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EMOTIONALLY INTELLIGENT CONSTRUCTION SAFETY MONITORING VIA INTEGRATION OF MACHINE LEARNING AND EXPERT-INFORMED ELECTROENCEPHALOGRAM-RELATED FEATURES

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Abstract. This article proposes an emotionally intelligent construction safety monitoring model that integrates machine learning and expert-informed Electroencephalogram (EEG)-related features as brain wave measurement device. The proposed safety prediction model is trained with risky behaviours, related emotional states, and expert-informed EEG-related features, incorporating brain waves and corresponding cortex locations. The architecture of the proposed emotionally intelligent safety monitoring system is detailed, utilizing real-world construction datasets and questionnaires. The value of the proposed emotionally informed ML framework lies in introducing EEG-related emotional constructs into construction safety assessment through an exploratory, expert-informed representation of emotional intelligence. The addition of a new dimension to the construction safety prediction models and consideration of the versatility of factoring in emotional states makes implications of this study beyond safety to other fields of construction management areas.

Keywords: emotional intelligent, electroencephalogram (EEG), machine learning, construction safety, project management, collaborative data gathering.

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1. Introduction

Machine learning (ML), with capacity for pattern discovery across historical data (Abad-Santjago et al., 2025; Mostofi et al., 2025; Mostofi & Altunişik, 2024; Park et al., 2025), now informs scheduling, monitoring, optimization, safety, and procurement. These efforts highlight ML's systemic potential under high uncertainty. Still, the integration of emotional intelligence into such intelligent systems remains largely unexplored, despite its centrality to workforce value (Butler & Chinowsky, 2006).

An effective management strategy must be responsive to complex and multifaceted construction site environments while considering all the challenges involved, including technical, behavioral, and emotional aspects. Emotion shapes risk-sensitive decision-making (Singh & Goel, 2022; Sorinas et al., 2023; Vicente-Querol et al., 2023). It defines the mental, internal, and affective human feeling and its context being crucial risk-based decision-making criteria (Tixier et al., 2014). Following Legg and Hutter (2006), intelligence can be defined as "the ability to successfully operate in uncertain environments by learning and adapting based on experience". Intelligence is adaptive action under uncertainty (Legg & Hutter, 2006), while emotional intelligence captures the capacity to manage personal and social emotions (Salovey & Mayer, 1990). As a performance marker (Dover & Amichai-Hamburger, 2023) and developmental skill (Sánchez-Álvarez et al., 2016), emotional intelligence influences safety, decision-making, and workplace behavior (Gribble et al., 2018; Ifelebuegu et al., 2019; Loi et al., 2021; Sunindijo et al., 2007; Sunindijo & Zou, 2013).

Emotions shape risk-based decisions (Tixier et al., 2014), but the challenge lies in its complexity and inherent subjectivity, which hinders their measurement and limits their practical application. Drawing upon the principle often attributed to Peter Drucker, "If you can't measure it, you can't improve it" (Jahanzeb et al., 2018), and a similar statement by Paisley and Henshaw, "If you can't measure it, you can't manage it" (Paisley & Henshaw, 2014), the necessity of measuring emotional intelligence to enhance the effectiveness of management strategies is concluded. In this respect, neuroimaging techniques offer a potential solution to this problem. An electroencephalogram (EEG) is a non-invasive measure of brain activity that can indicate a person's emotional state (Nhu et al., 2023; Vasuki & Aravindan, 2021). It measures electrical potentials on the scalp (Hemakom et al., 2023) by recording continuous neural activity of brain in different conditions such as during sleep (Mohammadi et al., 2022). The generated brain waves are associated with varying states of consciousness, cognitive processes, and, potentially, emotional states (Cai et al., 2022; Olamat et al., 2022; Yuvaraj et al., 2016). EEG technology enables the collection of real-time, quantitative brainwave patterns associated with various emotional states, forming the basis for ML models to predict emotional intelligence (De Lope & Graña, 2022; Sánchez-Reolid et al., 2022). The research demonstrated its capability to identify mental states and understand emotional complexities when combined with ML (Hemakom et al., 2023). Training ML classifiers with EEG signals allows the detection of a range of emotional states, from stress and fatigue (Li et al., 2023) to enjoyment (Fraiwan et al., 2021).

The project management body of knowledge (Project Management Institute [PMI], 2021) identifies emotional intelligence as pivotal in project resource management. It positions project managers as champions of emotional intelligence, articulated through self-awareness, self-regulation, social awareness, and social skills. These competencies shape collaborative environments conducive to team performance. Despite the recognized importance of emotional intelligence in project and safety management, current construction safety prediction models still rely predominantly on observable incident variables, historical records, or operational conditions. This leaves a critical gap between how safety risk is modeled and how workers actually perceive, react to, and behave under hazardous site conditions. In practice, risky behavior is not only procedural or environmental but also cognitive and emotional. Therefore, a more complete safety prediction framework should account not only for what happened in an incident, but also for the probable emotional and cognitive conditions associated with that behavior. Here, extensions of emotional intelligence theory add motivation as a fifth domain, which is especially relevant to ML–EEG safety models, where motivation drives worker behavior under hazardous conditions.

Accident-based (Mostofi & Toğan, 2023a, 2023b) and EEG-based (Wang et al., 2023) studies using diverse data (Fang et al., 2020; Liu et al., 2023; Qi et al., 2024; Ayhan & Tokdemir, 2019a, 2019b; Su et al., 2021; Tang et al., 2020) remain disconnected. Specifically, a critical gap persists: safety prediction models typically lack an explicit cognitive–emotional component, while EEG-based emotional studies are seldom integrated with accident prediction frameworks. Consequently, the influence of workers' emotional states on safety-related behaviors remains insufficiently represented. This study addresses this limitation by proposing an exploratory framework that systematically links risky behaviors, emotional states, and EEG-related features within a construction safety prediction context. By integrating EEG records with accident datasets and associating emotional states with risky behaviors, the framework introduces the concept of "emotionally aware" construction environments, embedding both neurocognitive and operational intelligence into predictive ML systems.

The remainder of the paper is organized as follows. Section 2 reviews related literature. Section 3 presents the framework of the proposed emotionally intelligent ML safety model. Section 3.1 describes the accident dataset and the expert-informed process linking risky behaviors with emotional states and EEG features. Section 3.2 presents Step 2, focusing on emotional states of construction personnel through collaborative data collection. Section 4 explains the model formulation and reports results. Section 5 discusses implications and limitations. The paper concludes with key findings and future research directions.

2. Related works

The construction sector is being reshaped by artificial intelligence (AI) automation. Digital twins (Cho et al. 2025), mixed reality systems, and robotics (Harichandran et al., 2023; Shim et al., 2023; Wu et al., 2023) leverage spatial data for digital-physical (Delmerico et al., 2022; Xu et al., 2024; Yan et al., 2022). Building information modeling (BIM) platforms (Chen et al., 2024; Saka et al., 2022; Wang et al., 2022; Ying et al., 2022) and 3D scanning (Chen et al., 2022; Kim et al., 2023; Park et al., 2022; Xia & Gong, 2022) extend into automated hazard analytics (Zhang et al., 2023), while vision-based methods process (Deng et al., 2026; Hacıefendioğlu et al., 2026; Sharafat et al., 2026) and reconstruct 3D models (Gao et al., 2021) directly from imagery. ML has been successfully applied to EEG data (Antonijevic et al., 2020; Bacanin et al., 2024; Radomirovic et al., 2024) and sentiment analysis (Kozakijevic et al., 2025; Mladenovic et al., 2024). In EEG studies, long short-term memory and recurrent neural network models, enhanced through metaheuristic optimization, improve detection and classification performance (Bacanin et al., 2024; Radomirovic et al., 2024), supporting their integration with emotionally relevant features.

The existing project management studies have established the importance of emotional intelligence in project settings (Zhang et al., 2018) and its success (Mazur et al., 2014). It affects leadership style (Butler & Chinowsky, 2006), communication and resolving complex issues (Khosravi et al., 2020), decision-making (Camplisson & Cormican, 2023; Ndawo, 2021), and overall project performance (Camplisson & Cormican, 2023), which are pivotal factors in devising effective management strategies. In the context of construction safety management, people's emotional status results in different risk perceptions (Tixier et al., 2014). Most of the developed safety prediction models treat workers as predictable variables within a controlled environment. More recent studies utilized EEG and ML models for predictions of states like workers fatigue (H. Li et al., 2019; X. Li et al., 2023) and their vigilance level (Wang et al., 2017). Considering the present site-specific challenges, the psychological perception of the site environment can affect site personnel's decisions and related responses. The definition of situational awareness grounds this statement as an intentional, active, and constant information retrieval from the environment and effective action based on the anticipated consequences (Artman, 2000). While construction project management literature has established the association between emotional intelligence and positive construction outcomes, the developed ML solutions still lack the emotional dimension.

Existing models in construction safety either analyze structured accident datasets (Mostofi & Toğan, 2023a, 2023b) or apply EEG data to estimate cognitive-emotional states such as fatigue (Wang et al., 2023). Data modalities span textual (Fang et al., 2020; Liu et al., 2023; Qi et al., 2024), numeric (Ayhan & Tokdemir, 2019a, 2019b), networked (Mostofi & Toğan, 2023b, 2024), visual (Su et al., 2021; Xiao et al., 2021), and video-based sources (Tang et al., 2020; Tang & Golparvar-Fard, 2021). Yet, EEG-emotional modeling and construction safety prediction remain siloed. These remain separate, with no cognitive–emotional integration. This study links risky behaviors, emotions, and EEG features in an exploratory framework to enable emotionally aware safety prediction. The main contributions of this study are as follows:

- An exploratory framework linking construction accident data with emotional states and EEG-related features.
- An expert-informed mapping approach connecting established risky-behavior labels to probable emotional states and EEG patterns.
- An emotionally informed ML model for safety severity prediction.
- A proof-of-concept foundation for incorporating cognitive–emotional dimensions into future safety analytics.

3. Framework of emotionally intelligent ML safety prediction model

Current trends in artificial intelligence research highlight a shift toward machines possessing cognitive and emotional intelligence (Chang et al., 2023). Integrating emotional intelligence with existing ML models introduces a new dimension to the existing solutions for managing different construction challenges. It is also a more feasible alternative to constant brain wave monitoring approaches for measuring emotional intelligence. The proposed ML strategy for emotional intelligence is a three-step methodology depicted schematically in Figure 1.

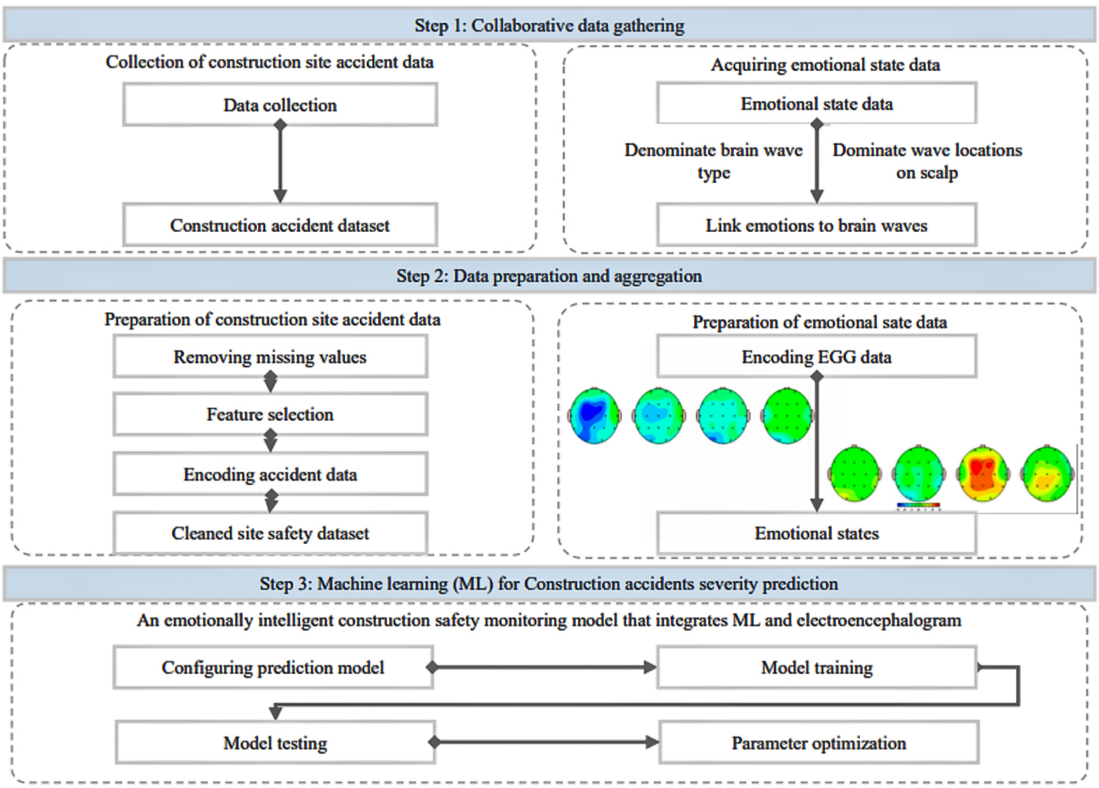

Figure 1. The framework of an integration of ML and EEG model for construction safety prediction

The research began by consolidating accident records with EEG-derived emotional data. Direct real-time EEG monitoring was deemed impractical due to cost (Rafiei et al., 2024), ethical considerations, noise interference, and worker discomfort (Al Jassmi et al., 2019). Instead, cross-domain questionnaires validated by a qEEG expert and a construction expert were used to establish a preliminary mapping from risky behaviors to emotional states and EEG-related features. The enriched dataset was then processed and structured to reflect both behavioral incidents and cognitive-affective dimensions. Accordingly, the ML–EEG component should be interpreted as an exploratory proof-of-concept framework rather than a fully empirically validated EEG-integrated model.

3.1. Collaborative data gathering: Step 1 – Collection of construction site accident data

This study uses an original dataset of 5,224 construction accident records collected from 73 projects and anonymized from Euro-Asian firms. After preprocessing and removal of incomplete, inconsistent, or non-analytical records, the final cleaned dataset used for ML modeling contained 5,105 records. It focuses on high-severity incidents, including medical treatment, lost workdays, and fatalities. The data flow was therefore defined as follows. First, the original accident database contained 5,224 accident records. Second, preprocessing was conducted to remove incomplete, inconsistent, or non-analytical records. Third, categorical variables were converted into machine-readable numerical form for model development. Fourth, the final cleaned dataset used for ML modeling contained 5,105 records. This distinction is important because 5,224 refers to the original accident database, whereas 5,105 refers to the cleaned dataset used in the predictive modeling stage.

Table 1 reports accident-related variables, including severity, worker occupation, age, experience, and incident attributes, along with their frequencies. The risky-behavior labels used in this work are derived from a structured accident-coding framework in which incident-triggering factors were systematically organized and refined using a Delphi process involving 11 experts selected based on defined educational and occupational health and safety experience criteria. This taxonomy was developed in Ayhan and Tokdemir (2019a) and subsequently reused in Ayhan and Tokdemir (2019b). In the present study, these labels function as input variables derived from accident records and are subsequently mapped, using expert-informed approaches, to emotional states and EEG-related features. As the emotional-state and EEG-related mappings were established through expert judgment, uncertainty remains in linking specific emotional and neurophysiological indicators to risky construction behaviors. Therefore, the mappings should be interpreted as exploratory and probabilistic rather than deterministic classifications.

Table 1. Details of the construction accident data utilized

Safety feature	Attribute	Frequency
Project	73 unique projects	5,224
Severity	Medium risk	3070
	High risk	1397
	Low risk	757
Occupation	Rough work crew	2140
	Mechanical assembly crew	1419
	Finishing work crew	649
	Repairman	412
	Others	221
	Construction equipment operator	141
	Engineer	140
	Administrative affairs	102
Age	19–35 years	3776
	36–50 years	1250
	51–65 years	195
	66–100 years	3
Experience	1–3 month	1832
	3–6 month	1255
	1 month	1028
	6–12 month	882
	12–24 month	227
Activity during the accident/incident	Daily activities	906
	Re-bar/formwork installation	805
	Assembly works	787
	The usage of hand-tool/equipment	707
	Lifting operations	470
	Welding/hot works	456
	Working with chemicals	348
	Mechanical, electrical, and plumbing (MEP) works	341
	Finishing works	133
	Transportation/construction equipment/the usage of vehicle	92
	Concreting	59
	Repair/maintenance works	24
	Excavation works	24
	Working at height	21
	Field measurement works	14
	Testing works	12
	Working with chemical materials	9
	Mobilization on/off-site	7
	Landscaping works	6
	Cable-pipe assembly/working with containments	2
	Geotechnical works	1
Type of hazardous event	Material drop	786
	Transport/vehicle movement	691
	Getting the foreign body in the eye	644

Continue of Table 1

Safety feature	Attribute	Frequency
	Being caught between two objects	615
	The usage of hand tool	404
	Falling object	362
	Striking by a moving object	318
	Striking with a stationary object	238
	Exposure to hazardous chemicals	227
	Fire/explosion	197
	Falling from height	194
	Pressure fluctuation	161
	Slipping, tripping, stumbling	85
	Electric shock	61
	Exposure to excess UV (welding operation)	48
	Machinery works	43
	Drowning	40
	Repetitive job	39
	Exposure to smoke and gas	20
	Arc flash	18
	Exposure to dust	13
	Contacting with sharp objects	9
	Using the display screen	6
	Other hazardous events	4
	Crash or rollover	1
Risky behaviours	Exposure to extreme temperatures (hot/cold)	1755
	Making wrong decisions or evaluating the risk	679
	Lack of attention to environment and work area	375
	Not knowing the existing dangers	338
	Not using the existing personal protective equipment (PPE)	296
	Individual violation	278
	Thoughtless routine activity	272
	Loss of concentration	207
	Rushing or using shortcuts	127
	Incorrect posture or position	122
	Working or moving fast	119
	Other	89
	Lack of attention or awareness	84
	Violation of safe working method	61
	Misuse of tools and equipment or using them for unintended purposes	59
	Unfixed equipment or material	55
	Misuse of PPE	52
	Not warning	35

Continue of Table 1

Safety feature	Attribute	Frequency
	Using equipment at an inappropriate speed	29
	Supervisor violation	27
	Placing tools and equipment in inappropriate places	24
	Incorrect loading and unloading	23
	Group violation	21
	Using defective tools and equipment	20
	Being unaware of the existing dangers	14
	Applying violence	13
	Disabling the guard, warning, or safety system	11
	Using equipment without authority	9
	Working above physical capacity	8
	Use of protective measures	7
	Joking around	5
	Use of damaged enclosure, warning, or safety system	5
	Procedures/rules	3
	Working on energy-loaded lines or equipment without cutting off power	1
	Alcohol and drug use	1
Hazardous cases	Repairing or maintaining energized equipment	2652
	Nonconformance records (NCRs) in the working environment	818
	NCRs in safety protection measures	754
	Others	382
	Mechanical hazards/NCRs	347
	NCR in the usage of hand-tool/equipment/construction equipment	176
	Natural hazards	51
	Radiation exposure	26
	Chemical hazards	18
Human factors	Fire, explosion	1493
	Problems resulting from incorrect management system	1187
	Problems resulting from the unbalanced workload	1096
	Insufficient skill and perception	441
	Physical disability	357
	Faulty management system	285
	Problems related to education level	275
	Others	90

End of Table 1

Safety feature	Attribute	Frequency
Workplace factors	Psychological disability	1037
	Problems with the method of statement	959
	Inadequate incident analysis systems	873
	Inadequate communication (general)	691
	The lack of a management system	485
	Inadequate maintenance/ repairment mechanism	445
	Insufficient control, tracking	365
	Others	202
	The lack of occupational health and safety training	107
	Incorrect protection measures	60

3.2. Collaborative data gathering: Step 2 – Emotional state of construction personnel during accidents

Continuous EEG measurement requires overcoming challenges such as invasion of privacy, environmental noises, and potential discomfort of the site personnel. Therefore, to substantiate the proposed emotionally intelligent construction safety prediction model, this study conducted a dual questionnaire from a construction management professional with 22 years of experience in construction management and a qEEG expert who have exercised EEG-driven therapeutic techniques over 12 years. The questionnaire augments the output of the EEG measurement device by correlating risky behaviors in the context of the collected construction safety dataset with the most probable emotion states and, subsequently, their concomitant brain wave activities. It should be noted that adopting a questionnaire over continuous EEG measurements was not solely a matter of convenience but also of ethical considerations. The limitation remains to be addressed by future studies through enhanced data collection systems at construction sites, which record workers' emotional states while addressing ethical concerns. First, the construction management expert was presented with a list of emotional states, whereby the most probable ones were shortlisted. The construction management professional was tasked with correlating risky actions with the emotional state that was believed to be most frequently linked to each specific conduct, as illustrated in Table 2.

After mapping risky behaviors and emotions, a second questionnaire was developed to connect them with EEG brainwave types and scalp positions. EEG provides non-invasive, real-time assessment of worker emotions, making it suitable for construction contexts (Chang et al., 2023). By attaching electrodes to the scalp, EEG records neural activity (Park et al., 2015), turning subjective emotions into measurable inputs for safety management. In the present study, however, EEG was not recorded from construction workers; the EEG-related attributes were incorporated through an expert-informed proxy mapping intended for exploratory framework development.

Table 2. Correlation of construction site risky behaviours with underlying emotional states

Correlation of construction site risky behaviours with underlying emotional states	Correlation of construction site risky behaviours with underlying emotional states
Alcohol and drug use	Stressed
Misuse of tools and equipment or using them for unintended purposes	Irritated
Repairing or maintaining energized equipment	Fatigued
Applying violence	Bored
Disabling the guard, warning, or safety system	Angry
Group violation	Pessimistic
Incorrect posture or position	Angry
Individual violation	Confused
Joking around	Confused
Lack of attention or awareness	Distracted
Lack of attention to environment and work area	Overwhelmed
Loss of concentration	Overwhelmed
Misuse of PPE	Distracted
Misuse of tools and equipment or using them for unintended purposes	Irritated
Not knowing the existing dangers	Fatigued
Not using the existing PPE	Irritated
Placing tools and equipment in inappropriate places	Distracted
Procedures/rules	Angry
Repairing or maintaining energized equipment	Fatigued
Rushing or using a shortcut	Distracted
Supervisor violation	Confused
Thoughtless routine activity	Confused
Use of damaged enclosure, warning, or safety system	Fatigued
Use of protective measures	Overwhelmed
Using defective tools and equipment	Distracted
Using equipment at an inappropriate speed	Overwhelmed
Using tools and equipment inappropriately	Anxious
Violation of safe working method	Irritated
Working above physical capacity	Pessimistic
Working on energy-loaded lines or equipment without cutting off power	Distracted

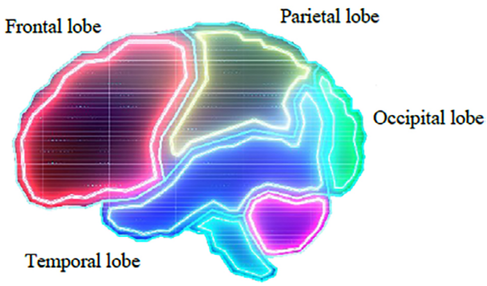

Figure 2. Lateral surface of main brain lobes

A key aspect of the proposed methodology involves developing an integrated ML and EEG framework tailored to construction safety applications and the reliable evaluation of emotional intelligence using EEG devices. Determination of the emotional state with an EEG device includes mapping the location of the dominant wave activities on the scalp. The brain can be divided into 52 distinct regions (Loukas et al., 2011), where each region is associated with a different brain function called a Brodmann area. Figure 2 displays the lateral surface of the main brain lobes.

The Brodmann atlas remains the dominant framework for functional brain mapping, providing labels such as anterior frontal (AF), frontal central (FC), central parietal (CP), frontal temporal (FT), and parietal occipital (PO) for cortical regions (Thatcher, 2021). Consistent electrode placement is achieved through standardized systems like the 10/20 scheme (Jurcak et al., 2007). Modern multi-channel EEG extends this with denser topographies in the 10/10 and 10/5 systems, the latter comprising ~345 electrodes (Oostenveld & Praamstra, 2001). Figure 3a depicts these layouts, where scalp electrodes register cortical activity as wave-like signals generated by neuronal discharges (Marzbani et al., 2016). Figure 3b shows EEG electrode outputs in oscillatory patterns, reflecting localized cortical activity tied to cognition and emotion. EEG provides quantifiable neural rhythms for detecting deviations in brain function. Figure 3c decomposes these signals using Z-score Fast Fourier transform (FFT), contrasting individual electrical activities (brain waves) with normative baselines and encoding deviations in a blue-to-red scale (hypoactivity to hyperactivity). FFT transforms temporal neural signals into frequency space, revealing Delta, Theta, Alpha, Beta, and Gamma bands, each linked to distinct behavioral and cognitive states (Marzbani et al., 2016).

Table 3, derived from Marzbani et al. (2016), summarizes common brain waves and associated emotional or cognitive tendencies, with specific waves selected by a qEEG expert as potentially relevant to construction safety contexts. These associations should not be interpreted as fixed one-to-one relationships, but rather as indicative and context-dependent patterns.

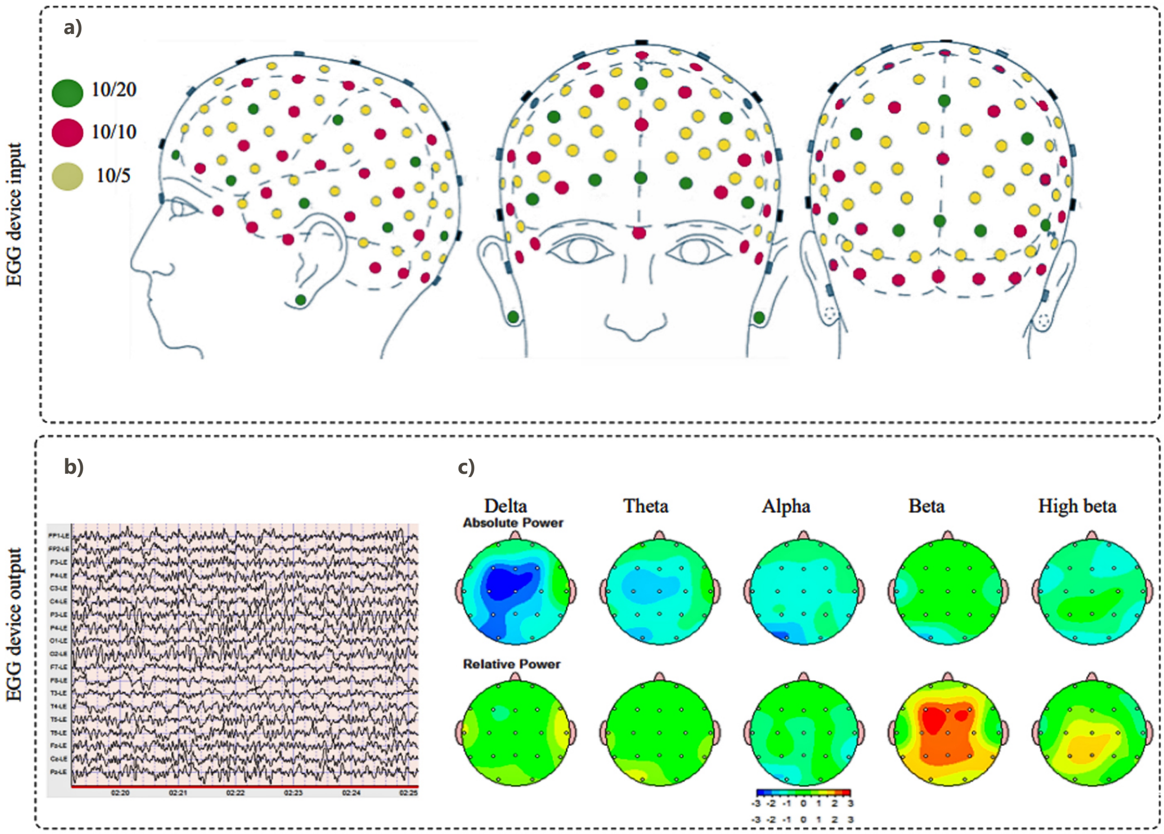

Figure 3. Electrode positions in the 10/5 system, with additional positions marked: a – Views cover lateral, anterior, and posterior perspectives. Standard 10/20 and 10/10 system positions are highlighted for reference; b – The EEG recording with linked ear reference highlights the absolute power metrics during an "Eyes Closed" condition; c – The Z-score FFT summary provides color-coded insights into deviations from normative brain activity (from blue indicating hypoactivity to red signifying hyperactivity)

Table 3. Brain waves and emotional mapping based on Marzbani et al. (2016)

Common brain waves	Selected by a qEEG expert	Frequency range (Hz)	Related emotions
Delta		1–4	Sleep, repair, complex problem solving, unawareness, deep unconsciousness
Theta	☑	4–8	Creativity, insight, deep states, unconsciousness, optimal meditative state, depression, anxiety, distractibility
Alpha	☑	8–13	Alertness and peacefulness, readiness, meditation, deeply relaxed
Lower Alpha		8–10	Recalling
Higher Alpha		10–13	Optimize cognitive performance
Sensorimotor rhythm (SMR)	☑	13–15	Mental alertness, physical relaxation
Beta		15–20	Thinking, focusing, sustained attention, tension, alertness, excitement
High Beta	☑	20–32	Intensity, hyper alertness, anxiety
Gamma		32–100 or 40	Learning, cognitive processing, problem-solving tasks, mental sharpness, brain activity

As shown in Table 3, Theta waves are mostly dominant during deep meditation, light sleep (Kane et al., 2017), or while in the dreaming state (Wang et al., 2017). They mostly dominate people with creative thinking (Marzbani et al., 2016), providing a space where individuals can connect experiences and insights. In the construction site environment, a dominant Theta activity during work hours might indicate site personnel who is not fully alert, which can be a safety concern. A worker exhibiting dominant Theta activity during active work hours can be at risk due to drowsiness or inattention. In a construction setting, a worker with dominant Alpha activity might be in a relaxed state (Kane et al., 2017) and aware of their surroundings (Wang et al., 2017), while a low Alpha suggests addiction to alcohol or anxiety. Sensorimotor Rhythm (SMR) is a brain wave essential for motor control, whereby its dominance indicates that an individual is in a state of "relaxed alertness" (Kober et al., 2013) and typically diminishes in intensity when sensory or motor regions are activated, such as during movements or the visualization of movement (Reichert et al., 2015). Construction personnel with a dominant SMR could be focused on a task that requires precision. Beta waves are the most common brain wave pattern that adults experience in their awake state. This wave becomes dominant when individuals are alert, attentive, engaged in problem-solving, judgment, decision-making, focused mental activity, and fear (Wang et al., 2017). Alternatively, they can be dominant due to drugs such as alcohol (Kane et al., 2017). For example, workers with a dominant Beta wave pattern will likely show active engagement in their tasks, showcasing alertness and focus. Lastly, High Beta waves often dominate the state of high alertness or anxiety (Marzbani et al., 2016). In construction environments, elevated High Beta activity in workers often reflects stress from demanding tasks, strict deadlines, or interpersonal pressures. Persistent activation at this frequency is linked to burnout, highlighting the need for proactive monitoring. Such high-stress states increase the risk of errors or accidents. In this study, accident records were mapped by associating risky behaviors with emotions and brainwave states. It is worth noting that, while in construction settings such associations may provide a useful conceptual basis for interpreting how emotional or cognitive conditions could relate to safety-relevant behavior, they should not be understood as universal one-to-one indicators of specific emotions. In the present study, accident records were therefore mapped through an expert-informed framework that associates risky behaviors with probable emotional states and EEG-related features. Questionnaire outcomes defining these emotional states are reported in Table 4.

4. Formulation of emotionally intelligent construction safety ML

Table 4 details the relationship between various emotional or cognitive states and their corresponding brain wave frequencies: Theta, Alpha Mean, SMR, Beta, and High Beta. The table further breaks down the patterns of these EEG signatures – either hyperactive or hypoactive – and associates them with their respective cortical regions, such as AF, FC, CP, FT, and PO. Detailed the relationships between specific brain areas and the associated safety issues that might arise due to hyperactive or hypoactive brain wave patterns in a construction environment. For instance, hyperactivity in the High Beta waves in the AF region can lead to impulse control issues, potentially causing workers to neglect necessary precautions when working with energy-loaded equipment.

The dataset consisted of 5,105 accident records, where the target variable Severity was categorized into three classes: with labels 0, 1, and 2 corresponding to low, medium, and severe safety risk, respectively. Non-informative administrative fields were removed, and categorical predictors were encoded numerically to ensure compatibility with ML models. The resulting dataset exhibited class imbalance, with distributions of 727, 3022, and 1356 across the three categories. Stratified sampling was implemented to maintain proportional representation during model development.

Table 4. Correlation between emotional states and associated EEG wave patterns and cortex locations

Risky behavior	Emotional state	Theta	Cortex location Theta	Alpha Mean	Cortex location Alpha	SMR	Cortex location SMR	Beta	Cortex location Beta	High Beta	Cortex location High Beta
Alcohol and drug use	Stressed	↑	FT	↓	FT					↑	FT
Misuse of tools and equipment or using them for unintended purposes	Irritated	↑	FC					↓	FC		
Repairing or maintaining energized equipment	Fatigued			↓	AF			↑	AF		
Applying violence	Bored	↑	CP					↓	CP		
Disabling the guard, warning, or safety system	Angry			↓	AF					↑	AF
Group violation	Pessimistic			↑	AF			↓	AF		
Incorrect posture or position	Angry			↓	FT					↑	FT
Individual violation	Confused	↑	AF					↓	AF		
Joking around	Confused	↑	CP					↓	CP		
Lack of attention or awareness	Distracted	↑	FC					↓	FC		
Lack of attention to environment and work area	Overwhelmed			↓	PO					↑	PO
Loss of concentration	Overwhelmed					↓	CP			↑	CP
Misuse of PPE	Distracted	↑	CP			↓	FC				
Not knowing the existing dangers	Fatigued	↑	CP					↓	CP		
Not using the existing PPE	Irritated					↓	FT			↑	FT
Placing tools and equipment in inappropriate places	Distracted	↑	CP					↓	CP		
Procedures/rules	Angry					↓	FC			↑	FC
Repairing or maintaining energized equipment	Fatigued	↑	FC					↓	FC		
Rushing or using shortcut	Distracted	↑	AF					↓	AF		
Supervisor violation	Confused	↑	CP				CP	↓			
Thoughtless routine activity	Confused	↑	PO					↓	PO		
Use of damaged enclosure, warning, or safety system	Fatigued	↑	AF					↓	AF		
Use of protective measures	Overwhelmed					↓	FC			↑	FC
Using defective tool and equipment	Distracted	↑	FC					↓	FC		
Using equipment at inappropriate speed	Overwhelmed			↓	AF			↑	AF		
Using tools and equipment inappropriately	Anxious			↓	FC					↑	FC
Violation of safe working method	Irritated	↑	FT			↓	FT				
Working above physical capacity	Pessimistic	↑	AF					↓	AF		
Working on energy-loaded line or equipment without cutting off power	Distracted	↑	FT					↓	FT		

Notes: AF – Anterior frontal; FC – Frontal central; CP – Central parietal; FT – Frontal temporal; PO – Parietal occipital. ↑ – Hyperactive; ↓ – Hypoactivity.

However, no oversampling or class-weighting strategies were employed, and thus the findings should be interpreted with consideration of this imbalance. Additionally, a stratified 70/30 split was used for class-distribution inspection, whereas a stratified 80/20 split was adopted for the comparative benchmark. Hyperparameters were selected using five-fold GridSearchCV (cv = 5) on the training subset. The explored parameter spaces included decision tree, random forest, AdaBoost, gradient boosting, XGBoost, logistic regression, support vector machines, k-nearest neighbors, Gaussian Naive Bayes, bagging, and multilayer perceptron with their respective hyperparameters.

It is worth emphasizing that the dataset used in this research consists of cleaned construction accident records supplemented with expert-informed emotional-state and EEG-related proxy variables. The original dataset provides incident-level safety details, including accident severity, worker characteristics, and risky-behavior classifications. The additional emotional-state and EEG-related variables were generated through expert mapping rather than direct EEG acquisition. As such, these variables should not be interpreted as measured EEG signals or directly observed emotional states, but rather as exploratory proxy indicators for evaluating the integration of emotionally informed features into construction safety prediction. Although not the central aim of this study, ML model accuracy was evaluated. Accident data were mapped to emotional states via predefined dictionaries that linked risky behaviors to EEG waveforms and scalp regions (Table 4). The integrated dataset, comprising incidents, cognitive states, and mapped neural features, was used to train ML classifiers. This fusion illustrates how emotions translate into regional brain activity, forming the basis of the ML–EEG safety prediction framework. Prediction outcomes for multiple classifiers are reported in Table 5.

To examine the role of the emotional-state and EEG-related variables, the study treated these variables as an exploratory feature layer added to the original accident dataset. Because these variables were generated through expert-informed mapping rather than direct EEG measurement, their contribution should not be interpreted as causal evidence of neurophysiological prediction. Instead, they are used as proxy indicators to test whether cognitive–emotional information can be represented within a construction safety prediction pipeline. Accordingly, the feature contribution is discussed as an exploratory sensitivity assessment rather than as proof of a substantial performance improvement. Based on the performance measurements presented in Table 5, gradient boosting and XGBoost showed comparatively higher performance among the evaluated models, with accuracies of 0.71 and 0.72, respectively, and relatively higher F1 scores. The proposed emotional intelligence ML model for the construction safety prediction model could classify construction accident events into low, medium, and high severity levels within the analyzed dataset. However, the performance should be interpreted with caution, as the best result (0.72 accuracy, 0.70 weighted F1) reflects only moderate performance, and differences among top models are minimal. Accordingly, the framework is better interpreted as an exploratory tool for risk stratification and comparative modeling rather than a deployable system for autonomous safety decisions. Its contribution lies in demonstrating the feasibility of integrating emotional and EEG-based features into predictive modeling, while emphasizing the need for further validation, improved feature engineering, and expanded datasets.

Table 5. Performance accuracy of the proposed emotionally intelligent framework

Model Name	Training time (s)	Accuracy	F1 Score	Precision	Recall	AUC
XGBoost	60.00	0.72	0.70	0.70	0.72	0.71
Gradient boosting	502.98	0.71	0.70	0.70	0.71	0.71
Bagging	14.32	0.71	0.69	0.70	0.71	0.70
Random forest	38.34	0.70	0.68	0.69	0.70	0.69
AdaBoost	8.26	0.68	0.65	0.66	0.68	0.66
K-nearest neighbors	3.14	0.67	0.64	0.65	0.67	0.65
Decision tree	2.25	0.64	0.62	0.62	0.64	0.65
Multi-layer perceptron	80.93	0s.62	0.60	0.59	0.62	0.62
Support vector machines	37.61	0.61	0.53	0.57	0.61	0.55
Naive Bayes	0.09	0.60	0.55	0.56	0.60	0.57
Logistic regression	1.48	0.59	0.48	0.48	0.59	0.52

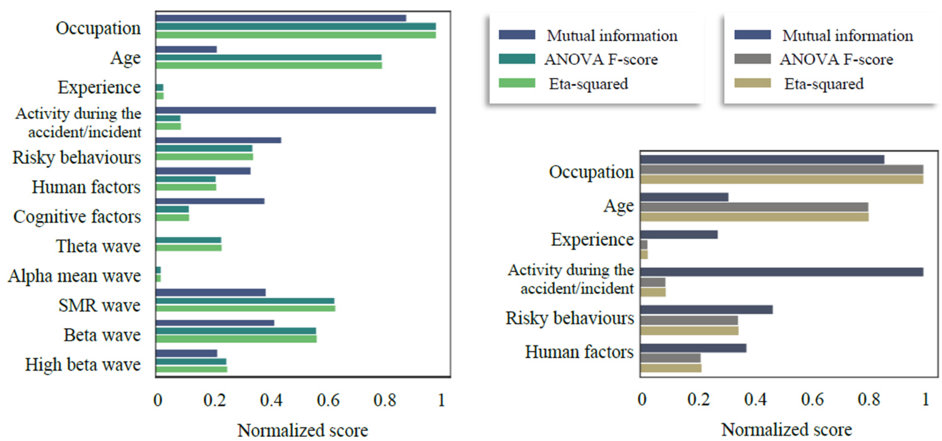

Figure 4. Exploratory feature-contribution analysis using normalized mutual information, ANOVA F-score, and eta-squared. The comparison shows that traditional accident-related variables remain dominant, while selected emotional-state and EEG-related proxy variables, particularly Beta wave, SMR wave, and Cognitive state, show measurable but non-dominant contribution in the emotionally enriched dataset

The broader objective is to illustrate the mechanism of an integrated framework. Besides, it is essential to recognize the study demonstrates the feasibility of integrating ML and EEG-based emotional-state data with accident records for construction safety prediction, rather than proposing a deployment-ready system. Therefore, the broader objective of this research in to demonstrate the mechanism of an integrated ML and EEG model that leverages the strengths of both traditional accident records and quantifiable emotional states discerned through EEG devices for the safety prediction of construction projects.

To further examine the contribution of the emotional-state and EEG-related variables, an exploratory feature-contribution analysis was conducted using normalized mutual information, ANOVA F-score, and eta-squared (Figure 4), comparing the baseline accident-related feature structure with the emotionally enriched feature structure. In the baseline accident dataset, traditional accident-related variables such as Activity During the Accident/Incident, Occupation, and Risky Behaviors showed the strongest relative contribution. After adding the expert-informed emotional-state and EEG-related proxy variables, selected added variables also showed measurable but non-dominant contribution. In particular, Beta wave, SMR wave, and Cognitive state appeared among the mid-ranked variables in the emotionally enriched feature set. However, traditional accident-related variables remained dominant.

5. Discussions

Prevailing ML frameworks in construction safety treat workers as deterministic inputs in controlled environments, neglecting the cognitive-emotional dynamism of human agents (Wang et al., 2017). However, empirical evidence shows emotional intelligence can attenuate workplace incivility (Loi et al., 2021) and promote knowledge acquisition (Gribble et al., 2018), enabling safer site ecosystems. Unaccounted emotional shifts may catalyze incidents even in ostensibly safe environments. In response, this study advances a hybrid model merging EEG-derived signals and structured data to embed emotional intelligence in ML-driven decision-support mechanisms for construction safety.

By treating affective states as model inputs through an expert-informed mapping, the proposed framework aligns with PMI's emphasis on emotional intelligence while offering a pathway toward future field-level risk prediction. This augmentation enables the system not only to anticipate safety violations but also to trace their emotional antecedents, thereby offering richer context for intervention. Eleven standard classification algorithms were benchmarked, with future iterations considering advanced paradigms like self-supervised learning (Rafiei et al., 2024), dynamic ensembles (Alam et al., 2020), and neural classification frameworks (Ahmadlou et al., 2010; Rafiei & Adeli, 2017).

The integrated ML–EEG framework proposed in this research offers an approach by combining neuroscience, computing, and construction science to outline how future safety interventions may incorporate mental-state assessment; in the current study, the EEG-related dimension is conceptual and expert-informed rather than directly measured. EEG data, when embedded within safety systems, can serve as an early warning mechanism for detecting psychological stressors or emotional dysregulation in site personnel.

PMI (2021) identifies emotional intelligence as a foundational attribute in effective project leadership and communication; however, it does not articulate how such emotional constructs can be objectively measured or operationalized. This research addresses that gap by proposing a quantifiable model incorporating self-awareness, self-regulation, and relationship management into construction safety.

The model transforms emotional intelligence from a conceptual value into a decision-support parameter, fostering an adaptive and emotionally responsive management paradigm for high-risk construction settings. Its adoption may not only enhance safety but also align with PMI's vision for emotionally intelligent project environments.

The dual-layered approach of this model optimizes the potency of safety interventions, making them more resonant and impactful. This duality refers to its ability to simultaneously harness accident data and structured, expert-informed emotional indicators. By doing so, it offers a comprehensive perspective on safety risks, integrating the "what happened" (from accident data) with the "why it might have happened" (from emotional states). Such a dual-layered analysis ensures that safety interventions are not just based on past incidents but are also cognizant of the underlying emotional factors that might contribute to potential future risks. Because the mapping process relied on a limited number of experts from two domains, the resulting emotional-state and EEG-related associations should be interpreted as preliminary and subject to expert judgment, and future studies should expand the expert pool to enable stronger reproducibility and inter-rater assessment.

The perspective of the proposed framework in construction safety management can be extended to other domains within construction and project management. Understanding the emotional triggers behind certain behaviors allows managers to make more informed decisions, anticipate potential errors, and implement measures to improve quality. For instance, decision-making in quality control can be enhanced using the proposed model to identify emotional patterns that may lead to lapses in quality assurance processes, addressing potential issues before they escalate. Moreover, as Love et al. (2023) suggest, shifting from a mindset of "errors must be prevented" to "errors happen" requires organizational change. The integrated ML and EEG model can facilitate this shift by providing data-driven insights that help project managers understand and navigate the emotional aspects of their team's decisions and behaviors. This informed approach can lead to more effective strategies that enable organizations to manage changes more effectively, facilitating a more progressive and adaptive construction environment. While the framework is conceptually generalizable, linking behavioral, emotional, and EEG-related features, the specific mappings in Tables 2 and 4 are context-sensitive. Variations across regions, safety cultures, and workforce conditions necessitate recalibration through local expertise and empirical validation.

Though key to construction safety, emotional intelligence is hard to quantify due to EEG artifacts (Chang et al., 2023). Real-time monitoring of neural dynamics among site personnel encounters systemic constraints, ranging from discomfort caused by EEG-integrated helmets (Wang et al., 2023) to the attentional load imposed by continuous monitoring. Though emotional intelligence may be relevant to construction safety, its operationalization through EEG-related methods raises substantial technical, ethical, and regulatory challenges. Real-time monitoring of neural dynamics among site personnel encounters systemic constraints, including discomfort caused by EEG-integrated wearables, attentional burden, and degraded signal fidelity under vibration, noise, and movement-rich construction conditions. In addition, any future deployment of emotionally intelligent monitoring systems would require careful attention to informed worker consent, privacy protection, data ownership, acceptable secondary use of neurocognitive data, and compliance with applicable legal and organizational governance requirements. Concerns regarding neuro-surveillance and power asymmetries between employers and workers also warrant caution. Accordingly, the present study should be understood as a conceptual and exploratory step rather than as a recommendation for immediate field deployment. Finally, it is important to note that the study relied exclusively on expert elicitation and did not involve the collection of EEG signals or personal data from construction workers; therefore, institutional ethics review was not required.

6. Conclusions

This study integrates ML and EEG emotional modeling to improve construction safety prediction. Using 5,224 accident records, EEG data was augmented via expert-validated questionnaires to link worker emotions to accidents and EEG patterns. Although accuracy wasn't the main goal, it was assessed to validate the model. The integration of EEG data adds an emotionally intelligent dimension to the utilized ML models. The strength of the proposed model lies in its capability to analyze accident data and emotional signals simultaneously. By synergizing accident data with emotional states, it allows comprehensive scenario analyses in construction safety. Given that no direct EEG data were collected from construction personnel, the EEG-related dimension in this study should be interpreted as conceptual and exploratory, rather than neurophysiologically validated. Future work could improve the model by combining historical accident datasets with real-time emotional indicators, allowing for more adaptive responses to the evolving conditions of construction sites, reducing false positives, and promoting a more proactive and inclusive safety culture.

Utilization of past accident data with live emotional metrics ensures that the model remains more responsive to the fluid nature of construction sites, minimizing false alarms and fortifying a safety culture that's both proactive and inclusive. Beyond adding brain waves and their scalp locations, the added layer of emotional state data is offered by the proposed model to anticipate future events based on the emotional states of the workers involved while still factoring information from past accident records. When a system can predict safety lapses-based on objective metrics and reading the underlying emotional currents, interventions can be more responsive, targeted, and reflective of the real-world construction environment.

Data availability statement

Some of the data used in this research are available upon reasonable request.

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