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Ear-EEG-based Stress Assessment for Construction Workers: A Comparison with High-Density Scalp-EEG

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Abstract: Mobile electroencephalography (EEG) can continuously and objectively monitor construction workers' psychological stress, thereby contributing to enhanced safety and health. Traditional EEG-based stress assessment techniques utilize headset-type devices that cover the scalp, including the frontal area, which is the most relevant brain part to stress. Yet, the invasiveness of such devices may pose a potential barrier to their field application. In response, ear-EEG technology presents a less intrusive alternative for continuous monitoring, potentially overcoming the limitations of scalp-EEG. The temporal regions monitored by ear-EEG hold anatomical and functional significance in the brain's response to stress, suggesting that ear-EEG could effectively detect stress. Despite its advantage, the effectiveness of ear-EEG in stress detection remains underexplored, largely due to the existing literature's focus on frontal brain regions. To address this gap, the authors aim to evaluate ear-EEG's effectiveness in measuring stress and compare it to high-density scalp-EEG. EEG signals were collected with ear- and scalp-EEGs from 10 subjects in a controlled laboratory while they performed the mental arithmetic tasks under time pressure and socio-evaluative threats to induce stress at different levels (high vs. low). Subsequently, the authors performed t-tests and point-biserial analysis to analyze differences between high and low-stress conditions in the most reliable stress biomarkers in literature: high-beta power in temporal regions for ear-EEG, and alpha asymmetry in frontal regions for scalp-EEG. The results indicate that both EEG techniques could effectively differentiate between stress levels, with statistical significance ($p < 0.001$ for both) and moderate effect size. Furthermore, the results demonstrate ear-EEG's comparable effectiveness to scalp-EEG in detecting stress-induced brain activity given the comparable statistical metrics, such as p-value and effect size. This study provides a groundwork for further explorations into leveraging ear-EEG as a practical tool for the early detection of stress, aiming to enhance stress management strategies within the construction industry.

Key words: Psychological stress, Ear-EEG, Scalp-EEG, Construction Safety

1. INTRODUCTION

The construction workforce increasingly suffers from high rates of mental health problems, largely attributed to psychological stress. This form of stress occurs when individuals perceive their environment as overwhelming, exceeding their capacity and posing a threat to their well-being [1]. A variety of work-related factors contribute to stress, including, such as time pressure, heavy workload, lower wages, ambiguity of job requirements, lack of training, lower supervisor support, and lower job security [2–4]. Research indicates that nearly one-third of male construction workers in the U.S. experience psychological stress [5], and this stress has been linked to a higher incidence of suicide ideation [5], injury incidents [6], and lower productivity [7]. The widespread and detrimental effects of stress among construction workers underscore the urgent need for effective strategies to identify and mitigate job site stressors.

Traditionally, the evaluation of stress in safety management has relied heavily on self-reported measures, such as the Perceived Stress Scale [8]. While these methods are useful and convenient, they are inherently subjective and may disturb workers during work [9]. An alternative approach involves the use of biomarkers, like salivary cortisol, to objectively gauge stress levels. However, despite their objectivity, biomarkers face challenges in the construction context due to their invasive collection process, delay in response (more than 30 minutes), and lack of capability for continuous monitoring in dynamic construction environments [9].

In response to these limitations, mobile electroencephalography (EEG) emerges as a promising solution, offering a less invasive and more continuous approach to monitoring diverse mental states, including stress. Specifically, mobile EEG can continuously monitor brain activity patterns in response to stressful events, facilitating the early detection of excessive stress levels [10]. This EEG-based stress detection stands out from other biosensors, such as wrist-worn sensors, because of the in-depth and rich information it collects from the brain — the central processing unit of human cognition and emotions. For instance, EEG uniquely offers insights into stress types, such as challenges and threats, which are known as beneficial and harmful to human performance and health, respectively, enabling selective stress interventions that alleviate the threat, while keeping the benefits from challenge [11].

Furthermore, the recent advancements in EEG technology have significantly enhanced the functionality and accessibility of mobile EEG, making its deployment increasingly practical in challenging environments, such as construction sites. Specifically, the advent of ear-EEG technology made brain activity monitoring more compact and accessible. In contrast to the bulky, traditional scalp-worn EEG headsets, ear-EEG utilizes electrodes placed strategically near the ears, to monitor the temporal regions. These areas are vital for processing emotions [12], learning [13], and memory [14], providing valuable insights into a person's cognitive and emotional state. Indeed, although ear-EEG does not encompass as broad a range of brain regions as scalp-EEG, research has demonstrated that ear-EEG can match the performance of scalp-EEG in detecting sleep stages [15], seizure [16], and auditory attention [17], highlighting its potential versatility. Additionally, ear-EEG devices are designed to be compatible with safety gear such as hardhats, addressing potential safety issues associated with wearing traditional scalp-EEG systems within hardhats.

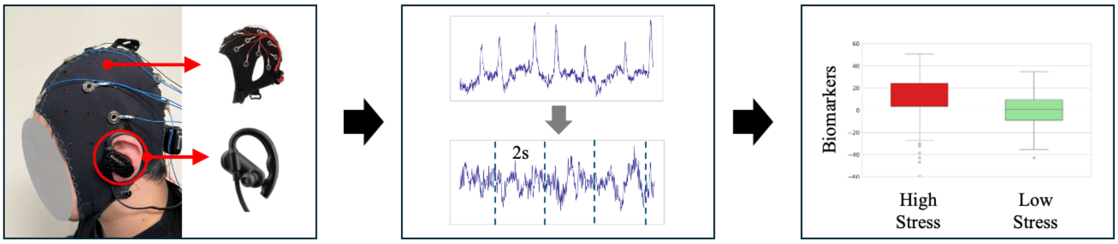
The use of ear-EEG for stress detection can be viable given the temporal regions' anatomical and functional connections to the brain's stress response. A meta-analysis of brain imaging studies (fMRI and PET) highlights the role of the superior temporal gyrus, situated just behind the ears, in the cognitive regulation of emotions which is initiated by the frontal areas in response to stress [18]. Furthermore, the temporal regions house the amygdala, a key area in stress response mechanisms. Despite its deeper location within the brain (which may not be reachable through EEG), the amygdala closely interacts with the more superficial regions of the temporal area (e.g., medial temporal lobe), especially in stress response. This interaction implies that stress-related brain activity influenced by the amygdala might be detectable through EEG monitoring.

While brain imaging research supports the potential of ear-EEG as a viable tool for monitoring stress-related brain activity, there remains a paucity of EEG research focused on determining the effectiveness of stress detection by solely analyzing brain activity in these specific regions. This gap is partly because conventional EEG-based stress assessment techniques have predominantly focused on the frontal brain regions that are easily accessible through conventional scalp-EEG as well as are particularly sensitive to stress due to their crucial role in emotional regulation [19]. Resultingly, we lack knowledge regarding the feasibility of using ear-EEG for stress detection and its comparative effectiveness against the more traditionally employed scalp-EEG.

To fill this knowledge gap, we aim to evaluate ear-EEG's effectiveness in differentiating stress levels (high vs. low) and compare it against scalp-EEG. We collected and analyzed EEG signals collected from 10 subjects, employing both ear- and scalp-EEGs simultaneously as they were exposed to different levels of stress in a controlled laboratory. The findings of this study are expected to enhance our understanding of the viability of ear-EEG as a tool for stress management, potentially enriching our strategies for monitoring and addressing job site stressors.

2. METHOD

In this study, we seek to assess the effectiveness of ear- and scalp-EEGs in differentiating between high and low-stress states. As illustrated in Figure 1, this study involves three stages. Initially, we collect EEG signals from participants using both EEG systems at different stress levels (high vs. low) (Figure 1a). Then, the EEG signal is cleaned to reduce noise in the EEG signals and is segmented to facilitate statistical biomarker extraction and analysis (Figure 1b). Finally, we extract stress-related biomarkers from the cleaned EEG data, which are then used for statistical analysis to see the effectiveness of both EEG systems in differentiating high and low-stress states (Figure 1c).



(a) EEG collection using ear- and scalp-EEGs

(b) EEG data processing (denoising & segmentation)

(c) EEG biomarker analysis (high vs. low stress)

Figure 1. The overall procedure of this study

2.1. In-Lab Data Collection

We recruited 10 graduate students from the University of Michigan, comprising 8 men and 2 women, with an average age of 27 years (SD = 2.9 years; age range: 23 – 34 years). Prior to data collection, participants were asked to report any physical and mental health issues that could affect their psychological and physiological reactivity to stress; none reported any relevant conditions. Each participant individually participated in the data collection, which mainly consisted of relaxation and stress-inducing tasks in a controlled lab environment.

To monitor brain activity throughout the data collection, we employed two EEG systems (i.e., ear-EEG and scalp-EEG), both worn simultaneously. As illustrated in Figure 2, the ear-EEG data was collected from two dry electrodes located at the temporal areas (T3 and T4) using the Emotiv MN8 system. Simultaneously, scalp-EEG data was gathered from twelve gel-based electrodes evenly distributed across the entire scalp (Fp1, Fp2, F3, F4, T3, T4, C3, C4, P3, P4, O1, O2) using the Emotiv Epoc Flex system. Both systems had a sampling rate of 128 Hz.

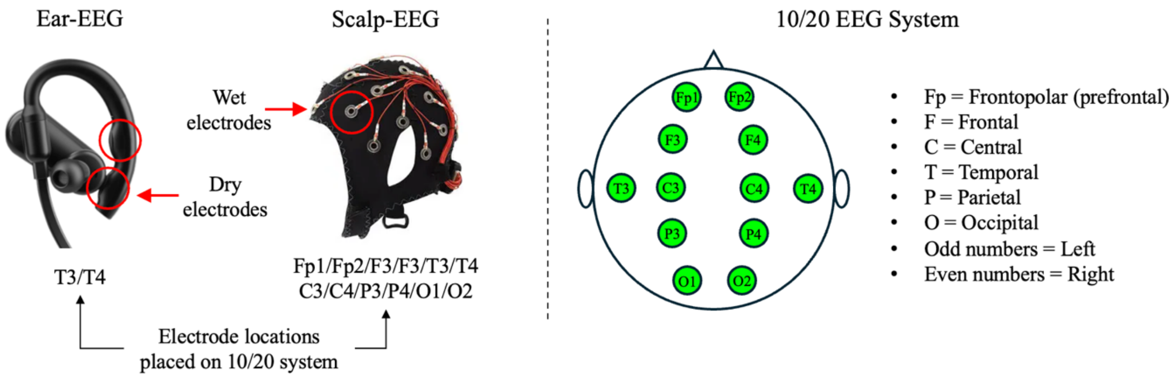


Figure 2. Ear- and Scalp-EEG systems and electrode location

The data collection began with a 10-minute relaxation period, designed to reduce the influence of any external stressors on participants and to collect EEG data under low-stress conditions. During this time, participants were shown a nature video clip with sound, delivered through the ear-EEG system connected to a laptop. EEG recordings from the final 5 minutes of this relaxation period (5 min) were labeled as low stress.

Following the relaxation period, subjects engaged in a computerized mental arithmetic task under time pressure and socio-evaluative threats [20], which are designed to induce acute cognitive stress effectively. This mental task was structured into 10 individual sub-sessions, each consisting of 20 arithmetic problems that participants were required to solve without using pen and paper. Immediately after each sub-session, subjects rated their arousal using the self-assessment Manikin (SAM) scale [21]. Participants' EEG signals collected during sub-sessions rated as high arousal (6 or more on the 9-point arousal scale) were labeled as high stress. Conversely, EEG signals from sub-sessions that received a low arousal rating —3 or below on the SAM scale— were classified as low stress, which then was combined with the low-stress dataset from the relaxation session. Given the significant correlation between levels of stress and arousal, SAM has been widely applied to annotate the level of stress [22,23]. Each sub-session with the self-reported survey took around 90 seconds, and participants were provided with 2-minute breaks between each sub-session.

To introduce time pressure, we initially allowed participants to complete a trial session (20 problems) at their own pace, establishing a benchmark for each participant. We then applied a time limit to each subsequent session, reducing their initial completion time by 10%, as suggested in [24]. For the social-evaluative threat, we informed participants that their performance outcomes—specifically, their successes, failures, and error rates—would be monitored and judged by the research team, heightening the fear of negative judgment as a stressor [25].

2.2. EEG Data Processing

The collected EEG data was processed to remove both extrinsic and intrinsic artifacts. The initial step involved applying a bandpass filter, with a higher cutoff frequency set at 64 Hz and a lower cutoff at 0.5 Hz, to eliminate common extrinsic artifacts responsible for slow and rapid fluctuations from both ear- and scalp-EEG data [10]. Following this, a 50 Hz notch filter was applied for both EEG datasets to mitigate electrical interferences caused by power lines. For the scalp-EEG data, an additional denoising step was implemented through independent component analysis (ICA). This ICA-based technique was specifically employed to isolate and eliminate eye blink artifacts, which can be easily found in frontal areas as shown in Figure 3. This eye-related artifact removal process was not necessary for the ear-EEG recordings as ear-EEG are not affected by eye-related artifacts due to their location near the ear [26]. After denoising, the EEG data were segmented into 2-second intervals, preparing them for biomarker extraction and statistical analysis in the subsequent session.

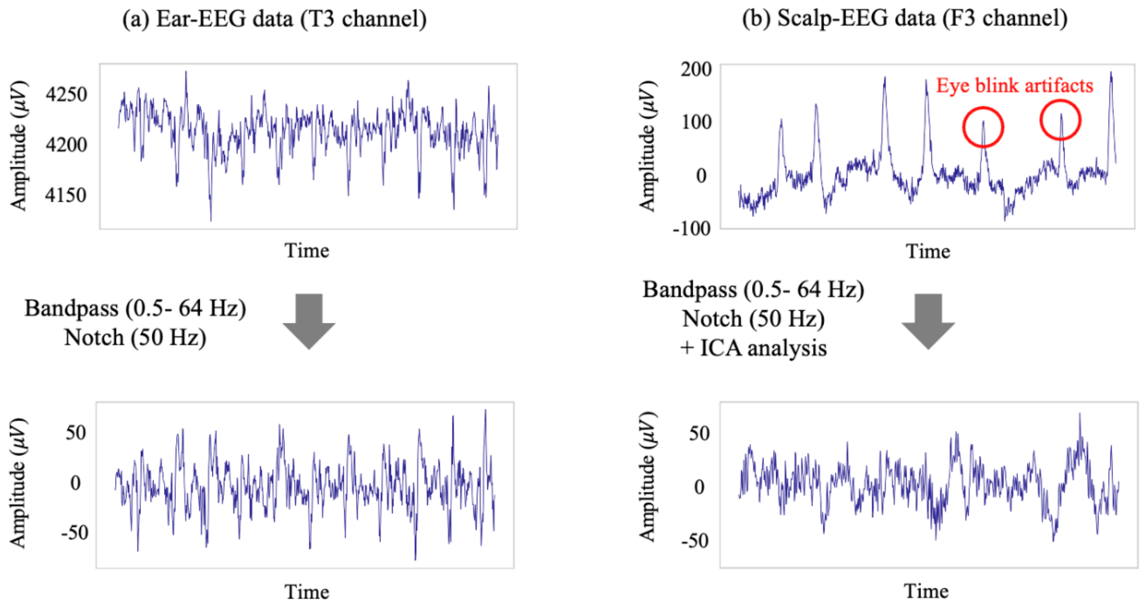


Figure 3. EEG artifact removal process

2.3. Statistical Analysis of EEG Stress Biomarker (High vs. Low Stress)

We first identified stress-specific biomarkers that are indicative of stress, focusing on spectral features that have been recognized in prior research for their strong association with stress responses. For the ear-EEG system, we focused on the high-beta power spectrum (18-40 Hz) located in the temporal regions (T3 and T4), informed by literature suggesting a direct correlation between increased high-beta power and elevated stress levels [27]. Conversely, for the scalp-EEG system, we selected alpha asymmetry (8-12 Hz) as the primary biomarker. Alpha asymmetry, defined as the difference in absolute alpha power between the right frontal hemisphere (F4) and its counterpart in the left hemisphere (F3), is well-documented as an effective indicator of stress responses in literature [19,28,29]. To compute these biomarkers, we analyzed every 2-second segment of the EEG dataset.

Subsequently, we performed a t-test to identify any statistically significant differences in biomarker values between the high and low-stress states. Following this, we applied the point-biserial correlation analysis. The point-biserial correlation, a specific form of the Pearson correlation, quantifies the strength and direction of the relationship between a continuous variable (the biomarker value) and a binary variable (the stress level: high vs. low). These analyses were designed to robustly assess and provide statistical validation for the discriminatory power of each EEG system in detecting stress.

Then, we compared statistical metrics (i.e., p-value, effect size, and point-biserial correlation coefficient) between the two EEG systems to examine their relative effectiveness in stress detection, offering insights into their comparative advantages and limitations.

3. Results and Discussion

The statistical analysis results, as summarized in Table 1, show the distinction between high and low-stress states as determined through ear-EEG and scalp-EEG systems. Specifically, For the ear-EEG system, which assesses high-beta power, the analysis revealed a mean value of 36.07 (SD = 12.74) in high-stress states compared to a mean of 21.24 (SD = 6.93) in low-stress states. The t-statistic of 4.73 highlights a statistically significant distinction between the stress levels ($p < 0.001$), with an effect size of 0.42, indicative of a moderate difference. Additionally, a point-biserial correlation coefficient of 0.2 suggests a positive relationship between high-beta power and stress level.

Similarly, the scalp-EEG system's measurement of alpha asymmetry presented a mean value of 9.89 (SD = 23.53) under high stress, contrasted with -0.43 (SD = 13.20) for low stress. This comparison yielded a t-statistic of 5.94, affirming a statistically significant variance ($p < 0.001$) with an effect size of 0.53, indicating a moderate difference between stress states. Furthermore, the point-biserial correlation coefficient was 0.25, slightly exceeding that observed with the ear-EEG system, suggesting a positive association between alpha asymmetry and stress level.

These results collectively affirm the utility of both ear-EEG and scalp-EEG systems in effectively differentiating between high and low-stress conditions. Noteworthy is the similarity in their statistical metrics—comparable t-statistics, p-values, and effect sizes, along with point-biserial correlation coefficients—highlighting their potential in stress level assessment.

Table 1. Statistical analysis results (high vs. low stress)

EEG systems (Biomarker)	**Condition**	**Mean (SD)**	**Independent t-test**			**Point-biserial correlation**
			t-statistics	**p-value**	**Effect size (Cohen's d)**	
Ear-EEG (High-beta power)	High Stress	36.02 (12.74)	4.73	<0.001	0.42	0.20
	Low Stress	21.24 (6.93)				
Scalp-EEG (Alpha asymmetry)	High Stress	9.89 (23.53)	5.94	<0.001	0.53	0.25
	Low Stress	0.43 (13.20)				

The distinct patterns of the biomarkers under different stress conditions are visually observed in Figure 4. In Figure 4a, the ear-EEG, measuring high-beta power, clearly shows elevated levels in the high-stress condition with greater variability as opposed to the low-stress states. This observation aligns with existing literature that suggests exposure to stress is correlated with an increase in high beta power activity [27]. In Figure 4b, the scalp-EEG, measuring the alpha asymmetry, presents a discernible difference between the high and low stress states. The mean value in the high-stress state remains positive, whereas it hovers around zero in the low-stress state. This observation aligns with existing literature that posits a link between alpha asymmetry and stress, where a higher alpha asymmetry value tends to be associated with stress [28,30]. However, the box plot for high stress exhibits an overlap with the low stress condition, and includes several outliers in negative values, suggesting that individual responses to stress may not be as uniform concerning alpha asymmetry.

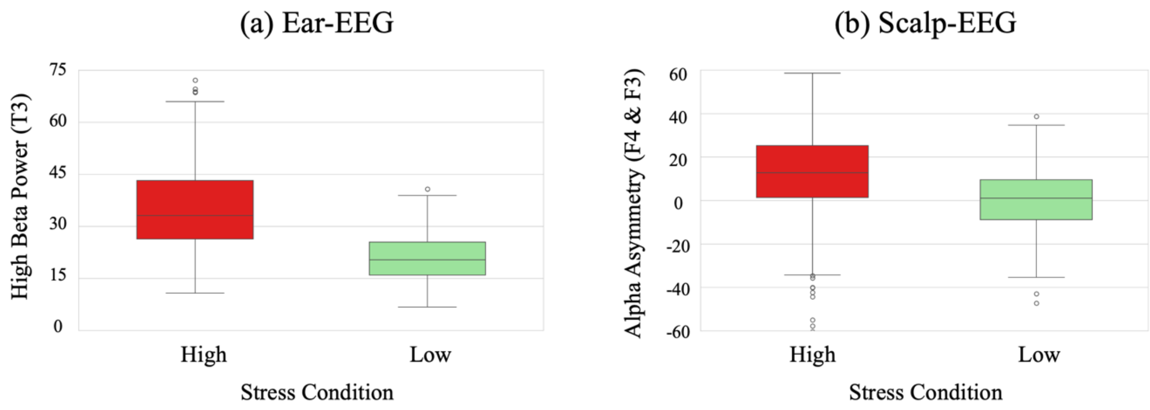


Figure 4. Boxplot of the EEG biomarkers between high and low stress

In summary, the findings highlight the potential of high-beta power in the temporal regions, as measured by ear-EEG, as a promising biomarker for stress assessment. Furthermore, ear-EEG can be a promising alternative to scalp-EEG for the monitoring of stress levels given the comparable statistical metrics (i.e., t-statistics, p-value, effect size, and point-biserial correlation coefficient). However, these metrics, while useful, do not provide a complete picture of their effectiveness for stress detection. A thorough evaluation of these EEG techniques should also take into account factors such as user comfort, signal quality, and their practicality across diverse environments.

In this study, the use of both EEG systems has elucidated their unique benefits in this context. Specifically, ear-EEG, by targeting brain regions near the ear, circumvents the challenge of artifacts related to eye movements, which is one of the major sources of EEG artifacts that is challenging to fully mitigate [31]. The employment of dry electrodes and an in-ear headphone-like device further underscore the practicality of ear-EEG, with participants reporting a high level of comfort and ease of use without assistance. Conversely, scalp-EEG, which employs wet electrodes, offers distinct advantages. The use of conductive gel facilitates more stable recording quality, especially during physical movement, compared to ear-EEG. Furthermore, although this research primarily compares specific biomarkers between the two EEG techniques, scalp-EEG has the capability to leverage more multi-dimensional data from various brain region, potentially enabling more accurate identification of stress-related brain responses.

Building on these findings, future research could employ sophisticated data analysis techniques, including machine learning, to further assess the effectiveness of stress detection between ear-EEG and traditional scalp-EEG systems. Furthermore, by investigating various mental states—ranging from emotional responses to cognitive load—future studies can leverage EEG technology's broad potential for monitoring a spectrum of psychological conditions. To enhance the generalizability of findings in this study, forthcoming research will expand the participant pool, ensuring the incorporation of enough individual variability in EEG signals. Additionally, implementing field tests in real-world settings will further validate the practical applicability and effectiveness of EEG technology in stress monitoring.

4. CONCLUSION

Compared to the traditional scalp-EEG, ear-EEG technology offers a more compact and accessible approach to monitoring brain activity, significantly enhancing the feasibility of tracking stress among workers in practical settings. Evidence from brain imaging research indicates that ear-EEG is potentially effective for stress detection, as the temporal regions it monitors are directly connected to the brain's stress response. However, the potential of ear-EEG has not been fully investigated, highlighting a notable gap in current research. To fill the gap, we assessed the effectiveness of both ear- and scalp-EEGs in differentiating between high and low-stress states, utilizing high-beta power and alpha asymmetry as spectral biomarkers for ear-EEG and scalp-EEG, respectively. The results indicate that both EEG techniques could effectively differentiate between stress levels, with comparable statistical metrics (i.e., t-statistics, p-value, effect size, and point-biserial correlation coefficient). These outcomes imply that ear-EEG could be a viable and more convenient alternative to traditional scalp-EEG for stress assessment, with the added benefits of enhanced portability and user comfort. It is worth noting, however, that these initial results, primarily based on spectral and statistical analysis, call for further investigation with sophisticated analytical techniques like machine learning, to fully examine the utility of ear-EEG in stress detection. This study lays a foundational stone for future explorations into leveraging ear-EEG as a practical tool for the early detection of stress, aiming to enhance stress management strategies within the construction industry.

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