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RESEARCH ARTICLE

Emotion Recognition in Virtual Reality: EEG and EDA-Based Analysis of Stress in High-Risk Scenarios

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ABSTRACT Virtual Reality (VR) is a powerful tool for analyzing human emotions in simulated crisis scenarios. This study integrates electroencephalography (EEG) and electrodermal activity (EDA) in VR environments to improve emotion recognition in dynamic, high-stress situations that are difficult to replicate in real-world settings. The experiment involved a simulated elevator sabotage scenario, during which participants' neurophysiological and physiological responses were recorded as the elevator descended. The collected data were compared with self-reported assessments. The primary objective was to evaluate whether combining VR and biosignal-based measurements enables objective analysis of emotional experiences. A hybrid emotion recognition system combining EEG and EDA was developed to quantify stress levels in dynamic crisis scenarios. Statistical analyses and SVM classification confirmed significant phase differences, with 91.67% accuracy and higher reliability of the combined EEG-EDA approach compared to standalone methods. The results indicate that this approach enhances the understanding of psychophysiological stress responses and provides a reliable tool for identifying emotional states during simulated security incidents. This system has potential applications in emotion research, security training, crisis simulations, and environmental psychology. These findings highlight the potential of VR and biosignal analysis for realistic crisis simulations, offering valuable insights for investigative methodologies and security personnel training.

INDEX TERMS Dynamic situations, electrodermal activity (EDA), electroencephalography (EEG), emotion recognition, high-risk scenarios, safety, simulated crisis scenarios, stress, virtual reality (VR).

I. INTRODUCTION

Virtual Reality (VR) is a multimodal sensory experience that extends or entirely replaces real-world sensory input with artificially generated content [1]. VR provides a highly immersive environment for eliciting emotional responses, as users are fully engaged in a controlled, distraction-free setting [2]. Due to its capability to simulate both realistic and extreme conditions in a controlled manner, VR is an ideal platform for emotion research, offering a high degree of presence and interactivity [1]. The integration of VR with implicit biosignal-based measurement techniques provides valuable insights into human behavior and emotional responses, influencing research and applications in fields

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such as psychology, forensic neuroscience, medicine, rehabilitation, therapy, education, security, and entertainment [1], [3], [4]. This fusion of technologies enables more precise detection of emotional states and facilitates a deeper analysis of biosignal changes often overlooked by traditional methods. Emotions play a fundamental role in decision-making processes, and their objective identification has broad implications in forensic neuroscience and affective computing [2]. Consequently, emotion recognition in VR has emerged as a critical area of research, focusing on assessing emotional states through biosignal analysis.

A. CURRENT APPROACHES TO EMOTION RECOGNITION IN VIRTUAL REALITY

Traditional emotion recognition methods rely on audiovisual cues, such as speech, facial expressions, and gestures [5]. However, recent advancements have shifted the focus towards physiological and neurophysiological signals, which offer a more detailed and objective assessment of emotional states. These biosignals can be broadly classified into autonomic nervous system (ANS) signals, including electrodermal activity (EDA), heart rate (HR), electrocardiography (ECG), and electromyography (EMG), and central nervous system (CNS) signals, especially electroencephalography (EEG) [5].

Neurophysiological signals, particularly EEG and physiological indicators such as EDA and HR, have emerged as key modalities for emotion recognition in VR environments [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]. Studies indicate that even cost-effective wearable devices can achieve high accuracy in emotion detection [7]. EEG provides insight into cortical activity, while EDA reflects autonomic arousal and stress levels through variations in skin conductance. Research suggests that combining EEG and EDA yields higher classification accuracy than utilizing these signals independently [6], [8], [11], [12]. However, studies examining this multimodal integration in VR scenarios remain limited. Furthermore, the lack of standardized methodologies for capturing emotional responses in complex, dynamic VR environments highlights the need for further investigation.

Multimodal approaches integrating synchronized biosignal acquisition via wearable sensors and VR stimuli represent a promising research direction in affective computing. These methods enable the objective analysis of psychophysiological responses to VR experiences and facilitate the correlation of subjective self-reports with physiological markers [1], [7], [9], [14].

Recent research efforts have explored various aspects of emotion recognition in VR using EEG and EDA, including emotion classification enhancement [6], [7], [16], presence perception [3], [9], preference and arousal recognition [2], stress reduction [8], motion sickness mitigation [4], therapeutic applications [10], support for individuals with specific needs [11], relaxation [12], and cognitive workload assessment [18]. Additionally, emotion recognition has been investigated in domains such as security [13], education [14], architecture [19], and training simulations [15], [17], [20]. Whereas most prior studies have focused on physiological rather than neurophysiological signals [1], [21], [22], [23], [24], [25], [26], [27], [28], [29], some have extended this research to augmented reality applications as well [30], [31].

Recently, emotion recognition via biosignals has emerged as a key research domain. Current findings confirm that EEG and EDA are effective modalities for emotion recognition in VR environments [2], [6], [7], [8], [10], [12], [13], [16], [18]. These signals facilitate the identification of emotional states such as stress, anxiety, and joy, thereby enhancing the understanding of affective responses in VR. Whereas VR enables the simulation of realistic experiences under controlled conditions, current emotion recognition methods in VR face several challenges. Key challenges include signal distortion due to motion artifacts, signal validation, algorithm optimization, increasing sample sizes, ensuring objective assessment, limited compatibility of EEG devices with VR headsets, and the absence of standardized analysis frameworks for biosignals in dynamic crisis scenarios. Factors such as user experience with VR, hardware compatibility, and the complexity of virtual environments can influence classification accuracy, necessitating further research [6], [7]. This study aims to address these limitations by validating a hybrid EEG-EDA system for measuring affective responses in VR-based dynamic crisis simulations. This system has potential applications in psychological research, crisis training, and security simulations, such as emergency responder training and stress-based decision-making assessments.

Given these insights, integrating EEG and EDA is gaining prominence as an objective tool for analyzing affective experiences. This study examines EEG and EDA responses in VR settings, emphasizing their combined potential to provide comprehensive insights into users' emotional reactions. Specifically, the research explores the applicability of this hybrid approach in crisis training, security simulations, and other scenarios where accurate stress detection in controlled environments is critical. VR technology serves as a platform for generating immersive yet controlled crisis scenarios, allowing for detailed emotion analysis. The integration of EEG and EDA can enhance the reliability of emotion recognition, unlocking new possibilities in security and education.

B. AIM AND SCOPE OF THIS WORK

This study focuses on detecting emotional responses measured via EEG and EDA to evaluate and compare emotional differences in a VR environment. The primary objective is to determine participants' emotional states through noninvasive acquisition and analysis of biological data during VR interaction and to assess the feasibility of integrating EEG and EDA for emotion recognition in complex, hard-to-replicate scenarios. The proposed hybrid EEG-EDA system enables the identification of emotional states in environments that would be challenging or hazardous to simulate in the real world. A secondary objective is to

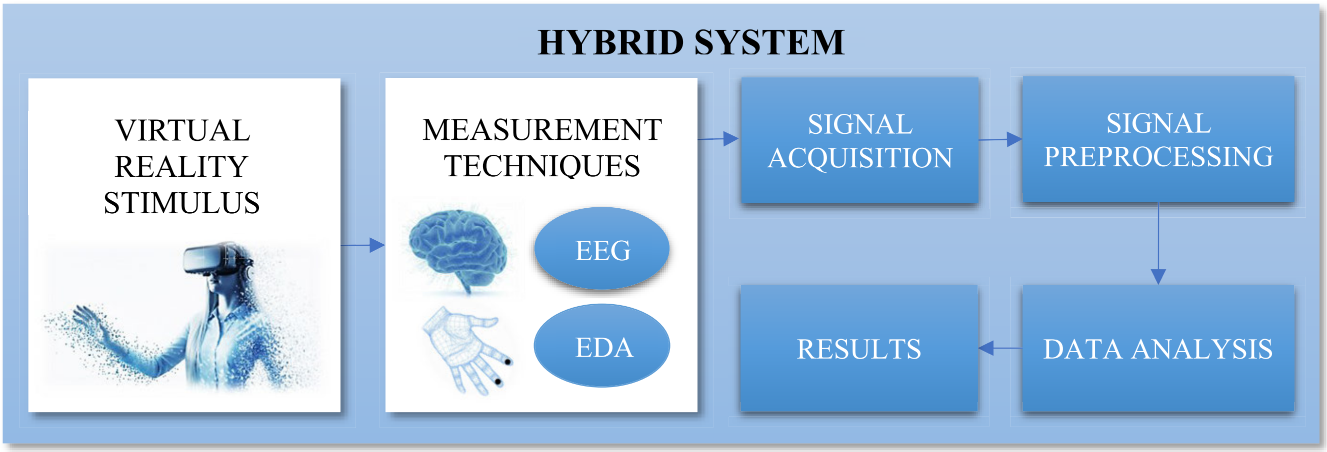


FIGURE 1. Schematic diagram of the proposed hybrid emotion recognition system.

examine whether there is a statistically significant increase in stress levels across different phases of the experimental scenario. This research combines objective EEG and EDA measurements with subjective assessments via self-report questionnaires. In addition, this study introduces a machine learning-based classification approach using Support Vector Machines (SVM) to objectively distinguish between baseline and stress states based on multimodal features. A comparative performance analysis of unimodal versus hybrid systems is included to demonstrate the benefit of signal fusion. Unlike previous studies, our approach integrates EEG and EDA within realistic crisis training scenarios, thus expanding VR applications in security and emergency preparedness. This enables a deeper understanding of users' stress responses and contributes to optimizing training protocols for simulated crises.

This paper is structured as follows. First, the proposed hybrid system and experimental design are introduced. Subsequently, the employed measurement techniques and their analytical procedures are detailed. Emotional responses elicited by participants in the simulated scenario are then compared and evaluated. Correlation analyses across EEG, EDA, and subjective ratings are provided, and statistical assumptions are tested using parametric and non-parametric approaches. The study also incorporates a questionnaire-based analysis of participants' self-reported feelings to ensure an accurate and quantitative assessment of environmental influences on subjective perception. A machine learning-based classifier is presented to evaluate the hybrid system's performance. Finally, the results are summarized, and a discussion is provided regarding the accuracy and applicability of integrating these technologies for emotion recognition in VR.

C. FORMULATION OF HYPOTHESES

This research investigates users' emotional responses in a simulated crisis scenario within virtual reality. The primary aim is to verify whether the combination of EEG and EDA signals enables more accurate detection of stress responses compared to using each modality independently. To evaluate the effectiveness of the proposed hybrid system, the following hypotheses were formulated:

1. The elevator drop event in the simulated VR environment induces significantly higher stress responses (as measured by EEG and EDA) than the control phase (typical elevator ride).
2. Integrating EEG and EDA provides a more reliable assessment of VR stress levels than using a single modality alone.

Testing these hypotheses will contribute to understanding multimodal biosignal analysis for assessing emotional experiences in controlled yet ecologically valid settings.

II. MATERIALS AND METHODS

A. PROPOSED HYBRID SYSTEM

We propose a hybrid system for emotion recognition in VR, integrating physiological and neurophysiological signals, specifically EEG and EDA. The proposed system was validated in a controlled VR experimental environment. The architecture of the hybrid system, illustrated in Fig. 1, demonstrates the integration of EEG and EDA measurements for detecting emotional responses in VR. This system enables synchronized analysis of biological signals, offering a comprehensive perspective on the user's emotional experience.

B. EXPERIMENTAL DESIGN

Hybrid systems are widely employed to achieve optimal results in human state analysis. Traditional stress assessment methods based on questionnaires and behavioral analysis present several limitations. This study explores the use of biosignals to assess stress levels objectively. In addition to physiological indicators considered in previous research, we also focus on EEG signals to analyze more complex responses to stimuli.

The experiment was designed to analyze neurophysiological and physiological responses to stimuli within a VR environment. By integrating EEG and EDA, it is possible to monitor various user states, including emotional arousal and attention levels. The primary objective of this study is to evaluate the accuracy of emotion recognition using EEG and EDA biosignals within a controlled VR scenario.

Emotional arousal in VR is accompanied by increased sweat gland activity, leading to changes in skin conductance. Simulated environments can also activate specific brain regions, reinforcing memory formation through immersive experiences. VR enables the creation of ecologically valid scenarios tailored to match real-world conditions and specific research objectives [22].

In the study's first phase, objective data were collected using EEG and EDA technologies. EEG signals were recorded noninvasively using the Emotiv EPOC+ headset (Emotiv) and obtained via the paid software EmotivPro (version 4.2.0.541). EDA signals were measured using the Polygraph LX6 device (Lafayette Instrument) and acquired with LXSoftware (version 11.8.3).

The study's second phase focused on EEG and EDA signal analysis using specialized software tools. EEG data were preprocessed and analyzed using MATLAB (R2020b) with the EEGLAB (version 2024.2) and ERPLAB (version 10.04) toolboxes. EDA data were preprocessed in MATLAB and further analyzed using the Ledalab toolbox (version 3.4.9). Emotion recognition accuracy was evaluated based on biosignals recorded during participant interaction with the VR scenario.

Additionally, a qualitative questionnaire survey was conducted among the participants. Subjective user assessments were compared with objective EEG and EDA biosignal measurements. The effectiveness of the proposed hybrid system, which integrates EEG and EDA for emotion recognition in VR, was evaluated based on predefined research hypotheses.

1) PARTICIPANTS

Thirty-four healthy participants voluntarily participated in the experiment (12 females, age range: 24–58 years, mean age: ∼42 years; 22 males, age range: 24–73 years, mean age: ∼39 years). Participants were members and students of Tomas Bata University (TBU) in Zlín. Four participants were excluded due to excessive EEG and EDA data movement artifacts. Consequently, the final analysis was conducted on a sample of 30 participants. All participants provided written informed consent prior to the experiment.

2) ELEVATOR SCENARIO

The experiment was designed to evaluate the integration of EEG and EDA for emotion recognition in a VR environment. The primary objective was to assess whether this technological combination enables high-accuracy detection of stress levels in a controlled setting. The experiment simulated an elevator malfunction scenario to elicit strong emotional responses, specifically a free-fall event caused by sabotage or a severe technical failure.

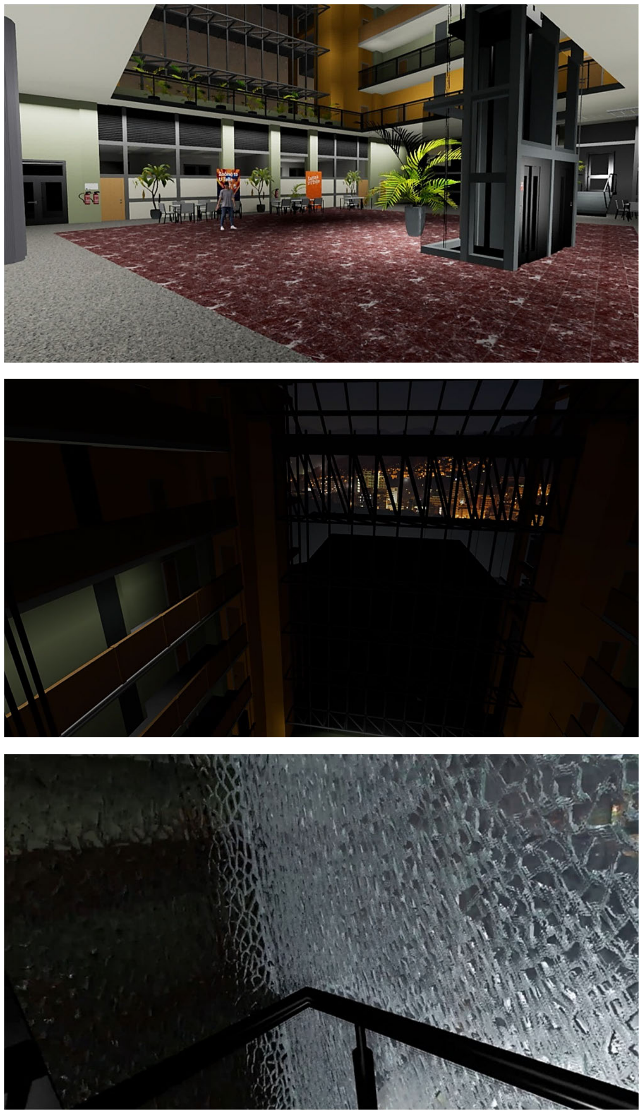


FIGURE 2. **Demonstration of the scenario created in VR.**

The experimental setup was based on the hypothesis that the quality of scene rendering and the accuracy of its reproduction significantly impact user immersion in VR. A digital twin of the atrium of the Faculty of Applied Informatics (FAI) at TBU in Zlín was manually modeled using architectural blueprints. The virtual environment was developed, strongly emphasizing realism and utilizing Physically Based Rendering (PBR) techniques to achieve accurate material representation. This approach was chosen to maximize participant immersion, given their familiarity with the real-world counterpart of the environment. Consequently, the authenticity of the virtual scene was a critical requirement. The 3D modeling process employed a combination of Blender and Unreal Engine 4.

The experimental scenario incorporated both software and hardware-based interactive elements to enhance the realism of the user experience. A demonstration of the VR environment is provided in Fig. 2.

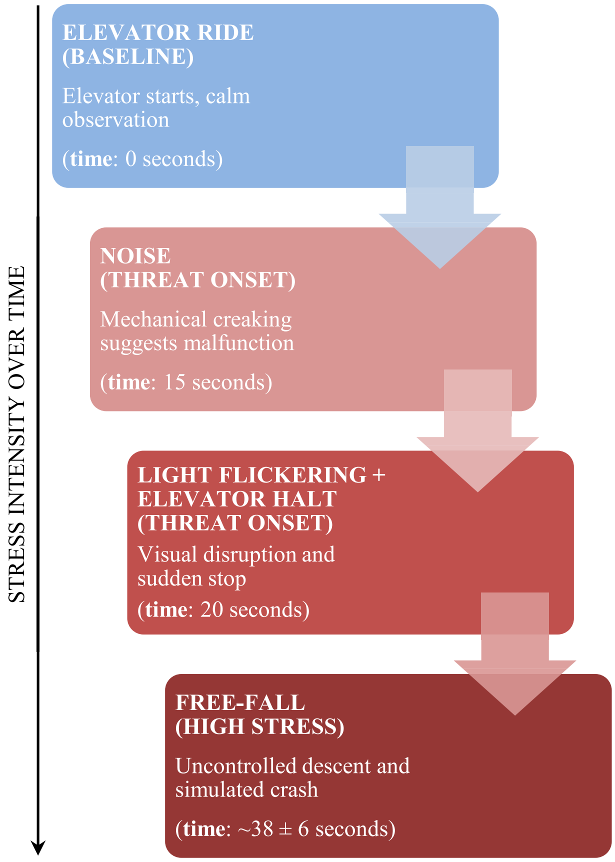


FIGURE 3. Sequential timeline of emotional stimulation in the VR scenario, illustrating the increasing stress intensity over time from a neutral elevator ride to the simulated free-fall event.

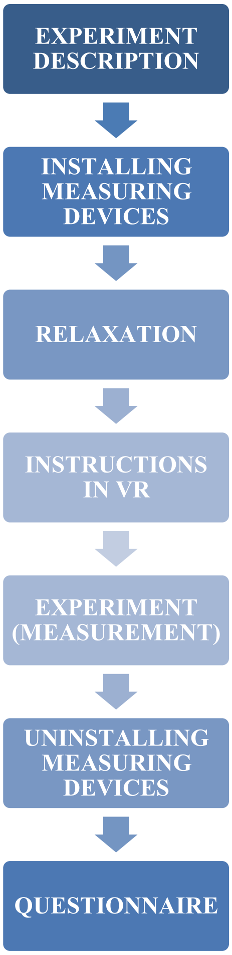


FIGURE 4. Diagram of the experimental procedure.

At the beginning of the experiment, participants were instructed to navigate to the dean's office. In real-world usage, the elevator is the most common transportation to this office. Within the VR environment, participants approached the elevator, activated an interactive button to summon it, and entered the cabin. After initiating the ride via another interactive control, participants were prompted to grip the railing (physically replicated in the experimental setup) and observe the surroundings.

During the simulation, the scenario commenced with a neutral elevator ride, representing the baseline phase. At 15 seconds, mechanical noises were introduced to simulate an early malfunction indicator. This was followed, at 20 seconds, by a sudden, unexpected halt of the elevator accompanied by flickering lights, representing a visual threat cue. The sequence culminated at approximately 38 seconds in a simulated free-fall event (an uncontrolled descent of approximately two meters and a sudden stop in a mezzanine) designed to induce a high-stress response. The elevator ride lasted approximately 38 seconds, with individual variability of ± 6 seconds in the fall onset. The temporal structure and order of these events were standardized across all participants to ensure consistency in emotional induction. As illustrated in Fig. 3, this structured sequence of auditory and visual stimuli was designed to evoke progressively increasing levels of emotional arousal, culminating in the stress phase. Two researchers manually marked the onset of key events in both recording systems during each session to enable accurate segmentation and synchronization of EEG and EDA signals.

The cabin sustained visible damage, including shattered glass, to reinforce the perception of a critical failure. A specialized drop system was engineered to enhance the sensation of free-fall. This system gave participants a slight physical drop via a motion platform, which they had unknowingly stepped onto before the experiment commenced.

Biological data were continuously recorded throughout the experiment; however, only predefined time intervals were extracted and processed for further analysis. Following the VR interaction, participants provided subjective feedback via standardized questionnaires, which were later compared against EEG and EDA data analyses.

3) EXPERIMENTAL PROCEDURE

The primary goal of the experiment was to analyze participants' emotional states during VR interaction through objective measurements of EEG and EDA signals, complemented by subjective self-reports collected via questionnaires.

FIGURE 5. Experimental environment and equipment.

A schematic representation of the experimental procedure is illustrated in Fig. 4.

Before the experiment, participants were briefed on the general procedure but were not informed about the specific details of the scenario. Initially, they were instructed to sit comfortably and cleanse their fingertips with an alcohol wipe to ensure optimal electrode contact for EDA measurements. Subsequently, EEG and EDA devices were deployed, and the VR headset was positioned over the EEG headset. Throughout the setup, participants were provided with explanations regarding the purpose and function of each device. EDA electrodes were affixed to the fingertips of the right hand while the EEG headset was deployed on the head. A test subject in an experimental environment equipped with individual devices is depicted in Fig. 5.

Following device installation, participants were instructed to remain relaxed and minimize movement to establish a stable baseline physiological state. The experiment commenced with the initiation of biological data recording and the presentation of on-screen VR instructions, which participants were required to follow. The VR environment featured interactive elements controlled using an HTC Vive controller in the left hand. A virtual representation of the hand and controller was displayed within the VR environment to enhance realism.

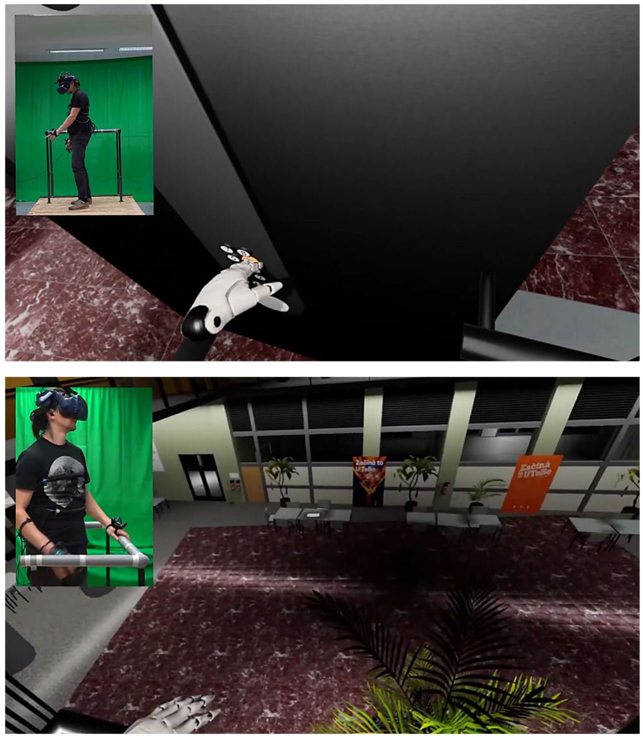


FIGURE 6. Examples of the VR scenario include participant interaction.

Throughout the VR interaction, EEG and EDA signals were continuously recorded. Upon completing the task, participants were presented with a concluding screen displaying a thank-you message and instructions to return to their initial position, after which the devices were removed. Participants then completed a standardized questionnaire assessing their subjective experience and emotional responses to different experimental phases.

A coordinator was present throughout the experiment to monitor proper execution and ensure data integrity. Auditory stimuli were delivered via wireless headphones. The VR scenario was rendered on a high-performance computer connected to the VR headset, as illustrated in Fig. 6. Visual documentation of the scenario is attached as a supplementary video (elevatorScenario.mp4).

The duration of the experiment was consistent across all participants. The entire procedure, from device installation to the completion of the VR interaction and data collection, lasted approximately 15 minutes per participant. In total, 34 individuals participated in the experiment, each subjected to the simulated elevator free-fall scenario. Questionnaires assessed stress levels subjectively, while objective biometric data provided quantitative insights into emotional responses.

4) EXPERIMENTAL CONDITIONS

The experiment was conducted in the Faculty of Applied Informatics laboratory at TBU in Zlín under controlled conditions to minimize external disturbances. To eliminate ambient light interference, the laboratory was darkened using blinds,

FIGURE 7. VR headset HTC Vive Pro.

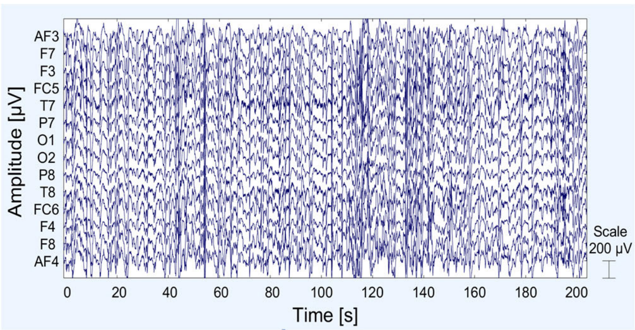


FIGURE 8. Example of raw EEG signal recorded during the experiment.

FIGURE 9. EEG headset Emotiv EPOC+.

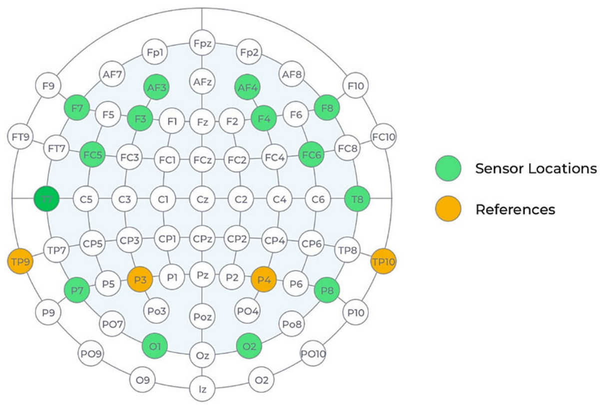


FIGURE 10. EEG electrode placement using the international 10-20 system for Emotiv EPOC+ headset [33].

ensuring a low-stimulus environment that could impact the quality of the VR experience. This approach maximized the immersive effect of VR and enhanced participants' sense of presence. A critical factor in the experiment was minimizing distractions to ensure conditions conducive to the validity of biological response measurements within the VR setting.

C. MEASUREMENT TECHNIQUES

This section outlines the methods employed for emotion recognition in VR within the designed experimental scenario.

1) VIRTUAL REALITY

The HTC Vive Pro VR headset was used to present the experimental scenario. This device features a resolution of 2880 × 1600 pixels (1440 × 1600 pixels per eye), a refresh rate of 90 Hz, and a 110° field of view (see Fig. 7) [32].

2) NEUROPHYSIOLOGICAL SIGNALS

Emotion recognition based on brain activity has become a pivotal research area leveraging noninvasive methods, particularly electroencephalography (EEG). EEG captures electrical brain activity through sensors placed on the scalp, providing high temporal resolution measurements in microvolts (μV) (see Fig. 8). Portable EEG headsets facilitate understanding brain dynamics underlying perceptual integration in various scenarios [5].

EEG is utilized in medicine, communication, entertainment, security, and emotion recognition applications. It enables the analysis of the relationship between brain activity and emotional states, facilitating objective identification of responses to various stimuli in real time [5], [9]. This study employed the Emotiv EPOC+ EEG device to record brain activity (see Fig. 9).

This device includes 14 active EEG electrodes (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4) positioned according to the international 10-20 system and two reference electrodes placed on the mastoids (see Fig. 10) [33]. The Emotiv EPOC+ was chosen for its fast and easy use, affordability, wireless signal transmission, and sufficient signal resolution.

Previous research has demonstrated that positive emotions are lateralized to the left hemisphere. In contrast, negative emotions and stress are associated with increased activation of the right hemisphere, particularly the frontal region [7], [14], [34], [35]. Several studies have confirmed

FIGURE 11. Placement of EDA electrodes on the participant's hand.

the hypothesis that negative stimuli exhibit higher perceptual processing efficiency compared to positive stimuli, indicating that negative stimuli evoke stronger emotional responses even in virtual environments [10], [14], [28]. It has been established that stress states lead to increased activity in the frontal region of the right hemisphere, which can be observed in the EEG electrodes F4 and F8 within the employed setup [10], [34], [36], [37], [38]. Given the oscillatory nature of EEG signals, stress analysis commonly relies on frequency domain analysis, particularly within the alpha and beta frequency bands [34], [36], [38].

3) PHYSIOLOGICAL SIGNALS

Electrodermal activity (EDA), also referred to as Skin Conductance (SC), represents a sympathetic nervous system response to emotional stimulation, leading to a temporary increase in sweat gland secretion and, consequently, changes in skin conductance [7]. An increase in EDA is, therefore, indicative of elevated stress levels due to sympathetic nerve activation [8]. Numerous studies have validated the applicability of EDA in assessing emotional states, and it is widely used for objectively monitoring physiological changes associated with emotional arousal, stress, and anxiety [1], [6], [8], [11], [12], [39]. EDA activity is expressed in microsiemens (μS), with changes in skin conductance occurring automatically, beyond conscious control. In emotionally demanding situations, automatic physiological processes such as increased heart rate, respiration, and sweat secretion are activated, which are reflected in EDA values. Due to its simplicity and minimal susceptibility to artifacts, EDA is a valuable physiological marker for various applications [39].

EDA measurement involves converting changes in skin impedance into an electrical signal [7]. The most prominent EDA responses occur in areas with a high density of sweat glands, particularly the palms, fingers, soles, forehead, and neck [7], [39]. In this study, the Polygraph LX6 device was used, with EDA electrodes placed on the fingertips of the right hand. These electrodes consist of two stainless steel electrodes, as illustrated in Fig. 11.

In the context of this study, the focus is on Event-Related Skin Conductance Responses (ER-SCR), which can be unequivocally attributed to a specific stimulus. SCRs are rapid, transient events observable in the EDA signal. SCR analysis includes amplitude evaluation, rise time assessment, and other parameters. The rise time of SCRs typically ranges between 0.5 and 5 seconds after stimulus application [39].

Various approaches are used for EDA analysis. A traditional method involves manual signal evaluation, allowing detailed control over detecting individual SCRs; however, this approach is time-consuming and subjective. Consequently, automated methods employing mathematical models, such as nonnegative deconvolution, have been developed to separate tonic and phasic components and enhance SCR detection accuracy. Modern algorithms facilitate the extraction of relevant metrics, such as amplitude and latency, thereby optimizing EDA analysis in the context of emotional and cognitive responses [39].

D. EEG AND EDA SIGNAL PROCESSING AND ANALYSIS

This study focuses on stress's physiological and neurophysiological manifestations, a key mechanism in managing critical situations. Psychological or physical challenges trigger the stress response. It is accompanied by the release of various hormones, leading to physiological changes such as increased heart rate, blood pressure, pulse rate, and accelerated respiration [38]. Consequently, stress induces significant changes in the autonomic and central nervous systems.

Stress can be assessed through various methods, including subjective questionnaires and objective physiological and neurophysiological signal analyses. This study measured stress responses using a combination of EEG, EDA, and self-reported assessments via questionnaires. The primary objective was to compare these methods and evaluate their effectiveness in stress detection.

1) SIGNAL ACQUISITION

EEG and EDA recordings were obtained from 34 participants throughout their interaction in a VR environment, enabling the quantification of stress levels across different phases of the experimental scenario. Data acquisition was conducted using noninvasive methods, followed by signal analysis to assess the suitability of EEG and EDA for emotion recognition in virtual reality.

A simulated elevator fall scenario was selected to elicit a stress response due to its well-documented ability to evoke strong emotional reactions. Before data collection, skin preparation was performed using an alcohol-based peeling procedure to remove dead cells, and high-adhesion electrodes with electrolyte gel were applied to optimize signal quality [6].

a: EEG SIGNAL ACQUISITION

EEG signals were recorded using the 14-channel Emotiv EPOC+ device, which employs wet sensors. Sensors were moistened with saline before recording to ensure optimal signal quality.

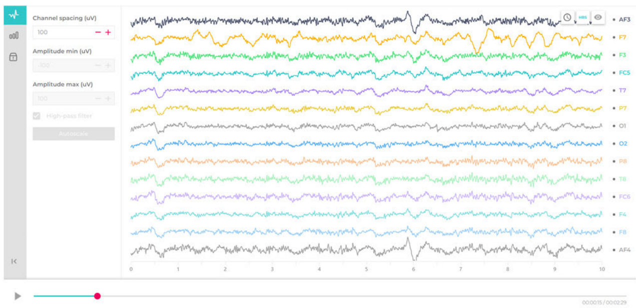


FIGURE 12. Raw EEG signal visualized in EmotivPro during the VR simulation.

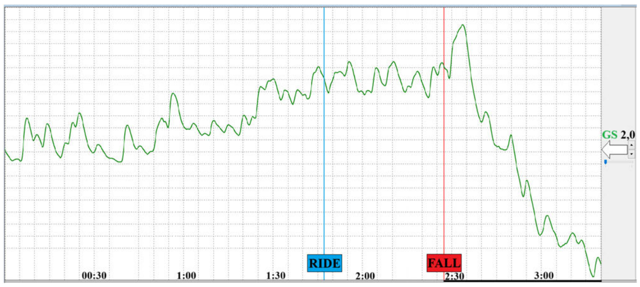


FIGURE 13. Raw EDA signal visualized in LXSoftware, showing changes during the ride and fall phases.

The EmotivPro system provides real-time electrode impedance metrics, allowing continuous monitoring of signal reliability. Each sensor was carefully positioned on the scalp beneath the hair to ensure adequate conductivity and minimize signal artifacts. An example of an EEG recording during participant interaction in VR under the proposed scenario is illustrated in Fig. 12.

EEG signals were sampled at 256 Hz and exported from the EmotivPro software for further processing and analysis.

b: EDA SIGNAL ACQUISITION

EDA was recorded using a dedicated device with two measurement electrodes placed on the fingers of the participant's dominant hand. Data were acquired at a sampling rate of 30 Hz and stored via LXSoftware (Fig. 13).

The collected data were then exported for further analysis, focusing on identifying variations in EDA associated with participants' emotional responses during the VR scenario.

2) SIGNAL PREPROCESSING

Before the collected data were analyzed, a preprocessing stage was necessary to ensure data integrity and consistency. Each subject's interaction with the virtual reality environment was annotated with events and markers, segmenting distinct activities within the scenario into well-defined time windows.

a: EEG SIGNAL PREPROCESSING

Upon completion of the experiment, the recorded EEG data were exported from EmotivPro in .csv format for subsequent processing. Due to varying recording durations, the exported files differed in the number of rows. Consequently, all 34 data files were imported into MATLAB for further adjustment.

The first step involved transforming the raw data into a format compatible with EEGLAB and ERPLAB toolboxes. This process included the removal of redundant metadata, such as electrode quality indices and other irrelevant information, via a MATLAB script. Subsequently, the modified data were imported into EEGLAB, where the electrode location corresponding to the device used was specified.

The EEG preprocessing pipeline comprised bandpass filtering, time-window segmentation, and artifact removal. EEG signals inherently contain environmental and physiological noise, necessitating noise suppression before analysis. A second-order Infinite Impulse Response (IIR) Butterworth bandpass filter was applied with cutoff frequencies of 0.1–30 Hz, aligning with the frequency range associated with emotional states [7]. The low-pass filtering component mitigated high-frequency noise, including electromagnetic interference, muscle activity, and electrical noise from surrounding electronic devices.

Following filtering, the data were segmented into two experimental conditions: elevator ride and elevator fall. Event markers were imported, and an event list was generated accordingly. Epoch extraction was conducted within a 0–1000 ms window post-event onset.

Brain wave activity is categorized into five principal frequency bands: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (30–70 Hz). Variations in these frequency bands reflect cognitive and emotional states [1], [2]. Stress responses are characterized by distinct EEG patterns, notably a reduction in alpha power and an increase in beta power under heightened stress conditions. Since stress responses originate in the brain, EEG-based processing is a crucial stress detection and assessment method. Positive emotions are predominantly processed in the left hemisphere, whereas negative emotions are more prominent in the right hemisphere. Stress-induced neurochemical changes occur primarily in the frontal cortex and are strongly correlated with increased beta-band activity [38]. Consequently, beta-band analysis was selected for this study. A Finite Impulse Response (FIR) filter with cutoff frequencies of 12–30 Hz was implemented to extract the beta component of the EEG signal. The F8 electrode was selected for subsequent analysis based on its relevance in monitoring stress-related neural activity (see Fig. 14).

EEG recordings are susceptible to various artifacts, including ocular and muscle activity, which can compromise signal quality [7]. However, some studies suggest that EEG exhibits lower susceptibility to artifacts compared to physiological signals such as Skin Conductance Level (SCL) and heart rate, benefiting from high temporal resolution [23]. To eliminate artifacts caused by eye movements, muscle activity, and electrode noise, an automated artifact rejection method, Simple Voltage Threshold, was applied in ERPLAB. The threshold for artifact detection was set at $\pm 100\ \mu$V, a standard

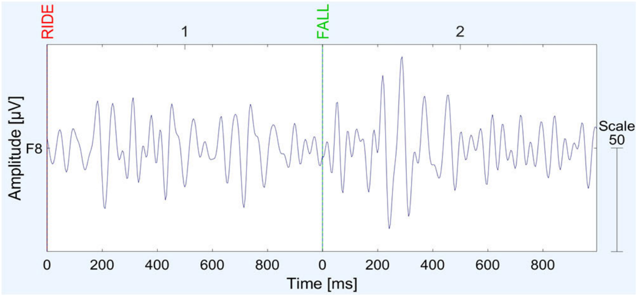


FIGURE 14. Preprocessed EEG data segmented into ride and fall events.

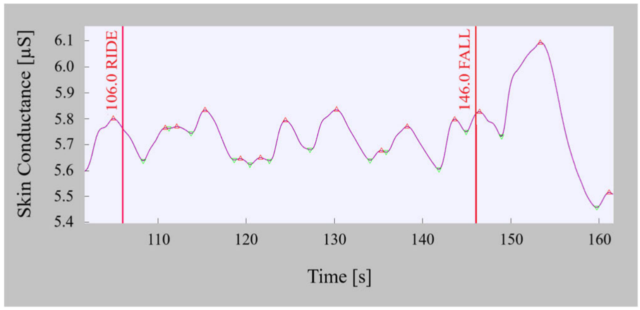


FIGURE 15. Preprocessed and segmented EDA signal used to extract SCR amplitude during the ride and fall phases, visualized in Ledalab.

parameter established in prior studies. The efficacy of filtering was validated through visual inspection, and epochs containing artifacts were excluded from further analysis, resulting in the removal of four subjects from the dataset.

Upon completion of preprocessing, valid beta-band data from electrode F8 were extracted for each participant across both experimental conditions. This phase yielded 60 valid observations, with each subject's data containing two experimental conditions within the VR scenario.

b: EDA SIGNAL PREPROCESSING

The LXSoftware enables exporting EDA data in ohms (Ω) corresponding to skin resistance values. Initially, the file structure was adjusted, and individual resistance values were transformed into microsiemens (μS) for seamless import into Ledalab, a MATLAB-based open-source tool widely used for EDA signal analysis [40], [41]. The software supports various data formats and provides various signal preprocessing functionalities. Upon import, event timestamps were integrated into the analysis.

The preprocessing pipeline in Ledalab encompassed signal filtering, down-sampling, and artifact removal to minimize noise interference. Electrodermal responses (SCRs) exhibit substantial inter-subject variability, posing challenges in data interpretation. Beyond genuine SCRs, artifacts stemming from subject movement, temperature fluctuations, and electrical interference may be present. Inadequate differentiation between artifacts and true SCRs compromises analytical precision. While manual artifact correction is feasible, it is considerably time-intensive.

Conventional noise suppression and motion artifact mitigation techniques in EDA processing often employ low-pass filtering. A Butterworth low-pass filter with a cutoff frequency of 1 Hz was applied to attenuate high-frequency noise unrelated to EDA analysis. This threshold was chosen to preserve the phasic response component of the signal while eliminating unwanted high-frequency artifacts [39], [42]. Filtering facilitated the isolation of the signal's key component, namely phasic activity.

The subsequent step involved down-sampling, aimed at reducing data volume, enhancing computational efficiency, and eliminating redundant noise while preserving relevant signal characteristics. Given that EDA signals predominantly exhibit slow temporal dynamics, the optimal sampling rate typically ranges from 4 to 10 Hz, as higher frequencies do not contain meaningful information for EDA analysis [39]. The sampling rate was reduced from 30 Hz to 10 Hz to ensure sensitivity to signal variations while minimizing noise. Fig. 15 illustrates the preprocessed EDA data in Ledalab.

3) DATA ANALYSIS

a: EEG DATA ANALYSIS

Emotion recognition based on EEG signals can be performed using various methods. One common approach for stress level assessment involves spectral analysis of EEG signals, where specific frequency bands, such as alpha and beta, are identified as key indicators of stress levels. Another widely adopted method employs machine learning algorithms to classify emotional states, including decision trees, support vector machines, k-nearest neighbors, and neural networks. Alternatively, the arousal-valence model can be applied, leveraging EEG features associated with arousal and emotional valence, which are subsequently compared against reference datasets. Each approach has inherent limitations; therefore, EEG analysis is often complemented with additional physiological measurements or subjective self-assessment methods for accurate stress detection.

This study analyzed stress levels by identifying beta-band activity in the right cerebral hemisphere, as this region is most strongly associated with stress-induced neural responses. Participants' reactions to a simulated elevator fall in a VR environment were examined, and stress level changes were analyzed compared to a usual elevator ride.

EEG signal processing and analysis were performed using MATLAB, incorporating EEGLAB and ERPLAB toolboxes. The Compute Averaged ERPs function was applied to compute event-related potentials (ERPs), with peak amplitude as the primary parameter for quantifying the stress response.

Specifically, the peak amplitude was extracted using the Measurement Tool in ERPLAB for MATLAB within the beta frequency range (12–30 Hz) at electrode F8, located in the right frontal cortex. This method identifies the maximum amplitude peak within the specified range. The analysis involved transforming the time-domain signal into the

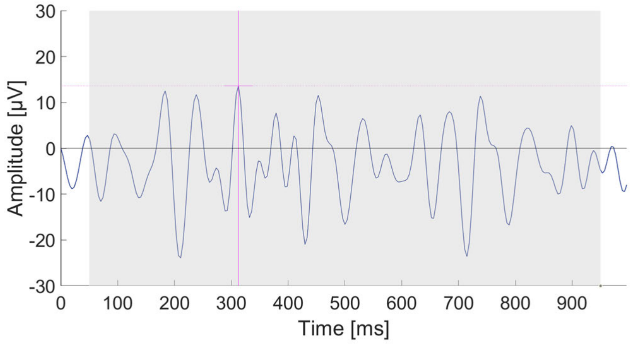


FIGURE 16. Peak beta-band EEG amplitude at electrode F8 during the ride phase.

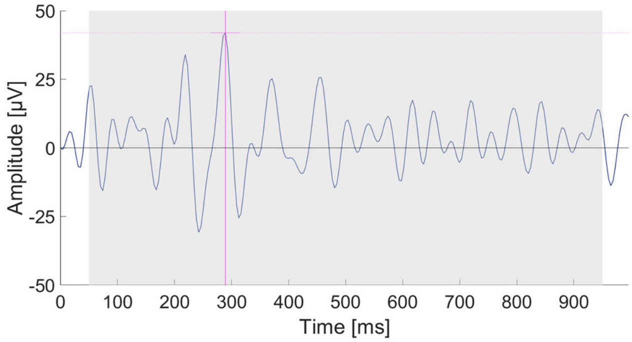


FIGURE 17. Peak beta-band EEG amplitude at electrode F8 during the fall phase.

frequency domain using an FIR filter. Although beta activity is distributed across various cortical regions, it is predominantly linked to cognitive activity, attentional processing, and stress responses in the frontal cortex. An increase in beta-band amplitude was interpreted to indicate elevated stress levels.

For each participant, the peak amplitude in the beta band at electrode F8 was computed under both experimental conditions (during the elevator ride (see Fig. 16) and the simulated fall (see Fig. 17)). EEG signals were segmented into non-overlapping 1000 ms windows, and each was analyzed separately.

The final analysis was conducted on 30 out of 34 participants, with participants 2, 20, 24, and 32 excluded due to a high number of signal artifacts.

Fig. 18 presents each participant's computed beta-band amplitude values at electrode F8 under both conditions. The results indicate that 27 out of 30 participants exhibited a significant increase in beta-band amplitude during the elevator fall compared to the usual ride, suggesting heightened stress.

The findings confirm that the simulated elevator fall significantly increased EEG beta-band activity, supporting the hypothesis that the VR-based crisis scenario elicited a genuine stress response.

b: EDA DATA ANALYSIS

EDA measurement represents a reliable, noninvasive method for capturing ANS responses, enabling the detection of physiological changes associated with emotional and stress-related states. ANS activity is particularly pronounced during negative emotional states such as stress [43].

EDA signals can be decomposed into two primary components. The tonic component reflects slow variations in skin conductance over time and is represented by the Skin Conductance Level (SCL), which provides insight into long-term ANS activation [39]. The phasic component captures rapid fluctuations in response to specific stimuli and is quantified through the Skin Conductance Response (SCR). This phasic component is crucial for analyzing immediate physiological reactions associated with stress and emotions [1], [8].

The phasic (rapid fluctuations) and tonic (slowly varying) components were separated for physiological response analysis. EDA signal decomposition, a critical step in stress response analysis, was performed using the Ledalab software. This tool provides two approaches for EDA analysis. The Continuous Decomposition Analysis (CDA) enables advanced modeling of skin conductance signals by performing a standard deconvolution to separate and extract continuous estimates of the phasic (SCR) and tonic (SCL) components, thereby reconstructing the underlying sudomotor nerve activity [40]. In contrast, the Discrete Decomposition Analysis (DDA) is more suitable for artifact-free data. CDA is preferred for studying physiological responses to specific stimuli, such as stress-inducing events, as it allows for more precise detection of phasic responses.

Key indicators in EDA signal analysis for stress response evaluation include the maximum SCR amplitude following stimulus presentation, the number of phasic responses (SCRs), the total cumulative SCR activity within a predefined time window, and the response latency [39], [40].

This study employed CDA to extract phasic response features, implemented in Ledalab within the MATLAB environment (see Fig. 19). SCRs were deconvolved using CDA and decomposed into continuous phasic and tonic components. Parameter optimization was performed using Ledalab's default settings, which are designed for generalized stress response detection. The response window was set to 0–5 seconds post-stimulus presentation, aligning with the typical latency of electrodermal responses [8]. A minimum amplitude threshold of 0.001 μS was established for significant SCR detection to minimize the impact of motion artifacts and device noise.

The data were segmented based on experimental events (elevator ride vs. simulated fall), and EDA values were compared across different experimental phases (see Fig. 20).

For quantitative comparison between experimental conditions, the maximum phasic amplitudes of SCR (CDA.PhasicMax [μS] in Ledalab) were analyzed and compared, representing peak phasic activity within the response window (see Fig. 21).

The results demonstrated increased stress levels in 29 out of 30 subjects, confirming the robustness of EDA as an indicator of stress responses. Furthermore, the findings suggest

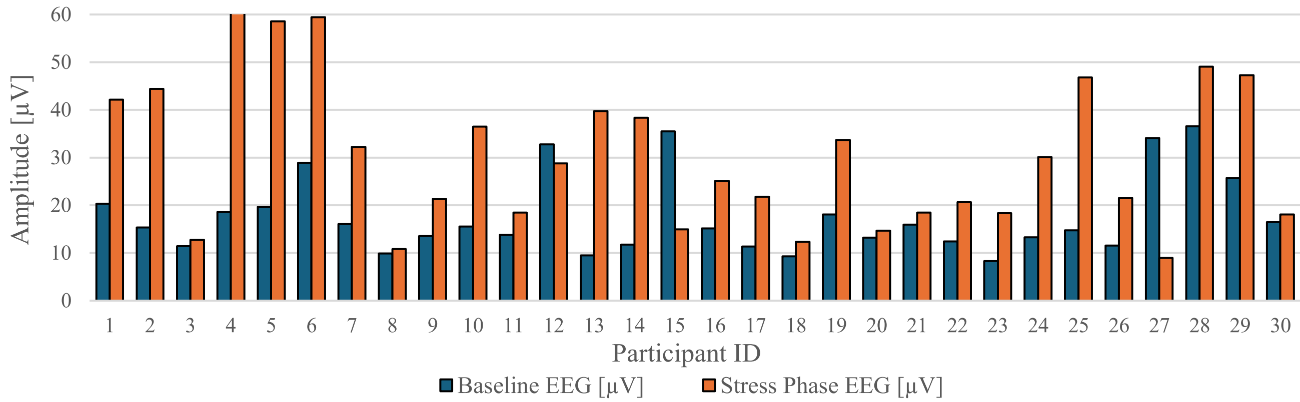


FIGURE 18. Comparison of EEG beta-band peak amplitudes between baseline and stress phases across participants.

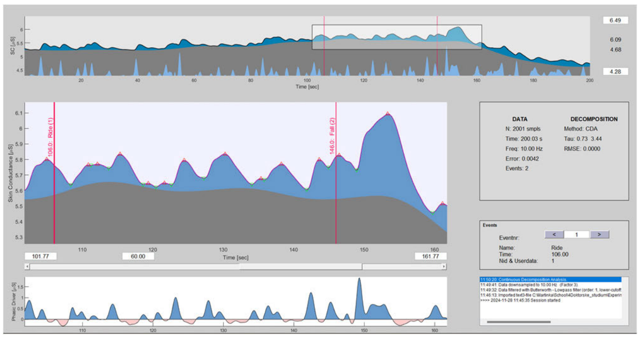


FIGURE 19. Output of EDA analysis in Ledalab using CDA.

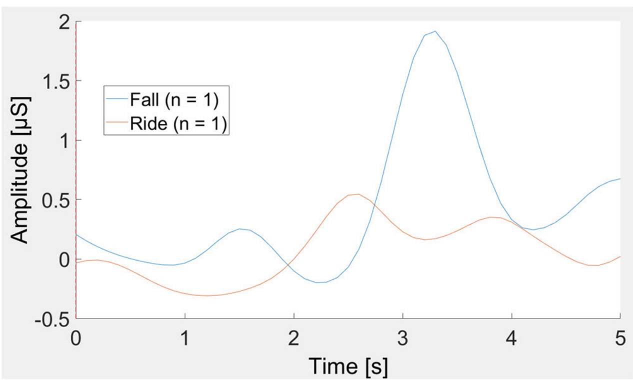


FIGURE 20. Comparison of EDA amplitudes between ride and fall conditions.

that EDA measurement remains viable even in dynamic environments, expanding its applicability in experimental movement studies.

c: QUESTIONNAIRE ANALYSIS

A custom-designed questionnaire was administered as a comparative method to evaluate the effectiveness and accuracy of stress level measurement using EEG and EDA in VR. The objective was to verify whether participants' subjective assessments correlated with the recorded biological signals. Fig. 22 presents the participants' subjective stress level ratings on a scale from 1 to 5, where 1 represents minimal stress and 5 indicates maximum stress.

The questionnaire results further support the validity of EEG and EDA as stress measurement tools, as most participants reported increased perceived stress levels corresponding to the recorded biosignal data. This alignment reinforces the feasibility of using multimodal biosignal analysis in VR-based stress assessment studies.

4) STATISTICAL ANALYSIS

The degree of emotional differentiation is a key indicator for assessing the accuracy of stress induction, specifically the alignment between the target emotion and participants' subjective evaluations. Statistical analysis of the relationships between experimental phases was conducted using a paired t-test, which enables the comparison of mean values between two dependent samples. To evaluate the impact of VR on affective responses to specific stimuli, paired t-tests were performed between the "ride" and "fall" phases. The objective was to determine whether the differences in stress levels recorded in EEG and EDA data were statistically significant.

Before the analysis, the data underwent thorough preprocessing to eliminate noise and ensure measurement accuracy. The following hypotheses were established:

- H_0: There is no significant difference between emotional responses in the "ride" and "fall" phases ($\mu_1 - \mu_2 = 0$).
- H_1: Emotional responses in the "fall" phase are more intense than those in the "ride" phase ($\mu_1 < \mu_2$).

The t-statistic was computed using the formula:

$$t = \frac{|\bar{X}|}{\frac{s}{\sqrt{n}}}, \tag{1}$$

where $\bar{X}$ represents the arithmetic mean of paired differences, s is the standard deviation, and n denotes the number of observations.

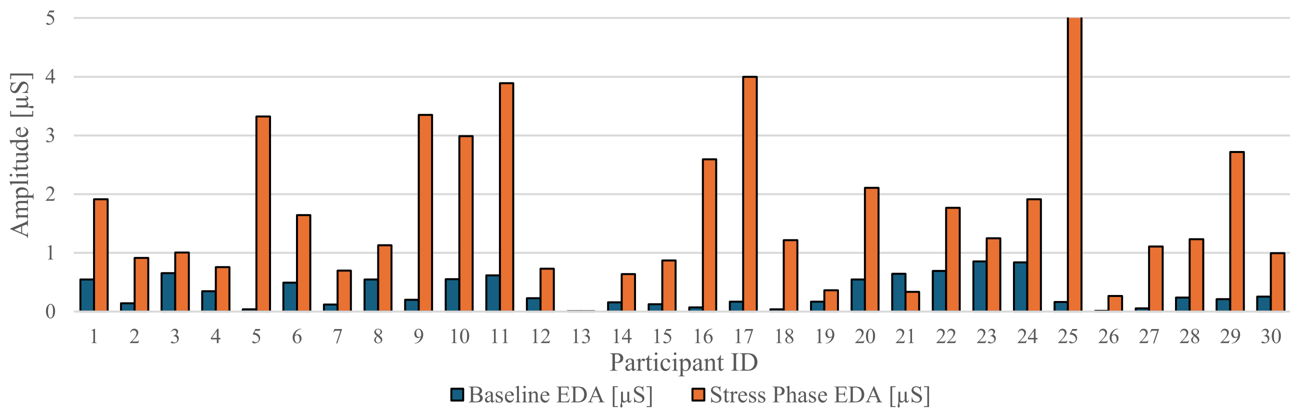


FIGURE 21. Comparison of EDA peak amplitudes between baseline and stress phases per participant.

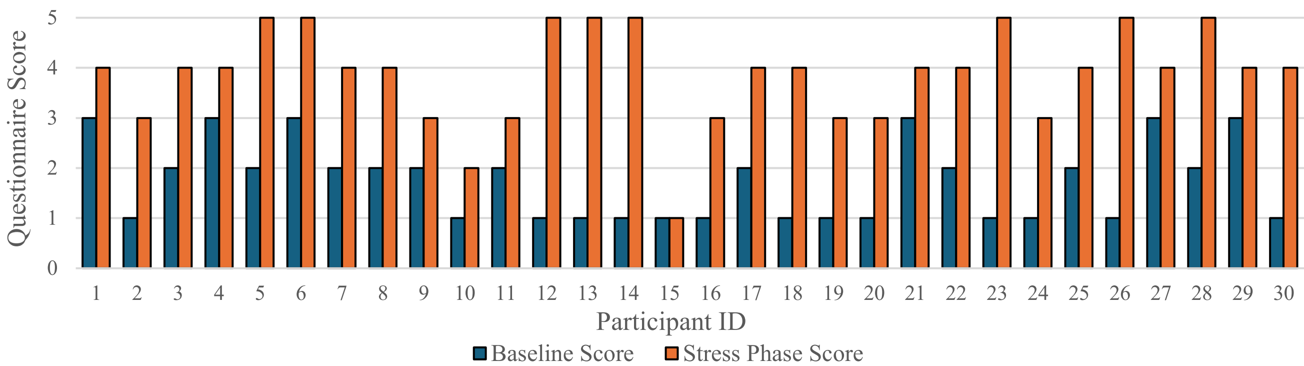


FIGURE 22. Comparison of self-reported questionnaire stress ratings between baseline and stress phases across participants.

a: EEG DATA STATISTICAL ANALYSIS

Statistical analysis of EEG data revealed a t-statistic value of $t = -4.46$, which belongs within the critical region W $(-\infty, -1.7)$ at a significance level of $\alpha = 0.05$. The resulting p-value ($p = 5.706 \times 10^{-5}$) was significantly lower than the predefined significance threshold, leading to rejecting the null hypothesis H_0 in favor of the alternative hypothesis H_1. This finding confirms a significant difference in emotional responses between the experimental phases, indicating higher EEG stress levels in the ‘‘fall’’ phase compared to the ‘‘ride’’ phase.

b: EDA DATA STATISTICAL ANALYSIS

A similar analysis was conducted for EDA data, yielding a t-statistic value of $t = -5.85$, also within the critical region W $(-\infty, -1.7)$. The corresponding p-value ($p = 1.199 \times 10^{-6}$) was lower than the predefined significance level, confirming the statistical significance of differences in emotional responses for EDA across experimental conditions. Consequently, the null hypothesis H_0 was rejected in favor of the alternative hypothesis H_1.

c: STATISTICAL ANALYSIS OF QUESTIONNAIRE DATA

Statistical analysis of subjective ratings revealed a t-statistic of $t = -10.57$ with a p-value of ($p = 9.33 \times 10^{-12}$), demonstrating a substantial increase in perceived stress levels in the ‘‘fall’’ phase compared to the ‘‘ride’’ phase. As a result, the null hypothesis H_0 was rejected, and the alternative hypothesis H_1 was accepted, confirming a statistically significant difference in emotional responses between the experimental phases based on subjective assessments.

5) COMPARISON OF EEG, EDA, AND QUESTIONNAIRE RESULTS

To evaluate the effectiveness of the proposed hybrid emotion recognition system in VR, a paired t-test was conducted to assess statistical significance in stress level variations across the two experimental phases using three distinct data sources: neurophysiological (EEG), physiological (EDA), and psychological (questionnaire-based).

The results indicate that both EEG and EDA data revealed statistically significant changes in emotional responses between the experimental phases. These findings confirm the reliability of EEG and EDA measurements even during movement in VR. Table 1 summarizes the comparison of stress level increases between the ‘‘ride’’ and ‘‘fall’’ phases among 30 subjects.

In summary, most subjects exhibited significantly lower stress levels before the fall phase than after it. These findings confirm the capability of biological data to reliably detect emotional states and further support the hypothesis regarding the pronounced effect of VR on emotional experiences.

TABLE 1. Comparison of EEG, EDA, and questionnaire results.

Participant ID	EEG Stress Response	EDA Stress Response	Questionnaire Stress Response
1	✓	✓	✓
2	✓	✓	✓
3	✓	✓	✓
4	✓	✓	✓
5	✓	✓	✓
6	✓	✓	✓
7	✓	✓	✓
8	✓	✓	✓
9	✓	✓	✓
10	✓	✓	✓
11	✓	✓	✓
12	✗	✓	✓
13	✓	✓	✓
14	✓	✓	✓
15	✗	✓	✗
16	✓	✓	✓
17	✓	✓	✓
18	✓	✓	✓
19	✓	✓	✓
20	✓	✓	✓
21	✓	✗	✓
22	✓	✓	✓
23	✓	✓	✓
24	✓	✓	✓
25	✓	✓	✓
26	✓	✓	✓
27	✗	✓	✓
28	✓	✓	✓
29	✓	✓	✓
30	✓	✓	✓

6) STATISTICAL ASSUMPTIONS AND ROBUSTNESS CHECKS

To ensure the statistical validity of our analyses, we assessed the distribution of paired differences (stress minus baseline phase values) for EEG, EDA, and subjective questionnaire scores. Normality was evaluated using the Lilliefors test and visual inspection of histograms. Wilcoxon Signed-Rank tests were additionally conducted as a non-parametric complement to the paired t-tests to enhance robustness. All analyses were performed in MATLAB (R2020b) with a significance level of $\alpha = 0.05$.

The Lilliefors test confirmed that normality was satisfied for EEG ($p = 0.2562$) but not for EDA ($p = 0.0010$) or subjective scores ($p = 0.0010$). These results were supported by visual inspection, revealing an approximately symmetric EEG distribution and skewed distributions with potential outliers for EDA and subjective data (Fig. 23).

Despite the observed deviations from normality, the Wilcoxon tests consistently corroborated the findings of paired t-tests, confirming statistically significant differences for all three measures (EEG: $Z = 3.77$, $p = 1.6046 \times 10^{-4}$, EDA: $Z = 4.70$, $p = 2.6033 \times 10^{-6}$, subjective scores: $Z = 4.76$, $p = 1.9455 \times 10^{-6}$).

The agreement between parametric and non-parametric results supports the robustness of our findings and confirms the validity of observed differences across conditions. Taken together, these results confirm that the use of parametric tests was statistically justified despite partial violations of normality.

III. RESULTS

This study utilizes noninvasive sensors to collect biological data from a specific sample of participants within a dynamic and interactive VR scenario. The primary objective was to evaluate the efficacy of EEG and EDA in detecting users' emotional states during a simulated security incident and to validate the functionality of the proposed hybrid emotion recognition system under the assumption that participants were in motion during the experiment. A total of 120 parameters extracted from EEG and EDA signals were analyzed from 30 participants. Two distinct phases of the scenario were examined: the elevator ride and its simulated free-fall.

A. EEG DATA ANALYSIS

EEG signal analysis was conducted in MATLAB using EEGLAB and ERPLAB toolboxes. The key parameter under investigation was the beta-band amplitude at electrode F8, which reflects stress response.

The results showed that in 27 out of 30 participants, the amplitude of EEG signals was higher during the fall phase than during the ride phase. The mean EEG amplitude was 17.62 μV during the ride and 30.19 μV during the fall. Statistical analyses confirmed a significantly higher amplitude in the fall phase, supporting hypothesis H_1. The observed increase in beta activity aligns with the assumption that higher stress levels are associated with elevated beta oscillation amplitudes in the frontal region.

B. EDA DATA ANALYSIS

EDA signal processing was performed using Ledalab software, where the signal was decomposed into tonic (SCL) and phasic (SCR) components. The maximum SCR amplitude was used as a key indicator of stress response.

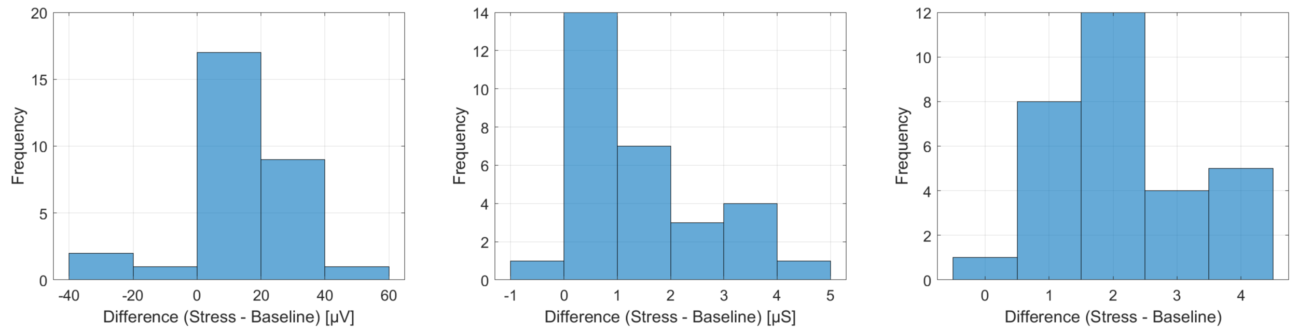
The findings revealed that in 29 out of 30 participants, stress levels increased during the fall phase compared to the ride phase. The mean SCR amplitude was 0.324 μS during the ride and 1.693 μS during the fall. Statistical analyses confirmed a significant difference between the experimental conditions, further supporting hypothesis H_1.

C. SUBJECTIVE SELF-REPORT ANALYSIS

The questionnaire analysis yielded results that were broadly consistent with objective biological measurements. In 29 out of 30 participants, the self-reported stress levels were higher in the fall phase compared to the ride phase.

D. STATISTICAL COMPARISON ACROSS MODALITIES

To compare the three measurement modalities' effectiveness, paired t-tests and Wilcoxon Signed-Rank tests were



a) distribution of EEG differences
b) distribution of EDA differences
c) distribution of questionnaire score differences

FIGURE 23. Distribution histograms of delta values for EEG (a), EDA (b), and questionnaire scores (c) used to assess normality and detect potential outliers.

TABLE 2. Statistical analyses of differences between the "Ride" and "Fall" Phases.

Measure	p-value (t-test)	p-value (Wilcoxon)	Significant Increase
EEG	5.71×10^{-5}	1.60×10^{-4}	✓
EDA	1.20×10^{-6}	2.60×10^{-6}	✓
Questionnaire	9.33×10^{-12}	1.95×10^{-6}	✓

conducted to assess differences between the "ride" and "fall" phases across EEG, EDA, and questionnaire-based assessments.

Statistical analyses confirmed a significant increase in stress levels during the free-fall phase, consistent across all three measurement methods (EEG, EDA, and subjective self-reports), as shown in Table 2. These findings support hypothesis H_1.

EEG and EDA responses aligned with subjective reports in 28 out of 30 participants, and complete consistency across all three modalities was observed in 26 cases, indicating high agreement among methods. The alignment between biological and subjective assessments further strengthens the validity of the results and enables objective assessment of stress levels in dynamic crises. Minor inconsistencies may be attributed to individual differences in stress perception, variability in physiological reactivity, or potential signal artifacts.

E. CORRELATION ANALYSIS OF MULTIMODAL STRESS MEASURES

To examine associations between biosignals (EEG and EDA) and subjective stress ratings, Pearson and Spearman correlation coefficients were computed across three data domains: baseline values, stress-phase values, and delta values (i.e., the difference between stress and baseline). This dual approach allows for the assessment of both linear (Pearson) and monotonic (Spearman) relationships among objective and subjective measures of stress.

Fig. 24 presents a Pearson correlation heatmap illustrating linear associations among EEG, EDA, and self-reported stress scores across all three domains. Darker red tones

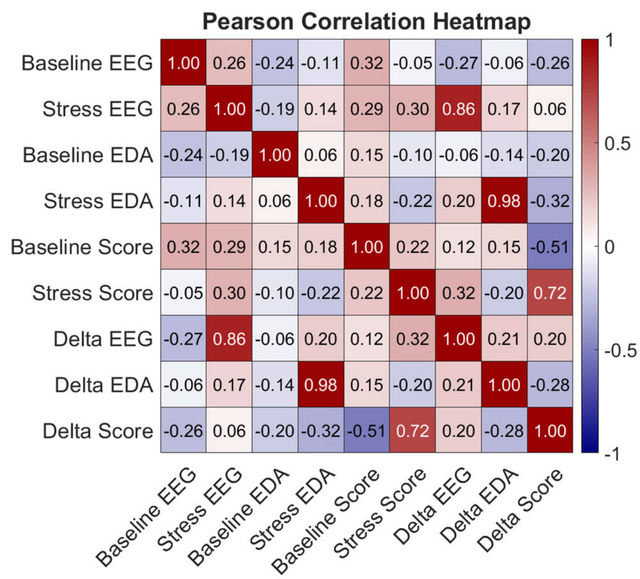


FIGURE 24. Pearson correlation heatmap showing linear relationships among EEG, EDA, and questionnaire-based stress ratings (baseline, stress phase, and delta values). Darker tones indicate stronger correlations.

represent stronger positive correlations, whereas blue tones indicate negative correlations. Fig. 25 depicts the corresponding Spearman heatmap, capturing monotonic trends and rank-order dependencies among the same variables.

The strongest correlation with self-reported stress ratings was observed for stress-phase EEG (Pearson $r = 0.30$; Spearman $\rho = 0.27$), suggesting a moderate association between increased cortical activation and perceived emotional stress. In contrast, stress-phase EDA showed a weak negative correlation with subjective ratings, particularly in Spearman correlation ($\rho = -0.30$), indicating inter-individual variability in sympathetic reactivity. Despite the inverse relationship, its direction aligns with established physiological responses to acute stress.

Delta metrics additionally revealed meaningful trends in biosignal reactivity. Delta EEG showed a modest association with delta subjective ratings (Pearson $r = 0.20$; Spearman

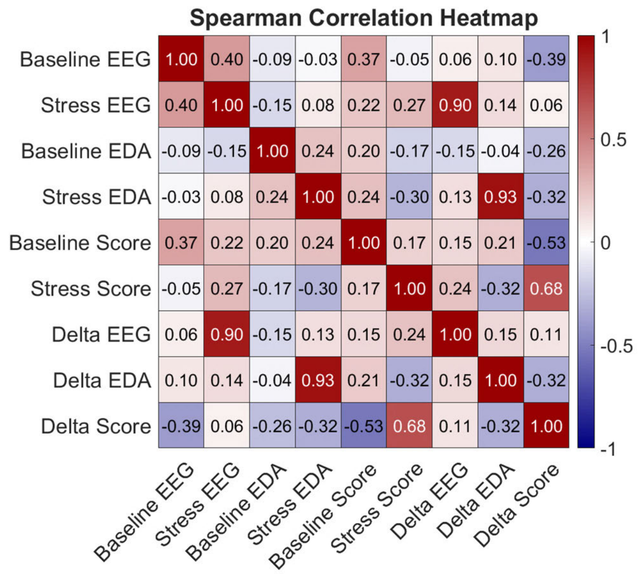


FIGURE 25. Spearman correlation heatmap showing monotonic relationships among the same variables, emphasizing rank-order associations.

$\rho = 0.11$), while delta EEG and delta EDA were weakly but positively correlated (Pearson $r = 0.21$; Spearman $\rho = 0.15$), reflecting partial synchrony between cortical and autonomic responses to stress.

Within-modal correlations highlighted differences in signal consistency across experimental phases. EEG measurements showed weak but consistent associations between baseline and stress phases (Pearson $r = 0.26$; Spearman $\rho = 0.40$), whereas EDA values exhibited minimal linear correlation (Pearson $r = 0.06$), with slightly higher monotonic consistency (Spearman $\rho = 0.24$). These findings highlight EDA's transient, stimulus-driven nature in contrast to more stable EEG activity patterns.

Strong correlations between phase-specific and delta metrics were also observed, indicating signal consistency within each modality. Specifically, stress-phase EEG was strongly associated with delta EEG (Pearson $r = 0.86$; Spearman $\rho = 0.90$), and stress-phase EDA was nearly identical with delta EDA (Pearson $r = 0.98$; Spearman $\rho = 0.93$), supporting the internal consistency of biosignal reactivity measures.

Overall, moderate correlations with subjective stress scores support the validity and complementary value of the proposed multimodal approach. The complementary strengths of EEG and EDA demonstrate the advantage of integrated analysis for improving detection accuracy and robustness in complex VR-based scenarios.

F. CLASSIFICATION PERFORMANCE OF THE HYBRID SYSTEM USING MACHINE LEARNING

To assess the effectiveness of the proposed hybrid system for stress recognition in virtual reality, a supervised machine learning approach was implemented using EEG and EDA features recorded during the baseline and stress-inducing phases. MATLAB's Classification Learner was initially used for exploratory comparison of multiple models, from which the Gaussian Support Vector Machine (SVM) with a radial basis function (RBF) kernel achieved the best results. This non-linear classifier maps inputs into a higher-dimensional space, enabling the modeling of complex biosignal relationships. The SVM internally determines the class label based on the position of the input feature vector relative to a decision boundary (hyperplane). The SVM-based decision mechanism enables replicable classification and provides a technically viable foundation for future real-time implementation in applied VR systems. The final model development was then implemented programmatically in MATLAB using a nested Cross-Validation (CV) scheme, with Leave-One-Subject-Out (LOSO) in the outer loop and 5-fold CV with Bayesian optimization in the inner loop for hyperparameter tuning (MaxObjectiveEvaluations = 100, feature standardization enabled). This design prevents subject leakage and ensures generalizability to unseen individuals.

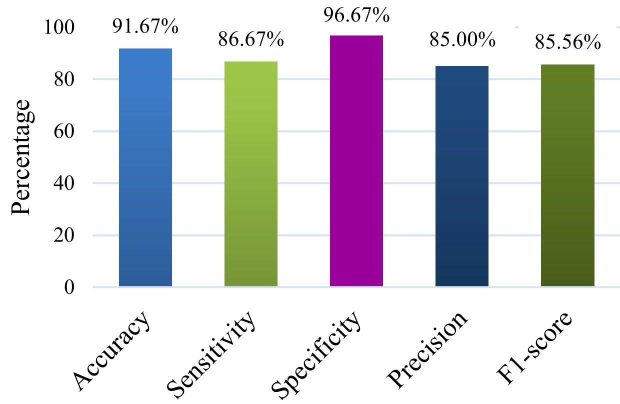


FIGURE 26. Performance metrics of the final SVM model.

The final dataset included 60 labeled samples (30 participants $\times$ 2 conditions), equally distributed across the two classes (baseline = 0, stress = 1), ensuring balanced representation and unbiased evaluation metrics. Aggregated group-level results, calculated as the mean across 30 subjects with 95% confidence intervals (CIs), were as follows: accuracy of 91.67% $\pm$ 7.08%, sensitivity of 86.67% $\pm$ 12.91%, specificity of 96.67% $\pm$ 5.08%, precision of 85.00% $\pm$ 13.11%, and F1-score of 85.56% $\pm$ 12.94% (Fig. 26).

These results confirm the system's ability to reliably distinguish between stress and non-stress states. The high specificity reflects a strong ability to reject false positives, while sensitivity and F1-score indicate effective detection of stress responses. The lower precision and F1-score, alongside wide CIs, are a direct consequence of including per-subject zero values due to the stringent LOSO and inter-individual variability (see Table 3).

While most participants achieved perfect classification across all metrics, a few subjects showed reduced performance, highlighting inter-individual variability or motion artifacts, which lowered the overall group averages

TABLE 3. Per-subject SVM performance using LOSO-CV.

Subject	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1 (%)
1	100	100	100	100	100
2	100	100	100	100	100
3	100	100	100	100	100
4	100	100	100	100	100
5	100	100	100	100	100
6	100	100	100	100	100
7	100	100	100	100	100
8	100	100	100	100	100
9	100	100	100	100	100
10	100	100	100	100	100
11	100	100	100	100	100
12	100	100	100	100	100
13	50	0	100	0	0
14	100	100	100	100	100
15	100	100	100	100	100
16	100	100	100	100	100
17	100	100	100	100	100
18	100	100	100	100	100
19	50	0	100	0	0
20	100	100	100	100	100
21	50	0	100	0	0
22	100	100	100	100	100
23	100	100	100	100	100
24	100	100	100	100	100
25	100	100	100	100	100
26	50	0	100	0	0
27	100	100	100	100	100
28	50	100	0	50	67
29	100	100	100	100	100
30	100	100	100	100	100

Note: per-subject metrics are based on only two samples (baseline and stress) and therefore take on discrete values. They should be interpreted with caution, as they primarily illustrate subject-dependent variability rather than precise individual-level estimates.

and widened CIs. This aligns with prior findings that biosignal-based emotion recognition is subject-dependent. To complement numerical metrics, classifier performance is visualized using a confusion matrix (Fig. 27) and a receiver operating characteristic (ROC) curve (Fig. 28).

The confusion matrix, aggregated across LOSO folds, illustrates the classification outcome for the two-class problem (0 = baseline, 1 = stress). Out of 60 instances (30 per class), the classifier correctly identified 29 baseline samples (true negatives) and 26 stress samples (true positives). This resulted in only one false positive (baseline misclassified as stress) and four false negatives (stress misclassified as baseline). The observed distribution demonstrates strong specificity and robust overall accuracy, which indicates the model's solid ability to discriminate between emotional states.

The ROC curve, derived from the aggregated predictions, demonstrates the trade-off between the true positive rate (sensitivity) and false positive rate across various decision thresholds, with the positive class defined as stress (1). The classifier achieved an area under the curve (AUC) of 0.95, confirming its strong discriminative capability and supporting its suitability for detecting stress responses in realistic virtual environments.

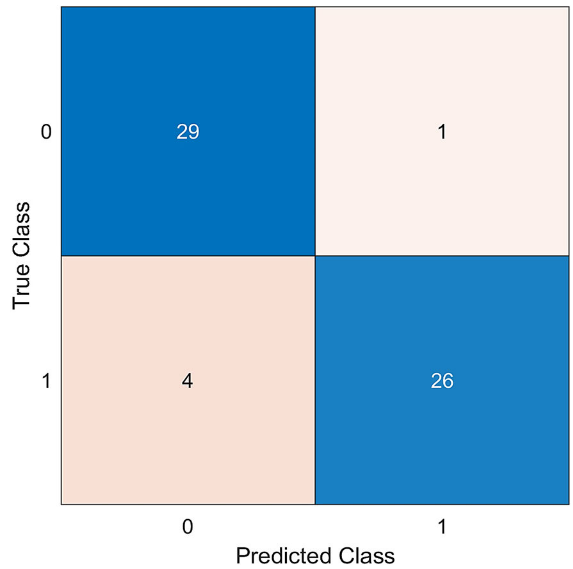


FIGURE 27. Confusion matrix of the final SVM model.

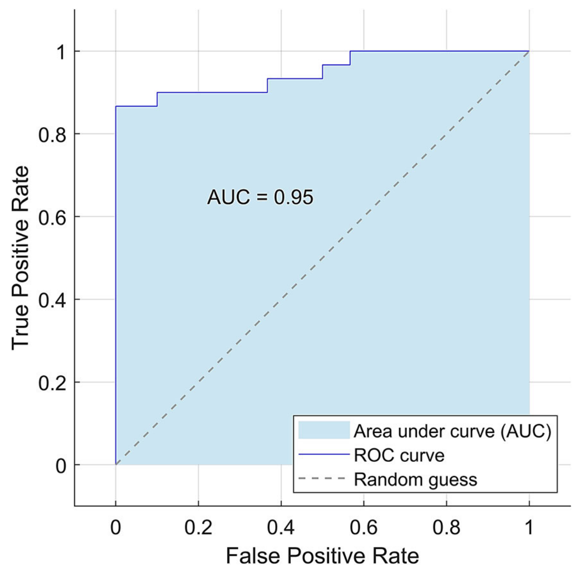


FIGURE 28. ROC curve of the final SVM model (AUC = 0.95, class = 1).

To prevent circular validation, subjective stress self-reports were excluded from model training. However, a comparison of self-reports confirmed increased stress during the stress-inducing VR phase, supporting the effectiveness of the proposed immersive scenario.

The results validate the proposed hybrid system's technical robustness and practical applicability for real-time emotion recognition in VR environments using combined biosignals.

G. COMPARISON OF INDIVIDUAL VS. HYBRID MODALITIES

Three classification models were trained using EEG-only features, EDA-only features, and combined EEG-EDA features to evaluate the added value of combining EEG and

TABLE 4. Classification performance comparison across signal modalities.

Metric	EEG	EDA	EEG + EDA (Hybrid)
Accuracy (%)	68.33 ± 11.48	85.00 ± 8.70	**91.67 ± 7.08**
Sensitivity (%)	73.33 ± 16.79	80.00 ± 15.19	**86.67 ± 12.91**
Specificity (%)	63.33 ± 18.30	90.00 ± 10.70	**96.67 ± 5.08**
Precision (%)	58.33 ± 15.57	75.00 ± 15.31	**85.00 ± 13.11**
F1-score (%)	63.33 ± 15.45	76.67 ± 15.03	**85.56 ± 12.94**

EDA signals. Each model was independently optimized using Bayesian methods and evaluated via nested CV, with LOSO in the outer loop and 5-fold CV in the inner loop for hyperparameter tuning, to ensure robust and unbiased performance estimates.

Table 4 summarizes the classification performance across modalities. The hybrid model achieved the highest accuracy (91.67%), clearly outperforming both unimodal models. EDA-only yielded stronger results than EEG-only, particularly in precision and specificity. This may be attributed to the higher susceptibility of EEG signals to motion artifacts and the limited use of a single EEG feature in this study. Nevertheless, the combined approach consistently outperformed both unimodal configurations across all metrics.

These findings confirm that the multimodal integration of EEG and EDA signals significantly improves classification performance for stress recognition in VR environments. While EDA alone offers strong predictive power, combining it with EEG improves sensitivity and specificity, highlighting the benefit of integrating complementary biosignals. The lower performance of the EEG-only model may be due to the minimal feature set used, as EEG-based classification typically benefits from advanced feature extraction and selection techniques. Despite this, our system achieved high accuracy using only a single EEG feature, suggesting notable robustness despite minimal feature complexity.

The proposed system successfully identified stress elevation in most participants using EEG and EDA signals, closely matching participants' subjective evaluations. Statistical analyses confirmed significant stress variation across experimental conditions, supporting hypothesis H_1 and demonstrating the ability of EEG and EDA to capture emotional responses even in the presence of motion-related artifacts. Moreover, the results emphasize the importance of frontal brain regions and beta-band EEG activity in stress detection within VR environments. Correlation analyses further revealed moderate associations between biosignals and perceived stress levels. Overall findings validate hypothesis H_2 by showing that multimodal integration enhances reliability in emotion recognition tasks.

In summary, the results underscore the complementary nature of multimodal assessment and confirm the reliability of EEG and EDA signals for stress detection in immersive VR environments, supporting both established hypotheses H_1 and H_2. The integration of these signals substantially improves classification accuracy and system robustness, highlighting the system's potential for adaptive VR training and real-time monitoring in high-risk, movement-rich environments.

IV. DISCUSSION

This study investigated the integration of EEG and EDA for detecting emotional responses in VR simulations. The findings confirm that a simulated elevator fall in VR elicits a significantly higher stress response than a standard elevator ride, as evidenced by neurophysiological, physiological, and subjective measures. In addition, the proposed hybrid system achieved high performance, validating the effectiveness of a multimodal approach for emotion assessment in realistic virtual scenarios and contributing to the development of objective methods for measuring emotional responses under dynamic conditions.

A. VALIDITY OF EEG AND EDA COMBINATION FOR EMOTION RECOGNITION

This work adds to the growing body of evidence supporting the utility of EEG and EDA for objective emotion measurement in ecologically valid simulated scenarios. Significant differences between experimental conditions were observed in EEG beta activity and phasic EDA amplitude, confirming that the simulated elevator fall induced a stress response. Although correlations between EEG and EDA were moderate and varied across individuals, their combined use improved reliability in detecting emotional states. The integration of both modalities yielded robust classification results, confirming the potential of multimodal emotion detection even in immersive VR. Accurately analyzing emotions in naturalistic settings remains challenging; however, VR offers a controlled yet immersive environment that enables the standardized elicitation of emotional stimuli. This study demonstrates that simulated crisis scenarios can evoke authentic emotional reactions and that their objective detection via EEG and EDA is feasible and effective even in dynamic VR environments.

B. INDIVIDUAL VARIABILITY AND FACTORS INFLUENCING MEASUREMENT DISCREPANCIES

The results highlight that individual predispositions can influence stress responses measured by EEG and EDA. Some participants exhibited inconsistencies between self-reports and biological data, including atypical amplitudes during baseline, possibly unrelated to emotional arousal. These were not considered statistical outliers based on visual inspection and classification patterns but may reflect subject-specific variation due to differences in stress perception, modality-specific sensitivity, or measurement noise. These discrepancies were reflected in the classification outcomes, where 5 of 60 instances (8.33%) were misclassified, likely due to signal artifacts or quality degradation. Despite multimodal input, model performance remains sensitive to data integrity and inter-individual variability. Correlation analysis supported this interpretation, revealing moderate associations between biosignals and stress ratings. While EEG activity correlated positively with self-reports, EDA showed weaker or inverse relationships, indicating variability in sympathetic reactivity.

Nevertheless, the hybrid system maintained high performance (accuracy 91.67%, sensitivity 86.67%, specificity 96.67%, precision 85.00%, F1-score 85.56%), effectively minimizing false positives despite individual variability. These findings underscore the importance of integrating multiple modalities to mitigate biases from individual variations and technical constraints. Future research should incorporate more diverse samples, apply robust artifact detection, and explore clustering or unsupervised learning to identify latent subgroups with distinct physiological profiles and assess their impact on system reliability and generalizability [21], [23], [39].

C. THE ROLE OF VR IN EMOTION RESEARCH AND SAFETY SIMULATIONS

VR enables the simulation of scenarios that are challenging to replicate in real-world conditions, such as accidents, crises, and emergency response operations. According to threat response theory, fear-inducing stimuli hold evolutionary significance and inherently attract heightened attention. VR experiments allow for examining these reactions in ecologically valid conditions that elicit natural emotional responses from participants. Integrating EEG and EDA in VR simulations provides valuable opportunities for analyzing emotional reactions, which can benefit crisis management, security training, and forensic neuroscience [10], [25].

D. TECHNOLOGICAL AND EXPERIMENTAL LIMITATIONS

Despite promising results, several technological and methodological limitations must be considered. Motion artifacts remain a key constraint, especially during dynamic VR interaction. EEG device compatibility with VR headsets is also an issue, as traditional high-density systems are often unsuitable for immersive applications. The Emotiv EPOC+ headset, while wireless and user-friendly, offers limited spatial resolution and a relatively low sampling rate compared to clinical-grade EEG systems [33]. Although the Polygraph LX6 provides reliable EDA signals, its wired connectivity may restrict movement and increase artifact risk. Replacing wired sensors with wireless alternatives and improving EEG robustness to motion artifacts would enhance signal quality and usability in dynamic VR conditions. While the minimal setup used in this study yielded strong classification results, future systems could benefit from a broader feature space, advanced feature selection, and improved signal processing.

Regarding ecological validity, the artificial nature of the VR scenario, despite high visual fidelity, may not fully replicate the unpredictability and complexity of real-world crises. Participants' prior familiarity with the environment and the constrained scenario structure could also have moderated emotional responses. Another limitation is VR-induced motion sickness, which may occur even during short simulations and subtly affect biological responses. Although no participants withdrew from discomfort, such effects cannot be ruled out and should be considered in future designs [4].

E. FUTURE DIRECTIONS

Further research should incorporate larger participant samples and a broader range of emotional stimuli to enhance the validity and generalizability of findings. Emotion recognition accuracy depends on data quality and the selection of optimal EEG and EDA parameters. Advancements in real-time processing, artifact reduction, wireless integration, and automated detection algorithms represent key directions for improving system performance and broader applicability in dynamic VR environments [6], [10], [39]. The lack of standardized methodologies for biosignal analysis in VR remains a challenge and should be addressed in future studies. Another promising direction is personalizing emotion recognition models based on individual characteristics, which could enhance user performance consistency. Further investigations should consider procedurally generated scenarios, longitudinal assessments, and user-perceived realism and immersion [31].

The findings of this study confirm that integrating EEG and EDA into VR experiments is a practical and effective approach for analyzing emotional responses in crisis scenarios. Potential applications extend from security training and crisis management to evaluating the psychological impact of various environments in fields such as medicine and entertainment. Biosignals obtained from accessible, wearable devices hold the potential to detect emotions with high accuracy, thereby enhancing the efficacy of crisis simulations in security research [7].

F. GENERALIZABILITY, SCALABILITY, AND TRANSFERABILITY

The proposed system was validated on a relatively homogeneous university sample. Future research should examine its robustness across diverse demographic groups, including age cohorts, cultural backgrounds, and professional experience levels. However, the modular architecture of the hybrid EEG-EDA system and the flexibility of VR environments support its scalability to various domains such as law enforcement training, medical simulations, fire evacuation, active shooter simulations, or architectural evaluations [17], [19], [21]. Although scenario-specific signal calibration and interface optimization may be required, the foundational pipeline for biosignal acquisition, preprocessing, and interpretation remains transferable.

To facilitate broader adoption, future adaptations may focus on exploring system deployment in mobile VR or standalone headsets that reduce hardware complexity. Further, investigating performance in augmented reality (AR) or mixed reality (MR) environments could expand applicability, as suggested in [30] and [31].

G. COMPARISON WITH RELATED STUDIES

The results of this study align with prior research emphasizing the benefits of combining EEG and EDA for emotion recognition in immersive environments. Similar to [6] and [7], our hybrid system outperformed single-modality approaches, achieving a classification accuracy of 91.67%.

Our observed increase in EDA mean amplitude (from 0.324 μS during baseline to 1.693 μS during the stress phase) corresponds with values reported by Perales et al. [1] (0.41–1.35 μS) and Antoniou et al. [14] (0.739–5.407 μS). Similarly, Radhakrishnan et al. [29] reported mean SCR amplitudes of 0.19 μS, indicating lower arousal in less intense tasks. Benedek and Kaernbach [41] confirmed that event-related SCR amplitudes may reach 2 μS while resting levels remain below 0.1 μS. These values support the validity and sensitivity of our measurements under immersive VR conditions.

Regarding EEG, an increase in beta activity is consistent with studies linking beta-band power to emotional arousal [13], [34], [36], [37], [38]. Although methodological differences across studies constrain direct comparisons, our trend aligns with prior findings, supporting the relevance of beta activity in stress detection.

Our classification results also outperform those of comparable systems. For instance, Hinkle et al. [6] achieved 89.19% accuracy using SVM, Yan et al. [13] reported 85.0% with Hidden Naïve Bayes, and Bhat et al. [15] reached 80.5% using gradient boosting. The strong performance of our model, despite its streamlined feature set, demonstrates the robustness and efficiency of the proposed system in active VR scenarios.

V. CONCLUSION

This study demonstrated the feasibility and effectiveness of combining EEG and EDA for emotion recognition in immersive VR scenarios involving active movement and stress induction. The proposed hybrid system achieved high classification accuracy (91.67%) and outperformed unimodal approaches, confirming the benefit of multimodal biosignal integration. Importantly, these results remained robust even after applying subject-independent validation (LOSO CV), confirming the generalizability of the proposed system across unseen participants. Significant differences between baseline and stress phases were observed in EEG and EDA data, supporting the hypothesis that the elevator drop induced heightened stress responses. Unlike previous studies, this work assessed emotion recognition in a physically engaging and ecologically valid VR context, where user movement was integral to the high-risk scenario. Despite the promising results, limitations include susceptibility to motion artifacts, limited sample diversity, and inter-individual variability. Future work should pursue broader validation, personalized models, real-time detection, artifact mitigation, and improved device compatibility. Integrating neurophysiological and physiological signals provides a robust foundation for adaptive VR systems capable of real-time emotion monitoring, with applications in crisis training, healthcare, education, and psychological assessment.

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