The Relationship between Stress Levels Measured by a Questionnaire and the Data Obtained by Smart Glasses and Finger Pulse Oximeters among Polish Dental Students

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Abstract: Stress is a physical, mental, or emotional response to a change and is a significant problem in modern society. In addition to questionnaires, levels of stress may be assessed by monitoring physiological signals, such as via photoplethysmogram (PPG), electroencephalogram (EEG), electrocardiogram (ECG), electrodermal activity (EDA), facial expressions, and head and body movements. In our study, we attempted to find the relationship between the perceived stress level and physiological signals, such as heart rate (HR), head movements, and electrooculographic (EOG) signals. The perceived stress level was acquired by self-assessment questionnaires in which the participants marked their stress level before, during, and after performing a task. The heart rate was acquired with a finger pulse oximeter and the head movements (linear acceleration and angular velocity) and electrooculographic signals were recorded with JINS MEME ES_R smart glasses (JINS Holdings, Inc., Tokyo, Japan). We observed significant differences between the perceived stress level, heart rate, the power of linear acceleration, angular velocity, and EOG signals before performing the task and during the task. However, except for HR, these signals were poorly correlated with the perceived stress level acquired during the task.

Keywords: stress level; dental education; wearable devices; heart rate; electrooculography; smart glasses; JINS MEME ES_R; linear acceleration; angular velocity

1. Introduction

Stress is the physical, mental, or emotional response to a change that is caused by an imbalance between the demands of an individual and the individual's ability to cope with them [1]. Despite the knowledge of the significant role of stress in the etiology of certain diseases (cardiac, mental, and many others) it is not classified as a separate ICD-10 or DSM V unit, but only considered a risk factor [2].

Stress has become a significant problem in modern societies and can lead to cognitive impairment, depression, and even cardiovascular diseases [3]. Stress affects not only mental health but also involvement in work and general attitude in everyday life [4–6].

The response to stress is related to the initiation of changes in its functioning. When a threat occurs, the autonomic nervous system (ANS) is stimulated and inhibits the activity of the parasympathetic system and activates the sympathetic nervous system. This reaction results in increased secretion of stress-related hormones, causing vasoconstriction, increased blood pressure, increased respiratory rate, increased muscle tone, heart rate (HR), and decreased heart rate variability (HRV). Among many different physiological stress...
indicators, such as blood pressure, cortisol level, increased skin conductivity, and head and body movements, HRV is considered one of the reliable methods for assessing the physiological response of the body in response to stress. HRV is caused by the interaction of the sympathetic and parasympathetic parts of the autonomic nervous system and can be analyzed in time and frequency domains [6–11].

Head movement behavior is considered a part of non-verbal communication that expresses itself in various aspects of everyday life. There are several actions, such as lowering, lifting, tilting, nodding, or shaking, which have specific meanings and are recognizable in intercultural communication. Head movement features have been used in a few studies assessing whether a patient is under stress—they are usually more frequent, faster, and more significant [10]. The application of electrooculography (EOG) in the design of brain-computer interfaces and activity recognition has been described in several studies [12–16]. Electrooculography (EOG) is a technique for measuring the resting electrical potential between the cornea and retina of the human eye by registering the electrical signal via electrodes placed around the eyes [12,17]. Based on the fact that electrooculography is often used to detect eye blinks [12,13], we can assess the level of stress using EOG and analyzing the dynamics of eye blinks [18].

There are indications that EOG-measured eye movements are consistent with brain activation in both the parietal and frontal cortex during attention-shifting tasks. As a consequence, stress can cause visual distractions which have a negative influence on task performance [19]. Much research has focused on cognitive and perceptual processing based on eye movements and fixations [20]. In [21] Rayner showed that the duration of eye fixation depends on cognitive processes; these data on eye movement may provide important and interesting knowledge about human information processing.

Many studies have shown that dental students are at higher risk of stress than students of other faculties and study programs because of unique stressors, such as the need to acquire an extensive body of theoretical knowledge combined with manual training, practiced in preclinical simulation centers and then in clinical practice [22–31]. These circumstances are related to high levels of stress in dental students worldwide in comparison with the general population [27,29,30,32,33].

2. Related Works

A popular approach to the assessment of stress level is using questionnaires due to their simple setup. A widely used instrument to measure stress is the PSS-10 scale. The PSS-10 assesses the extent to which a person perceived life as unpredictable, uncontrollable, and overloaded in the previous month [34]. One common tool used in stress studies in academia is the Dental Environment Stress (DES) questionnaire [35]. In addition to demographics, the questionnaire contains 41 items grouped into seven stress-inducing domains as follows: self-efficacy beliefs, faculty and administration, workload, patient treatment, clinical training, performance pressure, and social stressors.

While DES is useful for investigating the source of stress, it was not designed to measure stress levels among students. Another well-proven and reliable tool for measuring experiences related to depression, anxiety, and stress is the DASS-21 scale. In this context, depression is characterized by the absence of positive feelings, a sense of hopelessness, and loss of self-esteem, while anxiety is characterized by autonomic agitation and fearfulness [36–38].

The DASS scale was initially developed to measure the signs of depression and anxiety. The development of DASS scale resulted in developing the third part of the scale which measures the physiological stress. The basic version of the DASS scale is a 42-point scale (also known as DASS-42), which consists of three 14-point sub-scales which measure the level of depression, anxiety, and physiological stress [37]. This structure is in line with the tripartite model of anxiety and depression proposed by Clark and Watson [39–41]. The shorter version of DASS-42, known as DASS-21, has slightly better psychometric properties compared to the full DASS scale (DASS-42) [42].
Another tool frequently used for assessing anxiety is the Immediate Anxiety Measures Scale, which is used for assessing anxiety associated with a task [43,44]. It evaluates the cognitive and somatic symptoms of anxiety.

In addition to questionnaires [2,45–48], the level of stress may be assessed by monitoring physiological signals, such as photoplethysmogram (PPG), electroencephalogram (EEG), electrocardiogram (ECG), electrodermal activity (EDA), facial expressions, and head and body movements. The most common set of physiological signals involves heart rate variability (HRV) in combination with electrodural activity [10,11,49–52].

Thanks to the technological improvements, monitoring of stress level could be performed with various wearable devices, such as smart watches and smart glasses, e.g., Google Glass or JINS MEME ES_R (JINS Holdings, Inc., Tokyo, Japan) [53–61], or smartphones [62]. These devices may be used to estimate the level of one’s concentration; for instance, Ishimaru et al., conducted a study [63] which involved the use of JINS MEME ES_R smart glasses (JINS Holdings, Inc., Tokyo, Japan), further described in [61], to estimate the user’s concentration level by processing the EOG signal and head position.

The development of wearable smart sensors for measuring basic physiological parameters enables data collection in everyday activities and opens new research areas in signal processing and data classification [64].

3. Study Objective

The purpose of the study was to find the relationship of the perceived stress level reported in the questionnaires and the changes of heart rate, electrooculographic signals, and the linear acceleration and angular velocity of the head measured by a finger pulse oximeter and JINS MEME ES_R smart glasses (JINS Holdings, Inc., Tokyo, Japan).

The study was based on the hypothesis that the level of stress experienced by participants of the study is reflected in physiological signals (such as HR, EOG, and head movements). If the hypothesis was confirmed, it would be possible to use the aforementioned signals as markers of stress.

4. Materials and Methods

4.1. Experiment Setup

The study was conducted on twenty 3rd year students (18 females and 2 males, aged 22.19 ± 1.50 years) of the Medical University of Silesia, Faculty of Medical Sciences in Zabrze (Zabrze, Poland) during seminar classes between 1 October 2020 and 15 October 2020. At that time, seminar classes could be conducted because of the state and university regulations on teaching during the COVID-19 pandemic in Poland [65]. The imbalance between male and female participants, expressed as the percentage of women in the examined population (90%) was higher than the gender distribution at the university (73.51%) ([66], p. 45), academic programs in medical sciences (78.48%) ([66], p. 24) and medical universities (72.4%) in Poland ([66], p. 15).

The experiment consisted of two phases: The first phase was the relaxation phase in which the subjects watched a 4 min video of landscapes with relaxing music. After one minute of the video, we started acquiring the data via JINS MEME ES_R smart glasses (JINS Holdings, Inc., Tokyo, Japan). After another minute, the video was interrupted by a sound signal (“Space” timer ringtone in iPhone 7 set with the maximum volume 40–50 dB and frequency 0–296 Hz). For each subject, the exact moment of the sound signal occurrence was documented in the experiment sheet. The setup for the first phase was similar to the example shown in Figure 1.
Figure 1. An example of subject setup for the experiment.

The second phase of the experiment was to complete a task which served as a stress-inducing factor: to match the endodontic instruments and dental burs with their names. The endodontic instruments are shown in Figure 2 and the dental burs are presented in Figure 3.
There was not a strict time limit to finish the task; however, the EOG signal, linear acceleration, and angular velocity of the subject’s head were acquired for approximately one minute. The heart rate was recorded during the entire experiment.

The participants (students) were informed about the experiment outline but they did not know when the signal would occur and how long the data acquisition would last. All participants were provided with the same conditions: a noise-insulated room, adequately lit and ventilated, with sufficient space to complete the answers, and a comfortable seat.

The students were also asked to complete the questionnaire after completing the task. The questionnaire consisted of the following questions in which the participants marked their perceived stress level during each phase (before, during, and after performing the task):

1. How performing a task affects your perceived stress level:
   a. While watching the film (before the sound signal)?
   b. During the performed task (after the sound signal)?
   c. After completing the task?

2. How stressful was waiting for the signal to occur and to start performing the task?

The questionnaire design was based on a seven-point Likert scale (0, no stress; 6, high stress) [67]. The scale included values from 0 to 6, where 0 means no stress, 1 and 2—low level of stress, 3 and 4—medium level of stress, and 5 and 6—high level of stress. The answers to the last question were not considered in further analyses.

The study design was approved by the Ethical Commission of Medical University of Silesia under the resolution number KNW/0022/KB1/79/18 taken on 16 October 2018. All participants gave informed consent before the experiment.

4.2. Technology Used

Electrooculographic (EOG) signals and head movement (linear acceleration—ACC, and angular velocity—GYRO) signals were acquired with JINS MEME ES_R (JINS Holdings, Inc., Tokyo, Japan) smart glasses. The glasses are equipped with three-point EOG sensors and a six-axis inertial measurement unit (IMU) with a three-axis accelerometer and a three-axis gyroscope. The six-axis sensor detects speed, motion, and rotation and may be used to measure movements of the head and whole body. The EOG sensor registers the electrical potential of an eye and can be used to detect eye blinks and eyeball movements [61,63,68]. We chose such smart glasses because of their minimal impact on the

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**Figure 3.** Dental burs.
subject’s physical and psychological comfort, and the access to raw signal data [61]. The examples of registered raw signals are shown in Figures 4–6.

**Figure 4.** Linear acceleration of head during the experiment. Green vertical line denotes the occurrence of the sound signal.

**Figure 5.** Angular velocity of head during the experiment. Black vertical line denotes the occurrence of the sound signal.
Figure 6. EOG signal during the experiment. Black vertical line denotes the occurrence of the sound signal.

Figure 4 shows linear acceleration (signals from accelerometer) of the subject’s head during the experiment in X (red), Y (blue), and Z (black) axes.

Figure 5 presents the angular velocity (signals from the gyroscope) of the subject’s head during the experiment in X (red line), Y (blue dots), and Z (green dashed line) axes.

Figure 6 shows sample signals from the EOG sensor (electric potentials) acquired during the experiment on the left electrode (orange) and right electrode (violet), as well as horizontal (blue) and vertical (red) differences between them.

To measure the heart rate, we used a TM-PX30 finger pulse oximeter (Tech-Med, Warsaw, Poland), which was placed on the index finger of the non-dominant hand. The subjects did not have their nails polished during the study to provide the optimal conditions for measurement. The heart rate was registered during each phase of the experiment (before, during, and after the task) for each subject, but only one measurement was considered in the analyses.

4.3. Signal Processing

The EOG and linear acceleration and angular velocity of the subject’s head registered by smart glasses were divided into two parts, before the task and during the task, because the data had not been acquired after the task. The linear acceleration in each axis (X, Y, and Z) was combined into the total linear acceleration (ACC) as:

\[
ACC = \sqrt{ACC_x^2 + ACC_y^2 + ACC_z^2}
\]  

The ACC signal is shown in Figure 7.
Figure 7. Total linear acceleration of head during the experiment. Red dashed vertical line denotes the occurrence of the sound signal.

The angular velocity in each axis ($X$, $Y$, and $Z$) was also combined into the total angular velocity ($GYRO$) as:

$$GYRO = \sqrt{GYRO_x^2 + GYRO_y^2 + GYRO_z^2}$$

and the result is shown in Figure 8.

Figure 8. Total angular velocity of head during the experiment. Red dashed vertical line denotes the occurrence of the sound signal.
Based on the approach presented in [69], the electrooculographic signals in four channels (H, V, L, and R) were combined into the total EOG signal as:

\[
EOG = \sqrt{EOG_H^2 + EOG_V^2 + EOG_L^2 + EOG_R^2}
\]  

and the result is shown in Figure 9.

\[\frac{1}{N} \sum_{n=1}^{N} |x_n|^2 \]

Figure 9. Total EOG signal during the experiment. Red dashed vertical line denotes the occurrence of the sound signal.

The next step was calculating the power of the combined signal as:

where \( x_n \) is the \( n \)-th sample of the signal \( x \) and \( N \) is the signal length.

Figures 7–9 show that it is possible to determine the difference in the envelope of the ACC, GYRO, and EOG signals.

4.4. Statistical Analysis

The perceived stress level between the three related samples (before, during, and after the task) is expressed in an ordinal scale (0–6), so we chose Friedman’s test described in [70–72] to evaluate the differences between the analyzed phases of the experiment.

The heart rate in the three analyzed phases is expressed in the interval scale. In this case, we performed an all-sample normality test (Shapiro-Wilk test defined in [73]), and then we checked the compound symmetry of the data by performing the sphericity test further described in [74], and finally, we chose the Friedman’s test. The statistical significance of differences between analyzed phases was evaluated by Conover and Dunn-Bonferroni post-hoc tests which are typically used after performing Friedman’s test.

To analyze EOG, linear acceleration, and angular velocity, we chose the \( \chi^2 \) test. The relationship between the measured heart rate, EOG signal, head movement signals, and the reported level of perceived stress was evaluated with the Spearman’s rank correlation because of the use of the ordinal scale [75]. The level of statistical significance \( \alpha \) was set to 0.05.
5. Results

Before selecting the parametric test for the HR data, we performed the Shapiro-Wilk normality of distribution test for all phases (before, during, and after the task). The obtained results (before—$p = 0.0036$, during—$p = 0.7600$, and after—$p = 0.7530$) led to the rejection of the normality hypothesis in the before case. Thus, the statistical analysis was completed by performing the Mauchly’s and JNS sphericity test performed to evaluate the differences of variances between the phases. The results (JNS = 44.06, $p < 0.001$) indicated that the use of parametric tests was not applicable. Therefore, we decided to use Friedman’s test in further analyses.

The Friedman’s test results shown in Figure 10 confirm significant differences between the three phases of the experiment ($Fr = 23.68; p < 0.001$). The results of Friedman’s test were supported with Dunn-Bonferroni and Conover post-hoc tests (see Table 1) which proved that the heart rate before performing the task was significantly lower than the heart rate during the task ($p < 0.001$) and after the task ($p < 0.001$).

![Figure 10. Results of Friedman Two-Way Analysis of Variance by Ranks of the differences between the heart rate measured in subsequent phases of the experiment. Q₁-first quartile, Q₃-third quartile.](image)

| Dunn-Bonferroni |  
|-----------------|  
| **p** | Before the task | During the task | After the task |
| Before the task | <0.001 | <0.001 | <0.001 |
| During the task | <0.001 | <0.001 | 0.953 |
| After the task | <0.001 | 0.030 |  |

Figure 11 shows differences between the perceived stress levels in the subsequent phases of the task. The median of perceived stress level before the task was 2, during the task was 4, and after the task was 1.5. The highest perceived level of stress was 6 for participants in the “during the task” phase.

![Table 1. Results of post-hoc tests of the differences between the heart rate measured in subsequent phases of the experiment.](image)
Figure 11. Results of Friedman Two-Way Analysis of Variance by Ranks of the differences between the perceived stress level in subsequent phases of the task. Q1-first quartile, Q3-third quartile.

The Friedman’s test results shown in Figure 11 confirm significant differences between the three analyzed phases ($Fr = 18.35$, $p < 0.001$) and they were supported by Dunn-Bonferroni and Conover post-hoc tests (see Table 2) which proved that the perceived stress level during performing the task was significantly higher than the stress level before the task ($p < 0.001$) and after the task ($p < 0.001$).

Table 2. Results of post-hoc tests of the differences between the heart rate measured in subsequent phases of the experiment.

| Dunn-Bonferroni | Conover | Before the task | During the task | After the task |
|-----------------|---------|----------------|----------------|---------------|
| Before the task | <0.001  | 1.000          |                |               |
| During the task | <0.001  | <0.001         | 1.000          |               |
| After the task  | 0.134   | <0.001         | <0.001         | 1.000         |

The results of Spearman’s rank correlation analysis presented in Table 3 proved that the relationship between the heart rate and perceived stress level during the task was statistically significant ($p = 0.005$).

Table 3. The Spearman’s rank correlation between HR and perceived stress level in subsequent phases of the experiment.

| HR-Stress Level | Before the Task | During the Task | After the Task |
|-----------------|----------------|----------------|---------------|
| $r$             | 0.070          | 0.561          | 0.317         |
| $p$             | 0.385          | 0.005          | 0.087         |

The median power of total linear acceleration, angular velocity, and EOG signal before the task was $5.362 \times 10^5 \text{ s}^2$, $4.260 \times 10^6 \text{ s}^2$, and $7.533 \times 10^3 \text{ s}^2$, and the median power of total linear acceleration during the task was $5.483 \times 10^5 \text{ s}^2$, $4.330 \times 10^6 \text{ s}^2$, and $1.644 \times 10^5 \text{ s}^2$ (see Figures 12–14).
Figure 12. The differences between the power of EOG before the task and during the task.

Figure 13. The differences between the power of linear acceleration before the task and during the task.
The test $\chi^2$ showed differences between all signals in the phases before and during the task, but only for linear acceleration and angular velocity were the differences statistically significant ($p < 0.001$). To check the correlation between signals and perceived stress level, we conducted Spearman’s test.

The results of the Spearman’s rank correlation analysis presented in Tables 4–6 proved that this correlation was not statistically significant.

**Table 4.** The Spearman’s rank correlation between the power of total linear acceleration (ACC) and perceived stress level.

| ACC-Stress Level | Before the Task | During the Task |
|------------------|-----------------|-----------------|
| $r$              | −0.047          | 0.179           |
| $p$              | 0.844           | 0.450           |

**Table 5.** The Spearman’s rank correlation between the power of angular velocity (GYRO) and perceived stress level.

| GYRO-Stress Level | Before the Task | During the Task |
|-------------------|-----------------|-----------------|
| $r$               | −0.170          | 0.312           |
| $p$               | 0.475           | 0.181           |

**Table 6.** The Spearman’s rank correlation between the power of EOG and perceived stress level.

| EOG-Stress Level | Before the Task | During the Task |
|------------------|-----------------|-----------------|
| $r$              | −0.301          | 0.300           |
| $p$              | 0.197           | 0.199           |
6. Discussion

In this study, we attempted to find the relationship between the perceived stress level declared in the questionnaires and the linear acceleration, angular velocity of head, electrooculographic signals, and heart rate registered by smart glasses and a finger pulse oximeter. The role of the finger pulse oximeter was providing the heart rate, and the smart glasses were used to acquire the linear acceleration and angular velocity of the subject’s head and EOG signals, which may be used to capture eyeball movements and other activities [63].

The acquisition of heart rate and other signals to enhance the stress recognition accuracy was described by Ahn et al. in [3] and Meina et al., in [6]. Ahn et al. in [3] achieved the stress level measurement accuracy of 87.5% by processing the EEG and ECG signals registered simultaneously. Meina et al. in [6] presented an approach to recognize the stress in firefighters based on 24 h registrations of ECG and acceleration in combination with the results of self-assessment of stress level in questionnaires. The performance of their approach expressed by the area under the curve (AUC) index was between 0.57 and 0.7.

Heart rate is the frequency of cardiac contractions and is susceptible to changes of the physical and mental condition. Therefore, heart rate is considered as one of the most important health indicators [58]. Many studies confirm the relationship between the HR and stress or anxiety level; Trotman et al. in [8] proved that the perceived heart rate is more significantly related to the level of anxiety than the measured heart rate. These findings play an important role in stress and anxiety coping strategies.

In [9] Szyjkowska et al. confirmed that work-related stress is strongly correlated with the heart rate and blood pressure; work-related stress in men was usually in association with higher blood pressure, whereas more prominent heart rate variability was usually observed in women. Moreover, stress also affects cognitive abilities; people suffering from stress make more mistakes and perform tasks less accurately [1].

In our study, the results of the Friedman’s test and post-hoc tests prove that the heart rate before and during the task was significantly higher than after the task ($p < 0.001$), whereas the perceived stress level during performing the task was significantly higher than the stress level before and after the task ($p < 0.001$). The Spearman’s rank correlation between the perceived stress level and heart rate was 0.561 ($p = 0.005$), which could be considered as a significant correlation. These results prove the hypothesis that the stress level and heart rate are correlated.

The differences between the power of total linear acceleration and total angular velocity before the task and during the task were statistically significant; however, we did not observe such differences for the power of the total EOG signal. This finding proves that the eyeball movements may not be correlated with the fact of performing the task, contrary to the findings of studies conducted by Doniec et al. [14,76], Li et al. [77], Shirahama et al. [78], and Deng et al. [79].

The study conducted by Dumitrescu et al. on a group of 50 students of physiology showed, as in our study, no statistically significant differences in the horizontal and vertical EOG values between the control group and the study group, classified in terms of visual dispersion. The authors emphasize that the visual distraction used in this study may not have been significant enough to deteriorate student performance in exams [19].

The literature presents a wide range of developed approaches to the selection of analyses for multidimensional data and various application purposes. Many existing methods, such as mean and variance values in sequence or first-order derivatives, are based on prior knowledge and manual examination, causing difficulties in providing detailed information and problems with statistical validation. There are also several methods of EOG data based on a heuristic approach using information on the basic types of eye movement, such vibrations, fixations, or batting [80–83]. The problem of extraction and selection of appropriate features from EOG signals in terms of the recognition of actions has not been thoroughly investigated. EOG signals acquired with smart glasses contain...
lots of data, but the recognition of several cognitive activities (e.g., learning, relaxing, or stress) is challenging [14,76,78].

Meina et al., in [6] proved that the perceived stress level and physiological signals are strongly correlated based on the results of Welch’s t-test. In our study, the Spearman’s rank correlation between the power of total linear acceleration, angular velocity, and EOG signals show that the head movements and electrooculographic signals (electrooculograms) are poorly correlated with the perceived stress level.

The use of physiological observations for stress recognition began much earlier than the attempts to construct a polygraph—in ancient China, the testimony of an interrogated person was verified by testing for dry mouth with rice. Galvanometric methods use the fact of increased activity of sweat glands under stress resulting in changes of the resistance between the skin and the electrode [84]. In our study, we confirmed the relationship between increased HR and stress perception. Therefore, we recognize the necessity of using mixed methods to objectify the stress measurement.

6.1. Limitations of the Study

The limitations of the study are the lack of EOG and head movement data acquired after the performed task, a small study group from one university (20 dental students at the Medical University of Silesia, Zabrze, Poland), gender bias (the vast majority of the study group consisted of female dental students), and the fact that the heart rate was registered only once during each phase of the experiment. The number of subjects was limited due to the involvement of students of medical programs in combating the COVID-19 pandemic and the access to the university’s facilities for students.

To address them, we consider including more subjects in the study group with more diverse characteristics, acquiring signals with smart glasses in all three phases of the experiment and including more signal features in future studies. Another part of this study worth further research is the fact of no statistically significant correlations between the perceived stress level were reported for questionnaires, head movements, and EOG signals.

6.2. Practical Application

This study shows some important problems in categorizing stress. First, sensors are highly dependent on the level of motion and conductivity of the electrodes. The glasses, although non-invasive, do not completely adapt to the patient. Due to the individual characteristics, the glasses can slip off and the nasal electrodes can stick out. For this reason, a better method for detecting and removing artifacts and conduction errors should be implemented.

Session data captured with glasses during activities performed in real conditions are a valuable carrier of information, but also errors and noises caused by reflex gestures (e.g., fixing glasses that fall off). They are definitely different from data collected under laboratory conditions and as such require special algorithms and techniques for signal processing. This issue should be addressed in further research.

7. Conclusions

A positive and statistically significant correlation between HR and the level of stress perceived in the “during the task” phase confirms the possibility of using HR as a stress marker. The HR signal can be used to objectify the stress level measurement.

No statistically significant correlation was found between the EOG, ACC, or GYRO signals and the level of stress perceived in the study group. Although the aforementioned signals acquired with JINS MEME_R smart glasses failed to indicate stress level in our study, further research needs to be done.

However, based on the test results of the head movement signals and the perceived stress level for the analyzed phases (before, during the task), we can distinguish the phases of the experiment.
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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available in http://www.mdpi.com/1424-8220/xx/1/5/s2 (accessed on 13 September 2021).

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