns include unauthorized access to neural data, potential discrimination based on cognitive profiles, and the risk of coercive surveillance in the workplace. To address these issues, it is essential to implement comprehensive policies that ensure informed consent, data anonymization, and strict access controls [131]. Additionally, developing international standards and guidelines can provide a consistent approach to the ethical use of EEG in occupational settings, safeguarding workers' rights while leveraging the technology's benefits for enhancing safety and performance, as in Fig. 21.

Integrating EEG technology into construction safety systems necessitates stringent measures to protect data privacy and address ethical concerns. To safeguard sensitive neural data, employing robust encryption techniques is essential to prevent unauthorized access and potential misuse. Additionally, anonymization strategies, such as de-identification, can further mitigate privacy risks by ensuring that data cannot be traced back to individual workers. Given that EEG data are classified as personal under regulations such as the General Data Protection Regulation (GDPR), obtaining informed consent from workers is crucial [131,132]. This consent should clearly outline the purposes of data collection, storage duration, and any potential data sharing, ensuring transparency and respect for individual autonomy. Establishing comprehensive ethical and regulatory frameworks is vital to upholding workers' rights and fostering trust in the use of EEG technology within the construction industry. Fig. 22 illustrates a structured ethical integration framework for EEG and wearable technology in the construction industry. It begins with identifying ethical concerns, particularly data privacy, followed by establishing ethical safeguards like encryption, anonymization, and informed consent [38,107]. These measures inform the development of international standards, ensuring secure and ethical implementation.

The current research on the application of EEG technology in construction safety has highlighted several gaps that necessitate further exploration, along with specific remedial actions to address these issues, as in Table 4 and Fig. 23. To enhance the practical effectiveness of EEG-based interventions in construction safety, large-scale field studies in real construction environments are essential for validating their real-world applicability [14,38,44]. These interventions can be further strengthened through multimodal data fusion by integrating EEG with motion tracking, environmental sensors, and computer vision, providing a comprehensive view of worker states and potential hazards. Personalized models and adaptive systems should be developed to tailor interventions based on individual worker responses, ensuring precision and effectiveness [84,94,121].

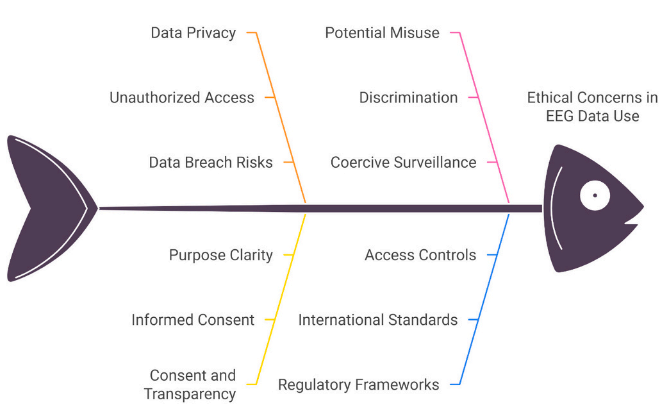

Fig. 21. Ethical integration of EEG in the construction industry.

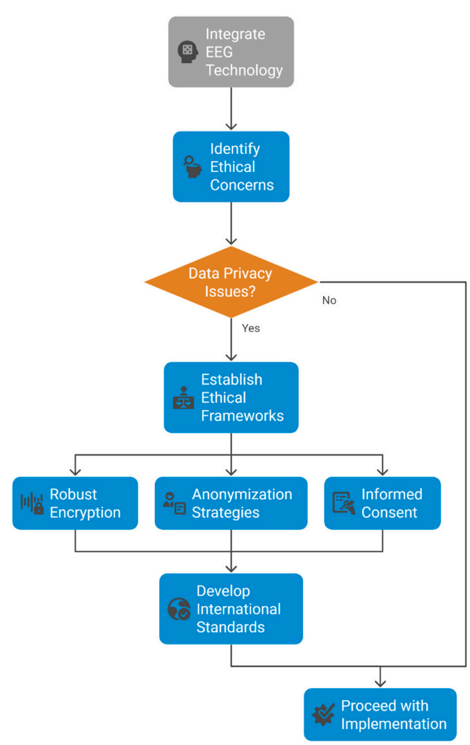

Fig. 22. Ethical integration flow chart for EEG in the construction industry.

Table 4
Future research and remedial actions for the current knowledge gaps of the screened sample.

Remedial Actions	Description	References
Large-scale field studies	Conducting more extensive studies in real construction environments to validate findings.	[14,38,44]
Multimodal data fusion	Integrating EEG data with other sources of information such as motion tracking, environmental sensors, and computer vision, to provide a more comprehensive understanding of worker states and hazard scenarios.	[63,68,82,140]
Personalized models	Developing models tailored to individual differences for targeted interventions.	[84,94,121]
Adaptive and closed-loop systems	Exploring the use of adaptive and closed-loop systems that can automatically adjust safety interventions or working conditions based on real-time EEG data and worker feedback.	[38,54,76,141]
Longitudinal studies	Investigating the long-term effects of EEG-based interventions on worker safety, productivity, and well-being.	[133–135]
AR/VR integration	Incorporating EEG data into augmented reality (AR) and virtual reality (VR) environments for immersive safety training and hazard visualization.	[65,97–101]
Hybrid BCI systems	Developing hybrid BCI systems that combine EEG with other neuroimaging techniques, such as fNIRS, for improved signal quality and information richness.	[136–139]
Explainable AI models	Exploring the use of explainable AI models to enhance the interpretability and transparency of EEG-based decision-making systems for construction safety.	[142–144]
Ethical and regulatory frameworks	Developing ethical and regulatory frameworks to address privacy, data ownership, and potential misuse concerns associated with the use of EEG and neuroimaging technologies in workplace settings.	[11,19,27,129]
Cross-industry collaboration	Fostering cross-industry collaboration between construction, neuroscience, engineering, and computer science to accelerate the development and adoption of EEG-based safety solutions. This collaboration leverages interdisciplinary expertise to develop cost-effective, scalable EEG-based safety solutions by integrating advanced technologies and shared resources.	[145–147]

Longitudinal studies are necessary to evaluate the long-term impacts of these EEG-based interventions on safety, productivity, and worker well-being [133–135]. Combining EEG data with augmented and virtual reality can create immersive safety training tools that enhance hazard recognition and risk mitigation. Hybrid brain-computer interface (BCI) systems, integrating EEG with other neuroimaging techniques such as functional near-infrared spectroscopy (fNIRS), alongside explainable AI models, would improve the quality and transparency of decision-making in safety systems [136–139]. Finally, ethical and regulatory frameworks must protect privacy, ensure data ownership, and prevent the misuse of neuroimaging technologies in the construction industry [19,27,129].

6. Discussion of the research questions

This section addresses the core research questions of the study by synthesising findings from the analysis of EEG applications in construction safety. Each research question is explored based on the results and insights drawn from the literature, data analysis, and identified trends in the field. The discussion answers the research questions and highlights the significance of EEG technology in advancing the psychological and mental health aspects of sustainable construction safety.

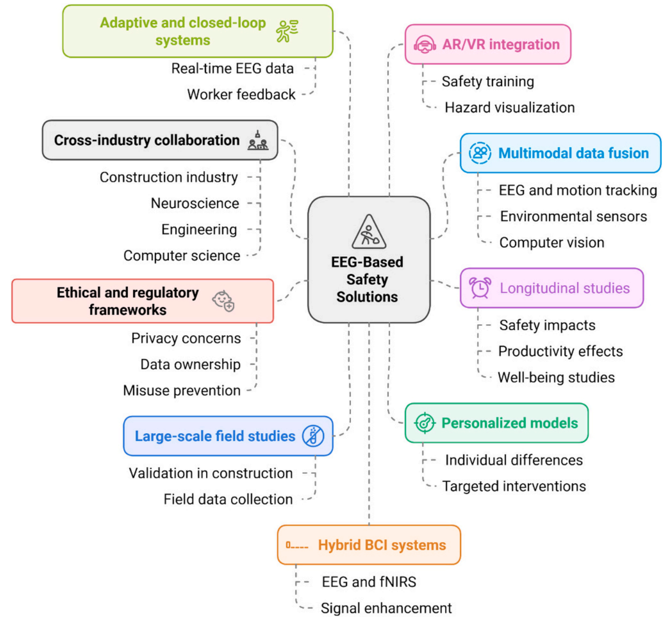

Fig. 23. Remedial actions and future research avenues.

Table 5 presents a summary of the responses to each research question.

Therefore, leveraging EEG technology leads to smarter, safer, and more sustainable construction practices, aligning with both industry needs and global sustainability objectives. Finally, the key recommendations of this paper are:

A. Research Methodology Perspective

1) Automate algorithmic systematic reviews (ASR) and the Search Paper Algorithm (SPA) using Natural Language Processing (NLP) to transform review papers into fully automated systematic reviews.
2) Ensure systematic reviews utilize multiple databases, as relying on a single database can omit substantial relevant literature, making results less dependable.
3) Develop and refine the Search Paper Algorithm (SPA) for effective literature filtering and selection from databases such as Scopus and Web of Science.

B. Construction Safety Perspective About EEG Applications

1) Conduct large-scale field studies in real construction environments to validate EEG-based interventions for practical effectiveness.
2) Implement multimodal data fusion by integrating EEG with motion tracking, sensors, and computer vision for comprehensive safety monitoring.
3) Develop personalized models and adaptive systems that tailor interventions based on individual worker responses for enhanced precision.
4) Perform longitudinal studies to assess the long-term effects of EEG-based interventions on safety, productivity, and well-being.

C. EEG Enhancement Perspective

1) Integrate EEG data with AR and VR to create immersive safety training tools for improved hazard recognition and risk mitigation.
2) Develop hybrid Brain-Computer Interface (BCI) systems combining EEG with other neuroimaging techniques, such as fNIRS, alongside explainable AI for better decision-making transparency.
3) Ethical and Regulatory Frameworks

Table 5
Research findings as responses to research questions (RQ).

RQs	Answers
RQ1: What is the current trend of annual research publications and citations?	Section 3.1 shows that the trend equation in Fig. 5, $y = 289.38\times - 196.67$ with an $R^2 = 0.9714$, indicates a strong positive linear relationship between publication year (x) and the number of citations (y) for EEG papers in construction safety. Moreover, the number of papers published in 2024 peaked at 24 papers. This suggests a growing trend and exploration in EEG research for construction safety.
RQ2: What are the influential keywords and recurrence relations?	Section 3.7 explains the network of keyword analysis based on four clusters and the relations between them. The most influential keywords are EEG, construction safety, attention, stress, recognition, and mental fatigue.
RQ3: What are the current research avenues in EEG for Psychological and Mental Health in Sustainable Construction Safety?	As in Fig. 14 and Section. 4. There are five key domains: automated psychological and cognitive assessment, hazard recognition and safety decision-making, advanced technology integration, situational awareness enhancement, and contributions to sustainability.
RQ4: How does EEG-based real-time monitoring of brain activity correlate with improvements in worker performance and safety in construction?	Section. 4.1.1 explains mental fatigue detection and monitoring, where early detection of mental fatigue enables timely interventions, such as suggesting breaks or rotating tasks, thereby maintaining safety and productivity [3,65].
RQ5: What role can EEG technology play in promoting sustainable construction safety through the early detection of cognitive impairments?	As in Fig. 19, Section. 4.5 explains that the EEG for construction safety contributes to SDGs.
RQ6: How effective are current machine learning (ML) algorithms in analysing EEG data for predicting mental health issues in high-risk construction settings?	As in Fig. 14 and Section. 4, ML can automate and analyse the following domains: automated psychological and cognitive assessment, hazard recognition and safety decision-making, advanced technology integration, situational awareness enhancement, and contributions to sustainability.
RQ7: What are the key challenges in integrating EEG technology with existing safety protocols in construction practices?	As in Table 3 and Section 5 explain the limited sample size, controlled experimental settings, participant selection bias, signal quality and noise, technological limitations, data processing challenges, individual differences, ethical considerations, integration with existing safety protocols, and cost and scalability are the key gaps and limitations.
RQ8: To what extent can EEG analysis contribute to sustainable construction by improving long-term mental health outcomes for workers?	As in Fig. 19, Section. 4.5.1 explains that the good health and well-being goal represents 34 % of the SDGs. EEG in construction safety directly contributes to SDG 3 by monitoring workers' mental health states, such as stress and fatigue, to ensure their well-being [14,50,53,76].
RQ9: What is the impact of EEG-based situational awareness evaluation on team coordination, communication, and decision quality in dynamic construction tasks?	As in section 4.4 and Fig. 18, EEG-based situational awareness enhancement (SWE) in construction safety uses brainwave monitoring to detect cognitive fatigue, distraction, or overload, enabling real-time feedback to prevent accidents. Among 92 studies, 28 focused on SWE, categorized into (1) Ergonomics Impact on Cognitive Performance and (2) Situational Awareness Evaluation.
RQ10: To what extent does EEG contribute to sustainable development goals (SDGs), particularly in promoting long-term mental health, decent work conditions, and innovation in construction safety practices?	As in section 4.5 and Fig. 19, EEG applications in construction safety support sustainability by enhancing worker well-being, reducing accidents, and minimizing resource waste. All 92 reviewed papers addressed SDGs, with most contributing to multiple goals, primarily Goals 3, 4, 8, 9, 11, and 12.
RQ11: What are the ethical, legal, and organizational implications of widespread EEG adoption for continuous worker monitoring in construction?	As in section 5 and Fig. 21, the integration of EEG in construction safety raises ethical concerns around mental privacy, data misuse, and potential workplace surveillance. Addressing these issues requires informed consent, anonymization, strict data controls, and international standards to ensure ethical and fair use while protecting workers' rights.
RQ12: How can EEG data support the development of adaptive, individualized safety protocols that respond to real-time cognitive states?	As in section 4.2, integrating EEG and wearable technology enables personalized construction safety systems by monitoring workers' cognitive states and providing real-time, tailored feedback. This approach enhances safety behaviours, reduces accident risks, and fosters a proactive, participatory safety culture on-site.

4) Establish ethical and regulatory frameworks to safeguard privacy, ensure data ownership, and prevent the misuse of neuroimaging technologies in construction.

7. Conclusions

This paper presented a comprehensive exploration of electroencephalography (EEG) applications in enhancing safety and sustainability within the construction industry. By systematically reviewing EEG's role in real-time monitoring of workers' cognitive and emotional states, the research underscores its potential in automating the detection of psychological hazards like stress and fatigue, thereby preventing accidents. The integration of EEG with advanced technologies such as robotics, virtual reality, and wearable sensors is highlighted to improve hazard recognition, decision-making, and situational awareness. Furthermore, the study addresses critical challenges, including data privacy and system scalability, providing practical insights for implementing EEG-based systems in construction settings. This research contributes significantly to the advancement of intelligent, responsive, and sustainable safety management systems in the construction sector.

Building upon this foundation, the study introduces an algorithmic systematic review (ASR) of EEG applications aimed at identifying psychological hazards and monitoring mental health for more sustainable construction safety practices. Employing the Search Paper Algorithm (SPA), the research systematically identifies and analyses relevant studies from comprehensive databases such as Scopus and Web of Science. A comprehensive framework is developed, outlining the deployment of EEG systems across five key application domains: automated psychological and cognitive assessment, hazard recognition and safety decision-making, advanced technology integration, situational awareness enhancement, and contributions to sustainability. The framework emphasises the synergy between EEG and other innovative technologies, highlighting their roles in promoting safety and sustainable practices within the construction industry.

In exploring human-machine collaboration, the study investigates how EEG-based methods can infer perceptual thresholds and decision confidence, enabling more effective collaboration between humans and machines. Innovations include the development of brain-computer interfaces and adaptive automated hazard alerting systems that leverage real-time EEG data. These advancements highlight the potential for improved safety outcomes through advanced human-machine interactions. Consequently, the findings contribute significantly to Industry 5.0 by emphasizing human-centric technologies that enhance worker safety, well-being, and productivity. The integration of EEG into neuro-safety frameworks facilitates proactive safety measures, fosters situational awareness, and advances the construction industry's shift toward more sustainable and intelligent systems.

Looking ahead, future research should focus on conducting large-scale field studies to validate EEG applications in real-world construction environments. Integrating EEG data with other modalities, such as motion tracking and environmental sensors, can provide a more comprehensive understanding of worker states and hazard scenarios. Developing personalized models tailored to individual differences will enable targeted interventions, while exploring adaptive and closed-loop systems can allow for automatic adjustments to safety interventions based on real-time EEG data and worker feedback. Longitudinal studies are also necessary to investigate the long-term effects of EEG-based interventions on worker safety, productivity, and well-being.

Additionally, incorporating EEG data into augmented reality (AR) and virtual reality (VR) environments can enhance immersive safety training and hazard visualization. Developing hybrid brain-computer interface (BCI) systems that combine EEG with other neuroimaging techniques, such as functional near-infrared spectroscopy (fNIRS), can improve signal quality and information richness. Exploring the use of explainable artificial intelligence (AI) models will enhance the interpretability and transparency of EEG-based decision-making systems for construction safety. Establishing ethical and regulatory frameworks is crucial to address privacy, data ownership, and potential misuse concerns associated with EEG and neuroimaging technologies in workplace settings. Finally, fostering cross-industry collaboration between construction, neuroscience, engineering, and computer science will accelerate the development and adoption of EEG-based safety solutions, leveraging interdisciplinary expertise to create cost-effective, scalable systems.

CRediT authorship contribution statement

Haytham Elmousalami: Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Felix Kin Peng Hui:** Writing – review & editing, Validation, Supervision, Conceptualization. **Lu Aye:** Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

Acknowledgment

Haytham Elmousalami thanks Professor Aboul Ella Hassanien, Professor Ashraf Darwish, Dr. Heba Asker, and Dr. Ali Hassan Ali for their teaching and guidance in the algorithmic systematic literature review procedure.

Data availability

The data that support the findings of this paper are available upon reasonable request.

References

[1] H. Elmousalami, M. Maxy, F.K.P. Hui, L. Aye, AI in automated sustainable construction engineering management, Automation in Construction 175 (2025) 106202, https://doi.org/10.1016/j.autcon.2025.106202.

[2] A.H. Ali, T. Zayed, M. Hussein, Crane safety operations in modular integrated construction, Automation in Construction 164 (2024) 105456, https://doi.org/10.1016/j.autcon.2024.105456.

[3] H. Yue, G. Ye, Q. Liu, X. Yang, Q. Xiang, Y. Luo, Impact of cognitive fatigue on attention and the implications for construction safety: a neuroscientific perspective, Journal of Construction Engineering and Management 150 (2024) 04024102, https://doi.org/10.1061/JCEMD4.COENG-14711.

[4] D. Meredith, M. Mohammadrezaei, J. McNamara, D. O'Hora, Towards a better understanding of farm fatalities: identification and estimation of farming fatality rates, J. Agromedicine 28 (2023) 239–253, https://doi.org/10.1080/1059924X.2022.2113196.

[5] M. Filomena, M. Picchio, Unsafe temperatures, unsafe jobs: the impact of weather conditions on work-related injuries, J. Econ. Behav. Organ. 224 (2024) 851–875, https://doi.org/10.1016/j.jebo.2024.03.015.

[6] Ministry of Manpower, Workplace Safety and Health Report. https://www.mom.gov.sg/, 2023 January-June (accessed September 26, 2024).

[7] Mental health in construction: building the next storey, British Safety Council. https://www.britsafe.org/safety-management/2023/mental-health-in-construction-building-the-next-storey, 2024 (accessed September 11, 2024).

[8] M. Turner, T. Mills, B. Kleiner, H. Lingard, Suicide in the construction industry: It's time to talk, in: *Proceedings of the Joint CIB W099 and TG48 International Safety, Health, and People in Construction Conference*, Central University of Technology, Free State, 2017, pp. 45–55.

[9] R. Blair Winkler, C. Middleton, O. Remes, A review on the prevalence of poor mental health in the construction industry. *Healthcare* Vol. 12, No. 5,, MDPI, 2024, p. 570.

[10] C. Sun, C.K. Hon, K.A. Way, N.L. Jimmieson, B. Xia, The relationship between psychosocial hazards and mental health in the construction industry: a meta-analysis, Saf. Sci. 145 (2022) 105485, https://doi.org/10.1016/j.ssci.2021.105485.

[11] Z. Zhang, T. Xiang, H. Guo, L. Ma, Z. Guan, Y. Fang, Impact of physical and mental fatigue on construction workers' unsafe behavior based on physiological measurement, J. Safety Res. 85 (2023) 457–468, https://doi.org/10.1016/j.jsr.2023.03.008.

[12] A. Ibrahim, C. Nnaji, M. Namian, A. Koh, U. Techera, Investigating the impact of physical fatigue on construction workers' situational awareness, Safety Science 163 (2023) 106103, https://doi.org/10.1016/j.ssci.2023.106103.

[13] Y. Wang, Y. Huang, B. Gu, S. Cao, D. Fang, Identifying mental fatigue of construction workers using EEG and deep learning, Automation in Construction 151 (2023) 104887, https://doi.org/10.1016/j.autcon.2023.104887.

[14] Z. Li, X. Xiahou, G. Chen, S. Zhang, Q. Li, EEG-based detection of adverse mental state under multi-dimensional unsafe psychology for construction workers at height, Developments in the Built Environment 19 (2024) 100513, https://doi.org/10.1016/j.dibe.2024.100513.

[15] K. Lee, S. Pooladvand, B. Esmaeili, S. Hasanzadeh, Understanding construction workers' risk perception using neurophysiological responses, J. Comput. Civ. Eng. 38 (2024) 04024039, https://doi.org/10.1061/JCCEE5.CPENG-5906.

[16] P. Lewis, D.M. Shaw, U. Wild, T.C. Erren, (side) effects of the rule of the road and neurophysiology on traffic safety: a hypothesis, Environ. Res. 183 (2020) 109246, https://doi.org/10.1016/j.envres.2020.109246.

[17] S. Pooladvand, S. Hasanzadeh, Neurophysiological evaluation of workers' decision dynamics under time pressure and increased mental demand, Automation in Construction 141 (2022) 104437, https://doi.org/10.1016/j.autcon.2022.104437.

[18] T. Jiang, Y. Fang, N. Zheng, J. Chen, Understanding construction workers' cognitive processes under risky scenarios through electroencephalography, Automation in Construction 166 (2024) 105674, https://doi.org/10.1016/j.autcon.2024.105674.

[19] A.G. Huth, W.A. De Heer, T.L. Griffiths, F.E. Theunissen, J.L. Gallant, Natural speech reveals the semantic maps that tile human cerebral cortex, Nature 532 (2016) 453–458, https://doi.org/10.1038/nature17637.

[20] O. Sporns, J.D. Zwi, The small world of the cerebral cortex, Neuroinformatics 2 (2004) 145–162, https://doi.org/10.1385/NI:2:2:145.

[21] G. Tinguely, L.A. Finelli, H.-P. Landolt, A.A. Borbély, P. Achermann, Functional EEG topography in sleep and waking: state-dependent and state-independent features, NeuroImage 32 (2006) 283–292, https://doi.org/10.1016/j.neuroimage.2006.03.037.

[22] V. Brodbeck, A. Kuhn, F. von Wegner, A. Morzelewski, E. Tagliazucchi, S. Borisov, C.M. Michel, H. Laufs, EEG microstates of wakefulness and NREM sleep, NeuroImage 62 (2012) 2129–2139, https://doi.org/10.1016/j.neuroimage.2012.05.060.

[23] Wireless ear EEG to monitor drowsiness, Nat. Commun. 15 (2024) 2162. https://www.nature.com/articles/s41467-024-48682-7 (accessed September 30, 2024).

[24] G. Niso, E. Romero, J.T. Moreau, A. Araujo, L.R. Krol, Wireless EEG: a survey of systems and studies, NeuroImage 269 (2023) 119774, https://doi.org/10.1016/j.neuroimage.2023.119774.

[25] J. Jeon, H. Cai, Wearable EEG-based construction hazard identification in virtual and real environments: a comparative study, Safety Science 165 (2023) 106213, https://doi.org/10.1016/j.ssci.2023.106213.

[26] Y. Shin, D. Choi, H. Park, M. Lee, T. Hong, C. Koo, Impact of heat stress on individual cognitive states: utilizing EEG metrics in immersive VR-based construction safety training, J. Manag. Eng. 40 (2024) 04024057, https://doi.org/10.1061/JMENEA.MEENG-6076.

[27] A.A. Alnaser, H. Elmousalami, Benefits and challenges of AI-based digital twin integration in the Saudi Arabian construction industry: a correspondence analysis

(CA) approach, Applied Sciences 15 (2025) 4675, https://doi.org/10.3390/app15044675.
[28] H. Elmousalami, A.A. Alnaser, F.K.P. Hui, Sustainable AI-driven wind energy forecasting: advancing zero-carbon cities and environmental computation, Artif. Intell. Rev. 58 (2025) 191, https://doi.org/10.1007/s10462-025-11191-0.
[29] A.A. Alnaser, M. Maxi, H. Elmousalami, AI-powered digital twins and internet of things for smart cities and sustainable building environment, Appl. Sci. 14 (2024) 12056, https://doi.org/10.3390/app142412056.
[30] H. Elmousalami, N. Elshaboury, A.H. Elyamany, Green artificial intelligence for cost-duration variance prediction (CDVP) for irrigation canals rehabilitation projects, Expert Syst. Appl. 249 (2024) 123789, https://doi.org/10.1016/j.eswa.2024.123789.
[31] H.H. Elmousalami, Closure to “artificial intelligence and parametric construction cost estimate modeling: state-of-the-art review” by Haytham H. Elmousalami, Journal of Construction Engineering and Management 147 (2021) 07021002, https://doi.org/10.1061/(ASCE)CO.1943-7862.0002049.
[32] H.H. Elmousalami, Artificial intelligence and parametric construction cost estimate modeling: state-of-the-art review, Journal of Construction Engineering and Management 146 (2020) 03119008, https://doi.org/10.1061/(ASCE)CO.1943-7862.0001678.
[33] H.H. Elmousalami, Comparison of artificial intelligence techniques for project conceptual cost prediction: a case study and comparative analysis, IEEE Transactions on Engineering Management 68 (2020) 183–196, https://doi.org/10.1109/TEM.2019.2907640.
[34] H.H. ElMousalami, A.H. Elyamany, A.H. Ibrahim, Predicting conceptual cost for Field Canal improvement projects, Journal of Construction Engineering and Management 144 (2018) 04018102, https://doi.org/10.1061/(ASCE)CO.1943-7862.0001561.
[35] H. Elmousalami, A.A. Alnaser, F. Kin Peng Hui, Advancing smart zero-carbon cities: high-resolution wind energy forecasting to 36 hours ahead, Applied Sciences 14 (2024) 1205, https://doi.org/10.3390/app14031205.
[36] H. Elmousalami, H.H. Elmesalami, M. Maxi, A.A.M. Farid, N.A.T. Elshaboury, A comprehensive evaluation of machine learning and deep learning algorithms for wind speed and power prediction, Decision Analytics Journal 10 (2024) 100527, https://doi.org/10.1016/j.dajour.2024.100527.
[37] B. Wei, B. Yang, W. Zhang, P. Liu, H. Fu, Z. Lv, F. Wang, Construction site Hazard identification and worker adverse reaction monitoring using electroencephalograms: a review, Buildings 14 (2024) 180, https://doi.org/10.3390/buildings14010180.
[38] Y. Zhang, M. Zhang, Q. Fang, Scoping review of EEG studies in construction safety, Int. J. Environ. Res. Public Health 16 (2019) 4146, https://doi.org/10.3390/ijerph16214146.
[39] W. Fang, D. Wu, P.E. Love, L. Ding, H. Luo, Physiological computing for occupational health and safety in construction: review, challenges and implications for future research, Advanced Engineering Informatics 54 (2022) 101729, https://doi.org/10.1016/j.aei.2022.101729.
[40] Z. Wang, V. Ramamoorthy, U. Gal, A. Guez, Possible life saver: a review on human fall detection technology, Robotics 9 (2020) 55, https://doi.org/10.3390/robotics9030055.
[41] L. Donisi, G. Cesarelli, N. Pisani, A.M. Ponsiglione, C. Ricciardi, E. Capodaglio, Wearable sensors and artificial intelligence for physical ergonomics: a systematic review of literature, Diagnostics 12 (2022) 3048, https://doi.org/10.3390/diagnostics12123048.
[42] B. Cheng, C. Fan, H. Fu, J. Huang, H. Chen, X. Luo, Measuring and computing cognitive statuses of construction workers based on electroencephalogram: a critical review, IEEE Transactions on Computational Social Systems 9 (2022) 1644–1659, https://doi.org/10.1109/TCSS.2021.3139681.
[43] S. Saedi, A.A.F. Fini, M. Khanzadi, J. Wong, M. Sheikhkhoshkar, M. Banaei, Applications of electroencephalography in construction, Automation in Construction 133 (2022) 103985, https://doi.org/10.1016/j.autcon.2021.103985.
[44] Z. Ding, Z. Xiong, Y. Ouyang, A bibliometric analysis of neuroscience tools use in construction health and safety management, Sensors 23 (2023) 9522, https://doi.org/10.3390/s23239522.
[45] R. Van Dinter, B. Tekinerdogan, C. Catal, Automation of systematic literature reviews: a systematic literature review, Inf. Softw. Technol. 136 (2021) 106589, https://doi.org/10.1016/j.infsof.2021.106589.
[46] K.R. Felizardo, J.C. Carver, Automating systematic literature review, in: M. Felderer, G.H. Travassos (Eds.), Contemporary Empirical Methods in Software Engineering, Springer International Publishing, Cham, 2020, pp. 327–355, https://doi.org/10.1007/978-3-030-32489-6_12.
[47] S. Jaspers, E. De Troyer, M. Aerts, Machine learning techniques for the automation of literature reviews and systematic reviews in EFSA, EFSA Supporting Publications 15 (2018), https://doi.org/10.2903/sp.efsa.2018.EN-1427.
[48] A. Aryal, A. Ghahramani, B. Becerik-Gerber, Monitoring fatigue in construction workers using physiological measurements, Automation in Construction 82 (2017) 154–165, https://doi.org/10.1016/j.autcon.2017.06.001.
[49] H. Jebelli, S. Hwang, S. Lee, EEG-based workers' stress recognition at construction sites, Automation in Construction 93 (2018) 315–324, https://doi.org/10.1016/j.autcon.2018.05.027.
[50] D. Wang, J. Chen, D. Zhao, F. Dai, C. Zheng, X. Wu, Monitoring workers' attention and vigilance in construction activities through a wireless and wearable electroencephalography system, Automation in Construction 82 (2017) 122–137, https://doi.org/10.1016/j.autcon.2017.06.008.
[51] H. Jebelli, S. Hwang, S. Lee, EEG signal-processing framework to obtain high-quality brain waves from an off-the-shelf wearable EEG device, Journal of Computing in Civil Engineering 32 (2018) 04017070, https://doi.org/10.1061/(ASCE)CP.1943-5487.0000719.
[52] S. Hwang, H. Jebelli, B. Choi, M. Choi, S. Lee, Measuring workers' emotional state during construction tasks using wearable EEG, Journal of Construction Engineering and Management 144 (2018) 04018050, https://doi.org/10.1061/(ASCE)CO.1943-7862.0001506.
[53] J. Chen, X. Song, Z. Lin, Revealing the “invisible Gorilla” in construction: estimating construction safety through mental workload assessment, Automation in Construction 63 (2016) 173–183, https://doi.org/10.1016/j.autcon.2015.12.013.
[54] X. Xing, B. Zhong, H. Luo, T. Rose, J. Li, M.F. Antwi-Afari, Effects of physical fatigue on the induction of mental fatigue of construction workers: a pilot study based on a neurophysiological approach, Automation in Construction 120 (2020) 103381, https://doi.org/10.1016/j.autcon.2020.103381.
[55] Y. Liu, M. Habibnezhad, H. Jebelli, Brain-computer interface for hands-free teleoperation of construction robots, Automation in Construction 123 (2021) 103523, https://doi.org/10.1016/j.autcon.2020.103523.
[56] C.-T. Lin, B.-S. Lin, F.-C. Lin, C.-J. Chang, Brain computer interface-based smart living environmental auto-adjustment control system in UPnP home networking, IEEE Syst. J. 8 (2012) 363–370, https://doi.org/10.1109/JSYST.2012.2221932.
[57] H. Li, D. Wang, J. Chen, X. Luo, J. Li, X. Xing, Pre-service fatigue screening for construction workers through wearable EEG-based signal spectral analysis, Automation in Construction 106 (2019) 102851, https://doi.org/10.1016/j.autcon.2019.102851.
[58] D. Wang, H. Li, J. Chen, Detecting and measuring construction workers' vigilance through hybrid kinematic-EEG signals, Automation in Construction 100 (2019) 11–23, https://doi.org/10.1016/j.autcon.2018.12.019.
[59] J. Chen, J.E. Taylor, S. Comu, Assessing task mental workload in construction projects: a novel electroencephalography approach, Journal of Construction Engineering and Management 143 (2017) 04017053, https://doi.org/10.1061/(ASCE)CO.1943-7862.0001345.
[60] C.R. Ahn, S. Lee, C. Sun, H. Jebelli, K. Yang, B. Choi, Wearable sensing technology applications in construction safety and health, Journal of Construction Engineering and Management 145 (2019) 03119007, https://doi.org/10.1061/(ASCE)CO.1943-7862.0001708.
[61] B. Cheng, C. Fan, H. Fu, J. Huang, H. Chen, X. Luo, Measuring and computing cognitive statuses of construction workers based on electroencephalogram: a critical review, IEEE Transactions on Computational Social Systems 9 (6) (2022) 1644–1659.
[62] J. Jeon, H. Cai, Multi-class classification of construction hazards via cognitive states assessment using wearable EEG, Adv. Eng. Inform. 53 (2022) 101646, https://doi.org/10.1016/j.aei.2022.101646.
[63] L. Wang, H. Li, H. Wu, Y. Yao, C. Yu, W. Umer, D. Han, J. Ma, Monitoring mental fatigue of construction equipment operators: a smart cushion-based method with deep learning algorithms, Journal of Management in Engineering 40 (2024) 04024044, https://doi.org/10.1061/JMENEA.MEENG-5913.
[64] B.M. Tehrani, J. Wang, D. Truax, Assessment of mental fatigue using electroencephalography (EEG) and virtual reality (VR) for construction fall hazard prevention, Eng. Constr. Archit. Manag. 29 (2022) 3593–3616, https://doi.org/10.1108/ECAM-01-2021-0047.
[65] I. Mehmood, H. Li, Y. Qarout, W. Umer, S. Anwer, H. Wu, M. Hussain, M. F. Antwi-Afari, Deep learning-based construction equipment operators' mental fatigue classification using wearable EEG sensor data, Advanced Engineering Informatics 56 (2023) 101978, https://doi.org/10.1016/j.aei.2023.101978.
[66] J. Ke, J. Du, X. Luo, The effect of noise content and level on cognitive performance measured by electroencephalography (EEG), Automation in Construction 130 (2021) 103836, https://doi.org/10.1016/j.autcon.2021.103836.
[67] I. Mehmood, H. Li, W. Umer, A. Arsalan, S. Anwer, M.A. Mirza, J. Ma, M.F. Antwi-Afari, Multimodal integration for data-driven classification of mental fatigue during construction equipment operations: incorporating electroencephalography, electrodermal activity, and video signals, Develop. Built Environment 15 (2023) 100198, https://doi.org/10.1016/j.dibe.2023.100198.
[68] I. Mehmood, H. Li, W. Umer, J. Ma, M.S. Shakeel, S. Anwer, M.F. Antwi-Afari, S. Tariq, H. Wu, Non-invasive detection of mental fatigue in construction equipment operators through geometric measurements of facial features, J. Safety Res. 89 (2024) 234–250, https://doi.org/10.1016/j.jsr.2024.01.008.
[69] X. Fang, X. Yang, X. Xing, J. Wang, W. Umer, W. Guo, Real-time monitoring of mental fatigue of construction workers using enhanced sequential learning and timeliness, Automation in Construction 159 (2024) 105267, https://doi.org/10.1016/j.autcon.2024.105267.
[70] Y. Li, M. Wang, X. Xie, W. Chai, X. Chen, Brain-inspired perception feature and cognition model applied to safety patrol robot, IEEE Trans. Industr. Inform. 20 (2024) 3183–3194, https://doi.org/10.1109/TII.2023.3336019.
[71] W. Wu, W. Sun, Q.J. Wu, Y. Yang, H. Zhang, W.-L. Zheng, B.-L. Lu, Multimodal vigilance estimation using deep learning, IEEE Transactions on Cybernetics 52 (2020) 3097–3110, https://doi.org/10.1109/TCYB.2020.3006523.
[72] J. Li, Y. Ouyang, X. Luo, Impact of age on construction workers' Preattentive and attentive visual processing for hazard detection, Journal of Management in Engineering 40 (2024) 04024008, https://doi.org/10.1061/JMENEA.MEENG-5760.
[73] Y. Liu, A. Ojha, S. Shayesteh, H. Jebelli, S. Lee, Human-centric robotic manipulation in construction: generative adversarial networks based physiological computing mechanism to enable robots to perceive workers'

cognitive load, Can. J. Civ. Eng. 50 (2023) 224–238, https://doi.org/10.1139/cjce-2021-0646.
[74] T. Hao, K. Xu, X. Zheng, J. Li, S. Chen, W. Nie, Towards mental load assessment for high-risk works driven by psychophysiological data: combining a 1D-CNN model with random forest feature selection, Biomedical Signal Processing and Control 96 (2024) 106615, https://doi.org/10.1016/j.bspc.2024.106615.
[75] J. Ke, M. Zhang, X. Luo, J. Chen, Monitoring distraction of construction workers caused by noise using a wearable electroencephalography (EEG) device, Automation in Construction 125 (2021) 103598, https://doi.org/10.1016/j.autcon.2021.103598.
[76] K. Guan, Z. Zhang, T. Liu, H. Niu, Cross-task mental workload recognition based on EEG tensor representation and transfer learning, IEEE Trans. Neural Syst. Rehabil. Eng. 31 (2023) 2632–2639, https://doi.org/10.1109/TNSRE.2023.3281002.
[77] R. Amirova, G. Dlamini, A. Repryntseva, G. Succi, H. Tarasau, Attention and concentration for software developers, IEEE Access 11 (2023) 91072–91083, https://doi.org/10.1109/ACCESS.2023.3307831.
[78] F. Wang, D. Chen, X. Zhang, A transcutaneous acupoint electrical simulation glove for relieving the mental fatigue of crane drivers in real building environment, Comput. Methods Biomech. Biomed. Engin. (2024) 1–14, https://doi.org/10.1080/10255842.2023.2301668.
[79] J. Chae, S. Hwang, W. Seo, Y. Kang, Relationship between rework of engineering drawing tasks and stress level measured from physiological signals, Automation in Construction 124 (2021) 103560, https://doi.org/10.1016/j.autcon.2021.103560.
[80] J. Lee, J. Lee, T.W. Kim, C. Koo, EEG-based Circumplex model of affect for identifying Interindividual differences in thermal comfort, Journal of Management in Engineering 38 (2022) 04022034, https://doi.org/10.1061/(ASCE)ME.1943-5479.0001061.
[81] X. Xiahou, Z. Li, J. Xia, Z. Zhou, Q. Li, A feature-level fusion-based multimodal analysis of recognition and classification of awkward working postures in construction, Journal of Construction Engineering and Management 149 (2023) 04023138, https://doi.org/10.1061/JCEMD4.COENG-13795.
[82] X. Zhou, P. Liao, Brain-regulated learning for classifying on-site hazards with small datasets, Comput. Aided Civ. Inf. Eng. 39 (2024) 458–472, https://doi.org/10.1111/mice.13078.
[83] M. Wang, Y. Zhao, P.-C. Liao, EEG-based work experience prediction using hazard recognition, Autom. Constr. 136 (2022) 104151, https://doi.org/10.1016/j.autcon.2022.104151.
[84] Q. Zhang, M. Liang, A.P. Chan, P.-C. Liao, Visual attention and cognitive process in construction hazard recognition: study of fixation-related potential, Automation in Construction 148 (2023) 104756, https://doi.org/10.1016/j.autcon.2023.104756.
[85] X. Zhou, P.-C. Liao, Weighing votes in human-machine collaboration for Hazard recognition: inferring a Hazard-based perceptual threshold and decision confidence from electroencephalogram wavelets, Journal of Construction Engineering and Management 149 (2023) 04023084, https://doi.org/10.1061/JCEMD4.COENG-13351.
[86] J. Wang, Y.-S. Su, P.-C. Liao, Re-investigation of the mediating effect of brain activities between dispositional factors and Hazard recognition: a multilevel logistic regression approach, KSCE J. Civ. Eng. 27 (2023) 3646–3658, https://doi.org/10.1007/s12205-023-1602-y.
[87] H. Huang, H. Hu, F. Xu, Z. Zhang, J. Yang, Electroencephalography-based assessment of worker vigilance for evaluating safety interventions in construction, Advanced Engineering Informatics 64 (2025) 102973, https://doi.org/10.1016/j.aei.2025.102973.
[88] P. Liu, C. Zhang, Evaluation of Effect of Different Safety Training Styles on Mental Workloads Using Electroencephalography, in: Proceedings of the 40th International Symposium on Automation and Robotics in Construction (ISARC 2023), IAARC Publications, 2024, pp. 420–427, https://doi.org/10.22260/ISARC2023/0054.
[89] X. Zhou, P.-C. Liao, EEG-based performance-driven adaptive automated hazard alerting system in security surveillance support, Sustainability 15 (2023) 4812, https://doi.org/10.3390/su15064812.
[90] M. Wang, P.-C. Liao, Personality assessment based on electroencephalography signals during Hazard recognition, Sustainability 15 (2023) 8906, https://doi.org/10.3390/su15118906.
[91] A. Zayed, N. Belhadj, K. Ben Khalifa, M.H. Bedoui, C. Valderrama, Efficient generalized electroencephalography-based drowsiness detection approach with minimal electrodes, Sensors 24 (2024) 4256, https://doi.org/10.3390/s24134256.
[92] M. Sharma, D. Deb, U.R. Acharya, A novel three-band orthogonal wavelet filter bank method for an automated identification of alcoholic EEG signals, Appl. Intell. 48 (2018) 1368–1388, https://doi.org/10.1007/s10489-017-1042-9.
[93] J. Jeon, H. Cai, Classification of construction hazard-related perceptions using: wearable electroencephalogram and virtual reality, Automation in Construction 132 (2021) 103975, https://doi.org/10.1016/j.autcon.2021.103975.
[94] J. Chen, Q. Xu, D. Fang, D. Zhang, P.-C. Liao, Perceptual decision-making 'in the wild': how risk propensity and injury exposure experience influence the neural signatures of occupational hazard recognition, Int. J. Psychophysiol. 177 (2022) 92–102, https://doi.org/10.1016/j.ijpsycho.2022.04.010.
[95] J. Wang, M. Liang, P.-C. Liao, Toward an intuitive device for construction Hazard recognition management: eye fixation-related potentials in reinvestigation of Hazard recognition performance prediction, Journal of Construction Engineering and Management 150 (2024) 04024028, https://doi.org/10.1061/JCEMD4.COENG-13675.
[96] H. Chauhan, A. Pakbaz, Y. Jang, I. Jeong, Analyzing trust dynamics in human-robot collaboration through psychophysiological responses in an immersive virtual construction environment, Journal of Computing in Civil Engineering 38 (2024) 04024017, https://doi.org/10.1061/JCCEE5.CPENG-5692.
[97] Y. Qin, T. Bulbul, An EEG-based mental workload evaluation for AR head-mounted display use in construction assembly tasks, Journal of Construction Engineering and Management 149 (2023) 04023088, https://doi.org/10.1061/JCEMD4.COENG-13438.
[98] M. Noghabaei, K. Han, A. Albert, Feasibility study to identify brain activity and eye-tracking features for assessing Hazard recognition using consumer-grade wearables in an immersive virtual environment, Journal of Construction Engineering and Management 147 (2021) 04021104, https://doi.org/10.1061/(ASCE)CO.1943-7862.0002130.
[99] D. Choi, S. Seo, H. Park, T. Hong, C. Koo, Forecasting personal learning performance in virtual reality-based construction safety training using biometric responses, Automation in Construction 156 (2023) 105115, https://doi.org/10.1016/j.autcon.2023.105115.
[100] D. Huang, X. Wang, J. Liu, J. Li, W. Tang, Virtual reality safety training using deep EEG-net and physiology data, Vis. Comput. 38 (2022) 1195–1207, https://doi.org/10.1007/s00371-021-02140-3.
[101] S. Shayesteh, A. Ojha, Y. Liu, H. Jebelli, Human-robot teaming in construction: evaluative safety training through the integration of immersive technologies and wearable physiological sensing, Safety Science 159 (2023) 106019, https://doi.org/10.1016/j.ssci.2022.106019.
[102] Y. Liu, M. Habibnezhad, H. Jebelli, Brainwave-driven human-robot collaboration in construction, Automation in Construction 124 (2021) 103556, https://doi.org/10.1016/j.autcon.2021.103556.
[103] M. Savković, C. Caiazzo, M. Djapan, A.M. Vukićević, M. Pušica, I. Mačužić, Development of modular and adaptive laboratory set-up for neuroergonomic and human-robot interaction research, Front. Neurorobot. 16 (2022) 863637, https://doi.org/10.3389/fnbot.2022.863637.
[104] F. Baek, D. Kim, G. Lee, B. Choi, S. Lee, Effect of human emotional responses on human-robot team pty in construction, Automation in Construction 166 (2024) 105608, https://doi.org/10.1016/j.autcon.2024.105608.
[105] D. Mizrahi, I. Zuckerman, I. Laufer, Electrophysiological features to aid in the construction of predictive models of human-agent collaboration in smart environments, Sensors 22 (2022) 6526, https://doi.org/10.3390/s22176526.
[106] S. Shayesteh, A. Ojha, H. Jebelli, Workers' Trust in collaborative construction robots: EEG-based trust recognition in an immersive environment, in: H. Jebelli, M. Habibnezhad, S. Shayesteh, S. Asadi, S. Lee (Eds.), Automation and Robotics in the Architecture, Engineering, and Construction Industry, Springer International Publishing, Cham, 2022, pp. 201–215, https://doi.org/10.1007/978-3-030-77163-8_10.
[107] Z. Li, F. Tian, G. Chen, S. Zhang, Q. Li, Pre-trained deep learning models for EEG-based cognitive state recognition for construction workers through transfer learning, Journal of Building Design and Environment 3 (1) (2025) 202518.
[108] K.V. Volkova, N.I. Dagaev, A.S. Kiselev, V.R. Kasumov, M.V. Aleksandrov, A. E. Osadchiy, The brain-computer Interface: experience of construction, use, and potential routes to improving performance, Neurosci. Behav. Physiol. 48 (2018) 1128–1139, https://doi.org/10.1007/s11055-018-0677-2.
[109] I. Awolusi, E. Marks, M. Hallowell, Wearable technology for personalized construction safety monitoring and trending: review of applicable devices, Automation in Construction 85 (2018) 96–106, https://doi.org/10.1016/j.autcon.2017.10.006.
[110] L. Shi, Y. Zhang, K. Tetsuo, Z. Shi, Y. Fang, P.J. Denoble, Y. Li, Simulated high altitude helium-oxygen diving, Aerospace Medicine and Human Performance 88 (2017) 1088–1093, https://doi.org/10.3357/AMHP.4802.2017.
[111] J. Lee, T. Wan Kim, C. Lee, C. Koo, Integrated approach to evaluating the effect of indoor CO2 concentration on human cognitive performance and neural responses in office environment, Journal of Management in Engineering 38 (2022) 04021085, https://doi.org/10.1061/(ASCE)ME.1943-5479.0000993.
[112] X. Xing, H. Li, J. Li, B. Zhong, H. Luo, M. Skitmore, A multicomponent and neurophysiological intervention for the emotional and mental states of high-altitude construction workers, Automation in Construction 105 (2019) 102836, https://doi.org/10.1016/j.autcon.2019.102836.
[113] Y. Ouyang, G. Huang, S. He, Design of safety warnings and risk perception inducement: a comparative study between safety signs and safety comics in construction workplaces, engineering, Construction and Architectural Management (2024), https://doi.org/10.1108/ECAM-01-2024-0077.
[114] H. Chen, I.Y.S. Chan, Effects of automation and transparency on human psychophysiological states and perceived system performance in construction safety automation: an electroencephalography experiment, Journal of Construction Engineering and Management 150 (2024) 04024055, https://doi.org/10.1061/JCEMD4.COENG-14205.
[115] N. Virmani, U.R. Salve, Significance of human factors and ergonomics (HFE): mediating its role between industry 4.0 implementation and operational excellence, IEEE Trans. Eng. Manag. 70 (2021) 3976–3989, https://doi.org/10.1109/TEM.2021.3075673.
[116] J. Chae, S. Hwang, Y. Kang, Measuring habituation to auditory warnings using behavioral and physiological data, Journal of Construction Engineering and Management 150 (2024) 04024063, https://doi.org/10.1061/JCEMD4.COENG-14450.
[117] J. Ni, W. Xie, Y. Liu, J. Zhang, Y. Wan, H. Ge, Driver emotion recognition involving multimodal signals: electrophysiological response, nasal-tip temperature, and vehicle behavior, Journal of Transportation Engineering, Part

A: Systems 150 (2024) 04023125, https://doi.org/10.1061/JTEPBS.TEENG-7802.
[118] B. Kim, K.R. Sri Preethaa, S. Song, R.R. Lukacs, J. An, Z. Chen, S. Kim, Internet of things and ensemble learning-based mental and physical fatigue monitoring for smart construction sites, Journal of Big Data 11 (1) (2024) 115.
[119] F. Wang, D. Chen, X. Zhang, A transcutaneous acupoint electrical simulation glove for relieving the mental fatigue of crane drivers in real building environment, Computer Methods in Biomechanics and Biomedical Engineering 28 (6) (2025) 725–738.
[120] J. Khubani, S. Kulkarni, PWO-C2A-AM: Attentional Deep Learning Model for Emotion Recognition Using EEG Signals, Biomedical Materials & Devices (2025) 1–34.
[121] J. Dyreborg, H.J. Lipscomb, K. Nielsen, M. Törner, K. Rasmussen, K.B. Frydendall, H. Bay, U. Gensby, E. Bengtsen, F. Guldenmund, P. Kines, Safety interventions for the prevention of accidents at work: a systematic review, Campbell Syst. Rev. 18 (2022) e1234, https://doi.org/10.1002/cl2.1234.
[122] F. Wang, M. Ma, X. Zhang, Study on a portable electrode used to detect the fatigue of tower crane drivers in real construction environment, IEEE Trans. Instrum. Meas. 73 (2024) 1–12, https://doi.org/10.1109/TIM.2024.3353169.
[123] M. Baygin, P.D. Barua, S. Dogan, T. Tuncer, T.J. Hong, S. March, R.-S. Tan, F. Molinari, U.R. Acharya, Automated anxiety detection using probabilistic binary pattern with ECG signals, Comput. Methods Programs Biomed. 247 (2024) 108076, https://doi.org/10.1016/j.cmpb.2024.108076.
[124] Y. Liu, M. Habibnezhad, S. Shayesteh, H. Jebelli, S. Lee, Paving the Way for future EEG studies in construction: dependent component analysis for automatic ocular artifact removal from brainwave signals, J. Constr. Eng. Manag. 147 (2021) 04021087, https://doi.org/10.1061/(ASCE)CO.1943-7862.0002097.
[125] M. Liu, M. Liang, J. Yuan, J. Wang, P.C. Liao, Time lag between visual attention and brain activity in construction fall hazard recognition, Automation in Construction 168 (2024) 105751.
[126] M. Mir, F. Nasirzadeh, H. Bereznicki, P. Enticott, S. Lee, Investigating the effects of different levels and types of construction noise on emotions using EEG data, Build. Environ. 225 (2022) 109619, https://doi.org/10.1016/j.buildenv.2022.109619.
[127] G. Albeaino, I. Jeelani, M. Gheisari, R.R. Issa, Assessing proxemics impact on Human-Robot collaboration safety in construction: A virtual reality study with four-legged robots, Safety Science 181 (2025) 106682.
[128] A. Ojha, S. Shayesteh, Y. Liu, H. Jebelli, A. Akanmu, Psychophysiological impacts of working with powered exoskeletons on construction sites, Automation in Construction 177 (2025) 106312.
[129] X. Zhou, P.-C. Liao, A privacy-preserving data storage and service framework based on deep learning and blockchain for construction workers' wearable IoT sensors, in: arXiv preprint arXiv:2211.10713, 2022, https://doi.org/10.48550/arXiv.2211.10713.
[130] C.A. Fidas, D. Lyras, A review of EEG-based user authentication: trends and future research directions, IEEE Access 11 (2023) 22917–22934, https://doi.org/10.1109/ACCESS.2023.3252588.
[131] Z. Li, Y. Yu, F. Tian, X. Chen, X. Xiahou, Q. Li, Vigilance recognition for construction workers using EEG and transfer learning, Advanced Engineering Informatics 64 (2025) 103052, https://doi.org/10.1016/j.aei.2025.103052.
[132] K. Chyl, G. Fraga-González, S. Brem, K. Jednoróg, Brain dynamics of (a)typical reading development-a review of longitudinal studies, npj Science of Learning 6 (2021) 4, https://doi.org/10.1038/s41539-021-00081-z.
[133] V. Noreika, S. Georgieva, S. Wass, V. Leong, 14 challenges and their solutions for conducting social neuroscience and longitudinal EEG research with infants, Infant Behav. Dev. 58 (2020) 101393, https://doi.org/10.1016/j.infbeh.2019.101393.
[134] G.G. Knyazev, A.N. Savostyanov, A.V. Bocharov, H.R. Slobodskaya, N.B. Bairova, S.S. Tamozhnikov, V.V. Stepanova, Effortful control and resting state networks: a longitudinal EEG study, Neuroscience 346 (2017) 365–381, https://doi.org/10.1016/j.neuroscience.2017.01.039.
[135] M. Hu, T. Shealy, Application of functional near-infrared spectroscopy to measure engineering decision-making and design cognition: literature review and synthesis of methods, Journal of Computing in Civil Engineering 33 (2019) 04019034, https://doi.org/10.1061/(ASCE)CP.1943-5487.0000848.
[136] D. Bandara, S. Velipasalar, S. Bratt, L. Hirshfield, Building predictive models of emotion with functional near-infrared spectroscopy, International Journal of Human-Computer Studies 110 (2018) 75–85, https://doi.org/10.1016/j.ijhcs.2017.11.001.
[137] X. Zhou, Y. Hu, P.-C. Liao, D. Zhang, Hazard differentiation embedded in the brain: a near-infrared spectroscopy-based study, Automation in Construction 122 (2021) 103473, https://doi.org/10.1016/j.autcon.2020.103473.
[138] M. Hu, T. Shealy, M. Hallowell, D. Hardison, Advancing Construction Hazard Recognition through Neuroscience: Measuring Cognitive Response to Hazards Using Functional near Infrared Spectroscopy, in: Proceedings of the Construction Research Congress 2018, American Society of Civil Engineers, New Orleans, Louisiana, 2018, pp. 134–143, https://doi.org/10.1061/9780784481288.014.
[139] X. Fang, H. Li, J. Ma, X. Xing, Z. Fu, M.F. Antwi-Afari, W. Umer, Assessment of construction workers' spontaneous mental fatigue based on non-invasive and multimodal in-ear EEG sensors, Buildings 14 (2024) 2793, https://doi.org/10.3390/buildings14072793.
[140] J. Chen, Z. Lin, Assessing working vulnerability of construction labor through EEG signal processing, in: Proceedings of the 16th International Conference on Computing in Civil and Building Engineering, Osaka University, 2016, pp. 1053–1059, in: http://www.see.eng.osaka-u.ac.jp/seeit/icccbe2016/Proceedings/Full_Papers/133-026.pdf.
[141] I. Hussain, R. Jany, R. Boyer, A.K.M. Azad, S.A. Alyami, S.J. Park, M.M. Hasan, M. A. Hossain, An explainable EEG-based human activity recognition model using machine-learning approach and LIME, Sensors 23 (2023) 7452, https://doi.org/10.3390/s23177452.
[142] X. Zhou, C. Liu, L. Zhai, Z. Jia, C. Guan, Y. Liu, Interpretable and robust AI in EEG systems: A survey, in: arXiv preprint arXiv:2304.10755, 2023. https://arxiv.org/abs/2304.10755.
[143] J.M. Górriz, I. Álvarez-Illán, A. Álvarez-Marquina, J.E. Arco, M. Atzmueller, F. Ballarini, E. Barakova, G. Bologna, P. Bonomini, G. Castellanos-Dominguez, Computational approaches to explainable artificial intelligence: advances in theory, applications and trends, Information Fusion 100 (2023) 101945, https://doi.org/10.1016/j.inffus.2023.101945.
[144] S. Piri, Enhancing construction site safety: a data-driven approach with Bayesian network analysis and wearable sensors?, in: SSRN preprint, 2024, https://doi.org/10.2139/ssrn.4811253.