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A SYSTEMATIC AND BIBLIOMETRIC REVIEW ON PHYSIOLOGICAL MONITORING SYSTEMS AND WEARABLE SENSING DEVICES FOR MENTAL STATUS MONITORING IN CONSTRUCTION: TRENDS, LIMITATIONS, AND FUTURE DIRECTIONS

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SUMMARY: *Advancements in physiological monitoring systems (PMSs) and wearable sensing devices (WSDs) have enabled real-time, objective assessments of workers' mental status in construction. However, existing studies lack a comprehensive synthesis of mental status monitoring and classification approaches used in construction, including data collection, preprocessing, as well as postprocessing techniques. This paper systematically and bibliometrically reviews 223 studies following PRISMA guidelines, providing a structured framework for PMS and WSD applications in construction. The findings identified ten sensor types used to assess four mental status factors: risk perception, mental workload and fatigue, mental stress, and emotional states. For each sensor, the review details data collection procedures, including sensor brands and models, placements, and sampling rates. Additionally, it examines preprocessing techniques (i.e., noise filtering and artifact removal) and postprocessing methods, including feature extraction and metric computation, data interpretation, as well as mental status classification using rule-based and AI-based methods. Identified limitations and future research directions are also discussed. This study serves as a comprehensive guide for researchers and practitioners, promoting the broader adoption of PMSs and WSDs for mental status monitoring in construction.*

KEYWORDS: *construction, safety, physiological monitoring system, wearable sensing device, mental status.*

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1. INTRODUCTION

Construction is one of the most hazardous industries, accounting for nearly 20% of annual workplace fatalities and more than 170,000 injuries per year in the US between 2014 and 2022 (US BLS, 2024). The dynamic nature of construction sites and tasks requires individuals to remain constantly alert to potential hazards while managing both physically and mentally demanding work, increasing the risk of mental fatigue (Boksem *et al.*, 2006; Boksem and Tops, 2008). In addition, high productivity demands, hazardous working conditions, and health issues further contribute to occupational stress and destabilize emotional states (Gómez-Salgado *et al.*, 2023). Together, these factors impair cognitive and behavioral functioning—including attention, situational awareness, motivation, emotion regulation, decision-making, and motor control (Boksem *et al.*, 2005, 2006; Fang *et al.*, 2016; Li, Li, *et al.*, 2019; Xing *et al.*, 2020)—which are also referred to as mental status (Martin, 1990). An impaired mental status weakens hazard recognition and slows response times, increasing the likelihood of human errors. These errors ultimately lead to unsafe behaviors (Hallowell, 2010; Zhang *et al.*, 2023), which account for 80% of hazards occurring on construction sites (Fang *et al.*, 2016; Li *et al.*, 2015; Sathvik *et al.*, 2023). Therefore, proactive monitoring of mental status is essential for effective hazard identification and prevention on construction jobsites.

Monitoring mental status is challenging, as it is not as easily observable as other risks such as physical hazards (e.g., slip, trip, and falls). Traditional assessment methods, such as self-reports and manual observations, are often subjective, time-consuming, and prone to bias. Additionally, these approaches often interrupt ongoing tasks and activities, making them impractical for real-time jobsite implementation (Hwang *et al.*, 2018). Recent advancements in sensing and computing technologies have introduced physiological monitoring systems (PMSs) and wearable sensing devices (WSDs) as effective tools for proactively monitoring mental status. Unlike traditional safety assessments, PMSs and WSDs collect real-time physiological and biomechanical data, offering continuous and objective insights into workers' safety behavior and psychophysiology without disrupting construction operations (Choi *et al.*, 2017). These advances have the potential to transform construction safety management from a reactive to a proactive approach.

Several studies have specifically explored the applications of PMSs and WSDs for monitoring mental status in construction. However, these studies have either focused on a single sensor type (i.e., electroencephalography) (Saedi *et al.*, 2022; Wei *et al.*, 2024), overlooking other sensing technologies currently used on jobsites, or have examined a single mental factor (i.e., mental fatigue) (Jamil Uddin *et al.*, 2024) while neglecting other mental status aspects reported in existing construction research – such as risk perception (Choi, Lee, *et al.*, 2019), mental stress (Jebelli, Hwang, *et al.*, 2018a), and emotional states (Chong *et al.*, 2022) – which align with commonly recognized mental status components in the psychological and clinical domains (Feist and Rosenberg, 2009; Martin, 1990). Other more general studies have reviewed the applications of PMSs and WSDs for construction safety, with mental status being considered as one of several safety aspects (Abuwarda *et al.*, 2022; Ahn *et al.*, 2019; Awolusi *et al.*, 2018; Chen *et al.*, 2023; Gao *et al.*, 2022; Heng *et al.*, 2024; Kim, Lee, *et al.*, 2024; Wang, Chen, *et al.*, 2024). Nevertheless, while some of these studies have provided guidance and systematically addressed certain aspects of data processing, none have offered a comprehensive, step-by-step framework that thoroughly covers the entire process of using PMSs and WSDs specifically for mental status monitoring and classification in construction. This includes data collection, covering sensor types and models, placement, and sampling rates, data preprocessing, including noise filtering and artifact removal techniques, as well as data postprocessing, including feature extraction, metric computation, data interpretation, and mental status classification using both rule-based and AI-based approaches.

This study conducts a systematic and bibliometric review to develop a structured framework that guides researchers and practitioners in leveraging PMSs and WSDs for comprehensive mental status monitoring and classification in construction. Specifically, the developed framework seeks to answer the following research questions: *(1) What mental status factors have been investigated and what bodily systems have been monitored? (2) What sensor types have been used and how are the data collected (sensor placement) and processed (preprocessing, postprocessing, interpretation, and classification) for each mental status factor? (3) What challenges are identified in the current literature, and what future research directions exist for the application of PMSs and WSDs for mental status monitoring in construction?*

To address these questions, the paper is organized as follows: Section 2 outlines the research methodology, while Section 3 presents the results and discussion. Specifically, Sections 3.1 to 3.3 cover publication trends, key authors, contributing institutions and countries, global collaborations, and publication venues. Sections 3.4 and 3.5 examine the identified mental status monitoring areas along with the sensor types and the physiological and biomechanical functions they monitor. Sections 3.6 to 3.15 provide an in-depth discussion of the procedures for using each sensor type to assess the identified mental status factors, detailing data collection, preprocessing, and postprocessing methods. Section 3.16 provides an overview of application trends of PMSs and WSDs for monitoring each mental status factor. Finally, Section 4 discusses the identified limitations and proposes a roadmap for future research. This study advances knowledge by providing a structured framework and research roadmap for leveraging PMSs and WSDs in mental status assessment in construction. This ultimately facilitates the integration of these technologies into construction safety practices, promoting their wider adoption and enhancing workplace safety.

2. RESEARCH METHODOLOGY

A systematic review of extant literature was conducted in this study to achieve the research goals. Systematic reviews provide reliable results through their explicit, objective, comprehensive, and repeatable research approach which involves identifying, collecting, analyzing, and synthesizing studies based on pre-defined eligibility criteria (Denyer and Tranfield, 2009; Phillips and Barker, 2021). Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, which provide a structured procedure to ensure transparency and completeness when reporting systematic reviews, were adopted in this study (Liberati *et al.*, 2009; Page *et al.*, 2021; Sohrabi *et al.*, 2021). PRISMA has been widely adopted by researchers across various domains (Hirst and Altman, 2012; Page and Moher, 2017), including medicine (Garbe *et al.*, 2011), agriculture (Velten *et al.*, 2015), as well as Architecture, Engineering, and Construction (AEC) (Ahn *et al.*, 2019; Albeaino *et al.*, 2019; Asadzadeh *et al.*, 2020). PRISMA guidelines consist of three main steps: (1) Identification; (2) Screening; and (3) Inclusion, details of which are discussed in subsections 2.1, 2.2, 2.3, and illustrated in Figure 1.

2.1 Identification

The initial step involved a comprehensive identification of papers potentially relevant to addressing the research questions. This step was carried out using keyword and syntax searches in Google Scholar, a free online academic search engine that thoroughly identifies full-text and multi-disciplinary publications from across the internet (Haddaway *et al.*, 2015; Zientek *et al.*, 2018). Google Scholar offers the advantages of broader coverage, faster indexing of recent publications, as well as more powerful citation tracking compared with other databases such as Compendex, Web of Science and Scopus (Cole *et al.*, 2018; Delgado López-Cózar *et al.*, 2019; Martín-Martín *et al.*, 2018; Schultz and McAllister, 2024). It enables the generation of an exhaustive list of publications on a topic of interest based on specific keywords and search syntax (Shultz, 2007; Zientek *et al.*, 2018). Recognizing that mental status reflects a complex interplay among psychological, physiological, and biomechanical factors, the search syntax was designed to incorporate a wide range of physiological and biomechanical parameters and technologies. This approach ensured the comprehensive inclusion of studies addressing mental status in construction safety—either directly or indirectly—even when varied terminology was used.

The following keywords and search syntax were used in this search: ("Construction Safety") AND ("Physiological" OR "Wearable Devices" OR "Monitoring System" OR "Sensor" OR "PPG Photoplethysmography" OR "EDA Electrodermal Activity" OR "GSR Galvanic Skin Response" OR "EKG Electrocardiography" OR "ECG Electrocardiography" OR "PCG Phonocardiogram" OR "IMU Inertial Measurement Unit" OR "Accelerometer" OR "Gyroscope" OR "Magnetometer" OR "EEG Electroencephalography" OR "Functional Near-Infrared Spectroscopy fNIRS" OR "Functional Magnetic Resonance Imaging fMRI" OR "EMG Electromyography" OR "Eye Tracking" OR "Heart Rate" OR "Blood Pressure" OR "Skin Temperature" OR "Breath Respiration"). As a result, a total of 1,343 articles were initially identified (Figure 1).

2.2 Screening

The second step encompassed screening the identified articles by their title and abstract based on the following criteria: (1) peer-reviewed journal or conference papers, with other publication types such as literature reviews, book chapters, theses, dissertations, and technical reports being excluded; (2) written in English; and (3) published within the last 25 years (2000–January 2025). As a result, 214 articles were excluded (Figure 1). Duplicate records (N=29) were also excluded, leaving a total of 1,100 articles eligible for further analysis (Figure 1).

2.3 Inclusion

The third step involved conducting a full-text examination of the remaining 1,100 articles to determine their eligibility based on established inclusion criteria. The inclusion criteria comprised experiments involving human participants, employing psychophysiological monitoring sensors and wearable devices to collect psychological, physiological, and biomechanical data, with the objective of monitoring mental status on construction sites. Studies focusing solely on environmental, location or proximity sensors without sensing human psychological, physiological, or biomechanical data were excluded from the review.

A total of 877 out of the 1,100 screened papers were excluded at this stage, as they: (1) did not pertain to the construction domain (N=120); (2) did not apply PMSs and wearable devices to monitor humans' psychological, physiological, and biomechanical states (N=356); (3) lacked human subjects, focusing only on developing devices without any experimentation involving participants (N=37); (4) did not utilize PMSs and wearable devices within the context of construction safety, but rather employed these sensors for other purposes such as improving productivity (N=23); or (5) did not monitor mental status, but rather focused on other construction safety applications, including physical exhaustion, work-related musculoskeletal disorders, and unsafe behaviors (N=341). A total of 223 articles met the established eligibility criteria and constituted the foundation of this systematic literature review.

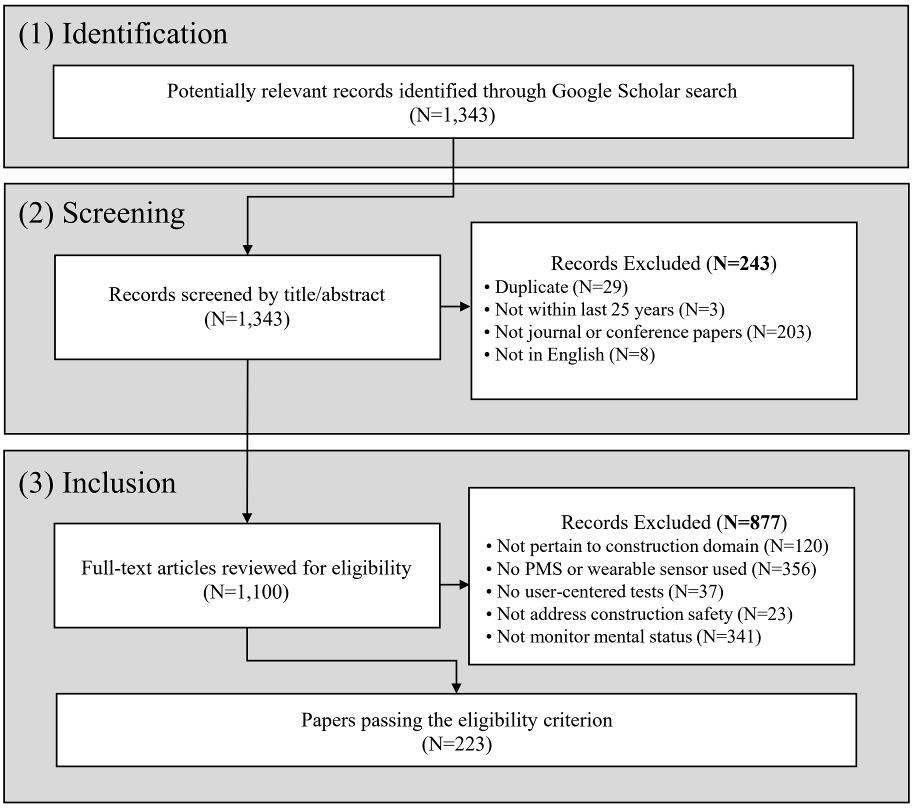


Figure 1: Adopted PRISMA procedure.

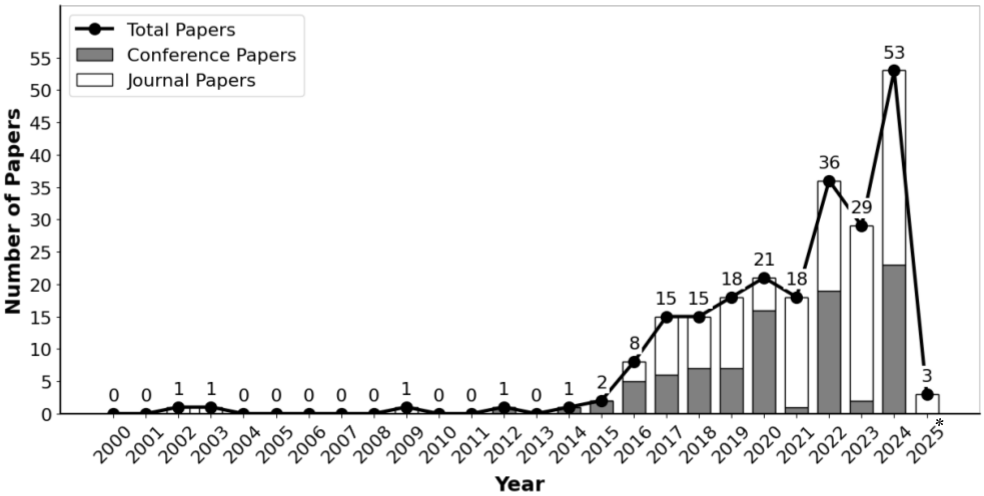
2.4 Data Analysis

Bibliometrics was employed for data analysis. Rooted in information science (Donthu et al. 2021), this approach utilizes mathematical and statistical techniques to quantitatively analyze bibliometric data from publications within a specific research domain (Broadus, 1987; Donthu *et al.*, 2021; Pritchard, 1969). Bibliometric analysis objectively examines the contributions and relationships of research constituents, providing insights into publication trends, collaboration patterns, geographical contributions, research themes, emerging trends, as well as research gaps which enables researchers to identify future research areas in a particular field (Aria and Cuccurullo, 2017; Broadus, 1987; Donthu *et al.*, 2021; Öztürk *et al.*, 2024). VOSviewer v.1.6.20 (Van Eck and Waltman, 2010), a widely used bibliometric mapping software, was utilized for this study to visualize and analyze bibliometric networks (Donthu *et al.*, 2021; Van Eck and Waltman, 2010). VOSviewer was selected for its capability to process large datasets and graphically represent bibliometric maps (Van Eck and Waltman, 2010). Descriptive statistics was used to interpret the social and conceptual structures of the research on the applications of PMSs and WSDs for monitoring mental status in construction.

3. RESULTS AND DISCUSSION

3.1 Publication Trends

The annual number of publications on PMSs and WSDs for monitoring mental status in construction is presented in Figure 2. Over the last 25 years, a total of 133 (59.64%) journal and 90 (40.36%) conference papers were published in the AEC domain. This period experienced a steady increase in publications since 2015, likely driven by advancements in wearable sensing technology. The highest number of studies was recorded in 2024, with 53 studies published. This increasing trend over the last decade reflects the growing interest of researchers and the potential of using PMSs and WSDs to monitor mental status for construction safety.



* Publication numbers in 2025 were retrieved only from January

Figure 2: Annual number of papers on PMSs and WSDs for mental status monitoring in construction.

3.2 Authors, Institutions, Countries, and Global Collaborations

Authors: A total of 440 researchers across 136 institutions worldwide contributed to the published articles included in this study. The most active scholars with more than 10 published journal and conference proceeding articles included Sogand Hasanzadeh (32, 14.35%), Houtan Jebelli (30, 13.45%), Sanghyun Lee (24, 10.76%), Behzad Esmaeili (21, 9.42%), Pin-Chao Liao (17, 7.62%), Michael D. Dodd (13, 5.83%), Jiayu Chen (13, 5.83%), and Heng Li (13, 5.83%). A co-authorship analysis was performed to examine the contributions and interactions among them, with the resulting network map presented in Fig. 3. It should be noted that the analysis was conducted based on the authors' affiliations at the time of publication.

Institutions: The top 10 contributing institutions by the number of publications were University of Michigan (26, 11.66%), Purdue University (26, 11.66%), Tsinghua University (26, 11.66%), Pennsylvania State University (21, 9.42%), City University of Hong Kong (18, 8.07%), Hong Kong Polytechnic University (18, 8.07%), University of Nebraska-Lincoln (16, 7.17%), Virginia Tech (14, 6.28%), Texas A&M University (14, 6.28%), George Mason University (9, 4.01%), Ewha Womans University (9, 4.01%), Huazhong University of Science and Technology (7, 3.14%), Yonsei University (7, 3.14%), Ajou University (6, 2.69%), University of Florida (6, 2.69%), North Carolina State University (5, 2.24%), and University of Washington (5, 2.24%).

Countries and regions: In terms of geographical contributions, the countries and regions associated with the authors' affiliations at the time of publication were counted and ranked based on the number of publications.

Overall, 21 countries and regions contributed to this research domain. Among the top 10 by publication volume, the United States led with 127 papers (56.95%), followed by Mainland China (65, 29.14%), Hong Kong (37, 16.59%), South Korea (22, 9.87%), Australia (12, 5.38%), the United Kingdom (9, 4.04%), Taiwan (4, 1.79%), Turkey (4, 1.79%), Germany (3, 1.35%), Japan (3, 1.35%), Saudi Arabia (2, 0.90%), Pakistan (2, 0.90%), India (2, 0.90%), Canada (2, 0.90%), Sweden (1, 0.45%), Spain (1, 0.45%), Philippines (1, 0.45%), New Zealand (1, 0.45%), Iran (1, 0.45%), Singapore (1, 0.45%), and Vietnam (1, 0.45%).

Global Collaborations: Active global collaboration was also observed among 17 countries and regions in co-publishing 60 papers on PMSs and WSDs for mental status monitoring in construction. Table 1 presents the countries and regions that collaborated on two or more studies. Among the participants involved in these 60 collaborative articles, the five most active were Mainland China (31, 51.67%), the United States (30, 50.00%), Hong Kong (29, 48.33%), South Korea (16, 26.67%), and the United Kingdom (9, 15.00%). Mainland China and Hong Kong had the strongest collaborative partnerships, co-publishing a total of 20 (33.33%) articles. This was followed by partnerships between South Korea and the United States (15, 25.00%), Hong Kong and the United States (9, 15.00%), China and the United Kingdom (7, 12.00%), China and Australia (6, 10.00%), Hong Kong and the United Kingdom (6, 10.00%), Australia and Hong Kong (2, 3.33%), Hong Kong and Pakistan (2, 3.33%), United States and Turkey (2, 3.33%), as well as Pakistan and the United Kingdom (2, 3.33%). Other single-paper collaborations included Canada and United States, Mainland China and Taiwan, China and Singapore, Vietnam and United States, Spain and United States, as well as Australia and Iran. Notably, some countries such as Germany and Japan, though higher in publication numbers, were not engaged in global collaboration.

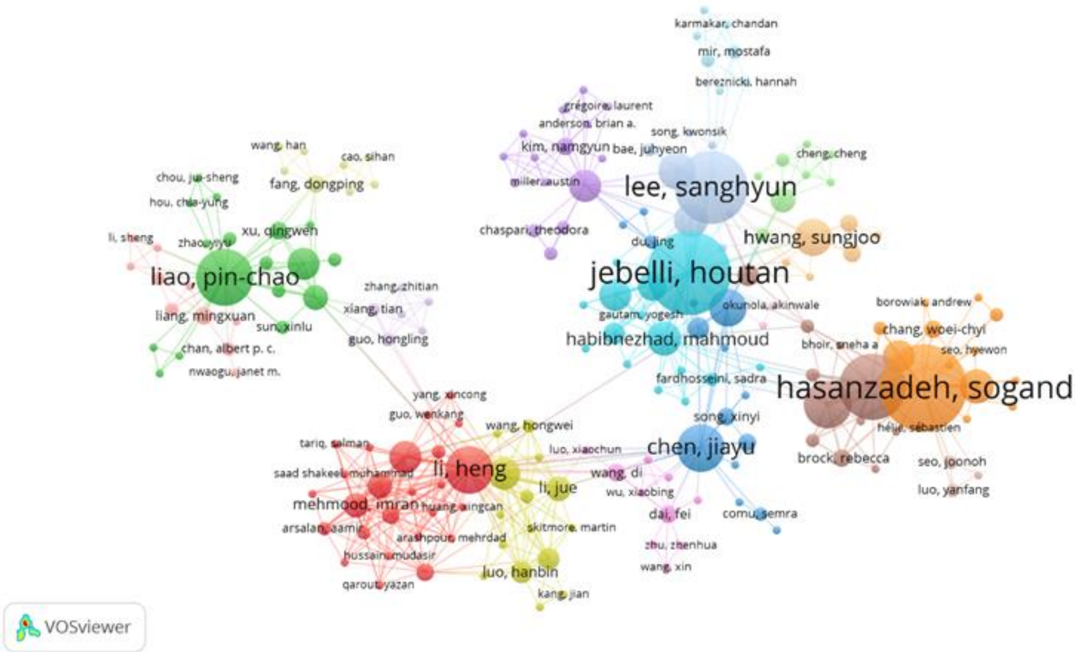


Figure 3: Co-authorship network.

The results above indicate that research on mental status monitoring in construction is highly concentrated within several research teams, primarily from the United States and East Asia. Contributions from underrepresented regions remain scarce. This is likely due to the availability of research resources, including infrastructure, funding, and specialized expertise in these two regions. Co-authorship appears most frequent within individual research groups, with limited cross-group collaborations (Figure 3). While concentration within a few groups may have helped refine study protocols and standardize data processing, broader cross-institutional collaborations—both national and international—are needed to diversify methodologies, establish shared standards, and better represent worker populations, environments, tasks, and data types. A small number of researchers linking separate national and global research groups (Figure 3) provide potential entry points for such collaborations, which could ultimately improve the generalizability and scalability of PMS- and WSD-based approaches for mental status monitoring in construction.

Table 1: Countries and regions involved in global collaboration on two or more studies.

	United States	Hong Kong	Mainland China	South Korea	United Kingdom	Australia	Saudi Arabia	Pakistan	Turkey	New Zealand	India
United States	0	9	5	15	0	1	1	0	2	0	1
Hong Kong	9	0	20	2	6	2	1	2	1	0	0
Mainland China	5	20	0	1	7	6	1	1	1	1	1
South Korea	15	2	1	0	0	0	0	0	0	0	1
United Kingdom	0	6	7	0	0	1	0	2	0	1	0
Australia	1	2	6	0	1	0	0	0	0	0	0
Saudi Arabia	1	1	1	0	0	0	0	0	0	0	0
Pakistan	0	2	1	0	2	0	0	0	0	0	0
Turkey	2	1	1	0	0	0	0	0	0	0	0
New Zealand	0	0	1	0	1	0	0	0	0	0	0
India	1	0	1	1	0	0	0	0	0	0	0

3.3 Journal and Conference Venues

A statistical analysis of the paper sources revealed distribution across 41 journals and the proceedings of 20 conferences. The top 10 publication venues, ranked by the number of papers, along with the corresponding journal Impact Factors (IF) from the 2023 Journal Citation Reports (JCR), are listed in Table 2. The publication venues highlight a diverse research approach in the application of PMSs and WSDs in monitoring mental status for construction safety, encompassing advancements in technology development and practical case studies.

Table 2: Top 10 publication venues for mental status monitoring using PMSs and WSDs.

Ranking	**Peer-Reviewed Journal or Conference Venue**	**Number of Publications**	**IF**
1	American Society of Civil Engineers (ASCE) Construction Research Congress (CRC)	38	-
2	Elsevier Journal of Automation in Construction	34	9.6
3	American Society of Civil Engineers (ASCE) Journal of Construction Engineering and Management	22	4.1
4	American Society of Civil Engineers (ASCE) International Conference on Computing in Civil Engineering (i3ce)	12	-
5	IAARC International Symposium on Automation and Robotics in Construction (ISARC)	11	-
6	Elsevier Journal of Safety Science	10	4.7
7 (tie)	Canadian Society of Civil Engineers (CSCE) Annual Conference	5	-
7 (tie)	Elsevier Journal of Advanced Engineering Informatics	5	8.0
7 (tie)	MDPI Journal of Sustainability	5	3.3
7 (tie)	American Society of Civil Engineers (ASCE) Journal of Computing in Civil Engineering	5	4.7
7 (tie)	American Society of Civil Engineers (ASCE) Journal of Management in Engineering	5	5.3
8	European Group for Intelligent Computing in Engineering (EG-ICE) International Workshop	4	-
9 (tie)	Taylor & Francis International Journal of Occupational Safety and Ergonomics	3	1.6
9 (tie)	Emerald Journal of Engineering, Construction and Architectural Management	3	3.6
10 (tie)	Elsevier Journal of Applied Acoustics	2	3.4
10 (tie)	Emerald Journal of Construction Innovation: Information, Process, Management	2	3.1
10 (tie)	Creative Construction Conference (CCC)	2	-
10 (tie)	International Conference on Computing in Civil and Building Engineering	2	-

3.4 Mental Status Application Areas: Term Co-occurrence Analysis and Definition

A term co-occurrence analysis was performed on titles and abstracts using VOSviewer to identify the applications of PMSs and WSDs for mental status monitoring in construction. This methodology determines core content within specific subjects by counting word occurrences (Sedighi, 2016). Using a minimum occurrence threshold of five, 292 of 5,104 terms were selected through the binary counting method. Further filtering for the top 60% relevant terms (175 words) and manually removing 47 unrelated terms resulted in 128 terms for network mapping. The

VOSviewer map settings included a minimum cluster size of 15, with others at default values. Figure 4 highlights the applications of PMSs and WSDs for mental status monitoring.

Four mental status factors emerged from the included 223 articles and resulting clusters. These included (1) risk perception (119 articles, 53.36%), which refers to the identification and intuitive judgment of dangers (Slovic, 1987); (2) mental workload and fatigue (67 articles, 30.04%), where mental workload represents the cognitive effort required to complete tasks (Chen, Ren, *et al.*, 2015), and prolonged cognitive efforts can lead to mental fatigue (Boksem *et al.*, 2005); (3) mental stress (32 articles, 14.35%), which is a generalized state of mental strain or tension that arises in response to perceived challenging or demanding situations (Feist and Rosenberg, 2009); and (4) emotional state (29 articles, 13.00%), which reflects rapid, temporary changes in human conscious experience and physiological responses to situations (Feist and Rosenberg, 2009) (Figure 4). It should be noted that the sum and percentages do not add up to 223 articles since 8 articles discussed the application of PMSs and WSDs for monitoring mental status in general, without focusing on a specific area of application, and 27 studies measured more than one mental status factors.

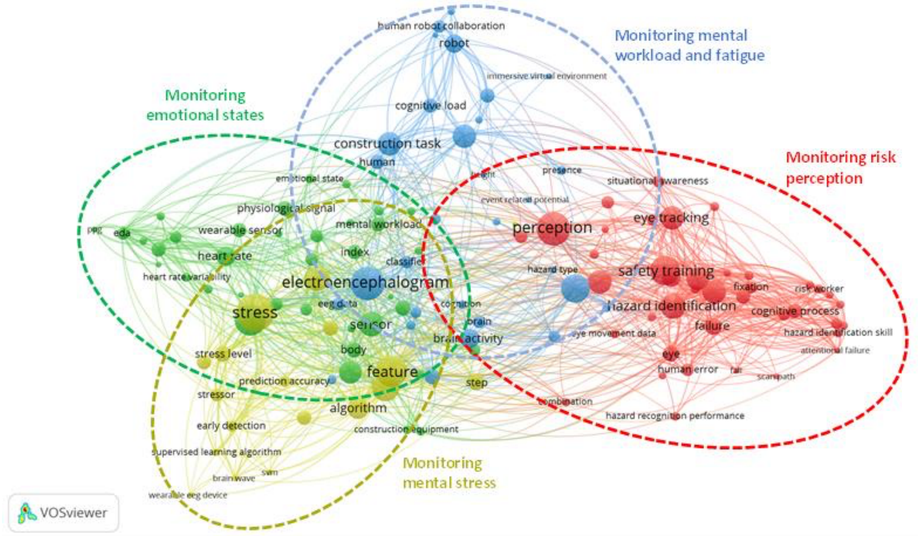


Figure 4: Applications of PMSs and WSDs for mental status monitoring.

3.5 PMSs and WSDs and Corresponding Monitored Physiological Systems

A total of ten types of PMSs and WSDs were used across the 223 mental status studies to improve construction safety and health. The types, brands, and models of these PMSs and WSDs along with the six corresponding physiological systems that were monitored using these devices are discussed in this section (Table 3).

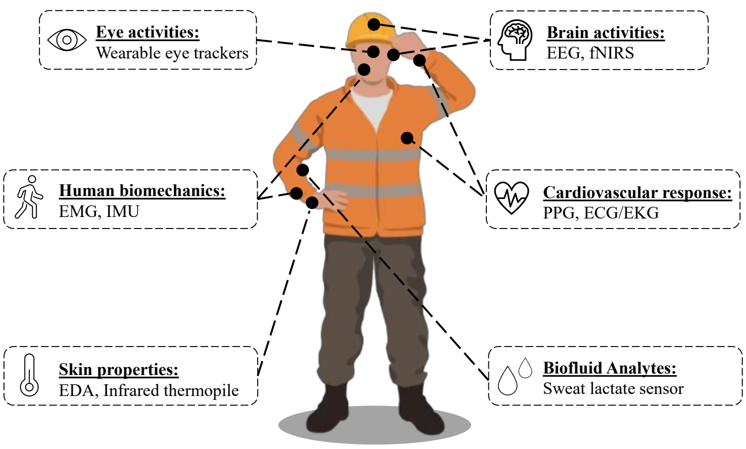


Figure 5: Sensor types and placement locations.

Table 3: Six physiological systems and ten sensor types for mental status assessment.

Category (N, %)	Sensors (N, %)	Mental Status Factors	Mechanisms Underlying the Monitoring of Mental Status Factors
Brain activities (112, 50.22%)	EEG sensors (101, 82.79%)	Risk Perception	Captures brainwave patterns linked to cognitive abilities essential for risk perception, including attention, vigilance, concentration, situational awareness, and hazard identification.
		Mental Workload and Fatigue	Captures brain activity patterns associated with cognitive load and fatigue.
		Mental Stress	Captures brainwave patterns associated with neural responses to stressors.
		Emotional States	Captures brain activity patterns associated with valence, arousal, and dominance.
	fNIRS sensors (11, 9.02%)	Risk Perception	Monitors activation in brain regions involved in risk perception, such as areas related to attention, decision-making, and working memory.
		Mental Workload and Fatigue	Monitors brain activation as indicators of cognitive resource utilization.
		Emotional States	Monitors activation level in brain regions associated with trust-building and negative emotions.
Eye activities (72, 32.29%)	Wearable eye trackers (72, 100.00%)	Risk Perception	Monitors visual patterns to provide insights into the visual attentional levels and distributions toward hazards.
		Mental Workload and Fatigue	Monitors visual attention levels as indicative of cognitive resource allocations and utilizations.
Skin properties* (42, 18.83%)	EDA sensors (41, 97.62%)	Risk Perception	Measures changes in skin conductance as an indicator of sympathetic nervous system arousal caused by perceived risks or sustained attention on hazards.
		Mental Workload and Fatigue	Measures changes in skin conductance as an indicator of sympathetic nervous system activity caused by cognitive resources exertion.
		Mental Stress	Measures changes in skin conductance caused by sympathetic nervous system arousal responses to stressors.
		Emotional States	Measures changes in skin conductance caused by sympathetic nervous system arousal as an indicator of emotional arousal.
	Infrared thermopiles (12, 28.57%)	Risk Perception	Measures changes in skin temperature caused by sympathetic nervous system arousal triggered by perceived risk.
		Mental Workload and Fatigue	Measures changes in skin temperature caused by sympathetic nervous system activity due to cognitive resources utilization.
		Mental Stress	Measures changes in skin temperature caused by sympathetic nervous system arousal responses to stressors.
		Emotional States	Measures changes in skin temperature caused by sympathetic nervous system arousal as an indicator of emotional arousal.
Cardiovascular responses (40, 17.93%)	PPG sensors (23, 57.5%)	Risk Perception	Detects cardiovascular activity as an indicator of shifts in the dominance between the sympathetic and parasympathetic nervous systems, driven by perceived risk or changes in attention level.
		Mental Workload and Fatigue	Detects cardiovascular activity resulting from the dominance of the sympathetic nervous system over the parasympathetic nervous system caused by cognitive effort exertion.

		Mental Stress	Detects cardiovascular activity resulting from the dominance of the sympathetic nervous system over the parasympathetic nervous system, serving as an indicator of sympathetic arousal in response to stressors.
		Emotional States	Detects cardiovascular activity as an indicator of shifts in the dominance between the sympathetic and parasympathetic nervous systems caused by fluctuations in emotional states.
	ECG sensors (17, 42.50%)	Risk Perception	Detects heart activity as an indicator of changes in the relative dominance between the sympathetic and parasympathetic nervous systems, driven by perceived risk or variations in attentional level.
		Mental Workload and Fatigue	Detects heart activity resulting from the dominance of the sympathetic nervous system over the parasympathetic nervous system due to cognitive effort exertion.
		Mental Stress	Detects heart activity resulting from the dominance of the sympathetic nervous system over the parasympathetic nervous system, serving as an indicator of sympathetic arousal in response to stressors.
		Emotional States	Detects heart activity as an indicator of shifts in the dominance between the sympathetic and parasympathetic nervous systems caused by fluctuations in emotional states.
Human biomechanics (4, 1.79%)	EMG sensors (2, 50.00%)	Risk Perception	Monitors facial muscle activity as an indicator of instantaneous cognitive responses to perceived risks.
		Emotional States	Monitors muscle activity from movements caused by fearful emotions in dangerous environments.
	IMUs (2, 50.00%)	Risk Perception	Measures head pitch angle to infer gaze direction toward hazards.
Biofluid analytes (1, 0.45%)	Sweat analyte sensors (1, 100.00%)	Mental Workload and Fatigue	Measures sweat lactate concentration as an indicator of the metabolic processes activated to meet the demands of ongoing tasks.

*11 studies used infrared thermopile along with EDA sensor

Brain activities: Brain activities refer to the neural signaling and associated physiological processes within the brain, forming the basis for functions such as cognition, motor control, and the regulation of bodily systems (Li *et al.*, 2022). The objectives of monitoring brain activities are to help understand humans' mental functioning and the cognitive mechanisms underlying unsafe behaviors, thus facilitating hazard prevention (Wang *et al.*, 2017). Electroencephalogram (EEG) and Functional Near-Infrared Spectroscopy (fNIRS) were employed to study humans' brain activities to monitor mental status (Table 3). EEG sensor measures the electrical activity within the brain by capturing electrical currents generated during the activation of brain cells (Teplan, 2002). These currents travel through the skull to the skin, where EEG sensors detect, amplify, and record them as measurable signals. On the other hand, fNIRS measures changes in blood oxygenation levels in the outer layers of cortex (Ferrari and Quaresima, 2012). It operates by emitting near-infrared light through the scalp and detecting the amount of light absorbed by oxygenated and deoxygenated hemoglobin (Tsunashima and Yanagisawa, 2009). A total of 86 out of 101 (85.15%) EEG-based studies and 10 out of 11 (90.91%) fNIRS-based studies reported their used sensor models. Most common EEG sensors that were used in two or more studies included Emotiv© EPOC+ (32, 31.68%), Emotiv© EPOC Flex (17, 16.83%), Neuracle© Neusen W32 (7, 6.93%), NeuroSky© TGAM (5, 4.95%), Emotive EPOC (4, 3.96%), Brain Products© actiCHamp EEG system (3, 2.97%), Muse© S (3, 2.97%), Emotiv© EPOC X (2, 1.98%), Mentalab© Explore (2, 1.98%), and LooxidLabs© Looxid Link (2, 1.98%). For fNIRS sensors, only two models were used: Artinis© Brite (7, 63.64%) and Huichuang© NirSmart (3, 27.27%).

Eye activities: Eye activities are the voluntary and involuntary actions of eyes, including pupil dilation, blinks, and gaze movements, driven by cognitive and autonomic processes (Eckstein *et al.*, 2017; Jin *et al.*, 2018). The objectives of monitoring eye activities are to provide insights into humans' cognitive development for perceiving and responding to their surroundings. Eye-tracking devices, available as either stationary or wearable sensors, were reported to be used for capturing eye activities. Since this review focuses on PMSs and WSDs, only wearable eye trackers were considered (Table 3). Eye trackers capture eye activities by illuminating users' eyes with infrared or near-infrared light and using camera to record the light reflected from the cornea (Vidal *et al.*, 2012). Out of 72 studies employing wearable eye trackers, 65 (90.28%) specified the sensor models used. Among these, the most commonly used models in two or more studies included the HTC© Vive Pro Eye (23, 31.94%), Tobii© Pro Glasses 2 (14, 19.44%), SR Research© Eye Link-II (9, 12.50%), Tobii© Pro Glasses 3 (3, 4.17%), Microsoft© HoloLens 2 (3, 4.17%), Pupil Labs© Pupil Core (3, 4.17%), Pupil Labs© HTC Vive add-on (2, 2.78%), Ergoneers© Dikablis (2, 2.78%), and SMI iView X HED (2, 2.78%).

Skin properties: Skin properties refer to the physical and biological characteristics of the skin, including skin conductance and skin temperature (ST), also known as peripheral temperature (Payne, 1991). The objectives of monitoring these skin properties are to provide insights into thermoregulatory processes that correlate with activation levels of nervous system, reflecting the body's responses to physical and mental exertion (Aryal *et al.*, 2017). Electrodermal activity (EDA) sensors and infrared thermopiles have been used to measure these properties (Table 3). EDA, also known as Galvanic Skin Response (GSR), measures changes in skin electrical conductance influenced by sweat secretion levels through electrodes attached to skin (Critchley, 2002). Infrared thermopile measures temperature over the body surface by detecting the infrared radiation emitted by the skin (Hymczak *et al.*, 2021). Among the 41 studies utilizing EDA sensors, 33 (80.49%) reported the sensor models used, while all 11 (91.67%) studies using infrared thermopiles provided this information. The most common EDA sensor models that were used in two or more studies included Empatica© E4 wristband (22, 53.66%), Shimmer© GSR (2, 4.88%), Huake© HKR-11C+ (2, 4.88%), and ErgoLab© Wearable Physiological Recording System (2, 4.88%). As for infrared thermopile, Empatica© E4 was the only sensor that was used more than once (9, 75.00%), followed by Basis© Peak Smartwatch (1, 8.33%) and Biopac© MP160 (1, 8.33%).

Cardiovascular responses: Cardiovascular responses are the physiological changes within the cardiovascular system in reaction to various stimuli such as stress and physical activity (Michael *et al.*, 1961; Raghuveer *et al.*, 2020). The objectives of monitoring these responses are to provide insights into the body's ability to sustain physical activity and mental well-being (Raghuveer *et al.*, 2020). Electrocardiogram (ECG, also referred to as EKG in some studies, but denoted as ECG throughout the remainder of this paper) sensors and Photoplethysmogram (PPG) sensors were reported in the literature as tools for monitoring humans' cardiovascular responses to assess mental status and improve construction safety and health (Table 3). ECG sensors provide a continuous measure of the heart's electrical activity through electrodes attached to skin (Kaplan Berkaya *et al.*, 2018). PPG sensors are optical devices that measure blood volume changes in microvascular tissues by emitting light, typically from an LED, onto the skin and analyzing variations in the intensity of the reflected or transmitted light (Orphanidou, 2018). It should be noted that 20 (86.96%) out of 23 PPG studies and 16 (94.12%) out of 17 of ECG studies specified the utilized sensor models. PPG sensors that were used in two or more studies included Empatica© E4 (9, 39.13%), Garmin© Vivosmart (2, 8.70%), and ErgoLab© Wearable Physiological Recording System (2, 8.70%). As for ECG devices, the sensor models that were used in two or more studies included Polar© H10 (4, 23.52%), Zephyr© BioHarness 3 (3, 17.65%), and Actiheart© 5 (2, 12.5%).

Human Biomechanics: Monitoring human biomechanics examines the movement of body segments and the forces acting on and generated within them during normal activities (Nordin and Frankel, 2001). The objectives of monitoring human biomechanics include investigating movement patterns and developing equipment and systems to prevent injuries and enhance performance (Özkaya *et al.*, 2017). Inertial Measurement Units (IMUs) and surface electromyography (sEMG) sensors have been utilized to monitor human biomechanics for mental status assessment (Table 3). IMU sensors consist of accelerometers that measure linear acceleration across x, y, and z axes, gyroscopes that track angular rotation, and magnetometers that enhance data accuracy by complementing gyroscopic measurement (Ahmad *et al.*, 2013). sEMG sensors monitor muscle activation levels by detecting electrical signals from muscle tissues through skin-mounted electrodes (Raez *et al.*, 2006). It is worth noting that all (2 out of 2, 100%) IMU studies as well as all (2 out of 2, 100%) sEMG studies provided device model details. The IMU sensors were embedded in Oculus© Rift Virtual Reality Headset (2, 100.00%), and the sEMG sensors were reported to be S&M© DL-140 (1, 50.00%) and DTing© Gesture Control Wristband (1, 50.00%).

Biofluid analytes: Biofluids, such as blood, sweat, and saliva, are the circulating liquids within living organisms that carry various analytes including cortisol, glucose, and lactate (Heikenfeld *et al.*, 2019). The objectives of measuring the concentration levels of these analytes are to provide insights into humans' immediate physiological reactions to physical and mental stressors, enabling timely interventions for potential health issues (Ma *et al.*, 2023). Sweat analyte sensors were used to track analyte concentrations in biofluids (Table 3). The only study using this type of technology developed its own sweat analyte sensor. The customized sweat analyte sensor, mounted on the skin, uses an organic electrochemical transistor (OECT) to capture electrical signals generated by the reactions between oxidase enzymes in the sensor and the analytes in sweat, enabling the detection of sweat lactate concentration levels (Huang *et al.*, 2022; Ma *et al.*, 2023).

Sections 3.6 to 3.15 examine the use of each sensor type in monitoring each of the four mental status factors – risk perception, mental workload and fatigue, mental stress, and emotional state. First, sensor locations and sampling rates are presented, followed by a discussion of the preprocessing techniques used for noise and artifact removal. Postprocessing techniques are then described, with a focus on feature extraction methods, data analysis, and mental status classification and prediction approaches, including both rule-based and AI-based methods.

3.6 Electroencephalography Sensors

Measured Factors, Sensor Location, and Sampling Rates: EEG sensors were used in 43 (38.05%) studies on monitoring risk perception, 43 (64.18%) studies on measuring mental workload and fatigue, 10 (31.25%) studies on assessing mental stress, and 13 (44.83%) studies on evaluating emotional states in construction. To collect brain data for assessing these mental status factors, most studies used off-the-shelf EEG headsets with scalp-attached electrodes. The electrode placement followed the International 10-20 System and its extensions, which map electrodes on the scalp to specific cerebral cortex lobes within the brain (i.e., frontal, temporal, central, parietal, and occipital). Each lobe is associated with unique cognitive functions. Specifically, the frontal lobe regulates perception, attention, emotions, personality, and body motion; the temporal lobe is involved in language comprehension and memory retrieval; the parietal lobe processes sensory information and contributes to spatial awareness; and the occipital lobe processes and interprets visual information (Javed *et al.*, 2025). Despite predominantly being installed on the head, two studies used ear-based EEG sensors for monitoring mental fatigue and mental stress (Bae *et al.*, 2024; Fang *et al.*, 2024). The EEG sampling rates reported in the studies varied between 1 Hz and 1000 Hz, depending on the utilized sensors.

Preprocessing: For risk perception studies, the most commonly used preprocessing techniques included: (1) band-pass filtering to eliminate noise originating from external sources, such as sensor vibrations and interference from nearby electronic devices, which typically fall outside the brainwave frequency range (Chae *et al.*, 2024a); (2) notch filtering to address power line interference with cutoff frequencies varying by regions (e.g., 50Hz in China, 60Hz in the USA) (Ombao *et al.*, 2016); and (3) Independent Component Analysis (ICA) to remove artifacts arising from human biological functions, such as muscle activity, eye movements, and heart rhythms, which partially overlap with brainwave frequencies (Jiang *et al.*, 2019). It should be noted that six risk perception studies specifically mentioned using Finite Impulse Response (FIR) filters for band-pass filtering (Jeon and Cai, 2021, 2022a, 2023; Ke *et al.*, 2019; Ke, Zhang, *et al.*, 2021; Wu *et al.*, 2023). Besides these common preprocessing techniques, two risk perception studies also reported using clustering techniques to reduce inter-channel interference between electrodes (Chen *et al.*, 2018; Wang *et al.*, 2019). Additionally, Artifact Subspace Reconstruction (ASR), which incorporated the use of Principal Component Analysis (PCA) (Blum *et al.*, 2019), was reported in one study to mitigate non-stationary artifacts such as motor-related signals (Kim *et al.*, 2023).

For studies on mental workload and fatigue, the same common preprocessing steps, including band-pass filtering, notch filtering, and ICA, were primarily applied. Both FIR filters (Fang *et al.*, 2024; Liu *et al.*, 2023; Qin *et al.*, 2024; Qin and Bulbul, 2023a; Wu *et al.*, 2023; Xing *et al.*, 2019, 2020) as well as infinite impulse response (IIR) filters were used for band-pass filtering (Wang *et al.*, 2023). Besides these common preprocessing techniques, some mental workload and fatigue studies adopted other methods to enhance signal quality. Specifically, a Dependent Component Analysis (DCA)-based method was utilized to eliminate intrinsic artifacts, and a discrete wavelet transforms adaptive predictor filter (DWT-APF) was used to reduce motion artifacts (Liu *et al.*, 2024). ASR was also reported for artifact removal (Tehrani *et al.*, 2021), and clustering techniques were applied for inter-channel interference reduction (Li, Wang, *et al.*, 2019). Additionally, smoothing filters, such as moving average filters, third-order one-dimensional median filters, and Savitzky-Golay filters, were used to suppress large signal spikes (Aryal *et al.*, 2017; Mehmood *et al.*, 2022; Mehmood, Li, Qarout, *et al.*, 2023; Mehmood, Li, Umer, *et al.*, 2023). Some EEG headsets also featured on-board noise cancellation for initial noise removal (Mehmood *et al.*, 2022; Mehmood, Li, Qarout, *et al.*, 2023; Mehmood, Li, Umer, *et al.*, 2023).

Mental stress studies only applied the common preprocessing techniques—band-pass filtering, notch filtering, and ICA—without reporting any additional methods or sensor specifications. For emotional state studies, the most common preprocessing steps were employed, including band-pass filtering, notch filtering, and ICA, with three studies specifying the use of FIR filters for band-pass filtering (Jang *et al.*, 2024; Wu *et al.*, 2023; Xing *et al.*, 2019).

These preprocessing techniques were most commonly implemented using MATLAB-based EEGLAB toolbox, while other software packages were also reported in a few studies, including MATLAB-based FieldTrip toolbox and Python-based MNE open-source package.

Postprocessing: The collected and preprocessed time-series EEG data, represented as continuous waveforms, were segmented into epochs and utilized to extract time-, frequency-, and time-frequency domain features for mental status analyses. Additionally, nonlinear features were also extracted in one study (Mir *et al.*, 2024). Time-domain features, such as the mean, root mean square, variance, standard deviation, skewness, and kurtosis of signal amplitude, were directly derived from the EEG data segments to examine brainwave signal changes over time (Ombao *et al.*, 2016). A key time-domain feature is the Event-Related Potential (ERP), characterized by distinct amplitude spikes in the EEG waveform within specific time windows following external stimuli or cognitive events, providing insights into humans' cognitive processes (Luck, 2014).

Frequency-domain features were extracted by applying Fast Fourier Transform (FFT) to time-series EEG data segments, which converts the signal from the time domain into the frequency domain. This transformation reveals the frequency components of the EEG signal. EEG signal frequencies are typically divided into five major bands, ordered from low to high, including: delta (δ), theta (θ), alpha (α), beta (β), and gamma (γ), each associated with specific cognitive states that are further discussed in (Saby and Marshall, 2012). However, the literature showed some variability in the boundaries defining these frequency bands across the reviewed EEG studies, potentially stemming from factors such as differing hardware configurations and population demographics, which can affect the interpretation of EEG features (Albada *et al.*, 2007; Newson and Thiagarajan, 2019). Among the extracted frequency-domain features, Power Spectral Density (PSD) was widely used in the reviewed studies. Specifically, PSD estimates the distribution of power across different frequency bands within the EEG signal, enabling the identification of dominant cognitive activities associated with specific frequency ranges (Tost *et al.*, 2024). Based on the PSD, the total power of each frequency band was computed and used either independently or in equations to derive indices that quantify specific cognitive states. Among these indices, the ratio of total power in one or more frequency bands to other bands within specific brain regions was most frequently used (i.e., ratio indices). These ratio indices reveal the relative dominance of neural activity patterns associated with cognitive functions as represented by specific frequency bands (Schmidt *et al.*, 2013).

Time-frequency domain features were extracted from time-series EEG data through Wavelet Packet Transform (WPT) or Short-Time Fourier Transform (STFT), capturing variations in EEG frequency contents over time (Morales and Bowers, 2022).

Aside from time-, frequency-, and time-frequency domain features extracted using traditional linear methods, one study also extracted features using nonlinear analytical methods (Mir *et al.*, 2024). These nonlinear features (i.e., entropy-based features, fractal dimension features, and detrended fluctuation analysis-based features) assess the self-similarity, complexity, and long-range correlations of EEG signals, revealing patterns not captured by linear features.

These time-, frequency-, time-frequency domain features, and nonlinear features formed the foundation for the factor-specific EEG-based mental status analyses, enabling the derivation of additional metrics and facilitating the identification and interpretation of brain activity patterns unique to various cognitive states. This will be further discussed in the subsequent factor-specific mental status analyses.

Risk Perception: Twenty-four out of the forty-three EEG-based risk perception studies have either analyzed risk perception-related ERPs or utilized the total power of specific frequency bands and ratio indices as indicators of risk perception, comparing them against baseline values established under controlled or normal conditions to examine variations in risk perception behavior (Chae *et al.*, 2024a; Chen *et al.*, 2020; Ke, Du, *et al.*, 2021; Ouyang and Luo, 2025; Shayesteh and Jebelli, 2022; Zhang *et al.*, 2022). The relationship between EEG features and risk perception abilities varied depending on the features and indices selected. Several studies provided summaries of these indices and their relationship with specific cognitive abilities (Choi *et al.*, 2023; Ke, Zhang, *et al.*, 2021; Mir *et al.*, 2024; Sur and Sinha, 2009).

For the other nineteen EEG-based risk perception studies, both rule-based and AI-based approaches were used for in-depth analyses. Specifically, three studies adopted rule-based approaches (Chen, Dai, *et al.*, 2017; Wang *et al.*, 2017, 2019), where a ratio index of alpha (α) band power to the total power of other frequency bands was computed to measure concentration level, and subsequently used to categorize workers' vigilance into six levels according to the EEG-vigilance stages model by Olbrich et al. (2009). The other sixteen studies employed AI-based approaches, in which the segmented EEG data were first labeled with either predefined hazard type, personality traits, or concentration levels. Personality labeling during risk perception was based on individuals' responses to the Big Five Personality Traits Questionnaire (Goldberg, 1990). Concentration levels were labeled based on self-reported attention assessments using the Mindful Attention Awareness Scale (Brown and Ryan, 2003), Attention-Related Cognitive Errors Scale (Cheyne *et al.*, 2006), Cognitive Failures Questionnaire (Broadbent *et al.*, 1982), Mind Wandering Scale (Mowlem *et al.*, 2019), and Karolinska Sleepiness Scale (KSS) (Åkerstedt and Gillberg, 1990). Additional concentration level labeling methods included individuals' performance in the Go/No-Go task (Georgiou and Essau, 2011) and ratings derived from the EEG-vigilance stages model by Olbrich et al. (2009). Time-, frequency-, and time-frequency domain features, along with nonlinear features were then extracted from the labeled segments and input into AI models to assess risk perception. Twelve out of the sixteen AI-based risk perception studies solely used EEG features to train AI models. Among these twelve studies, individuals' attentional states were successfully classified using a support vector machine (SVM) (Ke *et al.*, 2019; Ke, Zhang, *et al.*, 2021) and a Random Forest (RF) (Mir *et al.*, 2024). Hazard occurrence and types were effectively predicted using an SVM (Li, Ouyang, *et al.*, 2024), a Category and Boosting (CatBoost) model (Jeon and Cai, 2022a), a Convolutional Neural Network (CNN) (Zhou *et al.*, 2021; Zhou and Liao, 2024), and an extremely randomized trees (ExtraTrees) (Jeon and Cai, 2022b). Furthermore, individuals' risk perception performance was predicted using a Bayesian observer (Zhou and Liao, 2023a), a CNN (Zhou and Liao, 2023b), and a CatBoost (Jeon and Cai, 2021). Additionally, individuals' personality traits that are closely related to risk perception were categorized using a regression model (Wang and Liao, 2023).

The other four AI-based risk perception studies combined EEG data with additional sensor data. Table 4 summarizes these sensor fusion studies, outlining their objectives, sensor data combinations, benchmarks for data labeling and model performance evaluation, as well as the most effective models used.

Mental Workload and Fatigue: Thirty-one out of the forty-three EEG-based mental workload and fatigue studies utilized frequency bands power or computed ratio indices to quantify mental workload and mental fatigue, determining cognitive demand variations by comparing them against baseline values established under normal or low-demand conditions (Chen, Taylor, *et al.*, 2017; Li, Zhu, *et al.*, 2024a; Qin and Bulbul, 2023b). The relationships between indices and cognitive load and fatigue were dependent on the indices selected, as summarized in several studies (Choi *et al.*, 2023; Xing *et al.*, 2019). Besides the ratio indices, additional metrics were developed in some studies, including a mental fatigue score based on gravity frequency and power spectral entropy (Li, Wang, *et al.*, 2019), as well as a mental workload indicator derived from the wavelet approximate coefficients energy (Ke, Du, *et al.*, 2021).

The other twelve studies relied on AI-based approaches to classify mental workload and fatigue, and no rule-based approaches were employed. Specifically, EEG data were segmented and labeled by individuals' responses to subjective questionnaires, including the NASA-Task Load Index (NASA-TLX) (Hart and Staveland, 1988), 9-point Rating Scale (RS9) (Paas, 1992), Stanford Sleepiness Scale (SSS) (Hoddes *et al.*, 1973), KSS, Multidimensional Fatigue Inventory (MFI) (Smets *et al.*, 1995), Swedish occupational fatigue inventory (SOFI) (Åhsberg *et al.*, 1997), and a Modified Rating-of-Fatigue (ROF) scale (Fang *et al.*, 2024). Time-, frequency-, and time-frequency-domain features extracted from these labeled segments were input into AI models. Six out of the twelve AI-based studies solely relied on these EEG features, in which a Multilayer Perceptron (MLP) (Liu, Habibnezhad, *et al.*, 2021), a Long Short-Term Memory (LSTM) (Mehmood, Li, Qarout, *et al.*, 2023; Qin and Bulbul, 2023a), a Bidirectional Long Short-Term Memory (BiLSTM) (Mehmood, Li, Qarout, *et al.*, 2023), an ensemble classifier (Okunola *et al.*, 2024), a Gramian Angular Difference Field (GADF) along with CNN (Wang, Ma, *et al.*, 2024), and a developed 1D-CNN-LSTM model (Qin *et al.*, 2024) were demonstrated effective in mental workload and fatigue classification. The other six of the twelve studies integrated AI-based approaches with sensor fusion for mental workload and fatigue classification (see Table 4).

Mental Stress: Four out of the ten EEG-based mental stress studies quantified mental stress levels using either frequency band power or the Asymmetry Index (ASI) method (Lopez-Duran *et al.*, 2012), and compared the metric values to baselines established under normal or controlled conditions to monitor variations in stress levels. Among the used indices, beta (β) band power has a positive relationship with mental stress level (Bae *et al.*, 2024; Chae *et al.*, 2021). ASI, measuring the difference between the natural logarithms of power in the alpha (α) band within the left and right frontal brain regions, negatively correlates with stress levels (Bae *et al.*, 2024; Choi *et al.*, 2023; Ke, Du, *et al.*, 2021).

The other six EEG-based mental stress studies adopted only AI-based approaches for further mental stress classification, and no rule-based approaches were reported. Specifically, time- and frequency-domain features were extracted from data segments labeled based on either: (1) salivary cortisol level, a hormone highly associated with stress (Jebelli, Choi, *et al.*, 2019); (2) the Self-Assessment Manikin (SAM) scale (Bradley and Lang, 1994); or (3) the Korean Occupational Stress Scale (Chang *et al.*, 2005). These labeled features were fed into AI models, among which an Online Multi-Task Learning (OMTL)-VonNeuman (Jebelli, Khalili, *et al.*, 2019a), a GSVM (Jebelli, Hwang, *et al.*, 2018a), an SVM (Jebelli *et al.*, 2018), a CNN (Jebelli, Khalili, *et al.*, 2019b), and a Fully Connected Neural Network (FCNN) (Jebelli *et al.*, 2020) proved effective in classifying mental stress levels. In addition, one study classified the type of stress (i.e., positive stress, or negative stress) instead of mental stress levels, using a deep learning model composed of multiple convolutional and LSTM layers (Lee and Lee, 2022a). All these AI models were trained using EEG data only, and no sensor fusion was reported in the reviewed studies.

Emotional States: Emotional states were primarily assessed through valence and arousal levels based on the bipolar valence-arousal emotion model by Russell (1980). Valence is the level of pleasantness, whereas arousal indicates level of activation or intensity of an emotional experience (Russell, 1980). Dominance, defined as the feeling of control or power in a situation, was included in one study as an additional emotional dimension according to the tri-dimensional emotion model by Mehrabian (1995). Aside from these three emotional dimensions, trust—considered a type of emotion (Ekman, 1992; Plutchik, 1980)—was also measured in one study (Chen and Chan, 2024).

Twelve out of the thirteen EEG-based emotional states studies measured these emotional dimensions either using various PSD-based metrics or ERP amplitudes, and subsequently compared them to baseline values established under controlled or normal conditions to assess individuals' emotional fluctuations. Valence was measured using the frontal EEG asymmetry (FEA) method, which examines the difference in activation levels between the left and right frontal brain regions (Davidson *et al.*, 1990). This difference was quantified through indices derived from the power of alpha (α) and beta (β) bands recorded from two electrode channels (i.e., F3, F4 or AF3, AF4) within frontal lobe regions associated with emotion control (Choi *et al.*, 2023; Hwang *et al.*, 2020; Jebelli *et al.*, 2017; Shin *et al.*, 2024; Song *et al.*, 2022; Xing *et al.*, 2019, 2021). A positive index value indicates greater left frontal activation, reflecting higher valence (positive emotion), whereas greater right frontal activation corresponds to lower valence (negative emotion). Arousal was measured using either ratio indices or ERP amplitudes. For the ratio index approach, the emotional arousal was quantified using PSDs of alpha (α) and beta (β) bands from various channels (e.g., AF3, AF4, F3, F4). The relationship between index values and arousal levels varied depending on the equations used (Choi *et al.*, 2023; Hwang *et al.*, 2018; Shin *et al.*, 2024; Song *et al.*, 2022; Xing *et al.*, 2019, 2021). For the ERP-based approach, the Late Positive Potential (LPP) ERP amplitude was used as an indicator of emotional arousal, with larger amplitudes reflecting higher emotional arousal (Wu *et al.*, 2023). Dominance was assessed using the sum of alpha (α)/beta (β) power ratios from three channels (F6, F8, P8), where an increased index value indicated greater dominance (Xing *et al.*, 2019). Finally, trust was measured in one study using the alpha (α) band power relative to the total power across all frequency bands (Chen and Chan, 2024), where a higher relative alpha (α) band power was associated with a lower level of trust.

The remaining study relied on a rule-based approach by integrating EEG indices with heart rate measures to develop a noise annoyance level index that evaluates individuals' well-being in noisy environments (Xing *et al.*, 2021). No AI-based approaches were employed for EEG-based emotional state monitoring.

In summary, EEG sensors have been employed to monitor all four mental status factors, reflecting their capacity to directly capture neural activity underlying diverse cognitive and affective states (Jebelli, Hwang, *et al.*, 2018b). Across studies, EEG data preprocessing has been dominated by conventional workflows, including band-pass filtering, notch filtering, and ICA. However, these methods are reportedly not fully sufficient to address specific data quality issues, particularly in construction settings where intensive physical activity and dynamic site conditions introduce excessive noise and artifacts (Chen *et al.*, 2018; Liu *et al.*, 2020; Wang *et al.*, 2019). These challenges were addressed by employing additional preprocessing steps, targeting motion and ocular artifacts, reducing inter-channel interference, and smoothing signal spikes. Notably, these additional steps were reported only in studies collecting EEG data during active body movements, such as material transport and lifting, as well as simulated equipment operation. Preprocessing software adoption has leaned toward EEGLAB, likely due to its ease of use (Li, Kong, *et al.*, 2024; Martina, 2025). At the postprocessing stage, EEG features have been extracted primarily using linear methods, such as FFT and STFT. However, EEG signals are intrinsically non-stationary and nonlinear (Chen, Zhao, *et al.*, 2015; Kesić and Spasić, 2016), therefore nonlinear features can provide richer information and enhance both the accuracy and efficiency of mental status assessment (Kesić and Spasić, 2016; Li *et al.*, 2013; Mir *et al.*, 2024). Nevertheless, nonlinear EEG features were reported in only one study (Mir *et al.*, 2024), indicating an underexplored direction with significant potential to strengthen mental status analysis. In terms of data interpretation and classification, research on risk perception, mental workload and fatigue, and mental stress has advanced from statistical comparisons and rule-based approaches to AI-based models, where EEG features are applied independently or in combination with other sensors. Emotional state monitoring, in contrast, has not incorporated AI classification in any reviewed EEG studies, warranting further investigations. Hardware deployment also shows a gradual transition: while scalp electrodes remain predominant, recent studies have adopted ear-EEG and headset-embedded noise-cancellation, signaling movement toward less intrusive and more field-ready solutions, although these approaches have not yet been fully validated and tested on real-world construction jobsites.

3.7 Wearable Eye Trackers

Measured Factors, Sensor Location, and Sampling Rates: Wearable eye trackers were used in 65 (57.52%) studies on risk perception and 12 (17.91%) studies on mental workload and fatigue. These sensors were either integrated into Virtual Reality (VR) head-mounted displays (HMDs) or incorporated into specialized standalone eyewear to track eye activity. The sensor sampling rates ranged from 10 Hz to 200 Hz, depending on the deployed eye-tracking devices.

Preprocessing: Only a few studies reported preprocessing procedures to enhance data quality, while most studies using wearable eye trackers did not mention preprocessing the collected raw eye tracking data.

For risk perception, two studies preprocessed raw pupil size data by removing blinks and interpolating the resulting gaps (Kim *et al.*, 2021; Zeng, Chen, Zheng, He, *et al.*, 2023). Additionally, Zeng et al. (2023a) applied low-pass filtering and further data smoothing in alignment with previous research.

Similarly, studies on mental workload and fatigue reported pupil size preprocessing techniques such as blink removal and interpolation (Li *et al.*, 2020; Liu and Ham, 2024; Liu *et al.*, 2023; Zeng, Chen, Zheng, He, *et al.*, 2023), as well as low-pass filtering and data smoothing (Zeng, Chen, Zheng, He, *et al.*, 2023). In addition, one study applied a sliding-mean-type of rolling filter without indicating the specific type of noise it addressed (Liu *et al.*, 2023). Li et al. (2024b) also reported using a moving-average type rolling filter on collected gaze data without specifying the source of noise.

No software was predominantly used for eye tracking data preprocessing, with only a few studies reporting the use of some proprietary software packages, including Tobii© Pro Lab, ErgoLab© and R-based PupillometryR package.

Postprocessing: From the preprocessed eye tracking data, three core eye tracking metrics were extracted as basis for mental status analyses. These included fixations, saccades, and pupil size. Fixations refer to sustained gaze on an area of interest for a minimum duration (Bhoir *et al.*, 2015), which ranged from 100 ms to 200 ms in the literature (Akcay, 2022; Albeaino *et al.*, 2023; Kim *et al.*, 2022; Liu, Liao, *et al.*, 2021; Pooladvand and Hasanzadeh, 2023). Fixations are used to analyze visual attention by measuring two key aspects: fixation count, the number of times gaze is directed at a specific area, and fixation duration, the total time spent fixating on that area (Bhoir *et al.*, 2015). Saccades are rapid eye movements between fixations, measured by key metrics such as saccade count, velocity, duration, and amplitude, offering insights into attention shifts and speed of visual processing (Bhoir *et al.*, 2015; Kim *et al.*, 2021). Pupil size refers to the physical measurement of the pupil's diameter, which provides insights into attention (Luo *et al.*, 2024). Some additional measures derived from these three eye tracking metrics included ratios and percentages of on-target or off-target fixations, mean fixation durations and fixation counts, as well as time to first on-target fixation (Hasanzadeh *et al.*, 2017a; Jeelani *et al.*, 2018; Zeng, Chen, Zheng, Zhang, *et al.*, 2023). These metrics, which reflect eye activity as a direct measure of attention, provide insights into cognitive resource allocation and are used for factor-specific analyses, as discussed in the rest of this section.

Risk Perception: Among the sixty-five eye-tracking-based risk perception studies, sixty either analyzed fixation patterns to understand risk identification process or compared eye metrics against baseline values established under controlled or normal conditions to evaluate variations in attention (Albeaino *et al.*, 2023, 2025; Bhoir *et al.*, 2015; Hasanzadeh *et al.*, 2017b; Luo *et al.*, 2024; Pooladvand, Kiper, *et al.*, 2022). Longer fixations and higher fixation frequency on specific areas of interest, as well as increased pupil size, were considered indicators of sustained attentional allocation. The other five eye-tracking-based risk perception studies adopted only AI-based approaches to predict individuals' automaticity, attentiveness, and risk perception performance, with no rule-based approaches being reported. Specifically, eye tracking data were segmented and labeled with automaticity or attention level, as well as risk perception performance, to train AI models. Labeling of automaticity and attentiveness level was based on individuals' visual checking on potential hazards during data collection. Sylvester Onuchukwu et al. (2024) solely used eye tracking data to train an SVM model, which effectively classified individuals' levels of automaticity. Four out of these five AI-based risk perception studies combined eye metrics with additional sensor data as inputs to AI models (see Table 4).

Mental Workload and Fatigue: Nine out of the twelve eye-tracking-based mental workload and fatigue studies tracked and compared eye metrics to baseline values recorded under normal or controlled conditions to measure mental workload variations (Li, Li, *et al.*, 2019; Li, Zhu, *et al.*, 2024a; Liao *et al.*, 2021; Liu and Ham, 2024; Wang *et al.*, 2018; Zeng, Chen, Zheng, He, *et al.*, 2023). Elevated mental workload and fatigue were associated with higher fixation counts, longer fixation durations, increased blink rates, and prolonged blink durations. Furthermore, reduced pupil size was linked to greater mental fatigue (Li, Li, *et al.*, 2019; Liao *et al.*, 2021), whereas increased pupil diameter was linked to higher mental workload (Liu and Ham, 2024; Zeng, Chen, Zheng, He, *et al.*, 2023). The other three studies employed AI-based approaches to classify mental workload and fatigue, and no rule-based approaches were reported. Specifically, eye activity metrics were segmented and labeled based on self-reported workload using NASA-TLX, SSS, and Japanese Subjective Fatigue Symptoms Questionnaire (Sakai, 2002). Two out of the three AI-based studies solely used these labeled eye metrics for training AI models, where SVM, RF, and Linear Discriminant Analysis (LDA) achieved best performance in classifying mental fatigue (Li *et al.*, 2020; Li, Zhu, *et al.*, 2024b). The other AI-based study combined eye metrics with additional sensor measures to recognize general fatigue (Liu *et al.*, 2023), as summarized in Table 4.

In summary, wearable eye trackers have been applied more extensively to monitor risk perception than mental workload and fatigue, while no eye-tracking-based studies have addressed mental stress or emotional states. This points to a gap in applying eye tracking for stress and emotion monitoring in construction, despite such applications being demonstrated in other domains including neuroscience (Lim *et al.*, 2020; Tarnowski *et al.*, 2020; Yousefi *et al.*, 2022). Across both risk perception and mental workload and fatigue studies, preprocessing was minimally reported, with most analyses relying on raw collected data and only a few applying blink removal, interpolation, or smoothing filters on pupil measures. No dominant software packages were reported for eye tracking data, and proprietary platforms such as Tobii Pro Lab, ErgoLab, and PupillometryR were reported only occasionally. At the postprocessing stage, analyses primarily focused on three core metrics: fixations, saccades, and pupil size, supplemented by derived measures such as fixation ratios and blink rates. For data interpretation and mental status classification, most studies relied on statistical analyses of metric changes, with no adoption of rule-based classification. The absence of rule-based classification likely reflects the substantial individual variability in eye activity, which constrains the establishment of universal cutoff thresholds for mental status monitoring (Walcher et al., 2025). Only a limited number of studies applied AI-based approaches, using eye-tracking data either alone or in combination with other sensors. Notably, in AI sensor fusion applications, eye tracking data has always been paired with EEG features except for one study (Table 4). This frequent pairing indicates that researchers regard the two as complementary, with EEG capturing underlying neural activity and eye tracking providing contextual information on attention, thereby yielding a more comprehensive representation of mental status. Hardware deployment followed two main approaches: standalone smart glasses and modules integrated into VR HMDs. This division suggests complementary applications of eye trackers in research, with VR-integrated trackers supporting immersive training research and standalone systems enabling field monitoring.

3.8 Electrodermal Activity Sensors

Measured Factors, Sensor Locations, and Sampling Rates: EDA sensors were used in 8 (7.08%) studies on risk perception, 10 (14.93%) studies on mental workload and fatigue, 17 (53.13%) studies on mental stress, and 10 (34.48%) studies on emotional states. These sensors were integrated into wristbands or finger straps and collected data at sampling rates ranging from 4 Hz to 1000 Hz, depending on the devices deployed.

Preprocessing: For studies on risk perception, the most commonly used preprocessing techniques included applying high-pass filters to remove noise caused by variations in temperature, humidity, powerline interference, and EDA electrode impedance. In addition, rolling filters were commonly used to eliminate noise from sensor motion and muscle activity typically found in EDA data. Rolling filters were also used to remove large-magnitude spikes attributed to excessive body motion and electrode pressure, electromagnetic interference, as well as sensor adjustments (Choi, Jebelli, *et al.*, 2019; Taylor *et al.*, 2015). Low-pass filters, though less commonly used, were reported in two studies to remove motion noise and physiological artifacts such as respiration (Kim *et al.*, 2021; Lee and Hasanzadeh, 2024). It should be noted that two studies specifically mentioned the use of second-order filters for high-pass filtering (Choi, Jebelli, *et al.*, 2019; Choi, Lee, *et al.*, 2019), with one study specifying the filter type as a Hamming window FIR filter (Choi, Jebelli, *et al.*, 2019). In addition, two studies reported using moving average filters as the rolling filter (Choi, Lee, *et al.*, 2019; Lee *et al.*, 2021). Furthermore, the low-pass filtering was implemented using either a Butterworth IIR filter (Lee and Hasanzadeh, 2024) or a Blackman window FIR filter (Kim *et al.*, 2021).

For studies on mental workload and fatigue, low-pass filtering was the most frequently used preprocessing technique, which was employed to address common EDA noise from sensor motion noise, power line interference noise, magnetic field interference, and nearby machinery noise (Liu *et al.*, 2023; Mehmood *et al.*, 2024; Mehmood, Li, Umer, *et al.*, 2023; Sakib *et al.*, 2021). One study specified using a Butterworth IIR low-pass filter (Sakib *et al.*, 2021). High-pass and rolling filters were also used in three studies for the same purpose mentioned in the risk perception studies (Mehmood *et al.*, 2024; Mehmood, Li, Umer, *et al.*, 2023; Shayesteh *et al.*, 2023), with one study indicating the use of a moving average filter as the rolling filter (Shayesteh *et al.*, 2023). Finally, a band-pass filter and a DWT-APF were applied in one study to reduce noise from flicker and generation-recombination effects and to remove motion artifacts that partially overlapped with the frequencies of the collected EDA signal, respectively (Liu *et al.*, 2024).

Mental stress studies applied the same common preprocessing techniques used in the risk perception and mental workload and fatigue studies. Specifically, low-pass filters were most frequently used, followed by rolling filters and high-pass filters. It should be noted that two studies specified using Butterworth IIR filters for low-pass filtering (Ardecani *et al.*, 2024; Sakib *et al.*, 2021), and four studies reported using moving average filters as the rolling filters (Lee, Choi, Jebelli, *et al.*, 2020; Lee *et al.*, 2019; Lee and Lee, 2022b; Ojha, Shakerian, *et al.*, 2023). In addition to these common preprocessing techniques, Hampel filters were applied in three studies to remove outliers (Ardecani *et al.*, 2024; Jebelli, Choi, *et al.*, 2019; Ojha, Shakerian, *et al.*, 2023); a DWT-APF was adopted in two studies to mitigate motion artifacts with frequencies partially overlapping those of the collected EDA signal (Lee, Choi, Jebelli, *et al.*, 2020; Lee *et al.*, 2019); and a notch filter was used to mitigate powerline interference (Jebelli, Choi, *et al.*, 2019). In addition, a reference-signal-based method was proposed in two studies for removing respiration noise (Lee, Choi, Jebelli, *et al.*, 2020; Lee *et al.*, 2019).

For studies on emotional states, the most common preprocessing techniques included low-pass filters, rolling filters, and high-pass filters. Reasons behind applying these filters were similar to the ones discussed in risk perception as well as mental workload and fatigue studies. Three studies reported using Butterworth IIR filters for low-pass filtering, and two of these studies further specified the filters to be a first-order Butterworth low-pass filter (Xu *et al.*, 2024) and a third-order Butterworth IIR low-pass filter (Chong *et al.*, 2022). In addition, two studies identified the rolling filter as either a median filter (Chong *et al.*, 2022) or a moving average filter (Xu *et al.*, 2024).

These preprocessing steps were most commonly implemented using MATLAB-based Ledalab toolbox, while one study reported using a data processing platform named ErgoLab.

Postprocessing: The EDA-based studies either relied on the preprocessed EDA data or applied varying decomposition methods, including convex optimization-based EDA (cvxEDA), continuous decomposition analysis (CDA), and sparse decomposition, to decompose the preprocessed EDA signal into the tonic (electrodermal level, EDL) and phasic (electrodermal response, EDR) components. EDL represents general changes in sympathetic arousal over time, and EDR indicates acute sympathetic response to external stimuli (Choi, Lee, *et al.*, 2019). Time-domain features, such as mean, median, and standard deviation of EDA amplitudes, number of EDRs, and sum of EDR amplitudes, were directly calculated from time-series EDA, EDL, and EDR data. Frequency-domain features, such as mean frequency and spectral power were also extracted, although specific extraction methods were not detailed in the reviewed studies. These time- and frequency-domain features, reflecting variations in skin conductance primarily driven by sympathetic responses to different mental status factors, served as the foundation of factor-based mental status analyses.

Risk Perception: Four out of the eight EDA-based risk perception studies compared EDA features to baseline values collected under normal or controlled conditions to measure the variations in risk perception behavior, where higher amplitudes of EDA, EDL, and EDR have been associated with increased sympathetic arousal, reflecting greater attentiveness, alertness, and heightened perceived risk levels (Chae *et al.*, 2024a, 2024b; Choi, Jebelli, *et al.*, 2019; Lee and Hasanzadeh, 2024). The other four studies relied only on AI-based approaches for EDA-based risk perception assessment, and no rule-based approaches were used. Specifically, time-series EDA signals were segmented and labeled with risk levels based on safety hazards in images viewed by individuals during data collection. Time- and frequency-domain EDA features were extracted from these segments and input into AI models to classify perceived risk or inattentiveness. Only one study (Choi, Lee, *et al.*, 2019) relied solely on these EDA features for training a K-nearest neighbors (KNN) model, which successfully classified perceived risk. The other three AI-based studies combined EDA features with additional sensor data to monitor inattentiveness and perceived risks, details of which are summarized in Table 4.

Mental Workload and Fatigue: Two out of the ten EDA-based mental workload and fatigue studies compared EDA to baseline values collected under normal conditions, where an increase in EDA amplitude was associated with elevated mental workload and fatigue (Alotaibi *et al.*, 2024; Mehmood *et al.*, 2024). The other eight studies relied only on AI-based approaches for mental workload and fatigue classification, and no rule-based approaches were used. Specifically, time-series EDA data were segmented and labeled based on either participants' responses to NASA-TLX or a customized fatigue level survey (Liu *et al.*, 2023). From these labeled segments, time- and frequency-domain EDA features (e.g., mean amplitude and frequency of EDA, EDL, and EDR) were extracted. No AI-based studies relied solely on EDA features for mental workload and fatigue classification. Instead, all eight AI-based studies combined these EDA features with other sensor measures (e.g., heart rate, heart rate variability, pupil size, EEG, and ST) to train AI models for classifying mental workload and fatigue level (see Table 4).

Mental Stress: Twelve out of the seventeen EDA-based mental stress studies compared EDA amplitudes to baseline measures under normal or controlled conditions to observe fluctuations in stress levels, where elevated EDA levels were associated with heightened mental stress (Ardecani *et al.*, 2024; Chae *et al.*, 2021; Jebelli *et al.*, 2018; Muley and Wang, 2024). The remaining five studies employed only AI-based approaches for mental stress classification, and no rule-based approaches were reported. Specifically, time-series metrics (e.g., EDA, EDL, and EDR) were segmented and labeled based on stress levels assessed by construction professionals or measured using the CARMA self-annotation stress rating (Girard, 2014), the SAM scale, or individuals' salivary cortisol levels. From these labeled segments, time- (e.g., mean EDL, root mean square and standard deviation of EDR) and frequency-domain (e.g., mean frequency and spectral power of EDR) features were then extracted to train AI models for mental stress classification. All five AI-based EDA mental stress studies combined the extracted EDA features with additional sensor data for mental stress classification (see Table 4), and no study relied only on EDA features for such purposes.

Emotional States: Nine out of the ten EDA-based emotional states studies tracked changes in EDA amplitude by comparing them to baseline values collected under normal conditions, associating increased EDA magnitude with increased anxiety and emotional arousal (Lee and Hasanzadeh, 2024; Subedi *et al.*, 2021; Xu *et al.*, 2024). The remaining study employed an AI-based approach for emotional state classification (Chong *et al.*, 2022), and no rule-based approaches were reported. Specifically, time-domain features—such as the mean, standard deviation, and average rise time of EDA amplitude—were extracted from the preprocessed and segmented signals. These features were labeled with emotional valence categories (neutral, positive, or negative) based on the emotion types assigned to pictures from the International Affective Picture System database (Lang *et al.*, 1997), as well as participants' responses to the Positive and Negative Affect Schedule (PANAS) emotional self-rating scale (Watson *et al.*, 1988). These labeled EDA features were then used to train an SVM model, which achieved high accuracy for emotional valence classification. No sensor data fusion was reported for AI-based emotional states monitoring.

In summary, EDA sensors have been applied most widely to monitor mental stress, with fewer studies addressing mental workload, emotional states, and risk perception. This distribution reflects EDA's direct measure of sympathetic arousal, making it naturally suited for stress monitoring (Choi, Lee, *et al.*, 2019). Across EDA studies on the four mental factors, the most common preprocessing techniques included high-pass, low-pass, and rolling filters, but they were employed inconsistently and not combined into a streamlined pipeline. Additional methods were occasionally introduced to address artifacts overlapping with EDA signals, with respiration emphasized as the most challenging source because it inflates the EDA reading and causes overestimate of sympathetic arousal (Lee *et al.*, 2019). Only a few studies attempted to mitigate this issue, underscoring the need for more systematic solutions (Lee, Choi, Jebelli, *et al.*, 2020; Lee *et al.*, 2019). Despite the variety of techniques, no standardized preprocessing workflow has emerged, and choices remain study-specific. In terms of preprocessing software, Ledalab was the most commonly used, likely due to being an open-source software that is specialized in EDA analysis, while ErgoLab was reported only once. At the postprocessing stage, analyses either relied on EDA amplitudes directly or decomposed signals into tonic and phasic components, with amplitude-based features being the most frequently examined, whereas frequency-domain features were less considered. This narrow reliance on amplitude measures indicates that EDA research has not yet fully leveraged the richer information offered by frequency-domain analyses (Shukla et al., 2021), highlighting a direction for future investigation. In terms of EDA data interpretation and mental status classification, most studies relied on baseline comparisons and no rule-based approaches were reported. AI-based classification was applied across all four mental factors, with the majority of studies incorporating EDA alongside other physiological measures and only two relying on EDA features alone. This reliance on sensor fusion likely reflects a key limitation of EDA: while it provides robust indicators of sympathetic arousal, it cannot reliably differentiate between mental states that produce similar arousal patterns (Aldosky and Bari, 2025; Zhou *et al.*, 2023). The challenge is further compounded by non-mental influences such as physical activity, underscoring the need for complementary data sources to ensure accurate assessment (Aldosky and Bari, 2025; Zhou *et al.*, 2023). Hardware deployment has largely favored wrist-worn devices in both field and controlled conditions, with finger-strap systems only reported being used in controlled environments, reflecting an emphasis on practicality for field applications. Compared with other PMSs and WSDs that monitor mental status by inferring sympathetic arousal (e.g., PPG, ECG, infrared thermopile), EDA offers a unique advantage as it directly indexes sympathetic activity without parasympathetic influence, making it a useful marker of stress (Choi, Lee, *et al.*, 2019; Lee, Choi, Jebelli, *et al.*, 2020).

3.9 Photoplethysmography Sensors

Measured Factors, Sensor Locations, and Sampling Rates: PPG sensors were used in 5 (4.42%) studies on risk perception, 4 (5.98%) studies on mental workload and fatigue, 8 (25.00%) studies on mental stress, and 8 (27.59%) studies on emotional states. These sensors were embedded in wristbands or finger clips and collected data at sampling rates between 1 Hz and 1000 Hz depending on the sensing devices used.

Preprocessing: For risk perception studies, a band-pass filter was used in one study to mitigate noise from ambient light, temperature, and electromagnetic interference (Lee *et al.*, 2021). However, studies did not report on the specific type (i.e., IIR or FIR) of band-pass filters used.

Band-pass filters were also the most common preprocessing technique in the mental workload and fatigue studies. This type of filter was used for the same noise-reduction purpose discussed in the risk perception studies. In addition, one study used concave filtering to reduce powerline interference noise (Liu *et al.*, 2023).

For studies on mental stress, band-pass filtering was similarly employed, with additional preprocessing techniques reported in one study, including a notch filter to eliminate power line interference, a Hampel filter to remove outliers, and a rolling filter to smooth the data (Jebelli, Choi, *et al.*, 2019). However, no specific rolling filter type was specified.

Finally, emotional states studies reported using band-pass filters for the same noise-reduction purpose discussed in the risk perception as well as the mental workload and fatigue studies. In addition, one study reported using a first-order Butterworth IIR low-pass filter, although no specific targeted noise was indicated (Xu *et al.*, 2024).

Notably, no specific software packages or tools were reported being used to perform these PPG data preprocessing steps.

Postprocessing: The preprocessed PPG data, which captures blood volume changes in microvascular tissues (i.e., blood volume pulse, BVP), were analyzed as indicators of heart activity due to heart's role in regulating blood circulation. Heart activity was primarily assessed using heart rate (HR) and heart rate variability (HRV) by analyzing the intervals between periodic peaks in the BVP signal. HR quantifies the number of heartbeats per minute, while HRV measures the variation in inter-beat intervals (IBI), which is the time between adjacent heartbeats (Mccraty and Shaffer, 2015; Shaffer and Ginsberg, 2017). Specifically, HR and HRV serve as indicators of the dynamic relative dominance between the sympathetic and parasympathetic branches of the autonomic nervous system (ANS). The sympathetic branch dominates during mental tension, while the parasympathetic branch is more active during relaxation. While HR was determined directly by measuring the number of heartbeats per minute, HRV was quantified using several metrics, with the most common being Standard Deviation of Normal-to-Normal intervals (SDNN), the Root Mean Square of Successive Differences (RMSSD), as well as percentage of successive Normal-to-Normal intervals that differ by more than 50 milliseconds (pNN50). Time- and frequency-domain features were derived from these time-series measures for more detailed mental status analyses. Typical time-domain features included mean, variance, and median value of PPG signal, average HR, SDNN, RMSSD, and pNN50, while frequency-domain features included low-frequency power (LF), high-frequency power (HF), and LF/HF ratio of HRV. It is important to note that HF reflects parasympathetic activity, LF represents contributions from both sympathetic and parasympathetic systems, and the LF/HF ratio indicates the relative dominance of these two systems (Malik *et al.*, 1996; Shaffer and Ginsberg, 2017). Both HR and HRV metrics reflect cardiovascular modulation due to ANS activity in response to various mental status factors (Lee, Choi, Ahn, *et al.*, 2020), forming the basis for PPG-based mental status analyses.

Risk Perception: Four out of the five PPG-based risk perception studies examined individuals' HR, HRV, or both, comparing variations under different conditions with varying risk levels (Hasanzadeh *et al.*, 2020; Hasanzadeh and de la Garza, 2020; Pooladvand, Kiper, *et al.*, 2022; Zou *et al.*, 2020). Increased HR and lower HRV were associated with higher perceived risk levels. The remaining study relied on an AI-based approach to predict individuals' perceived risk levels (Lee *et al.*, 2021), and no rule-based approaches were used. Specifically, time-series PPG data were segmented, and time- and frequency domain features were extracted and labeled with risk levels based on task being performed during data collection. These features were then used in combination with additional sensor data as input to AI models for predicting individuals' perceived risk levels (see Table 4). No AI-based risk perception studies relied only on PPG features for risk perception evaluation.

Mental Workload and Fatigue: Two out of the four PPG-based mental workload and fatigue studies compared PPG metrics measured under working conditions with varying cognitive demands (Liu *et al.*, 2023; Seong *et al.*, 2022). Decreased HRV and increased LF/HF ratio were associated with increased fatigue. Three out the four PPG-based mental workload and fatigue studies relied on AI-based approaches for mental workload and fatigue classification, and no rule-based approaches were reported. Specifically, PPG data were segmented and labeled with mental fatigue states based on individuals' pupil size and working hours, NASA-TLX responses, SSS, SOFI, and MFI, or Reaction Time Test results. Time- and frequency-domain features of HRV were then extracted and combined with other sensor data to train AI models (see Table 4). No study relied solely on PPG features to train AI models for classifying mental workload and fatigue.

Mental Stress: Four out of the eight PPG-based mental stress studies compared heart metrics against baseline values recorded under normal conditions, interpreting higher HR and lower HRV as indicators of increased mental stress level (Ardecani *et al.*, 2024; Jebelli *et al.*, 2018; Kazar and Comu, 2022; Newton, 2022). The remaining four classified mental stress using either rule-based or AI-based approaches. Specifically, one study deployed a rule-based approach by identifying distress when the PPG pulse rate exceeded a predefined threshold, though the specific threshold limit was not indicated (Angelia *et al.*, 2021). The other three mental stress studies applied AI-based approaches for mental stress classification. These studies extracted time- and frequency-domain features from PPG data segments and labeled them with varying stress levels based on individuals' cortisol levels, perceived arousal levels rated using the SAM scale, as well predefined stress levels of different tasks. These features were then combined with additional sensor data for training AI models in all three studies (see Table 4). No study relied only on PPG features for AI-based mental stress classification.

Emotional States: All eight PPG-based emotional states studies compared PPG metrics (HR, HRV, or both, and BVP) to baseline values measured under normal or controlled conditions. Increased HR or decreased HRV were associated with negative valence, heightened anxiety, elevated emotional arousal, positive emotion, and increased emotional intensity (Guo *et al.*, 2017; Habibnezhad *et al.*, 2019; Jang *et al.*, 2024; Newton, 2022; Subedi *et al.*, 2021; Xu *et al.*, 2024; Zhang *et al.*, 2018). Neither rule-based nor AI-based approaches were used for PPG-based emotional states classification.

In summary, PPG sensors have been applied to monitor all four mental status factors, with the heaviest use in studies on mental stress and emotional states. This pattern reflects the physiological mechanisms underlying PPG, as HR and HRV provide robust indicators of ANS activity. Across studies on all four mental factors, PPG data preprocessing consistently involved band-pass filtering to reduce ambient light, motion, and electromagnetic noise, with additional methods occasionally applied for outlier removal and data smoothing. However, no dedicated software packages were reported for these steps, likely because no standardized toolbox currently exists (Goda *et al.*, 2024), underscoring the need for such development. Postprocessing centered on HR and HRV metrics, with time-domain and frequency-domain features widely used to capture the dominance between sympathetic and parasympathetic systems. In terms of data interpretation and classification, most studies compared HR and HRV variations against baseline values. Rule-based approaches were nearly absent, apart from one stress study that applied a pulse-rate threshold, while AI-based approaches were reported in studies on risk perception, workload and fatigue, and stress, but not in studies on emotional states. Notably, PPG data were never used as a standalone input but were consistently paired with other sensor data for AI model training. This consistent use of sensor fusion in AI-based classification may stem from the difficulty of inferring specific mental states (e.g., emotion) from the generalized sympathetic arousal captured by PPG alone (Grzeszczyk *et al.*, 2023), underscoring both the importance and the research opportunities of incorporating additional sensor modalities to enhance classification accuracy (How *et al.,* 2023). Finally, hardware deployment has leaned toward wristbands for field practicality, with finger clips remaining only applied in controlled settings.

3.10 Electrocardiography Sensors

Measured Factors, Sensor Locations, and Sampling Rates: ECG sensors were used in 2 (1.77%) studies on risk perception, 6 (8.95%) studies on mental workload and fatigue, 7 (21.88%) studies on mental stress, and 5 (17.24%) studies on emotional states. These sensors monitored heart electrical activity through electrodes attached to either the chest or wrist and collected data at sampling rates ranging from 1Hz to 1000 Hz, depending on the devices used.

Preprocessing: In both risk perception studies, band-pass filters were applied to eliminate noise from powerline interference and baseline wander. However, neither specified the used band-pass filter type (i.e., IIR or FIR) (Ouyang *et al.*, 2023; Sugimoto *et al.*, 2020).

For mental workload and fatigue studies, only two reported ECG data preprocessing techniques. One study used an IIR Butterworth filter and a wavelet transform method to mitigate noise, including baseline wander, but did not specify whether the used IIR Butterworth filter was low-pass, high-pass, or band-pass (Fang *et al.*, 2024). The other study employed a moving-window threshold approach to address artifacts such as ventricular extrasystoles and undetected heartbeats (Hashiguchi *et al.*, 2021).

For mental stress studies, two reported ECG data preprocessing techniques. The first study employed a window-based thresholding technique to remove artifact caused by body motion and poor sensor connection (Begum *et al.*, 2012). The second study applied a moving-window threshold approach to eliminate ventricular extrasystoles artifacts and missing heartbeats (Hashiguchi *et al.*, 2021).

No emotional states studies reported details pertaining to the preprocessing techniques for the collected ECG data. In addition, no common preprocessing tools or software packages were identified across the ECG studies; however, two studies indicated using Kubios, and one study used VivoSense for ECG signal preprocessing.

Postprocessing: The preprocessed ECG signal was analyzed to monitor heart activity by detecting R-waves—the tallest peaks in the ECG waveforms—using the Pan-Tompkins algorithm (Pan and Tompkins, 1985). Heartbeats were then identified by measuring intervals between successive R-wave peaks (i.e., RR intervals), from which two key heart measures—HR and HRV—were calculated. HR measured heartbeats per minute, and HRV was quantified by various metrics, such as standard deviation of RR intervals (SDRR) and RMSSD between successive

RR intervals. Both time- and frequency-domain features were subsequently extracted from these time-series heart measures for mental status analyses. Typical time-domain features included average HR, percentage heart rate reserve (%HRR), mean RR interval, pNN50, SDRR, and RMSSD. Frequency-domain HRV features were also extracted using either Lomb–Scargle periodogram (Clifford and Tarassenko, 2005) or FFT. Typical frequency-domain features included LF, HF, LF/HF ratio, very-low-frequency power (VLF), ultra-low-frequency power (ULF), as well as total power (TP). Notably, VLF and ULF, similar to HF, also reflect parasympathetic nervous system (PNS) activity, and TP measures the overall ANS activity (Malik *et al.*, 1996; Shaffer and Ginsberg, 2017). Additionally, nonlinear HRV features were extracted, including approximate entropy, sample entropy, standard deviation along the minor axis (SD1) and the major axis (SD2) of the Poincaré plot (Contreras *et al.*, 2006), as well as the SD1/SD2 ratio. Entropy was used to measure irregularity of R-waves, and the SD1/SD2 ratio was used to assess sympathetic nervous system (SNS) arousal (Ouyang *et al.*, 2023). These features reflected heart activity driven by the ANS across various mental status factors, providing the foundation for mental status analyses.

Risk Perception: Both ECG-based risk perception studies indicated the relationship between heart metrics and risk perception, where decreased HRV and increased HR indicated SNS activation associated with sustained attention and heightened risk perception (Ouyang *et al.*, 2023; Sugimoto *et al.*, 2020). These two studies utilized this relationship and employed AI-based approaches for risk perception monitoring, with no rule-based approaches used. Specifically, time-series ECG data were segmented, from which time- and frequency-domain features were extracted in both studies, while one study (Ouyang *et al.*, 2023) additionally extracted nonlinear features (i.e., SD1/SD2 ratio). These features were labeled either with specific incident types or according to individuals' self-rated attention level, and subsequently integrated with other sensor data as input to AI models for inattention and hazard type prediction (see Table 4). No study relied only on ECG features for AI-based risk perception evaluations.

Mental Workload and Fatigue: Three out of the six ECG-based mental workload and fatigue studies compared heart metrics against baselines collected under normal conditions, associating lower HRV, increased HR, and increased LF/HF ratio, with higher mental workload and fatigue (Chang *et al.*, 2009; Hashiguchi *et al.*, 2021; Zhang *et al.*, 2023). The remaining three studies applied only AI-based approaches for mental workload and fatigue classification, with no rule-based approaches used (Fang *et al.*, 2024; Sakib *et al.*, 2020, 2021). Specifically, time- and frequency-domain features were extracted from segmented time-series HR and HRV data, and were labeled with subjective cognitive load using NASA-TLX or with mental fatigue level using a modified ROF scale (Fang *et al.*, 2024). All three AI-based studies combined these features with other sensor data to train AI models for classifying mental workload and fatigue (see Table 4). No study relied only on ECG features for AI-based mental workload and fatigue classification.

Mental Stress: Four of the seven ECG-based mental stress studies compared individuals' heart rate metrics collected under varying working conditions and times with varying stress levels, and interpreted decreased HRV, decreased HF, as well as increased LF/HF ratio and increased %HRR as indicative of increased ANS imbalance associated with heightened mental stress (Hashiguchi *et al.*, 2021; Lee *et al.*, 2017; Muley and Wang, 2024; Nwaogu and Chan, 2021). The remaining three mental stress studies applied only AI-based approaches for mental stress classification, with no rule-based approaches being reported. Specifically, all three studies extracted time- and frequency-domain features from time-series ECG data segments and labeled them with stress levels according to expert evaluations or CARMA. Begum et al. (2012) relied only on these ECG features to train a Case-Based Reasoning (CBR)-based model, which achieved a classification accuracy comparable to experts' judgments of individuals' stress levels, whereas the other two AI-based studies combined ECG features with other sensor data for mental stress classification, as summarized in Table 4 (Sakib *et al.*, 2020, 2021).

Emotional States: Two of the five ECG-based emotional states studies compared heart metrics against baseline values recorded under normal conditions to measure emotional arousal (e.g., fear and anxiety) (Kodithuwakku Arachchige *et al.*, 2023; Xu *et al.*, 2019). Increased HR was associated with fear and anxiety (Kodithuwakku Arachchige *et al.*, 2023). The remaining three studies implemented only rule-based approaches for emotional states classification, and no AI-based approaches were reported. Specifically, two studies used HR thresholds determined by Emotional Heart Zones (Karvonen *et al.*, 1957) to classify the emotional states (Lee and Migliaccio, 2014, 2016). The third rule-based study developed a noise annoyance level index based on EEG signals and ECG-based HRV data, and established a threshold to determine individuals' mental well-being in noisy environments (Xing *et al.*, 2021).

In summary, ECG sensors have been applied across all four mental status factors, with only limited applications in risk perception. This distribution reflects ECG's ability to capture cardiac electrical activity at high fidelity, providing robust indices of ANS activity. Across studies, reported ECG preprocessing practices lacked consistency, with workflows ranging from band-pass filtering and window-based thresholding to artifact rejection, but no standardized approaches were evident. Software use showed a similar pattern, with only occasional reports of Kubios or VivoSense. At the postprocessing stage, analyses consistently relied on HR and HRV metrics, with both time- and frequency-domain features widely applied. Nonlinear indices (e.g., entropy, Poincaré plot measures) were introduced in one recent study to capture irregularities in autonomic modulation, highlighting a potential direction for future work. In terms of data interpretation and classification, baseline comparisons were reported across all four mental factors, while emotional state studies were notable for retaining rule-based classifications based on HR and HRV thresholds. AI-based approaches have been applied to risk perception, workload and fatigue, and stress. Most studies combined ECG with other sensors, with only one relying on ECG alone. Prior research shows that HR alone is challenging to use for mental states classification as it is highly variable across individuals and contexts (Chen, 2024) and may not fully capture distinct mental states (Wang and Wang, 2025). This underscores the need for complementary sensor data to improve classification accuracy (Elgendi and Menon, 2019) and marks an important direction for future research. Hardware deployment has centered on chest worn electrodes, with wrist-attached electrodes that were reported only in limited studies. Compared with PPG, ECG provides greater accuracy and robustness under motion. However, PPG is more cost-effective, less invasive, and more easily integrated with other sensors such as EDA into multi-sensor wearables (e.g., smartwatches) (Sattar and Chhabra, 2023; Schäfer and Vagedes, 2013; Sibomana et al., 2025; Umer et al., 2022), making it suitable for continuous field monitoring.

3.11 Functional Near-Infrared Spectroscopy Sensors

Measured Factors, Sensor Locations, and Sampling Rates: fNIRS sensors were used in 5 (4.42%) studies on risk perception, 5 (7.46%) studies on mental workload and fatigue, and 1 (3.45%) study on emotional states. These sensors obtained data using optodes embedded in fNIRS caps or headbands, at sampling rates of either 10 Hz or 12 Hz, depending on the specific sensor deployed.

Preprocessing: For risk perception studies, three reported using band-pass filters to eliminate unwanted signals, specifically those originating from the cardiovascular and respiratory systems (Lee *et al.*, 2024; Pooladvand, Kiper, *et al.*, 2022; Seo *et al.*, 2024). However, none indicated the type (i.e., IIR or FIR) of band-pass filter used. A fourth-order Butterworth IIR low-pass filter was also used in one study as an alternative method to eliminate unwanted signals (Zhou *et al.*, 2021). In addition, motion artifacts were mitigated using either wavelet filtering (Seo *et al.*, 2024) or a moving standard deviation with spline interpolation technique (Zhou *et al.*, 2021).

The same fNIRS preprocessing techniques used in the risk perception studies were also used in studies on mental workload and fatigue, including band-pass filtering, low-pass filtering, and the moving standard deviation with spline interpolation technique. Two studies reported using a fourth-order Butterworth IIR filter for low-pass filtering (Liao *et al.*, 2021; Sun and Liao, 2019). No studies reported on the type (i.e., IIR or FIR) of band-pass filter used.

As for the emotional state study, a band-pass filter was similarly applied for removing unwanted physiological signals (e.g., respiration and cardiovascular signals), while the filter type (i.e., IIR or FIR) was not specified (Chang *et al.*, 2025).

MATLAB© and the Homer toolbox were the most commonly used software and packages for preprocessing the raw fNIRS data.

Postprocessing: After preprocessing, the fNIRS data, initially measuring light intensity, were transformed into optical density, an intermediate measure reflecting light absorption changes caused by hemoglobin concentration variations (Huppert *et al.*, 2009). These optical density values were subsequently converted into hemoglobin concentration measures using the Modified Beer-Lambert Law (Delpy *et al.*, 1988; Sitaram *et al.*, 2007), and were interpreted as indicator of brain activity. Three key hemoglobin measures—concentrations of oxygenated hemoglobin (oxy-Hb), deoxygenated hemoglobin (deoxy-Hb), and total hemoglobin (total-Hb)—were extracted for mental status analyses. Among these measures, oxy-Hb was preferred due to its lower vulnerability to cross-talk between fNIRS signals (Strangman *et al.*, 2003). It should be noted that the temporal changes in hemoglobin concentrations were measured by the Hemodynamic Response Function (HRF) using the General Linear Model (GLM) method. Beyond hemoglobin concentrations, additional features such as slope and variance of the fNIRS signals were also derived for advanced analyses. These fNIRS metrics and features reflect activation in brain regions associated with various mental status factors, which established the basis for mental status analyses.

Risk Perception: Three out of the five fNIRS-based risk perception studies examined temporal changes in hemoglobin concentration by comparing them to baseline values established under controlled and normal conditions (Pooladvand, Ay, *et al.*, 2022; Pooladvand, Kiper, *et al.*, 2022; Seo *et al.*, 2024). Increased oxy-Hb and total-Hb, as well as decreased deoxy-Hb within prefrontal cortex were interpreted as indicators of greater attentional allocation and heightened risk perception. The remaining two studies employed AI-based approaches (Lee *et al.*, 2024; Zhou *et al.*, 2021), and no rule-based approaches were used. Specifically, fNIRS features (oxy-Hb, deoxy-Hb, total-Hb, and combination of oxy-Hb and deoxy-Hb) were extracted from segmented time-series data and labeled with either specific hazard types or whether the hazard was detected. These features were then used solely as training input to an LDA classifier and a CatBoost, which effectively classified risk types or identified individuals' abilities to identify risks, respectively. No sensor fusion was used for fNIRS-based risk perception monitoring.

Mental Workload and Fatigue: Four out of the five fNIRS-based mental workload and fatigue studies compared the oxy-Hb concentrations to baseline values collected under normal conditions, interpreting elevated oxy-Hb levels in the prefrontal cortex as an indicator of increased mental workload (Hu *et al.*, 2018; Liao *et al.*, 2021; Pooladvand and Hasanzadeh, 2022; Sun and Liao, 2019). The remaining study relied on an AI-based approach to classify mental workload (Pooladvand *et al.*, 2024), and no rule-based approaches were reported. Specifically, time-series fNIRS data were segmented and labeled with predefined mental demand levels corresponding to varying task conditions. Time-domain features (e.g., mean, maximum, and standard deviation of oxy-Hb) were extracted from these labeled segments, and were used solely to train an ensemble model, which successfully classified mental workload into low, moderate, and high. No sensor fusion was used for mental workload monitoring.

Emotional States: The fNIRS-based emotional state study measured trust—a type of emotion (Ekman, 1992; Plutchik, 1980)—by comparing oxy-Hb levels across various brain regions before and after distrust-triggering events (Chang *et al.*, 2025). Decreased trust levels were associated with increased activation in the right prefrontal cortex, a region closely linked to trust-building and negative emotions. No rule-based or AI-based approaches were employed to further classify trust levels.

In summary, fNIRS sensors have been mainly applied to monitor risk perception and mental workload and fatigue, with very limited use in emotional states and no studies targeting stress. This distribution reflects fNIRS's strength in capturing localized hemodynamic changes in the prefrontal cortex, which are closely associated with cognitive processing (Hu *et al.*, 2018; Liao *et al.*, 2021; Pooladvand and Hasanzadeh, 2022; Sun and Liao, 2019). Nevertheless, research in the biomedical domain has demonstrated the feasibility of using fNIRS for stress monitoring (Al-shargie *et al.*, 2016), indicating a potential research direction within the construction domain. Across studies, preprocessing commonly involved band-pass or low-pass filtering to remove respiratory and cardiovascular noise, with occasional use of motion artifact correction techniques. MATLAB and the Homer toolbox were most frequently reported for preprocessing. At the postprocessing stage, analyses centered on hemoglobin concentration changes (oxy-Hb, deoxy-Hb, and total-Hb), with oxy-Hb favored due to its robustness against cross-talk. Temporal changes were often modeled using the Hemodynamic Response Function, while additional features such as slope and variance were occasionally introduced, suggesting further exploration of these features for construction applications. In terms of interpretation and classification, most fNIRS applications relied on baseline comparisons, with no rule-based methods reported. A few studies adopted AI-based approaches using fNIRS measures alone, demonstrating its capacity to provide direct insights into brain activity. Hardware deployment has centered on optodes positioned over the prefrontal cortex. Compared with EEG, fNIRS is less sensitive to body motion artifacts (Mehta and Parasuraman, 2013; Perrey, 2008; Pooladvand and Hasanzadeh, 2022) and offers higher spatial resolution for identifying active brain regions related to varying mental states, as inter-channel interference in EEG signals complicates precise localization (Hu *et al.*, 2018; Liao *et al.*, 2021; Pooladvand and Hasanzadeh, 2022). In contrast, EEG provides more robust temporal resolution, capturing rapid brain dynamics at the millisecond level and thereby enabling faster detection of mental activities (Blanco *et al.*, 2024; Chen and Lin, 2016; Lee *et al.*, 2024). Therefore, fNIRS is more suitable for monitoring longer and sustained cognitive processes (Blanco *et al.*, 2024). Moreover, fNIRS is typically more costly than EEG (Flanagan and Saikia, 2023), likely contributing to its limited use in construction research.

3.12 Infrared Thermopiles

Measured Factors, Sensor Locations, and Sampling Rates: Infrared thermopiles were used in 1 (0.88%) risk perception study, 3 (4.48%) mental workload and fatigue studies, 8 (25.00%) mental stress studies, and 3 (10.34%) emotional states studies. These sensors were embedded in wristbands, chest worn PMSs, and hardhats, collecting data at sampling rates ranging from 0.02 Hz to 4 Hz depending on the sensing devices being deployed.

Preprocessing: For the one study on risk perception, a Hampel filter was applied to remove outliers caused by unstable sensor-skin contact. No specific preprocessing techniques were reported for studies on mental workload and fatigue. For studies on mental stress, three reported preprocessing the raw ST data. Specifically, two studies reported using Hampel filters for outlier removal, low-pass filters to eliminate noise caused by environmental factors (e.g., ambient light and thermal noise), excessive movement, and sensor adjustments, notch filters to mitigate power line interference, and rolling filters (moving average filters) for data smoothing (Jebelli, Choi, *et al.*, 2019; Ojha, Shakerian, *et al.*, 2023). However, the filter type (i.e., IIR or FIR) used for low-pass filtering was not specified. The third study used a high-pass filter without specifying the filter type (i.e., IIR or FIR) or noise targeted (Kazar and Comu, 2022). For studies on emotional states, only one study reported preprocessing ST data, where a Hampel filter was used for outlier removal and an FIR filter was adopted for data smoothing (Ojha, Jebelli, *et al.*, 2023). Whether the FIR filter used was low-, high-, or band-pass was not specified. No common software packages or tools were reported being used for preprocessing the ST data.

Postprocessing: From the preprocessed time-series ST data, time- and frequency-domain features were extracted for mental status analyses. Typical time-domain features included mean and standard deviation of ST, while frequency domain features included mean and median frequency of ST. These features reflect the thermoregulation process driven by SNS arousal under various mental conditions, offering valuable insights into each mental status factor.

Risk Perception: While ST is influenced by SNS activity due to perceived risk (Table 3), the risk perception study did not report a relationship between ST and risk perception. The included study employed an AI-based approach to predict perceived risk levels (Lee *et al.*, 2021). No rule-based approaches were reported. Specifically, time- and frequency-domain ST features, extracted from segmented time-series data, were labeled with risk level based on the tasks performed during data collection. These features were combined with additional sensor data to train AI models for risk level prediction (see Table 4). No AI-based studies relied solely on ST features for risk perception assessments.

Mental Workload and Fatigue: One study out of three ST-based mental workload and fatigue studies compared the ST metric values to baselines recorded under controlled condition (Zhang *et al.*, 2023), associating decreased ST with increased mental fatigue. The remaining two studies applied only AI-based approaches for advanced mental workload and fatigue monitoring (Sakib *et al.*, 2020, 2021), and no rule-based approaches were used. Specifically, time-domain ST features were extracted from segmented time-series data and labeled with mental workload levels. Both studies combined these ST features with additional sensor data to train AI models for mental workload classification (see Table 4). No study relied only on ST features for AI-based mental workload and fatigue classification.

Mental Stress: Three out of the eight ST-based mental stress studies compared ST either across different working times or against baseline values established under controlled conditions, associating decreased ST with heightened mental stress level (Angelia *et al.*, 2021; Kazar and Comu, 2022; Ojha, Shakerian, *et al.*, 2023). The remaining five studies applied only AI-based approaches for mental stress classification (Eskandar and Razavi, 2020; Jebelli, Choi, *et al.*, 2019; Lee and Lee, 2022b; Sakib *et al.*, 2020, 2021), with no rule-based approaches reported. Specifically, time- and frequency-domain ST features were extracted from segmented time-series data and were labeled with stress levels based on subjective stress measured by CARMA, SAM scale, or cortisol level, and were then integrated with additional sensor data to train AI models for mental stress classification, as summarized in Table 4. No study relied only on ST features for AI-based mental stress evaluation.

Emotional States: All three ST-based emotional states studies compared the ST to baseline values recorded under controlled or normal conditions, associating increased ST with elevated emotional intensity or arousal, positive emotion, and emotional engagement (Guo *et al.*, 2017; Jang *et al.*, 2024; Ojha, Jebelli, *et al.*, 2023). No rule-based or AI-based approaches were reported to be used for ST-based emotional state classification.

In summary, infrared thermopiles have been applied primarily to monitoring mental stress, with additional use in emotional states and mental workload and fatigue, and limited applications in risk perception. This pattern reflects the physiological characteristic of ST as an indirect marker of sympathetic activation. Across the reviewed studies, preprocessing was inconsistently reported and typically involved Hampel, low-pass, or rolling filters, with no dominant software tools identified. Postprocessing primarily focused on simple time-domain features such as mean and standard deviation of temperature, while frequency-domain features were rarely applied, highlighting the need to explore their potential for providing additional insights into sympathetic activation in construction settings. For data interpretation and mental status classification, some studies compared feature changes against baseline values, and no rule-based methods were reported. AI-based approaches were observed in studies on risk perception, mental workload and fatigue, and stress, but not in emotional states, highlighting a research gap. Across all studies using AI-based approaches, ST features were always paired with EDA features, and occasionally combined with features from other signals as inputs to AI models (Table 4). This consistent pairing suggests that researchers likely regard EDA as complementary for ST, with EDA offering a direct measure of sympathetic arousal that offsets the susceptibility of ST to environmental and physical influences (Herborn et al., 2015), thereby improving the robustness of AI-based mental status classification. Hardware deployment has ranged from wristbands to chest-worn devices and helmet-mounted systems, offering flexibility for integration with other sensors for field applications.

3.13 Electromyography Sensors

Measured Factors, Sensor Locations, and Sampling Rate: sEMG sensors were used in 1 (0.88%) study on risk perception and 1 (3.45%) study on emotional states. These sensors collected data through electrodes attached to face and wrist, respectively. Only one of these two papers indicated using a 1000 Hz sampling rate sEMG (Sugimoto *et al.*, 2020).

Preprocessing: The risk perception study reported preprocessing raw EMG data by applying a high-pass filter, although the noise addressed and filter type (i.e., IIR or FIR) were not specified (Sugimoto *et al.*, 2020). The emotional state study noted artifacts caused by unwanted muscle tension, but did not detail the corresponding preprocessing steps (Xu *et al.*, 2019).

Postprocessing: From the preprocessed time-series EMG data, the maximum EMG amplitudes were identified. These peaks in the EMG signal waveforms were used to indicate sudden muscle tension in response to external stimuli, forming the basis for EMG-based mental status monitoring.

Risk Perception: The risk perception study compared facial EMG amplitudes before and after exposure to construction hazards in a VR environment (Sugimoto *et al.*, 2020). A spike in signal magnitude was associated with heightened risk perception. The study employed an AI-based hazard detection approach, where EMG signal peaks were identified and labeled based on the presence or absence of hazards. These labeled signals were then combined with additional sensor data to train AI models for hazard recognition (Table 4). No study relied solely on EMG features for AI-based risk perception assessments.

Emotional States: The emotional state study compared EMG signals collected from individuals' wrists before and during exposure to fall hazards in a VR-based safety training, associating heightened EMG amplitudes with fearful emotions (Xu *et al.*, 2019). No AI-based or rule-based analysis was performed in this study.

In summary, EMG has been minimally applied in construction mental status monitoring, underscoring both its potential and its limitations. On one hand, its sensitivity to rapid muscle activation makes it well suited for capturing acute mental responses such as fear or heightened vigilance (Sugimoto *et al.*, 2020; Xu *et al.*, 2019). On the other hand, EMG signals are highly susceptible to motion artifacts and require precise electrode placement. The two reported studies provided limited detail on preprocessing, constraining reproducibility, and interpretation is further complicated by the fact that EMG reflects both cognitive and physical processes during active construction tasks (Xu *et al.*, 2019). Despite these challenges, EMG holds value for detecting acute mental responses.

3.14 Inertial Measurement Units

Measured Factors, Sensor Locations, and Sampling Rate: IMU sensors were used in 2 (1.77%) studies on risk perception. These sensors were embedded in HMDs, whereas the sampling rate was not reported in any study.

Preprocessing: Neither study reported preprocessing IMU data.

Postprocessing: In the postprocessing phase, IMU data capturing head movements were used to calculate gaze direction within the VR environment via the Ray-Casting method. Gaze direction was used to monitor visual attention allocation, which served as a foundation for IMU-based mental status analyses.

Risk Perception: Only one IMU-based risk perception studies compared individuals' visual attention to hazards under controlled and experimental conditions, interpreting a decrease in number of visual checks on hazards as an indication of reduced attention and situational awareness (Hussain *et al.*, 2024). The other study applied a rule-based approach for risk perception evaluation (Shi *et al.*, 2019), associating a gaze direction between 0° and 45° with high perceived risk (Avineri *et al.*, 2012). No AI-based approaches were used for IMU-based risk perception monitoring.

In summary, IMU applications in construction mental status monitoring have been rare, confined to risk perception studies where head movements were used to approximate gaze direction in VR environments. This suggests that IMUs may serve as a potential alternative for inferring visual attention when dedicated eye tracking is unavailable, although their lack of sensitivity to eye movements prevents advanced analyses of cognitive states. Compared with wearable eye trackers, which directly capture fixations, saccades, and pupil dynamics, IMUs provide only a coarse proxy of attentional allocation. Their value therefore lies in functioning as a pragmatic fallback in VR-based research or as a complementary sensor within multimodal frameworks, rather than as a primary tool for mental status monitoring.

3.15 Sweat Analyte Sensors

Measured Factors, Sensor Locations, and Sampling Rate: A custom sweat lactate sensor was used in 1 (1.49%) study to measure combined fatigue, which included mental fatigue (Ma *et al.*, 2023). Data were collected from the forearms, but sensor sampling rate was not reported.

Preprocessing: No data preprocessing techniques were reported in this study.

Postprocessing: In the postprocessing phase, the collected data were used to determine sweat lactate concentration, which was analyzed as an indicator of metabolic processes triggered by cognitive demands. Sustaining high workloads was associated with increased metabolic activity, leading to elevated production of metabolic analytes such as lactate.

Mental Workload and Fatigue: The fatigue study compared sweat lactate concentration before and during a simulated construction equipment operation task. An increase in subjective fatigue level was associated with increased sweat lactate concentration. No rule-based or AI-based approaches were employed for further fatigue level classification.

The use of sweat analyte sensor for mental status monitoring remains at an exploratory stage, with only one study linking lactate concentration to fatigue. While lactate is a promising biochemical marker of metabolic activity, it reflects combined physiological and cognitive load (Ma et al., 2023), making its interpretation as a direct indicator of mental fatigue ambiguous. Moreover, variability introduced by sweat rate, hydration status, and environmental conditions further complicates its application in construction. No preprocessing protocols or mental status classification methods have been reported, indicating that further research is needed to advance this mental status monitoring approach. Despite these limitations, sweat analyte sensors offer unique value by providing biochemical markers that cannot be captured by conventional physiological sensors (Huang et al., 2022; Ma et al., 2023). Future work should establish standardized data processing protocols, investigate additional analytes, control for confounding factors, and evaluate the feasibility of integrating sweat sensing into WSDs for continuous monitoring in construction environments.

Table 4: AI-based approaches with sensor fusion for monitoring mental status in construction.

Mental Status Factors	References	Objectives	Fused Sensor Data	Benchmarks for Data Labeling and Model Performance Evaluation	Most Effective Models
Risk Perception	(Sugimoto *et al.*, 2020)	Predict safety hazard type	ECG, EMG	Specific safety hazard types	Gaussian Naïve Bayes Classifier
	(Noghabaei *et al.*, 2021)	Predict hazard identification performance	EEG, Eye tracker	Time when a hazard is identified by individuals	GSVM
	(Kim *et al.*, 2021)	Predict inattentiveness	Eye tracker, EDA	Individuals' checking and non-checking behaviors	SVM
	(Lee *et al.*, 2021)	Classify perceived risk level	EDA, PPG, ST	Risk level of task being performed during data collection	GSVM
	(Choi *et al.*, 2023)	Predict safety training performance	EEG, Eye tracker	Individuals' scores in post-safety-training test	SVR
	(Ouyang *et al.*, 2023)	Classify inattention	EDA, ECG	Predefined attentional level during data collection and self-rated attention level	SVM
	(Wang, Liang, *et al.*, 2024)	Predict hazard identification performance	EEG, Eye tracker	Individuals' hazard recognition performance	SVM
	(Chou *et al.*, 2024)	Classify safety hazard type	EEG, Eye tracker	Specific safety hazard types	RF
Mental Workload and Fatigue	(Sakib *et al.*, 2020, 2021)	Classify mental workload	EDA, ECG, ST	Self-rated mental workload in NASA-TLX	LR, SVM, and DT
	(Liu *et al.*, 2023)	Classify general fatigue	EEG, Eye tracker, EDA, PPG	Pupil size and working hours	L2-SAE
	(Mehmood, Li, Umer, *et al.*, 2023)	Classify mental fatigue	EEG, EDA	Self-rated mental fatigue level based on NASA-TLX	DT
	(Shayesteh *et al.*, 2023)	Classify mental workload	EEG, EDA, PPG	Self-rated mental workload in NASA-TLX	LSTM
	(Liu *et al.*, 2024)	Classify mental workload	EEG, EDA	Self-rated mental workload in NASA-TLX	Ensemble LR
	(Kim, Sri Preethaa, *et al.*, 2024)	Classify mental fatigue	EEG, PPG	Self-rated mental fatigue level based on SSS, SOFI, MFI, and Reaction Time Test	Ensemble learning model
	(Fang *et al.*, 2024)	Classify mental fatigue	EEG, ECG	Self-rated fatigue level in the modified ROF scale	ROSELM-DFF
Mental Stress	(Jebelli, Choi, *et al.*, 2019)	Classify mental stress	EDA, PPG, ST	Cortisol levels	GSVM
	(Eskandar and Razavi, 2020)	Classify mental stress	EDA, PPG, ST	Stress level of task being performed during data collection	CNN-LSTM
	(Sakib *et al.*, 2020, 2021)	Classify mental stress	EDA, ECG, ST	Self-rated stress level in CARMA system	LR, SVM, and DT
	(Lee and Lee, 2022b)	Classify mental stress	EDA, PPG, ST	Construction-expert-rated stress level and self-rated arousal levels in SAM scale	GSVM, DNN
Emotional States	Not Applicable	Not Applicable	Not Applicable	Not Applicable	Not Applicable

3.16 Application Trend of PMSs and WSDs for Mental Status Monitoring

An analysis of sensor usage across all studies and all four mental status factors highlights clear application trends (Table 5). Overall, risk perception and mental workload and fatigue have received the greatest attention, whereas studies on mental stress and emotional states remain comparatively limited. This limited development likely reflects the complexity and multidimensional nature of mental stress and emotions, which complicates their definition and classification, but also highlights a promising avenue for future research.

The usage of PMSs and WSDs demonstrates a strong correspondence between the type of mental factor and the monitored biological functions (Table 5). Specifically, risk perception and mental workload and fatigue—both closely tied to cognitive processing (Martin, 1990; Mehmood et al., 2024; Paas, 1992)—are primarily assessed through brain (EEG in particular) and eye (wearable eye trackers) activities. Although EEG ranked as the second most frequently used sensor for monitoring mental stress and as the leading sensor for emotional states, the total count of sensors monitoring sympathetic activity (EDA, PPG, ECG, and infrared thermopiles) substantially surpassed all other sensors (including EEG) when monitoring mental stress and emotional states. This is likely because mental stress and emotional states are affect-related (Feist and Rosenberg, 2009), which is directly related to sympathetic arousal (Chu *et al.*, 2024). Additionally, several relatively underutilized sensors—namely sEMG, IMU, and sweat analyte sensors—demonstrate potential for future investigations.

Table 5: PMSs and WSDs rankings by frequency for monitoring each mental status factor.

Mental Status Factors	**Top Five Sensor Types for Monitoring Each Mental Factor (in Descending Order)**					**Others**
Risk Perception (119 studies)	Wearable eye trackers (65, 57.52%)	EEG sensors (43, 38.05%)	EDA sensors (8, 7.08%)	fNIRS sensors (5, 4.42%)	PPG sensors (5, 4.42%)	IMU sensors (2, 1.77%), ECG sensors (2, 1.77%), sEMG sensors (1, 0.88%), Infrared thermopiles (1, 0.88%)
Mental Workload and Fatigue (67 studies)	EEG sensors (43, 64.18%)	Wearable eye trackers (12, 17.91%)	EDA sensors (10, 14.93%)	ECG sensors (6, 8.95%)	fNIRS sensors (5, 7.46%)	PPG sensors (4, 5.98%), Infrared thermopiles (3, 4.48%), Sweat lactate sensors (1, 1.49%)
Mental Stress (32 studies)	EDA sensors (17, 53.13%)	EEG sensors (10, 31.25%)	PPG sensors (8, 25.00%)	Infrared thermopiles (8, 25.00%)	ECG sensors (7, 21.88%)	–
Emotional States (29 studies)	EEG sensors (13, 44.83%)	EDA sensors (10, 34.48%)	PPG sensors (8, 27.59%)	ECG sensors (5, 17.24%)	Infrared thermopiles (3, 10.34%)	fNIRS sensors (1, 3.45%), sEMG sensors (1, 3.45%)

4. LIMITATIONS AND FUTURE RESEARCH ROADMAP

Several limitations have been identified and reported in the literature preventing the full adoption of automated, continuous, real-time, and low-cost mental status monitoring on jobsites using PMSs and WSDs. The limitations, which have been categorized into (1) ecological validity; (2) data processing; (3) hardware; and (4) human factors, are presented in Table 6.

To address the ecological validity limitations, future studies should refine experimental settings to ensure findings are valid and applicable to real-world construction workforce and jobsites. Specifically, future studies should involve larger and more diverse samples, considering factors such as age, gender, experience levels, trades, and personality traits. Collecting field data from real workers with varying experience is also critical, while laboratory- and VR-based studies should enhance environmental realism and task complexity to reflect the physically and mentally demanding nature of construction work. Additionally, future research should examine mental status variations in long-term and collaborative group-based task contexts, which are integral to construction work but often overlooked in previous studies. Addressing these gaps will enhance the generalizability, applicability, and validity of research outcomes.

Regarding data processing, future studies should focus on developing automated frameworks to improve the efficiency and accuracy of mental status monitoring. This includes developing automated data preprocessing techniques that ensure consistent and continuous noise detection and removal. Additionally, constructing multimodal AI models that integrate biological, demographic, environmental, and task-related parameters—while accounting for their interdependencies—will enhance the accuracy and adaptability of mental status classification. This data-fusion AI approach requires thorough research on how these factors interact, as well as the identification of optimal sensor fusion strategies, feature combinations, and ensemble AI models tailored to specific mental status factors across various construction tasks. Establishing large, representative AI training datasets through industry-academia collaboration is essential for improving model generalizability and real-world applicability. Further efforts should also focus on fine-tuning AI models to enhance computational efficiency, facilitate automation and real-time safety feedback, and reduce hardware, software, and personnel burdens. Finally, developing user-friendly, industry-standard software will support non-technical users and drive the widespread adoption of PMSs and WSDs for mental status monitoring in construction. These advancements will improve data processing accuracy and efficiency, ultimately enhancing monitoring reliability.

Table 6: Limitations in implementing PMS and WSD for mental status monitoring in construction.

Categories	Limitations
Ecological validity	• Small, non-diverse samples with limited industry exposure (e.g., students) reduce research generalizability. • Heavy reliance on controlled environments and simplified tasks weakens research validity. • Limited research on mental status during long shifts and collaborative work creates gaps.
Data processing	• Lack of standardized preprocessing protocols reduces data consistency. • Rule-based classification fails to account for individual, environmental, and task-specific variations, leading to false alarms and missed detections. • AI-based classification is constrained by small, scenario-specific datasets, limiting generalizability and accuracy while requiring substantial computational resources for training. • Real-time hazard detection remains challenging due to reliance on manual and post-hoc analysis, while automation increases hardware, software, and personnel demands, complicating implementation.
Hardware	• Frequent malfunction, low sensor resolution, short battery life, limited data storage, and low onboard data processing capacity cause inaccuracy, latency, and disruptions in mental status monitoring. • Insufficient durability for harsh construction environments increases maintenance costs. • Incompatibility with standard PPE causes discomfort and restricts movement.
Human factors	• Shortage of trained personnel limits effective implementation. • Data security concerns hinder the adoption of PMSs and WSDs. • Mental discomfort leads to additional mental status impact.

Addressing hardware limitations is also essential for reliable long-term monitoring. Future research should explore the development of self-calibrating and high-resolution sensors to minimize malfunctions and enhance measurement reliability. Additionally, energy-efficient devices and alternative power sources, such as solar-assisted or kinetic energy harvesting technologies, should be investigated to extend battery life and ensure continuous data collection. Enhancing onboard data storage and optimizing data transmission protocols, such as adopting 5G or satellite networks, could enable real-time, uninterrupted data flow. Improving sensor board computational capabilities will further accelerate hazard identification and provide immediate feedback. Advancements should also prioritize ruggedized, impact-resistant sensors to improve durability and reduce maintenance costs. Furthermore, miniaturization and seamless PPE integration should be emphasized to enhance comfort, mobility, and affordability. Finally, continuous industry involvement in the design process will ensure practical refinements, facilitating widespread adoption in construction settings.

Finally, the successful deployment of PMS and WSDs for mental status monitoring will also depend on several human factors (Table 5). One of the primary barriers to adoption is the lack of personnel training, preventing them from properly installing sensors, calibrating them, and using them to collect data and assess mental states on jobsites. To address this, standardized deployment guidelines and regular training sessions should be established for researchers and field personnel to ensure consistent sensor setup and calibration, as well as proper data handling. Additionally, ethical considerations must be addressed to enhance transparency and trust in data collection and usage. Specifically, future research should focus on developing industry-wide ethical frameworks that define permissible data use, access rights, and legal liabilities. This includes regulatory policies, construction-specific privacy guidelines, and voluntary participation frameworks that protect workers' rights while encouraging the adoption of PMSs and WSDs. Furthermore, investigating the potential mental and behavioral impacts of wearing PMSs and WSDs will help refine usage guidelines and policies for broader implementation.

5. CONCLUSION

This study conducted a comprehensive systematic and bibliometric review to establish a structured framework for using PMSs and WSDs in mental status assessment in construction. EEG sensors, wearable eye trackers, EDA sensors, PPG sensors, ECG sensors, fNIRS sensors, infrared thermopiles, EMG sensors, IMUs, and biofluid analyte sensors were identified for monitoring four key mental status factors: risk perception, mental workload and fatigue, mental stress, and emotional states. These factors were represented by six physiological and biomechanical functions: brain activities, eye activities, skin properties, cardiovascular responses, human biomechanics, and biofluid analyte concentration. For each sensor, the review detailed data collection procedures, including sensor brands and models, placements, and sampling rates. It also examined data preprocessing techniques (e.g., noise filtering and artifact removal) and postprocessing methods, including feature extraction, metric computation, data interpretation, and mental status classification using rule-based and AI-based approaches. Several broader insights emerge regarding the application of different sensor types to monitor mental status factors. Research on PMS- and WSD-based monitoring in construction shows uneven emphasis, with risk perception and mental workload and fatigue receiving the most attention, while mental stress and emotional states remain comparatively underexplored. Advancing these applications will require extending the use of sensors to less-studied factors, expanding the use of alternative data features (e.g., frequency-domain and nonlinear metrics), and adopting more systematic approaches for data processing and classification. Identified limitations in the reviewed studies were categorized into ecological validity-, data processing-, hardware, and human-related limitations. A research roadmap was proposed based on each of the four limitation categories.

This study contributes to the body of knowledge by providing a structured and actionable framework for using PMSs and WSDs in mental status assessment, ultimately facilitating broader adoption of these technologies and improving construction safety. One limitation of this review lies in the exclusive use of Google Scholar. While Google Scholar offers broader coverage, rapid indexing, and powerful citation tracking, it falls short in terms of search precision and advanced filtering. To further strengthen comprehensiveness and rigor, future reviews should incorporate additional databases such as Scopus and Web of Science to complement Google Scholar's breadth. Future research should also investigate the application trends and limitations of PMSs and WSDs beyond mental status assessment, to include their use in monitoring other safety-critical factors in construction, such as physical exhaustion, work-related musculoskeletal disorders, and unsafe behaviors like falls, slips, and trips—areas that are currently underexplored. This would offer a more comprehensive understanding of how these technologies can contribute to construction safety. Additionally, future studies should emphasize the development of integrated assistive technologies and adaptable sensor systems that can monitor and classify mental states alongside other physical and behavioral safety factors, enabling real-time and proactive safety interventions while enhancing overall risk management and worker well-being on construction sites.

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