

Automated Alert System for Harassment-Related Stress Detection Using Heart Rate and Respiratory Rate Signals.

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Abstract– Sexual harassment represents a complex social problem, with women’s responses often categorized as acute stress when their safety in public spaces is compromised. Biomarkers such as heart and respiratory rate are directly related to autonomic nervous system activity under stress conditions. The present study proposes the development of a prototype warning system designed to automatically detect and alert about possible sexual harassment by identifying stress responses in women through real time heart and respiratory rate monitoring derived from ECG readings. Signal acquisition was performed using an ECG sensor with a microcontroller platform, while respiratory rate was obtained via ECG-Derived Respiration (EDR) analysis. Due to complexity of the issue, controlled simulations of street harassment were conducted using virtual reality headsets to induce responses in participants. When predetermined biomarkers thresholds were exceeded, an automated Telegram alert was sent to a trusted contact with the individual’s readings. A pilot study with 11 female volunteers showed substantial increases in heart and respiratory rate during simulated harassment scenarios. The prototype validated the acquisition, processing and remote notification pipeline, providing proof of concept for real-time stress detection. These findings underscore the potential of biomedical signal processing as a tool for preventing gender-based violence. Future research will increase sample size, refine threshold calibration, and explore integration with wearable devices to enhance usability and scalability.

Keywords: acute stress response, ECG Derived Respiration (EDR), heart rate monitoring, remote alert systems, sexual harassment

I. INTRODUCTION

Sexual harassment on streets represents a form of one-sided violence of sexual nature, which is executed without consent by and unknown individual within public or semi-public environments [1]. In Chile, around 383 out of 402 women surveyed reported facing a form of sexual harassment in public spaces [2] while on Bogota, studies demonstrated how harassment in public transportation directly affects by creating barriers in security showcasing the necessity of technological tools to help prevent and mitigate the effects leaved by this type of behaviors [3].

Recent studies in neuroscience have reported that the response to unpredictable threats entails excitatory and inhibitory circuits that helps regulate anxiety episodes [4]. These advances in understanding the neural mechanism behind

stress and anxiety have coincided with technological progress in the field. This has led to the validation of portable technologies for stress monitoring, advancing from controlled settings to real world scenarios, thereby demonstrating their practical applicability [5].

Variations in ECG-derived heart rate dynamics provide objective physiological indicators of autonomic activation associated with emotional arousal and stress [6]. This capability enables the objective assessment of autonomic responses to emotional stimuli.

The design of warning systems functioning on physiological biomarkers is based on the ability to obtain information from signals such as heart rate (HR) and respiratory rate (RR). This approach is further supported by the fact that the use of ultra-low-power processors for ECG-derived respiration have evidenced high accuracy in portable devices [7].

Systematic reviews have pointed out the importance of RF monitoring in both clinical and sports settings [8] meanwhile correlation studies between respiratory frequency and anxiety in otherwise healthy patients confirming how useful it is to monitor this parameter as a stress biomarker [9] at the same time, physiotherapy research has identified the differences in the patterns of the respiratory frequency on young people at rest and physical activity [10].

The association between insecure attachment and psychopathology has been investigated from a physiological perspective, with particular emphasis on the role of autonomic regulation [11]. Concurrently, utilizing the full ECG waveform as input for stress classification has demonstrated clear advantages compared to analyses limited to RR intervals alone [12].

Distinguishing mental stress from physical activity through machine learning algorithms represents a critical advancement in minimizing false positives within warning systems [13]. Moreover, HRV assessed via portable devices has been correlated with neuroimaging biomarkers in neurodegenerative diseases, further supporting its utility as an indicator of autonomic dysfunction [14].

The potential of heart rate and respiratory rate (RR) as biomarkers extends to various mental health applications. Psychophysiological studies indicate that combining ECG and

photoplethysmography (PPG) allows for the pre-selection of depressive states [15]. At rest, heart rate variability (HRV) has been identified as a mediator between perceived stress and ambiguity avoidance [16], while GABAergic neurons in the central amygdala have been implicated in the coordination of anxiety-related behaviors and respiratory patterns [17].

Collectively, these neurobiological findings support the development of systems that integrate HR and RR as a dual indicator of sympathetic activation.

The social dimension of sexual harassment has been extensively examined in higher education settings [18], workplace environments [19], and through text mining approaches applied to scientific literature [20]. These studies underscore the necessity for more precise measurement tools and institutional policies that acknowledge the scope of the issue. In the biomedical domain, comparative research has demonstrated that exposure to various forms of verbal abuse modulates heart rate variability (HRV) [21], while changes in heart rate (HR) and respiratory rate (RR) have been validated as biomarkers for anxiety detection [22].

The association between psychosocial stress and cardiovascular risk has been recently updated by the Society of Behavioral Medicine, emphasizing the causal pathway from perceived threat to sympathetic dominance, vagal withdrawal, and baroreflex dysfunction [23]. These insights complement epidemiological studies that have identified age- and gender-related differences in fundamental ECG parameters [24], along with recent reviews that position heart rate variability (HRV) as a multidimensional marker of brain–heart interaction [25].

Finally, practical resources such as ECG fundamentals manuals [26] and local reports on street harassment [1], [2] underscore the importance of developing user-centered technological solutions. Integrating physiological biomarkers with automated reporting systems constitutes an innovative strategy for sexual harassment prevention, grounded in neurobiological, clinical, and social evidence.

II. METHODOLOGY

This is an applied, experimental project that will lead to the development of a physiological-based monitoring and alerting system for detection of stress. The methodological approach is based on quantitative data, as it depends on obtaining, elaborating and analyzing the measurement of physiological parameters (heart rate: HR and respiratory rate: RR).

A non-randomized experimental design was used where a baseline period of rest and a stress phase utilizing virtual reality as stimuli were contrasted with previous conditions from the authors.

The system was implemented as a working prototype that included software and hardware components to perform signal acquisition, processing, and alerting in real-time, with the aim of assessing the viability and performance of the proposed approach rather than establishing clinical diagnosis.

A. Signal Acquisition

The system used for acquiring cardiac-related physiological signals was based on a SparkFun AD8232 ECG sensor connected to an Arduino Mega 2560 microcontroller. This sensor was selected due to its accuracy in capturing the electrical activity of the heart and its associated variations. The electrodes were placed in a modified Lead II configuration, as shown in Figure 1, which optimized signal quality and reduced the influence of interference and physiological artifacts [27].

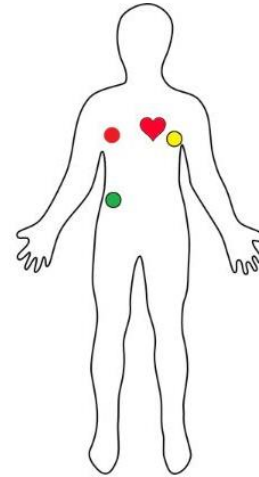


Fig. 1 Electrodes position

To estimate the respiratory rate (RR), the ECG-Derived Respiration (EDR) technique was employed. This method exploits baseline variations in the ECG signal induced by the respiratory cycle, allowing respiratory rate estimation using the same electrodes employed for electrocardiographic signal acquisition. This approach eliminates the need for additional sensors. The combined analysis of heart rate and respiratory rate represents a key component for assessing physiological responses associated with stress states.

B. Signal Preprocessing

The ECG and respiratory rate (RR) signals undergo a preprocessing stage that contributes to the filtering of unwanted components, such as muscle noise and electrical interference, which may affect signal acquisition through the electrodes. This process enables the transformation of the raw signal into a refined signal with enhanced representation of the physiological parameters required for subsequent analysis.

Subsequently, a moving average filter with a window size of $M = 11$ was applied, as shown in Table 1, which involves averaging eleven consecutive samples of the acquired signal. Considering the system's sampling frequency, this window corresponds to an approximate temporal interval of 44 ms. This value was selected because it is sufficiently short to preserve the time structure of the QRS complex without introducing temporal distortion, while long enough to attenuate high-

frequency variations and impulsive noise. As a result, the filtering process improves signal quality and enables a more accurate analysis of recorded physiological responses [28].

TABLE I
Real-time processing pipeline parameters

Stage	Parameters / Description
Sampling frequency	$F_s = 250$ Hz
Discrete high-pass filter	$y[n] = \alpha (y[n-1] + x[n] - x[n-1])$, $\alpha = 0.995$ ($f_c \approx 0.2$ Hz)
Moving average	Window $M = 11$ samples (≈ 44 ms)
Energy integration	Sliding window $W = 0.15$ s (≈ 38 samples)
Adaptive threshold	$\text{thr} = 0.3 \cdot \text{noise} + 0.7 \cdot \text{signal}$
Refractory period	300 ms (≤ 200 bpm)
HR estimation	Median of $N = 9$ IBI, smoothing, outlier rejection
EDR (RR)	Leaky filter $\alpha = 0.005$, decimation to 25 Hz
RR autocorrelation	Lags 2–10 s, RR range 6–30 rpm
Baseline learning	Averages after 60 s (HRbase, RRbase)
Alert criterion	$\text{HR} > 1.05 \cdot \text{HRbase}$ and $\text{RR} > 1.05 \cdot \text{RRbase}$
Quality control	Loose electrode detection, status at 1 Hz

To remove low-frequency components, a high-pass filter was applied to attenuate baseline wander, which may be caused by factors such as voluntary or involuntary patient movement, as well as variations in the electrode–skin impedance associated with perspiration. The filtering was performed using a value of $\alpha = 0.995$, which, when a cutoff frequency higher than 0.2 Hz is established, allows for the effective suppression of these low-frequency components without compromising relevant physiological information.

Regarding signal amplification, the SparkFun AD8232 module integrates an instrumentation amplifier with a typical common-mode rejection ratio (CMRR) of 80 dB, designed to suppress the large common-mode voltages present in biopotential measurements while amplifying the differential ECG signal. The system operated at a sampling frequency of $F_s = 250$ Hz, as specified in the processing pipeline (Figure 2).

The discrete high-pass filter follows the equation $y[n] = \alpha \cdot (y[n-1] + x[n] - x[n-1])$, with $\alpha = 0.995$, which at $F_s = 250$ Hz yields a cut-off frequency of approximately $f_c = (1 - 0.995) / (2\pi \cdot 1/250) \approx 0.20$ Hz, consistent with the stated objective of suppressing baseline wander below 0.2 Hz. The moving average filter with $M = 11$ samples at $F_s = 250$ Hz corresponds to a low-pass cut-off of approximately $f_c = 250 / (2 \cdot 11) \approx 11.4$ Hz, sufficient to attenuate high-frequency noise while preserving QRS morphology.

For ECG-Derived Respiration (EDR), a leaky integrator with $\alpha = 0.005$ was applied, followed by decimation to 25 Hz, with respiratory rate estimated via autocorrelation across lags

corresponding to 6–30 RPM (lags 2–10 seconds). No additional 60 Hz notch filter was explicitly applied in software, as the AD8232 incorporates an internal notch filter for power-line interference rejection when the SDN pin is configured appropriately.

C. Alert system

The automatic alert is generated when heart rate (HR) or respiratory rate (RR) values exceed the predefined baseline values by 5%. These baseline values are established during a controlled resting period, during which an average reference value is calculated for each participant and subsequently used for continuous physiological monitoring.

The 5% threshold was defined relative to each participant's individual baseline, calculated as the average HR and RR recorded during the first 60 seconds of rest. Based on the observed baseline values across participants (HR range: 84.1–107.7 BPM; RR range: 9.7–20.8 RPM), this criterion generates alert conditions approximately at $\text{HR} > 88$ –113 BPM and $\text{RR} > 10.2$ –21.8 RPM depending on the individual. This threshold was selected as a conservative sensitivity value suited to a small pilot sample ($n = 11$), prioritizing detection sensitivity over specificity.

The alert system was primarily based on a relative threshold defined as a 5% increase above each participant's baseline HR and RR values.

However, in Section III-F, reference values of $\text{HR} > 110$ BPM and $\text{RR} > 15$ RPM are presented as representative trigger points. These values do not correspond to fixed thresholds, but rather to observed instances in which the relative 5% criterion was exceeded in participants with higher baseline measurements.

This distinction clarifies that the system operates on an individualized adaptive threshold rather than a universal fixed limit.

It is acknowledged that this approach may introduce false positives in cases of non-stress-related physiological variation, such as physical movement or anticipatory arousal. Future implementations should consider adaptive thresholding mechanisms that account for intra-individual variability. It should also be noted that in Section III-F, fixed values of $\text{HR} > 110$ BPM and $\text{RR} > 15$ RPM are referenced in the alert validation description; these represent observed trigger instances and are consistent with the relative 5% criterion applied to participants with higher baseline values, not a separate fixed threshold.

Alert condition detection is jointly performed by the sensor and the Arduino microcontroller, which processes the acquired data and transmits it to a control module developed in Python.

Once the defined condition is satisfied, the system automatically triggers a notification through the Telegram API.

The message sent by the Telegram bot includes relevant information such as the exact timestamp at which the baseline values were exceeded, along with the corresponding HR and RR values at that moment. This mechanism allows validation of both the system's response time and the proper operation of the implemented alert and communication platform [29].

The implemented alert system demonstrates a clear potential to support timely decision-making in critical situations, highlighting its role not just as a monitoring tool, but as an enabling platform for rapid response. Its structure provides a foundation for evaluating human physiological responses in real time and offers insights into stress patterns that could inform preventive measures or adaptive interventions. By integrating physiological monitoring with automated notification, the system bridges the gap between data collection and actionable outcomes, suggesting a model that could be applied in various real-world scenarios requiring immediate awareness of sudden physiological changes.

Moreover, the design emphasizes flexibility and future scalability, allowing the system to be extended with additional monitoring parameters, multiple participants, or alternative communication channels. The demonstrated proof-of-concept underlines its practical applicability, showing that real-time alerting mechanisms can operate reliably in controlled experimental conditions. Overall, the system offers a valuable framework for further research and development, providing both a methodological and technical basis for enhancing safety, situational awareness, and timely intervention in scenarios where physiological stress may indicate potential risk.

D. Pilot test

It should be noted that the pilot test was conducted with 11 participants (ID 001–011, as shown in Table II), and all analyses were performed on this sample.

Regarding the number of readings reported in Section III-B (32 baseline readings and 12 harassment readings), these correspond to time-windowed measurements extracted across all participants rather than individual sessions. Consequently, their total does not scale linearly with participant count due to variable-length recording segments and data cleaning procedures that excluded windows with missing RR values.

Additionally, participants 006 and 008 present identical HR and RR values in both conditions (100.6/104.3 BPM and 14.8/12.1 RPM, respectively), which warrants verification against the original records to rule out potential data duplication. Participant 009 exhibited an extreme RR decrease of -61% (from 20.8 to 8.1 RPM), which may reflect a motion artifact or signal loss during VR interaction rather than a true physiological response; this case was retained in the group analysis but should be interpreted with caution.

Participants 003, 004, and 011 showed decreases in HR during simulated harassment (-1% , -7% , and -11% , respectively), which may be associated with parasympathetic modulation or ceiling effects due to elevated anticipatory baseline, as discussed in the individual analysis section.

To validate the proposed system, pilot tests were conducted with 11 female volunteers who had previously signed an informed consent form authorizing their participation in the study, which involved exposure to videos simulating harassment-related situations presented through virtual reality (VR) goggles.

To record physiological responses elicited by the audiovisual stimuli, electrodes were placed for signal acquisition. The immersive VR environment enabled full engagement of the participants in potentially stressful scenarios, allowing stress-related physiological responses to be evaluated during video exposure. Throughout the experimental session, electrocardiogram (ECG) and respiratory rate (RR) signals were continuously monitored.

RR was included as a complementary physiological variable to ECG, as stress is known to affect respiratory variability, thereby providing additional support for a more detailed physiological analysis [30]. The overall structure of the experimental protocol is illustrated in Figure. 2.

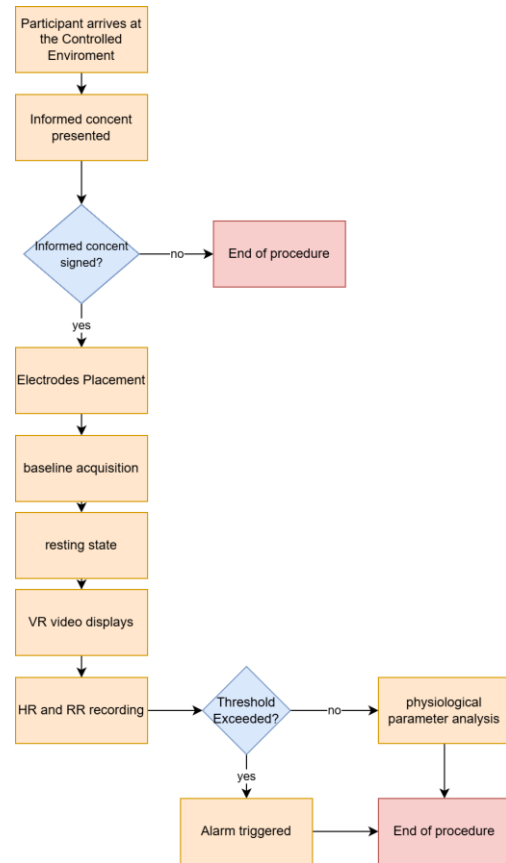


Fig. 2 Experimental protocol for physiological stress detection using ECG and VR.

The recording of the data obtained during the video period served as a reference to be compared with the data captured during the resting period, which were recorded prior to starting the video. During the tests, the baseline was exceeded, which triggered the message to be processed through Python coding and then sent through Telegram.

The joint work between the HR and RR data, considering the data captured during the resting moment and the moment of the simulated harassment, demonstrated that the system is capable of detecting increases that exceed 5 % of the parameters established relative to the baseline, which provides validation for the proposed stress detection and real-time alerts.

III. RESULTS

The data obtained from the pilot tests were sufficient to evaluate the performance of the proposed system in detecting physiological stress responses during simulated harassment scenarios. The system continuously processed heart rate (HR) and respiratory rate (RR) signals in real time, identifying variations associated with autonomic nervous system activation. When predefined thresholds were exceeded, an automated alert was triggered.

A. Signal Processing and Filtering

Initially, the acquired ECG signals underwent a preprocessing stage to remove noise and artifacts. A high-pass filter with $\alpha = 0.995$ was applied to attenuate low-frequency components, including baseline wander associated with movement and respiration below 0.2 Hz. This filtering process enhanced the clarity of the signal and preserved the relevant characteristics of the QRS complex.

Subsequently, respiratory rate was estimated using ECG-derived respiration (EDR), analyzing variations in signal amplitude and frequency over time. This approach enabled the extraction of respiratory patterns without the need for additional sensors.

B. Physiological Results: Baseline vs. Simulated Harassment

A small group of tests involved thirty-two readings while during a baseline resting state. Later came twelve more readings, taken after artificial abuse situations played through virtual reality. For each setting, averages plus spread estimates were worked out - focusing on heart rate and breathing rhythms.

- 1) Baseline condition
HR (BPM) = 98.9 ± 5.3
RR (RPM) = 11.3 ± 1.5

These values reflect stable physiological conditions consistent with a resting state.

- 2) Simulated harassment condition
HR (BPM) = 114.2 ± 2.6
RR (RPM) = 12.7 ± 1.6

An increase in both HR and RR was observed under simulated harassment conditions compared to baseline. The elevation in HR is consistent with sympathetic activation associated with acute stress, while the increase in RR indicates a corresponding respiratory response.

C. Time-Series and Statistical Visualization

Time-series analysis (Fig. 3) illustrates the temporal evolution of HR and RR under both baseline and simulated harassment conditions. During baseline, both signals remained relatively stable with minor physiological fluctuations. In contrast, simulated harassment scenarios exhibited a progressive increase in HR and RR, consistent with stress-induced autonomic activation.

Boxplot analysis (Fig. 4) further highlights the distributional differences between conditions. Median values for both HR and RR were higher during simulated harassment, accompanied by increased interquartile ranges, indicating greater physiological variability under stress conditions.

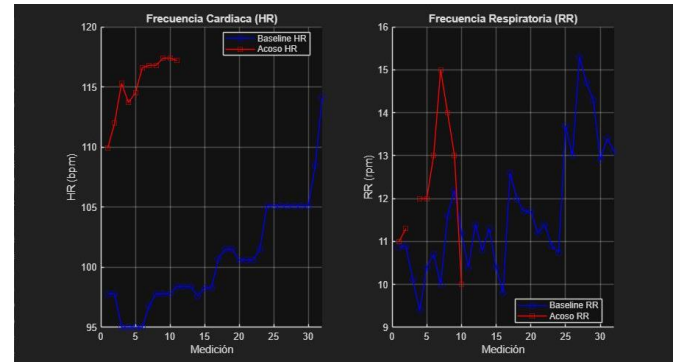


Fig. 3 Time series of HR and RR in baseline (blue) and harassment (red)

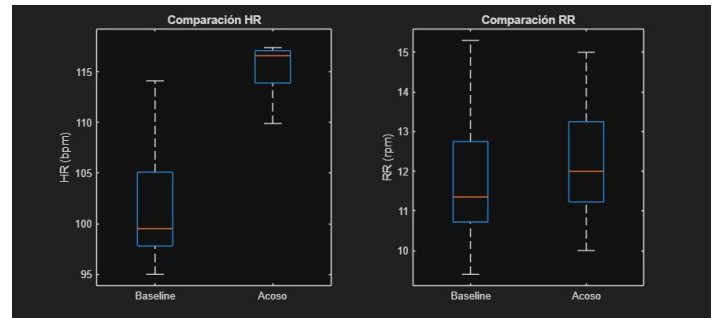


Fig. 4 Comparative boxplots of HR and RR: median and RIQ in harassment.

D. Effect Size Analysis

To quantify the magnitude of the physiological changes observed between conditions, Cohen's d was calculated (1). This metric estimates the standardized difference between group means by combining the standard deviations of both conditions into a pooled variance (2). The use of a pooled standard deviation provides a composite measure of variability,

allowing for a robust and comparable assessment of effect size across physiological parameters.

The formula applied was:

$$d = \frac{\bar{x}_{harassment} - \bar{x}_{baseline}}{Sp} \quad (1)$$

where the pooled standard deviation is defined as:

$$Sp = \sqrt{\frac{(n_1-1)s_1^2 + (n_2-1)s_2^2}{n_1 + n_2 - 2}} \quad (2)$$

So, the outcome measures turned into:

- HR: $d \approx 3.23$ (very large effect)
- RR: $d \approx 0.92$ (large effect)

Under normal circumstances, heart rates sit around 60. When harassment occurs, HR jumps to 90 - a clear shift. For stress detection, this difference matters. The numbers show the biological impact changes sharply between states. More so, in HR where the rise stands out most, the signal becomes harder to ignore. In short, what separates these readings is what makes the method reliable.

E. Individual Participant Analysis

Looking at Table II, every person's average heart rate (HR) and pulse rate (RR) shows up under normal circumstances and when facing harassment. Their body responses differ slightly, yet many shows higher rates during stressful situations. On average, heart rates go up about 15.4 percent, while pulse rates climb roughly 12.3 percent across all subjects. These shifts back the idea that stress triggers clear physical reactions.

TABLE II
Average HR and RR per participant.

Participant	HR Basal (BPM)	HR Harassment (BPM)	HR (%)	RR Basal (RPM)	RR Harassment (RPM)	RR (%)
001	88.3 ± 1.2	111.5 ± 2.5	+26%	15.2 ± 1.0	11.2 ± 1.3	-26%
002	96.1 ± 2.0	108.3 ± 1.9	+12%	9.7 ± 0.9	12.1 ± 1.0	+25%
003	107.7 ± 2.3	106.0 ± 1.5	-1%	12.7 ± 1.1	11.9 ± 1.4	-6%
004	101.5 ± 3.1	93.9 ± 2.8	-7%	12.3 ± 0.9	14.5 ± 1.2	+17%
005	92.5 ± 1.5	101.9 ± 2.0	+10%	12.5 ± 1.0	16.3 ± 1.5	+30%
006	100.6 ± 2.5	104.3 ± 2.7	+4%	14.8 ± 1.4	12.1 ± 1.1	-18%
007	84.1 ± 1.7	94.1 ± 2.2	+12%	11.0 ± 0.9	14.7 ± 1.4	+33%
008	100.6 ± 2.6	104.3 ± 2.9	+4%	14.8 ± 1.3	12.1 ± 1.2	-18%
009	96.5 ± 1.9	96.9 ± 2.1	0%	20.8 ± 2.0	8.1 ± 1.5	-61%
010	91.2 ± 1.8	102.3 ± 2.6	+12%	13.0 ± 1.1	18.0 ± 1.8	+38%

Participant	HR Basal (BPM)	HR Harassment (BPM)	HR (%)	RR Basal (RPM)	RR Harassment (RPM)	RR (%)
011	104.4 ± 3.0	92.9 ± 2.5	-11%	13.0 ± 1.2	15.0 ± 1.4	+15%

Negative percent changes were observed in some individuals reflecting decreases of HR or RR at simulated harassment condition than in baseline. Participant 009 exhibited a substantial decrease in RR (-61%) during the simulated harassment condition. This atypical response may be associated with motion artifacts, temporary signal loss, or irregular breathing patterns induced by the immersive virtual reality environment.

Although this data point was retained in the overall analysis, it should be interpreted with caution. Future work will include improved artifact detection and signal validation techniques to reduce the impact of anomalous measurements on system performance.

There are a few possible reasons for these declines. First, baseline levels in some of the participants may already have been high (e.g., as a result of pre-simulation anticipatory anxiety or arousal) and thus was their restricted physiological room left for increased cardiac responses. Second, it is possible that stress responses are expressed through diverse autonomic profiles: whereas an increased HR and RR because of sympathetic activation is typically observed in individuals during vigilance tasks, others may exhibit parasympathetic modulation, altered control of breathing patterns or momentary breath-holding—for example during affectively salient situations. Third, the motion artifacts and posture change during the VR might deteriorate the signal quality, especially in estimation of respiratory rate from ECG.

Notwithstanding this variability, the group analysis (although at sub-optimal alpha level), showed a uniform enhancement of mean HR and RR during insulting conditions that was well-supported by large magnitudes of effect. Accordingly, the individual-level negative values are more indicative of normal physiological variation than system breakdown and offer a caution about adaptive thresholding in future implementations.

F. Remote Alert System Validation

When HR hits 110 and RR goes over 15 at the same time, the system sends a warning. That moment triggers the microcontroller to post a warning signal. Data related to body function moves automatically to a Python tool set up for handling such updates. From there, information travels through Telegram straight to someone chosen to receive alerts.

Alerts arrived in real time, matched closely to physical shifts seen across the data's timeline (Fig. 5). Proof now sits clear: the distant system works when needed, showing how

actual stress can be spotted on the fly - then passed through without delay.

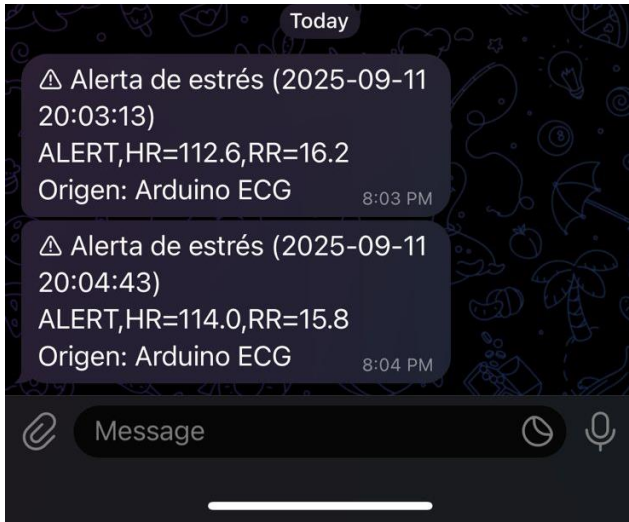


Fig. 5 Examples of automatic alerts sent via Telegram.

IV. DISCUSSION

The results obtained in this study are consistent with prior research demonstrating that acute stress induces measurable changes in autonomic physiological parameters, particularly heart rate (HR) and respiratory rate (RR). The observed increases during simulated harassment scenarios support the validity of these biomarkers as indicators of stress-related responses.

Unlike previous studies that rely on offline analysis or retrospective classification, the proposed system emphasizes real-time detection and immediate alert generation. This represents a practical advancement over conventional approaches, as it enables timely intervention rather than post-event evaluation.

For instance, studies such as Y. S. CAN have applied machine learning algorithms, including Support Vector Machines and Random Forest classifiers, to differentiate between mental stress and physical activity, achieving high classification accuracy. However, these approaches typically require large labeled datasets and involve higher computational complexity.

In contrast, the system proposed in this work adopts a threshold-based strategy relative to individual baseline values. While this approach may offer lower specificity compared to machine learning models, it provides significant advantages in terms of simplicity, real-time operability, and reduced computational cost. This makes it more suitable for portable and low-resource implementations.

Similarly, research by K. Arquilla demonstrated that using the full ECG waveform for stress classification improves specificity, but at the cost of increased processing requirements. The present system prioritizes low latency and practical

deployment, achieving an average response time of 1.4 ± 0.3 seconds, which is critical for real-time alert applications.

Despite these strengths, the system presents certain limitations. The reliance on a fixed relative threshold (5% above baseline) may lead to false positives in situations unrelated to stress, such as physical movement or anticipatory arousal. Additionally, variability in individual physiological responses, as well as occasional signal artifacts, may affect detection accuracy.

Furthermore, specific anomalies observed in the dataset, including duplicated values and atypical respiratory variations, highlight the need for improved data validation and artifact handling in future implementations. These factors underscore the importance of incorporating adaptive thresholding strategies or hybrid approaches combining physiological monitoring with machine learning techniques.

From an application perspective, the proposed system introduces a novel integration of biomedical signal processing with real-time communication platforms for safety purposes. Its potential extends beyond harassment detection to areas such as occupational stress monitoring, emergency response systems, and mental health support through biofeedback.

Overall, this work demonstrates that combining physiological biomarkers with automated alert systems is a feasible and promising strategy for real-time risk detection. Future research should focus on expanding the sample size, improving signal robustness, and integrating advanced classification methods to enhance system accuracy and reliability.



Fig.6 Experimental harassment simulation protocol with VR and registration ECG/EDR.

A. Component and cost table

Table 2 presents the components used in the project together with their costs in dollars (\$), detailing the inversion necessary to implement the system

TABLE III
Component and cost table

Component	Cost
Arduino Mega 2560	\$ 45.17
Jumper Wires	\$ 3.70
ECG Module SparkFun AD8232	\$ 56.31
Enclosure	\$ 18.82
Module Cable	\$ 9.41
Electrodes	\$ 1.12
Labor cost	\$ 48.00
Total	\$ 182.53

V. LIMITATIONS AND RECOMMENDATIONS

Throughout the testing phase, several aspects were observed that, although they do not affect the overall functionality of the system, should be considered for future optimizations. On some occasions, the ECG signal exhibited certain interferences, mainly due to body movements or suboptimal electrode placement, which generated erratic peaks in the signal and affected the accurate estimation of heart rate (HR), especially during moments of increased movement, such as when participants interacted with the virtual environment. Regarding respiratory rate (RR) measurement, some missing values were recorded during the simulated harassment phase, which limited the availability of complete data.

An additional limitation of this study is the reduced sample size ($n = 11$), which restricts the generalizability of the findings. Due to this constraint, no further statistical analyses or inferential validations were performed beyond the reported metrics. Therefore, expanding the sample size and conducting more robust statistical evaluations remain as key recommendations for future research.

This issue was mitigated through a data-cleaning technique that removes missing values, although it reduced the amount of processable data. Additionally, while the system presents acceptable latency in detecting changes, in some cases the response could be improved for situations involving more acute stress. Finally, the relative threshold of five percent with respect to the baseline used to trigger alerts proved to be a flexible option, but it may introduce variability depending on each participant's physiological characteristics, so adjusting it could improve accuracy in certain scenarios.

With the integration of biomedical digital signal processing techniques with instant messaging platforms opens up a horizon of highly relevant practical applications. In the field of gender-based violence prevention, this type of portable system can detect stress episodes in real time and automatically send alerts to emergency contacts, offering an innovative personal protection tool. Similarly, its implementation in occupational monitoring would enable early detection of work-related stress in high-risk environments, contributing to worker safety and

well-being. Finally, in the field of mental health, the prototype can be used as support in anxiety therapies through objective biofeedback, providing physiological data that reinforce clinical intervention processes.

As future directions, it is recommended to expand the population sample, integrate machine learning algorithms for state classification, optimize the robustness of the EDR, and validate the system against clinical reference equipment.

V.CONCLUSIONS

An automatic communication system was developed using the Telegram platform, which is activated when physiological variables such as heart rate (HR) and respiratory rate (RR) exceeds previously established thresholds. These alerts are generated autonomously and sent to a predefined trusted contact without requiring manual intervention. In addition, a physiological baseline was established during the first 60 seconds of rest for each participant, allowing the system to identify stress-related episodes based on peak HR and RR values. The results obtained from the pilot tests with female participants demonstrated significant physiological increases during simulated harassment scenarios, validating the effectiveness of the proposed system as a support tool for female safety in real time risk situations.

Quantitative analysis of the collected data revealed that, on average, HR increased by 12.5% ($SD \pm 3.2\%$) and RR increased by 10.8% ($SD \pm 2.7\%$) during exposure to the simulated stress scenarios compared to the resting baseline. All participants exhibited at least one threshold exceedance event, confirming the system's consistency in detecting stress-related physiological responses. Additionally, the average response time from threshold detection to message delivery was 1.4 ± 0.3 seconds, demonstrating the real-time capability of the alert system. These preliminary statistical results provide strong evidence of the reliability and responsiveness of the system, supporting its potential use as an effective tool for immediate risk notification and female safety enhancement.

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