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SingStress: Sensor Analysis in Acute Psychological Stimulation

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Abstract:

Acute stress results in significant risks to the cardiovascular and immune systems, so monitor and manage effectively is important. Existing studies frequently utilize sensors such as photoplethysmography (PPG) and electrodermal activity (EDA) to monitor and evaluate stress, however, they often miss to compare the sensitivity of these sensors. In this experiment, we collected PPG and EDA data from 26 participants during resting and public speaking tasks. Participants were also asked to complete a stress-related questionnaire. Pearson's correlation coefficients were calculated from the analysed data and questionnaire score. The results indicate that for the male group, the correlation with stress for PPG sensors ($\boldsymbol{\rho}\mathbf{SH} = 0.5796$) was stronger than for EDA sensors ($\boldsymbol{\rho}\mathbf{SR} = 0.1036$). Oppositely, for the female group, EDA sensors showed a stronger correlation with stress ($\boldsymbol{\rho}\mathbf{SR} = 0.6265$) compared to PPG sensors ($\boldsymbol{\rho}\mathbf{SH} = 0.2093$). These findings suggest that PPG sensors are more sensitive for male students, while EDA sensors are more sensitive for female students.

Keywords: acute physiological stress, wearable sensors, correlation, mHealth.

1. Introduction

Psychological stress is defined as feelings of nervousness, anxiety, irritability and insomnia due to conditions at home or at work [1]. And it can be roughly divided into chronic and acute stress [2]. In contrast to chronic stress, acute stress is usually caused by a sudden increase in major stress mediators [3]. And this stress can trigger acute coronary heart disease (CHD) events in susceptible patients [4], and it also has profound, rapid, short-term and variable effects on some components of the immune system [5,6]. To do a good job, an artisan needs the best tools, pressure detection equipment and methods with good sensitivity give more accurate data and more precise results. Medical practitioners and psychologists consider psychometric questionnaires are appropriate traditional methods for assessing stress [7]. And chemical biomarkers such as α-0amylase and copeptin markers are more reliable in stress assessment [8,9]. However, even though these methods are reliable indicators of stress, they do not allow for continuous stress detection. Therefore, another common method of stress assessment is the use of wearable sensors such as photoplethysmography (PPG) and electrodermal activity (EDA, also known as galvanic skin response; GSR) to measure physiological changes in the body's response to stress [10-12]. More than that, stress measurement also using physiological signals like electroencephalography (EEG) data [13], skin temperature (SKT) [14], blood volume pressure (BVP) [15], heart rate (HR) [16], electrocardiography (ECG) data [17], heart rate variability (HRV) [18], electromyography or the combination these bio-signals [19]. For example, Aamir Arsalan and Muhammad Majid had volunteers wear EEG, EDA, and PPG to collect data on their resting states and public speaking states [20-22], analysed the data to distinguish between these two states. Dong-Wan Ryoo et al. developed a wearable system that senses physiological data through PPG, EDA and SKT, determines emotional states and performs services based on emotions [23]. They proposed a perceptual stress classification method that outperforms existing ones. And all these existing studies have focused on monitoring and assessing the stress levels and data collection but have not compared the sensor sensitivity of monitoring data. Therefore, our study aims to evaluate and compare the sensitivity of the PPG and the EDA sensors in detecting acute stress. We expected that

PPG and EDA have difference in the accuracy in measuring stress levels and hope the results of the experiment can provide a reference for the selection of sensors for stress measurement and enhance the effectiveness of stress monitoring device.

2. Methodology

2.1 Participants

This experiment selected 26 participants (13 male and 13female) aged from 18 to 25(male: 20.62±1.73, female: 20.08±1.21). Participants should have no history of mental illness, cardiovascular or cerebrovascular disease, and had not consumed alcohol or alcoholic beverages within the past 24 hours. Before the experiment, all participants were asked to fill the information sheets.

2.2 Procedure & Data collection

A C++ based Arduino code was compiled and uploaded to the Seeeduino XIAO nRF52840. This code ensured that the PPG (PulseSensor-86462000020) and EDA (Grove-GSR Sensor V1.2) sensors that connected to the board could simultaneously collect data with 100 Hz frequency while operating independently off a computer. The data was then saved onto an SD card attached to the Seeeduino XIAO expansion board. Participants were invited to the testing room and sat beside the assistant experimenter and the main experimenter. The experiment was divided into three parts: TalkI phase, Sing phase, TalkII phase, each part lasted 60 seconds. PPG and EDA sensors were placed on participant's hands as shown in Fig.1 to measure blood volume change and skin electric conductance respectively. Before the experiment started, we did calibration for the device, we connected the board to a computer to check whether the data readings were stable. Once the data curves were uniform, we cleared the SD card's data and disconnected the board from the computer.

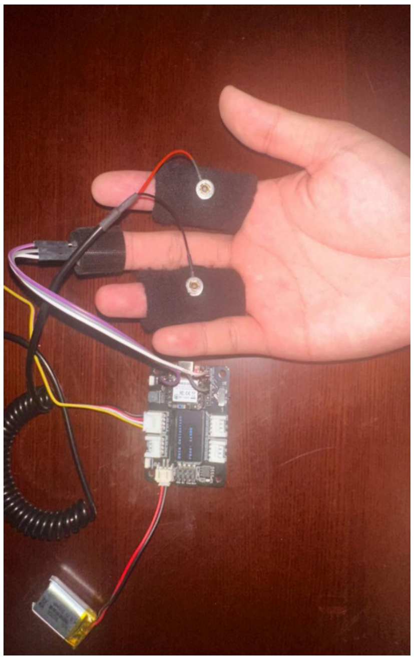

Fig. 1. Wearing the sensors.

In the TalkI phase (0~60 seconds), the tester chatted with the participants casually to make the participants chill down as much as possible from the stimulation at the beginning of the experiment. In the singing phase (60~120 seconds), the experimenter made a requirement for the participants "sing a song right now". During the whole singing phase, the experimenter should only repeat "sing a song right now" command even if the participants failed to sing the song or ask the experimenter. In the TalkII phase (120~180 seconds), the experimenter chatted with the participants casually again to make them gradually relax from the pressure of singing. After one minute, the PPG and EDA data collection was stopped. Then, the participants were asked to complete a questionnaire (see Fig. 2) to assess the participants' inner stress fluctuation.

	Never 0	Almost Never 1	Sometimes 2	Fairly Often 3	Very Often 4
1.In the experiment, how often have you felt that you were unable to control the important things in your life?	☐	☐	☐	☐	☐
2.In the experiment, how often have you felt confident about your ability to handle your personal problems?	☐	☐	☐	☐	☐
3. In the experiment, how often have you felt that things were going your way?	☐	☐	☐	☐	☐
4. In the experiment, how often have you felt difficulties were piling up so high that you could not overcome them?	☐	☐	☐	☐	☐
5. Did this experiment make you feel uncomfortable?	☐	☐	☐	☐	☐
6. During the experiment, did you feel any strong physical reactions, like sweating or blushing?	☐	☐	☐	☐	☐
7. Do you feel nervous or anxious when you recall this experiment?	☐	☐	☐	☐	☐
8. Did the stimulus just now make you unable to think logically in the experiment?	☐	☐	☐	☐	☐
9. When the stimulation is over, do you feel relieved?	☐	☐	☐	☐	☐
10. Would you feel stressed if you encounter such a stimulus frequently?	☐	☐	☐	☐	☐
11. In the experiment just now, did you feel that it was difficult to control your emotions?	☐	☐	☐	☐	☐
12. Would you be willing to try another experiment which is similar to this one?	☐	☐	☐	☐	☐

Fig. 2. Acute stress assessment scale.

2.3 Data analysis

26 data (13 male and 13 female) were collected overall. Data were stored and processed in MATLAB R2022A. As EDA sensor outputs a voltage value which is detected between 2 probes [24], these raw data were converted into skin resistance by applying a function [25]. After that the converted data were smoothed by using an average filter to reduce the fluctuation. The conversion function is expressed as follows:

$$\text{Skinresistance}(\Omega) = (1024 + 2\text{SerialPortReading}) \times 10000 \div (512 - \text{SerialPortReading}) \quad (1)$$

The PPG sensor reports an impulse while blood passes by the probe [26]. Each high peak can represent one heartbeat, but vibration will cause high-frequency noise throughout the measurement process. So, a low-pass filter with a 3 Hz (180 bpm) cut-off frequency was applied to the PPG signal. To figure out all the desirable peaks, a suitable threshold was set (threshold might vary between different people) to erase some other small peaks except the QRS wave. The current heart rate can be inferred from the time interval(ms) between the two peaks (Function (2)). The conversion method is expressed as follows:

$$\text{Heartrate}(\text{bpm}) = 6000 \div \text{Timeinterval} \quad (2)$$

Heart rate's (HR) mode (H_M) and mean(H_A) was obtained by the PPG sensors, while skin resistance (R) mode (R_M) and mean (R_A) were recorded by the EDA sensors. The data collection lasts for 180 seconds, including TalkI (0~60S), Sing (60~120S), and TalkII (120~180S). TalkI and TalkII are considered relaxation parts, while "Sing" is the test part. To eliminate the stimuli that the experiment itself brought to the participants, we used data from (55~60S) to represent "TalkI", the data of (60~120S) to represent "Sing", and the data of (170~175S) to represent "TalkII" in order to get the value after the participants are completely relaxed to exclude the influence of the stimulation part on the relaxation part.

To obtain the fluctuation characteristic in parameters during the "Sing" phase, we got the difference value of the heart rate and difference value of resistance data between the relaxation phase and experiment phase for each participant, resulting in the parameters ΔR and ΔH. To eliminate individual-specific, we normalized each participant's parameter changes by dividing it to the corresponding relaxation phase parameter values, thereby obtaining the r parameter change rate, which reflects the individual's response to psychological stress. The processing formulas for each person are as follows:

$$\Delta\text{H\_M1\_Nor}=(\text{H\_M\_Sing}-\text{H\_M\_TalkI})\div\text{H\_M\_TalkI} \quad (3)$$

$$\Delta\text{H\_M2\_Nor=(H\_M\_Sing-H\_M\_TalkII)÷H\_M\_TalkII} \tag{4}$$

$$\Delta\text{H\_M0\_Nor=max}\left(\Delta\text{H\_M1\_Nor,}\Delta\text{H\_M2\_Nor}\right) \tag{5}$$

$$\Delta\text{H\_A1\_Nor=(H\_A\_Sing-H\_A\_TalkI)÷H\_A\_TalkI} \tag{6}$$

$$\Delta\text{H\_A2\_Nor=(H\_A\_Sing-H\_A\_TalkII)÷H\_A\_TalkII} \tag{7}$$

$$\Delta\text{H\_A0\_Nor=max}\left(\Delta\text{H\_A1\_Nor,}\Delta\text{H\_A2\_Nor}\right) \tag{8}$$

$$\Delta\text{R\_M1\_Nor=(R\_M\_TalkI-R\_M\_Sing)÷R\_M\_TalkI} \tag{9}$$

$$\Delta\text{R\_M2\_Nor=(R\_M\_TalkII-R\_M\_Sing)÷R\_M\_TalkII} \tag{10}$$

$$\Delta\text{R\_M0\_Nor=max}\left(\Delta\text{R\_M1,}\Delta\text{R\_M2}\right) \tag{11}$$

$$\Delta\text{R\_A1\_Nor=(R\_A\_TalkI-R\_A\_Sing)÷R\_A\_TalkI} \tag{12}$$

$$\Delta\text{R\_A2\_Nor=(R\_A\_TalkII-R\_A\_Sing)÷R\_A\_TalkII} \tag{13}$$

$$\Delta\text{R\_A0\_Nor=max}\left(\Delta\text{R\_A1,}\Delta\text{R\_A2}\right) \tag{14}$$

From which, Δ represents the difference between two phases,
H represents heart rate,
R represents skin resistance,
A represents the mean of the parameter,
M represents the mode of the parameter,
TalkI, Sing, TalkII are three phases in our experiment,
Nor means normalized value

Our questionnaire consisted of 4 PSS-4 questions and 8 self-made questions, among which questions 5 to 11 were closely related to this experiment [27]. To ensure the questionnaire has referential value, reliability analysis is necessary. We chose Cronbach's α [28] to measure the internal consistency of our questionnaire [28]. The formula is as follows:

$$\alpha = \frac{k}{k-1}\left(1-\frac{\sum_{i=1}^{k}\sigma_{yi}^2}{\sigma_y^2}\right) \tag{15}$$

From which, k represents the number of items in the measure,

σ_{yi}^2 the variance associated with each item, σ_y^2 the variance associated with the total scores ($y=\sum_{i=1}^{k} y_i$)

A linear correlation analysis was applied between the parameter change rates for male and female groups and the normalized questionnaire scores to get the Pearson correlation coefficients [29]. The sensor with the largest positive value is selected as the one with the best detection effect. Later, we calculated the P-values for the parameters with the highest correlation coefficients to determine whether there was a correlation between the parameter change rate and the normalized questionnaire score.

3.Result

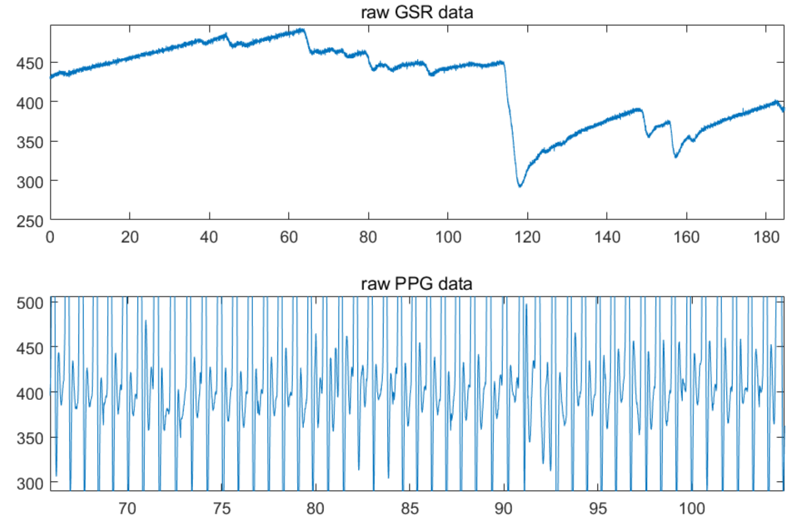

Fig. 3. Raw EDA and PPG data.

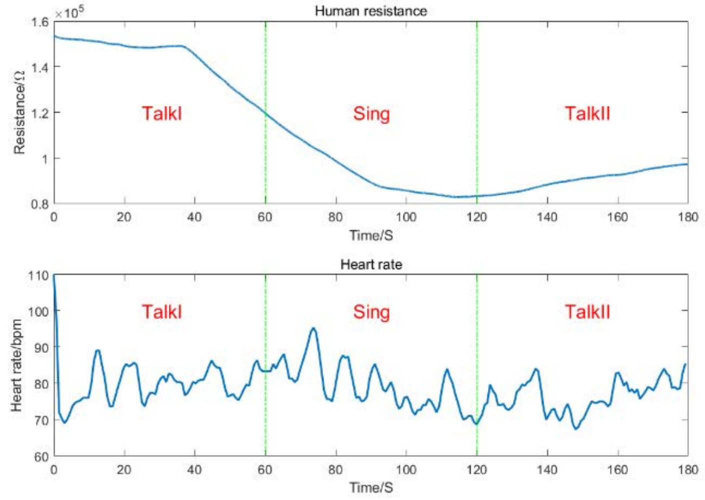

Fig. 4. Resistance and Heart rate.

Figure 3 shows the raw data collected by EDA and PPG from Male 2. But it doesn't directly represent the level of stress. The skin resistance and heart rate values of this participant after data processing can be seen in Figure 4. When people are nervous, they sweat, which causes the body resistance to decrease and the heart rate to increase. Figure 4 shows that the skin resistance of the participant (Male 2) continued to decrease during the "Sing" phase, and slowly increased during the "TalkII" phase, but did not reach the highest point, indicating that the participant gradually relaxed from the tension, but the recovery was slow. The heart rate increased significantly when the participant was suddenly asked to sing, and then gradually decreased. Figure 5 shows the waves of skin resistance and heart rate during the characteristic time of each of the three parts from Male 2.

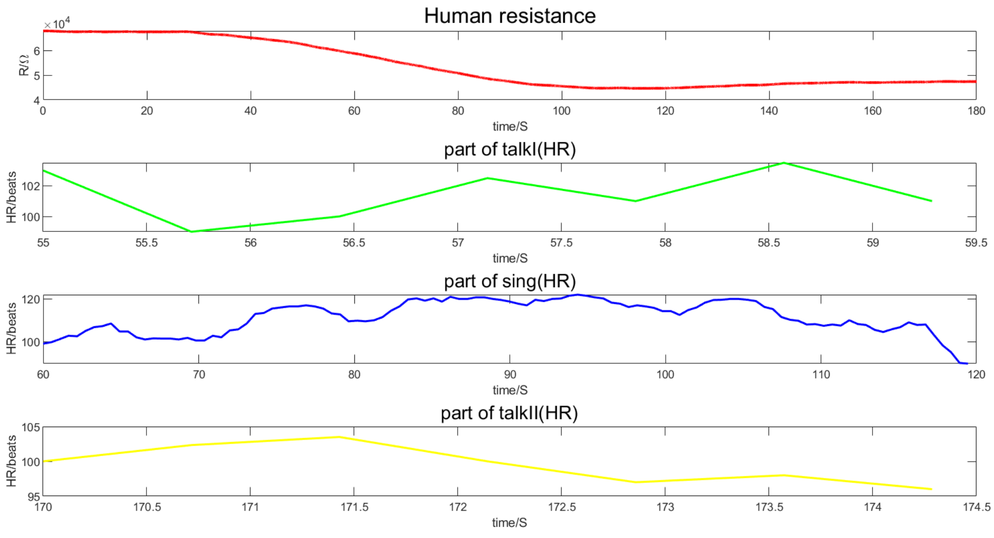

Fig. 5. Data analysis in Skin resistance and Heart rate.

Table 1 shows the Cronbach's alpha of 2 different parts of the questions in the questionnaire. Following the reliability analysis of the questionnaire, it determined that question 5 to 11 were meaningful, however question 1 to 4 were less reliable.

Table 1. Questionnaire reliability analysis.

Questions	Sample Size	Cronbach's α
1~4	26	0.422
5~11	26	0.752

Table 2. Pearson Correlation Coefficients(P-values).

	Male	Female	Both
Score and Resistance(average)	-0.1340(0.94)	0.6265(0.02)	0.3668(0.07)
Score and Resistance(mode)	0.1036(0.17)	0.5612(0.05)	0.3530(0.08)
Score and Heart Rate(average)	0.5796(0.04)	0.2093(0.48)	0.1780(0.38)
Score and Heart Rate(mode)	0.4848(0.10)	-0.2551(0.41)	0.0524(0.80)

Table 2 were the Pearson correlation coefficients with P-values for each feature for male, female and both. Figure 6 and Figure 7 showed the skin resistance change rate, the heart rate change rate and normalized questionnaire scores for each participant. In the legend box, the value of skin resistance changes rate and heart rate change rate respectively shown by ΔR (From EDA) and ΔH (From PPG). Table 3 were the normalized questionnaire score collected from each participant.

Table 3. Normalized Questionnaire Score.

ID	Score	ID	Score
Male 1	0.91	Female 1	1.00
Male 2	0.45	Female 2	0.35
Male 3	0.73	Female 3	0.41
Male 4	0.55	Female 4	0.47
Male 5	0.64	Female 5	0.76
Male 6	0.64	Female 6	0.18
Male 7	1.00	Female 7	0.76
Male 8	0.55	Female 8	0.41
Male 9	0.82	Female 9	0.24
Male 10	0.27	Female 10	0.76
Male 11	0.45	Female 11	0.24
Male 12	0.45	Female 12	0.41
Male 13	0.54	Female 13	0.76

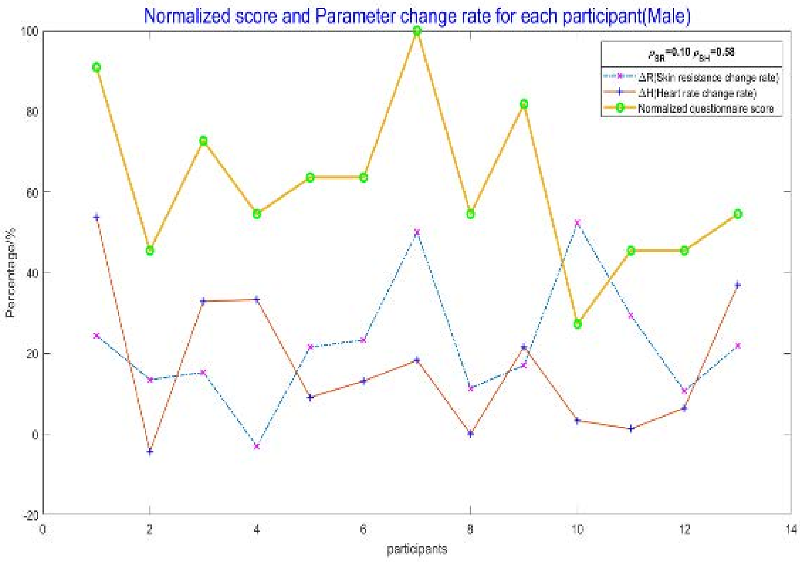

Fig. 6. Figure for Male Normalized questionnaire score and parameter change rate for each participant.

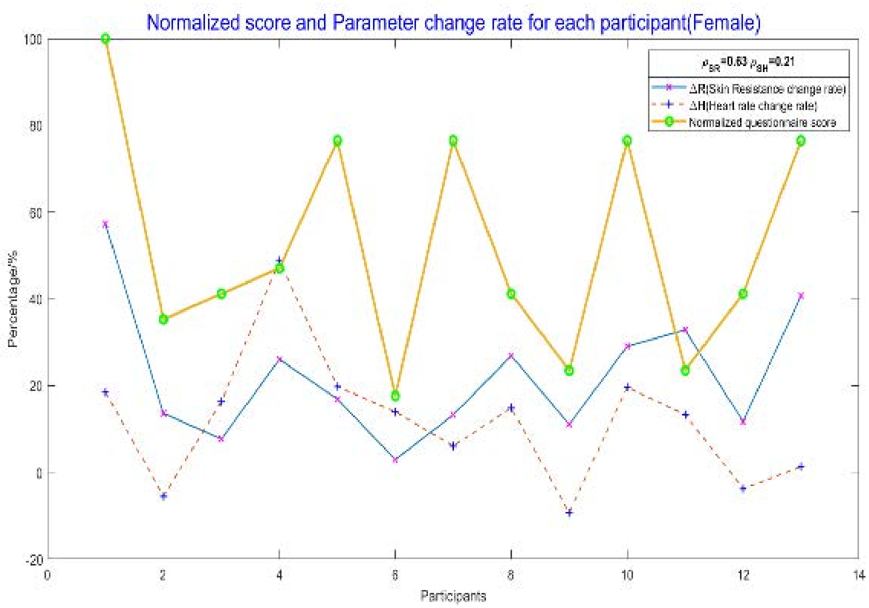

Fig. 7. Figure for Female Normalized questionnaire score and parameter change rate for each participant.

4. Conclusion

In our research, our study showed that there was a linear relationship between the questionnaire score and the skin resistance change rate for women and heart rate change rate for men. For men, $\rho_{SR} = 0.1036 < \rho_{SH} = 0.5796$ (P-Value=0.038), which suggested that stress measured by PPG was better correlated with stress measured by the questionnaire designed by us. For women, $\rho_{SR} = 0.6265$ (P-Value=0.022) > $\rho_{SH} = 0.2093$, which indicated that there exited a good correlation of the stress detected by EDA with the stress level quantized by our questionnaire. We found the PPG sensor was more reliable for male participants, while the EDA sensor was more reliable for female participants when facing short term psychological stimulation.

From the results we got we observed that, like Giraud [22], we have the skin conductivity and heart rate increasing while exert stress on participants. However, when considering about gender differences, different to our conclusion mentioned above, Kothgassne and another researcher had their research showing no gender influencing stress response [21,32]. In contrast to Kothgassne's research which is like us, Szell and Stefan's social network research did have difference in male and female results.

However, based on the results we got we can notice that there are some possible limitations exist. Firstly, although the questionnaire developed in this experiment has a certain effect on quantifying stress, we still need a proven gold standard to evaluate the short time stress level more accurately. Secondly, during the experiment, the hand shaking caused by singing will cause bad data and it's difficult to realize. Thirdly, due to the limited experimental time, the participants may not be completely relaxed, which will lead to initial differences in each person's physiological state. In the future study, we considered to combine EDA and PPG to develop a more accurate stress prediction and detection device and comparing it with the single measurement methods of EDA and PPG to enhance its practical application potential. Additionally, we plan to use a more authoritative stress scale as a standard to measure acute stress changes. This accomplishment was founded on the acute stress scale we created, and it objectively assessed the accuracy of stress detection sensors based on different theories using correlation analysis. And we believe it can be used to help design mobile health devices with the function of stress identification.

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