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ORIGINAL ARTICLE

Assessment of mental fatigue and stress on electronic sport players with data fusion

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Abstract
Stress and mental fatigue are in existence constantly in daily life, and decrease our productivity while performing our daily routines. The purpose of this study was to analyze the states of stress and mental fatigue using data fusion while e-sport activity. In the study, ten volunteers performed e-sport duty which required both physical and mental effort and skills for 2 min. Volunteers' electroencephalogram (EEG), galvanic skin response (GSR), heart rate variability (HRV), and eye tracking data were obtained before and during game and then were analyzed. In addition, the effects of e-sports were evaluated with visual analogue scale and d2 attention tests. The d2 tests are performed after the game, and the game has a positive effect on attention and concentration. EEG from the frontal region indicates that the game is partly caused by stress and mental fatigue. HRV analysis showed that the sympathetic and vagal activities created by e-sports on people are different. By evaluating HRV and GSR together, it was seen that the emotional processes of the participants were stressed in some and excited in others. Data fusion can serve a variety of purposes such as determining the effect of e-sports activity on the person and the appropriate game type.

Keywords Electroencephalogram · Attention test · Electronic sports · Eye tracking system · Galvanic skin response · Heart rate variability · Mental fatigue · N-back test · Stress

1 Introduction

Being from the biggest problems today, stress and mental fatigue create challenges to realize the daily routines. It is considered that it is searched by using objective measures to determine these two situations reducing the life quality from the point of public health. Psychophysiological researches are defined as using physiological signs to examined psychological events [1]. The most important part of psychophysiological researches in relation with game focuses on the effects of the game on players and medical or social responses of such effects.

Cognitive ability refers to the ability of the human brain to process, store, and extract information and can be classified into attention, working memory, perception, reasoning and judgment, decision-making, and so on. Attention and working memory are two important cognitive abilities [2]. Previous studies have shown that cognitive level is highly correlated with working memory [3]. Neural responses elicited by cognitive effort can be measured by various physiological parameters. Therefore, it makes sense to make a cognitive load pattern using physiological measurements [4]. EEG signals are widely used in the assessment of cognitive ability. For example, Anderson and Bratman (2008) demonstrated that EEG signals have become an indispensable tool in cognitive ability research by proving that changes in cognitive stimulation levels can predictably change EEG signals [5]. Their experiments showed that EEG features based on short-time principal components analysis can be classified by simple linear discriminant analysis. Mohamed et al. (2018) used different classifiers to correctly classify three levels of the

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two cognitive skills, including focused attention and working memory [6]. They analyzed the time and frequency domains to extract a set of 20 features (15 time domain and 5 power features), which were used to train different classifiers.

While some studies show that when cognitive load increases, alpha power decreases [7, 8], other studies found that alpha power increases when cognitive load increases [9–11]. The study of Gündoğdu et al. (2019) determines the effects of different modes of the n-back test which is one of the measurement tools frequently used in the measurement of working memory on the electroencephalography (EEG) [12]. According to the obtained results, alpha, and theta frequency bands' power in the frontal cortex (AF7+AF8) increased with the n-back test score and difficulty level of the game. The study of Castro-Meneses et al. (2020) indicates that when cognitive load increases, theta power increases [11]. Theta power and alpha suppression of the EEG are valid objective measures of average cognitive load [4].

The focal point of the researched was sensors which could be used by those demanding to trace their stress levels regularly and did not affect the daily activities. It was stated that calculating technics had capacity to allow automatic data analysis to determine the most suitable sensor fusion and define and classify stress [13]. It was indicated that EEG signals changed with mental workload of individual and that there was relation between brain activities and stress. It was notified that EEG signals could provide information about stress levels beyond the blood pressure and heath rate. It was asserted that EEG indicated the difference in rest levels (opposite of stress), which cannot be indicated by blood pressure and heart rate [14].

N-back task is a criterion of working memory used frequently in a cognitive way. It has been accepted widely in neuroscience researches and other fields in the last 10 years [15]. N-back task reflects and updates the process of memory by replacing working memory contents with new ones [16]. When effects of 0-back and 2-back tests, which were mentioned to cause mental fatigue, on the central nervous system were examined by means of EEG, it was found out that different mental fatigue types caused different changes on spontaneous EEG variances [17]. It was seen that the level of decrease on power belonging to alpha frequency band in the visual cortex had positive correlation with weak performance of cognitive task (2-back test). It was indicated that performing the duty causing mental fatigue caused extreme activation in visual cortex and that it was related to cognitive disorder [18].

The d2 Test of Attention is a widely used neuropsychological test, and its structure validity is supported in many European samples. d2 test is a valid measuring tool to determine visual scanning (selective attention) and psychomotor speed [19].

Using physical signals simultaneously such as brain's electrical activity, eye action, face expression, and galvanic skin response to define emotion increases the performance of defining emotion and response of user [20].

In our previous study [21], heart rate variability, galvanic skin response, and eye tracking records and analyzes were performed in order to determine effect of Tetris game play time. The aim of the this study is to determine cognitive performance, working memory, and changes in scale of stress/fatigue by means of neuropsychological d2 test, 2-back task, and visual analogue scale (VAS) tests while electronic player plays Tetris (known as electronic sport), and to find out the correlation of the obtained results with physical and physiological measures. It is considered that interpretation of data obtained during the study make significant contribution to those who are engaged in works requiring attention and skill.

The motivation of this paper is to evaluate mental fatigue, stress, and attention measures on electronic sport players with data fusion. People who regularly play or watch e-sports are estimated to be 234 million in 2021 (215 million in 2020) worldwide [22], the number of regular video game players is even higher [23]. It has become important to determine the effects such as stress, attention, and fatigue affecting daily life on the e-sports players whose number is increasing day by day. This study is thought to contribute to the evaluation of the effects of games that can be played on all platforms such as mobile phones and computers on individuals.

The main contributions of this paper are (i) to see the effect of the electronic sport on attention and working memory; (ii) to investigate physical and physiological measures for game evaluation; (iii) to find a relationship between EEG AF8 alpha power and LF/HF ratio (HRV parameter), cognitive load increase and skin conductance, and HRV and skin conductance parameters; (iv) to show the gaze of participants who get high points from Tetris are intensively in area where the parts are only come from, change and parts consist of blocks; and finally (v) assessment of mental fatigue and stress on electronic sport players with data fusion.

2 Material-methods

2.1 Experimental setup

The study was approved by the Medical Ethical Committee of the Akdeniz University and the experiment was undertaken in compliance with national legislation and the Declaration of Helsinki.

Ten health adults (2 female and 8 male) with a mean of 32.3± 7.5 (mean ± standard deviation) years, ranging from 24 to 42 years, participated in the experiment. All of the volunteers had normal sleeping patterns, had normal or

Fig. 1 Recording of physical and physiological signals from volunteers

corrected-to-normal vision, no history of psychiatric complaints, and were right hand. Each participant was provided with an explanation about the research including period and procedure. Due to the fact that EEG data of only one participant deteriorated, EEG analysis of that individual was not performed. An example of a participant's photo is illustrated in Fig. 1.

Volunteers performed VAS, d2 test and N-back test, and tasks, respectively, in order to determine stress and mental fatigue, attention, and mental workload before and after the electronic sport. EEG, HRV, GSR, and eye tracker signal records were received before and during the electronic sport. The outline of the aimed process is shown in Fig. 2.

Visual analogue scale (VAS) is a simplified instrument for individuals to visually indicate their psychometric response on a linear scale. VAS has a long history of measuring subjective experience [24, 25]. VAS has many advantages over self-reported questionnaires for reasons such as ease of understanding, minimum language requirements, visual format, minimum administration, and completion time [25].

VAS was used to evaluate stress and mental fatigue before and after electronic sport. This scale is suitable especially for clinical evaluation on the stress [26]. Previous studies have shown that the VAS was valid for subjective evaluation of mental fatigue [27–29]. Participants were asked to perform ratings before and after the stress and fatigue-inducing phase in order to assess the change in subjective emotions. VAS rulers are presented in Fig. 3 and were used for participants, and the measuring scales were between 0 and 10 cm.

The d2 attention test was developed by Brickenkamp in 1962 for attention measuring such as psychomotor speed, concentration, etc., whose aim was to evaluate attention and skill of visual scanning [30]. Figure 4 is an example of a sample.

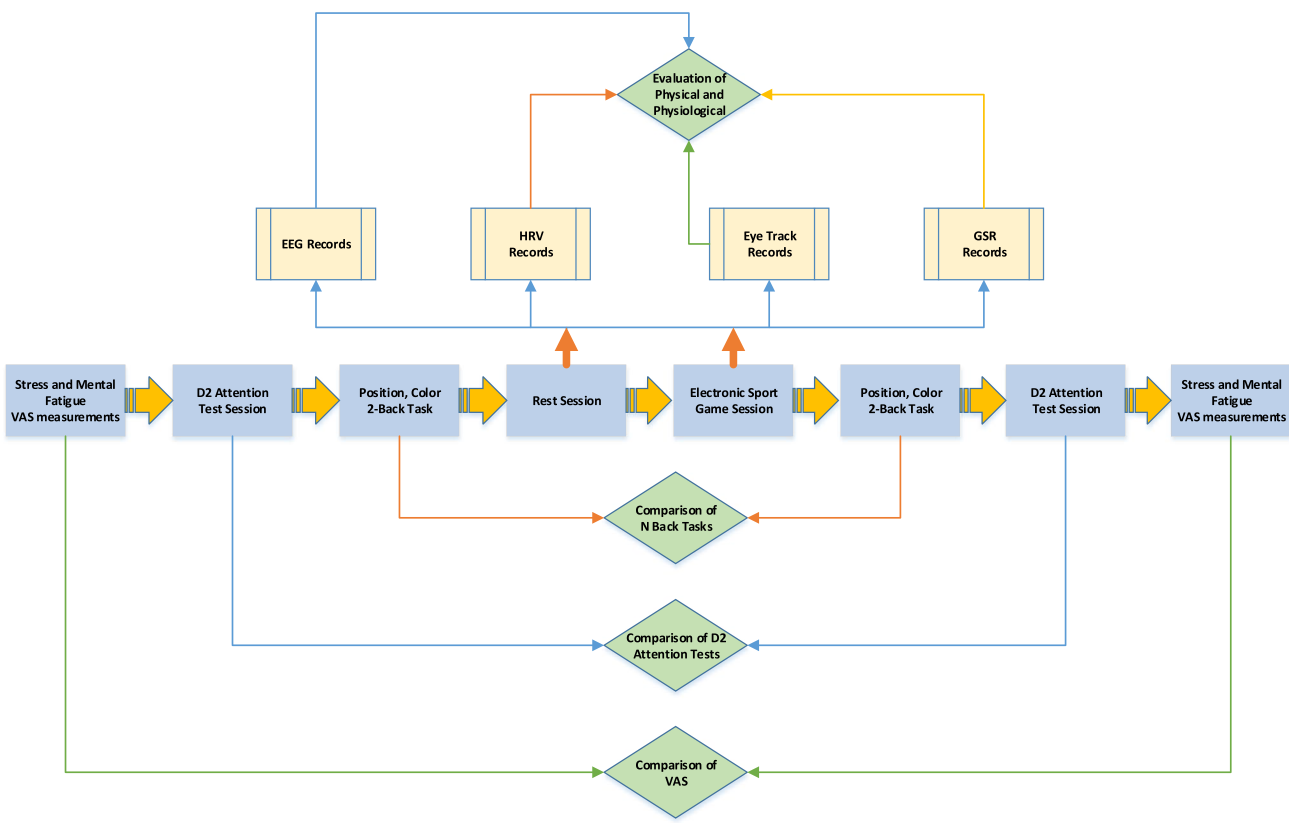

Fig. 2 Experimental tasks and design

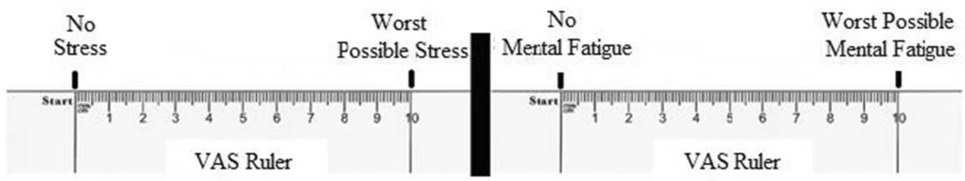

Fig. 3 VAS rulers used to determine stress and mental fatigue

Fig. 4 Sample row of the d2 test

Public domain software named Brain Workshop v.4.8.1 was used for N-back task [31]. Participants completed the task of 'position, color 2-back' mode from N-back tasks. The photo taken while carrying out this task is indicated in Fig. 5.

During the collection of data, volunteers placed Muse mobile EEG device [32]. Muse headbands are frequently used in neuroscience researches due to their low-cost and ease of application [33]. Data was recorded from four channels in the positions AF7, AF8, TP9, and TP10 defined by international 10–20 systems.

The low-cost and easy-to-use Muse headband has been used to recognize users [34] and various activities (watching movies, playing computer games, listening to music, relaxing, and reading) [35], facial expressions [36], movements (head and eye movements) [37], etc. Researchers have provided strong evidence that the Muse can be used outside of previous meditation functions and become an effective portable tool for attention measurement while performing various assigned tasks [35, 38, 39]. For example, Muse was used in experiments [40] where users' focus was measured while listening to recorded lectures [41] or playing video games [39]. Abujelala et al. (2016) aimed to measure the pleasure of the participant with the EEG activity differentiated during two games with the Brain-EE system they presented. To measure EEG, Brain-EE used the Muse EEG headband. In a similar study, Przegalinska et al. (2018) measured the level of focus of the listeners during the lesson using the muse headband [40].

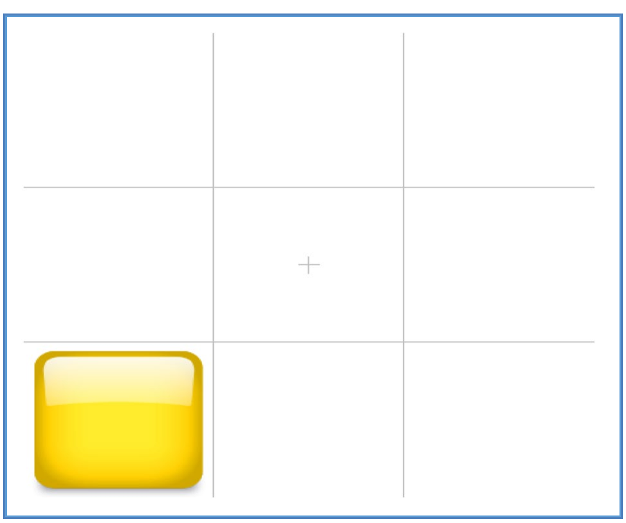

Fig. 5 Position color 2-back task

A Muse EEG device is way more simple to set up than typical EEG. It connects via Bluetooth to a computer where data can be analyzed directly. It has five dry application sensors, one used as a reference point (Fpz) and four (AF7, AF8, TP9, TP10) to record brain wave activity. These electrodes do not require cleaning or skin preparation, and also these electrodes attach to the skin without the need for any liquid.

The prefrontal cortex (PFC) serves our highest level of cognitive abilities. However, it is the brain region that is most susceptible to the harmful effects of stress exposure. While mild acute stress causes a dramatic and rapid loss of prefrontal cognitive abilities, chronic stress causes architectural changes in the prefrontal dendrites [42]. Studies on attention deficit hyperactivity disorder reveal that, in most cases, attention disorders are the product of damage to the prefrontal cortex [43]. Since this study deals with stress, mental fatigue, and attention, Muse's two front electrodes were used. Data were recorded from two prefrontal EEG channels (AF7–AF8).

For measuring HRV, Polar V800 (https://www.polar.com/en), a multisport GPS clock, was preferred to determine reliability and validity of index of heart rate variability of Mesquita et al. [44].

Eye actions of electronic sportsmen were analyzed by using Tobii Dynavox PCE Mini eye tracker having IR video stream (eye point, eye position, etc.) in 30 Hz (https://www.tobiipro.com).

NeuLog GSR sensor, indicated in Fig. 6 and used by Kim and Lee [45] in their studies, was utilized in order to determine galvanic skin response of volunteers. Maximum sampling rate of device was 100 (S/sec) and analogue/digital converter resolution was 16 bit (https://neulog.com/gsr/). GSR measuring unit used in the study was microsiemens.

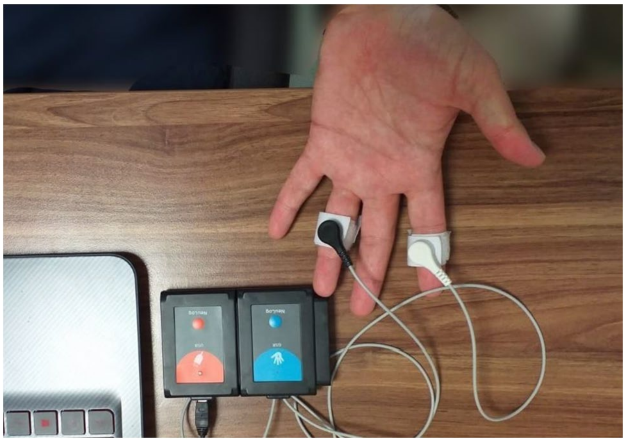

Fig. 6 GSR sensor and USB connection module

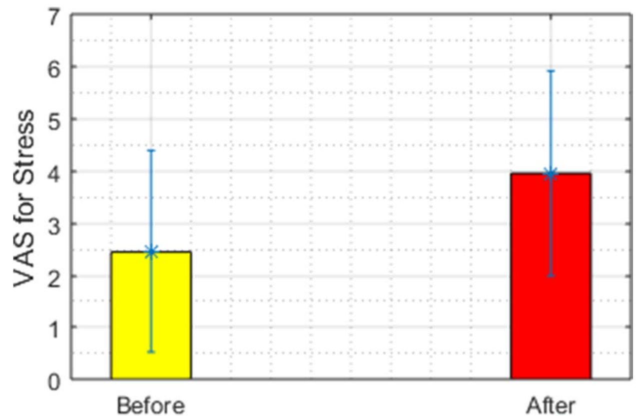

Fig. 7 Comparing VAS scores before and after the game for measuring stress.

Sensors were placed to forefinger and ring finger of participants.

2.2 Signal processing

Analyses were done by using data obtained by means of eye tracker, EEG, HRV, and GSR devices on the participants during rest and Tetris playing.

A number of techniques were developed in order to analyze EEG signals. Spectral analysis is a method utilized in order to examine characteristics of EEG signals in frequency plane. Wavelet transformation is a time-frequency analysis method and has the capacity of representing local characteristics in the frequency and time domain, and this feature is a great advantage for signal processing applications. Because, in the low frequency, it has a lower time resolution and high frequency resolution, the high frequency part has the high time resolution and lower frequency resolution [46].

EEG signals were obtained with 256-Hz sampling frequency. These signals were first filtered with a band-pass filter from 0.5 to 40 Hz using 2nd order Butterworth filter. The EEG signals were then decomposed and reconstructed using the discrete wavelet transform (DWT) which has wide application areas in the analysis of stationary and nonstationary signals [47]. Having 256-Hz sampling frequency, EEG signal was separated as 6-level wavelet by means of Daubechies 4 just like what Orosco et al. and Geethanjali et al. [48, 49] did before. The power of the signals divided into subbands was calculated and converted into logarithmic expression. Finally, all powers were normalized at 0–1.

HRV records were obtained by using heart rate monitor. Time- and frequency-domain analyses were performed with real heart rate variability taken from volunteers by using MATLAB program. As a result of time domain analysis, average, standard deviation of NN intervals (SDNN), average heart rate, average RR interval, and root mean square of successive differences (RMSSD) values were obtained. As a result of frequency-domain analysis, power at low frequency (LF) and high frequency (HF) and LF/HF ratio were determined by considering power spectral density.

Eye tracking evaluations were performed by using heat maps indicating where and how long volunteers looked at.

Data related to galvanic skin response of volunteers was obtained by virtue of NUL-217 GSR sensor logger. In order to determine GSR feature related to this data, statistical methods such as minimum, maximum, average, standard deviation, power, median, maximum-minimum, skewness, kurtosis, and efficient value were used and analyzed.

All statistical analyses were performed using IBM SPSS Statistic 24 software. The Wilcoxon signed rank test was used to compare the evaluated parameters. In the tests, p <0.05 was considered significant for the significant difference.

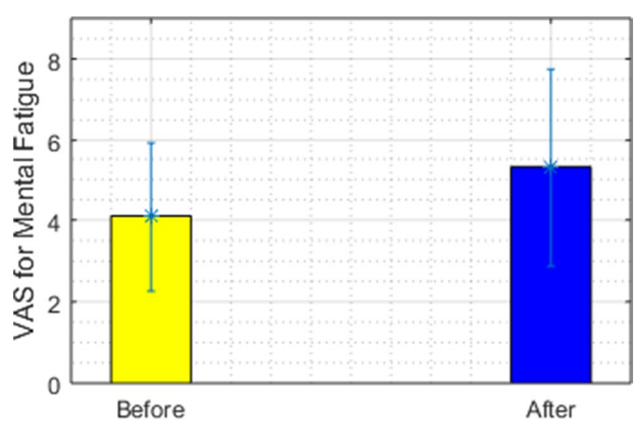

Fig. 8 Mental fatigue VAS scores before and after the game

Table 1 Results of d2 test of attention

d2 parameters	Before		After	
	$\overline{X}$	σ	$\overline{X}$	σ
Total number of items processed (TN)	517.50	61.05	577.60	59.55
The number of omission errors (E1)	39.20	20.00	29.30	17.55
Total error (E, %)	8.86	5.33	6.44	5.10
Fluctuation rate (FR)	12.60	3.86	9.30	4.72
Total items minus errors (TN-E)	472.30	65.51	541.90	73.41
Concentration performance (CP)	176.20	40.35	223.40	50.37

$\overline{X}$ mean value, σ standard deviation

3 Results

3.1 VAS for stress and mental fatigue

Figure 7 indicates the comparing process before and after the game obtained by means of averages and standard deviations of data belonging to stress VAS scores of 10 individuals. It was observed that average VAS scores belonging to stress obtained after the game (3.96±1.96, average ± standard deviation) increased in a significant level comparing with the values before the game (2.46±1.94, average ± standard deviation). There are statistically significant differences between before and after the game in terms of stress (p=0.027<0.05).

Figure 8 indicates the comparing process presenting averages and standard deviations of mental fatigue VAS data of participants. When examining average VAS scores belonging to mental fatigue, it was observed that there was an increase after the game (5.31±2.44, average ± standard deviation) comparing with the values before the game (4.10±1.84, average ± standard deviation). There are no statistically significant differences between before and after the game in terms of mental fatigue (p=0.251>0.05).

3.2 Evaluation of d2 attention test

The mean ($\overline{X}$) and standard deviations (σ) of the scores obtained from the d2 attention test before and after the game are summarized in Table 1.

Figure 9 indicates the concentration scores and average values obtained from d2 test of participants as a graphical. The concentration performance of participants after the game increased comparing with the values before the game. There are statistically significant differences between before and after the game in terms of CP (p=0.005<0.05), TN-E (p=0.005<0.05), and E (p=0.022<0.05).

3.3 Evaluation of N-back task

Participants completed ‘position, color 2-back’ mode task. Figure 10 indicates the comparing process before and after the game, obtained by means of averages and standard deviations of N-back scores belonging to 10 individuals. ‘Position, color 2-back’ score average obtained after the game (41.40 ± 20.15, average ± standard deviation) decreased

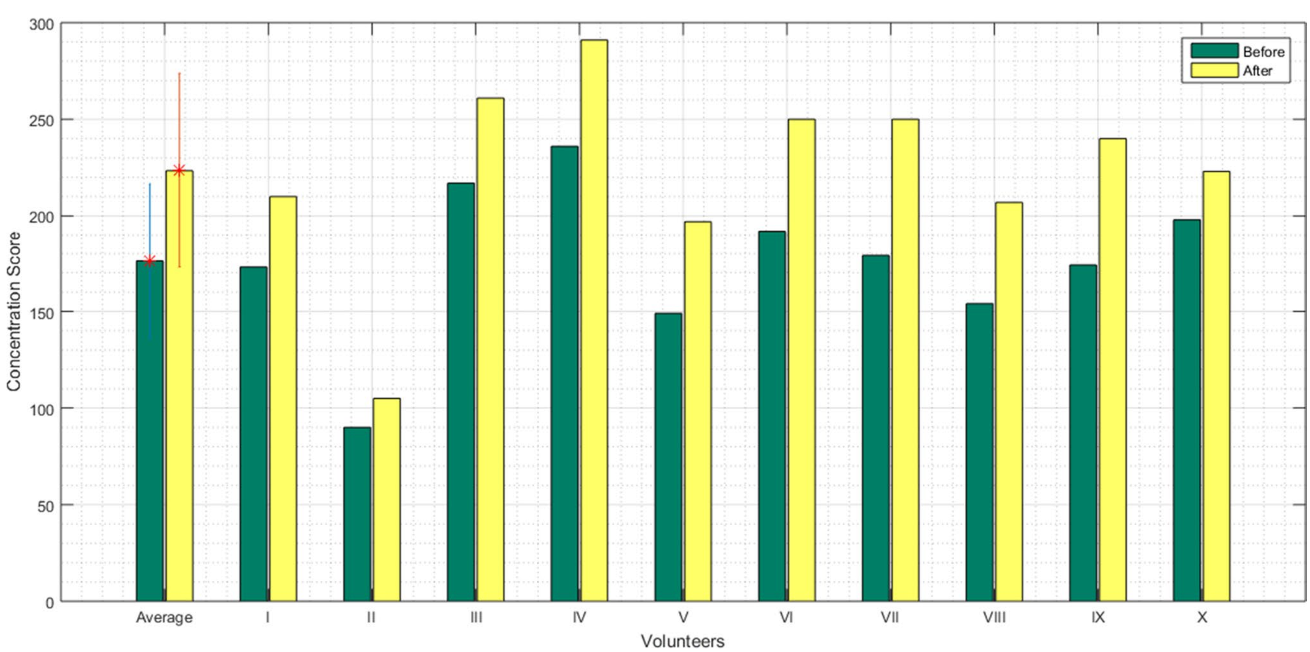

Fig. 9 d2 concentration scores belonging to volunteers before and after the game

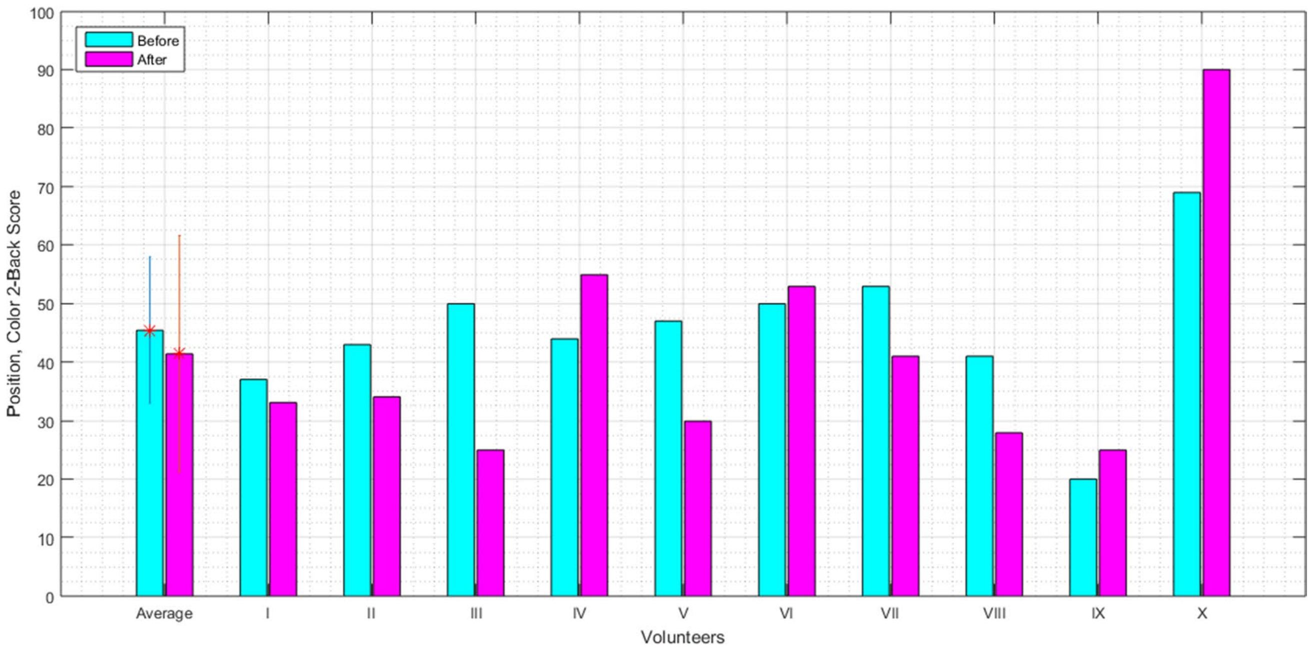

Fig. 10 Working memory scores before and after the game

comparing with the values before the game (45.40 ± 12.48, average ± standard deviation). There are no statistically significant differences between before and after the game in terms of N-back score (p=0.333>0.05).

3.4 EEG data analysis

Figure 11 indicates normalized power values of alpha bands taken from AF7 and AF8 during rest (prior to game) and

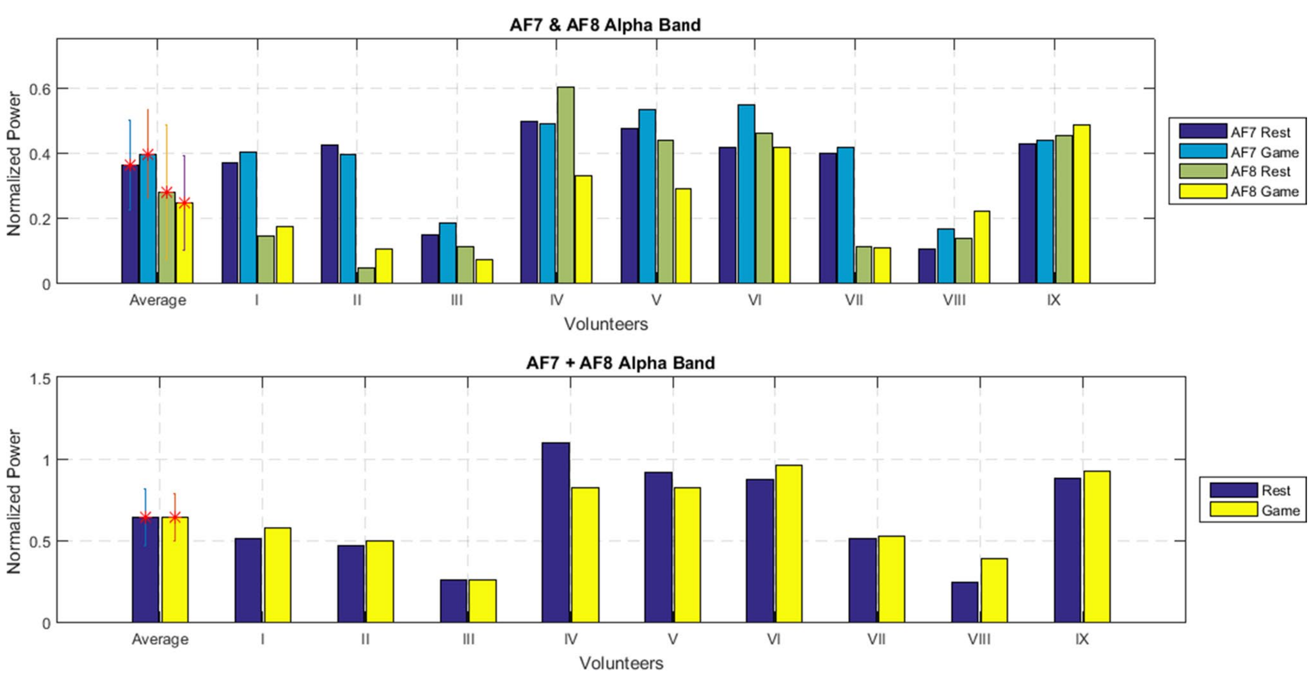

Fig. 11 Comparison of normalized powers of EEG alpha signals generated by volunteers during rest and game: **a** AF7 and AF8 regions; **b** sum of AF7 and AF8 regions

game. While AF7&AF8 shows the signals from both left and right forehead separately, AF7 + AF8 specifies total alpha power taken from forehead.

When the normalized powers of EEG alpha waves summed in frontal AF7 and AF8 regions, it is seen that the average value of game status (0.6414) is a minor increase in comparison with the rest status (0.6401).

Figure 12 indicates normalized power values of beta bands taken from AF7 and AF8 during rest (prior to game) and game. While AF7&AF8 shows the signals from both left and right forehead separately, AF7 + AF8 specifies total beta power taken from forehead.

When the normalized powers of EEG beta waves summed in frontal AF7 and AF8 regions, it is seen that the average value of game status (0.6331) is a minor increase in comparison with the rest status (0.6212).

Figure 13 indicates normalized power values of theta bands taken from AF7 and AF8 during rest (prior to game) and game. While AF7&AF8 shows the signals from both left and right forehead separately, AF7 + AF8 specifies total theta power taken from forehead.

When the normalized powers of EEG theta waves summed in frontal AF7 and AF8 regions, it is seen that the average value of game status (0.6701) is a minor increase in comparison with the rest status (0.6648).

Figure 14 indicates normalized power values of alpha+theta bands taken from AF7 and AF8 during rest (prior to game) and game. While AF7&AF8 shows the signals from both left and right forehead separately, AF7 + AF8 specifies total alpha+theta power taken from forehead.

When the normalized powers of EEG alpha+theta waves summed in frontal AF7 and AF8 regions, it is seen that the average value of game status (1.311) is a minor increase in comparison with the rest status (1.305).

Figure 15 indicates normalized power values of alpha+beta+theta bands taken from AF7 and AF8 during rest (prior to game) and game. While AF7&AF8 shows the signals from both left and right forehead separately, AF7 + AF8 specifies total alpha+beta+theta power taken from forehead.

When the normalized powers of EEG alpha+beta+theta waves summed in frontal AF7 and AF8 regions, it is seen that the average value of game status (1.944) is a minor increase in comparison with the rest status (1.926).

Figure 16 indicates normalized power values of alpha/beta bands taken from AF7 and AF8 during rest (prior to game) and game. While AF7&AF8 shows the signals from both left and right forehead separately, AF7 + AF8 specifies total alpha/beta power taken from forehead.

When the normalized powers of EEG alpha/beta waves summed in frontal AF7 and AF8 regions, it is seen that the average value of game status is a minor decrease in comparison with the rest status.

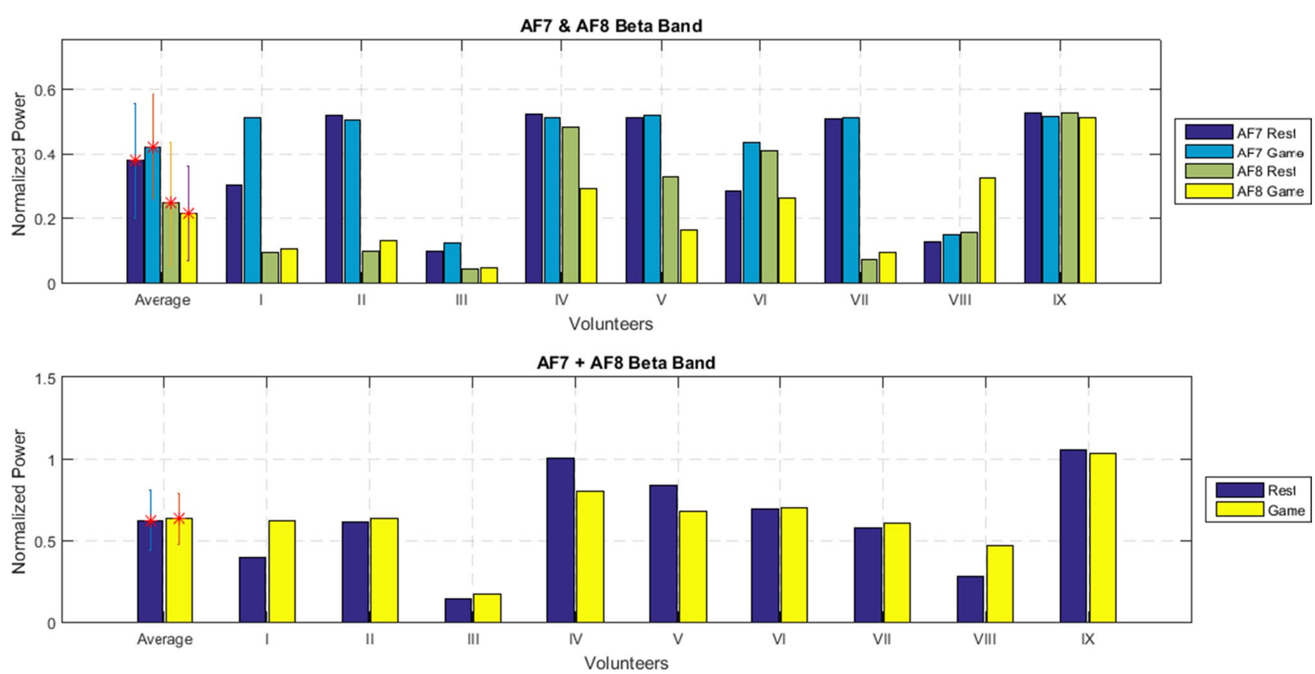

Fig. 12 Comparison of normalized powers of EEG beta signals generated by volunteers during rest and game: **a** AF7 and AF8 regions; **b** sum of AF7 and AF8 regions

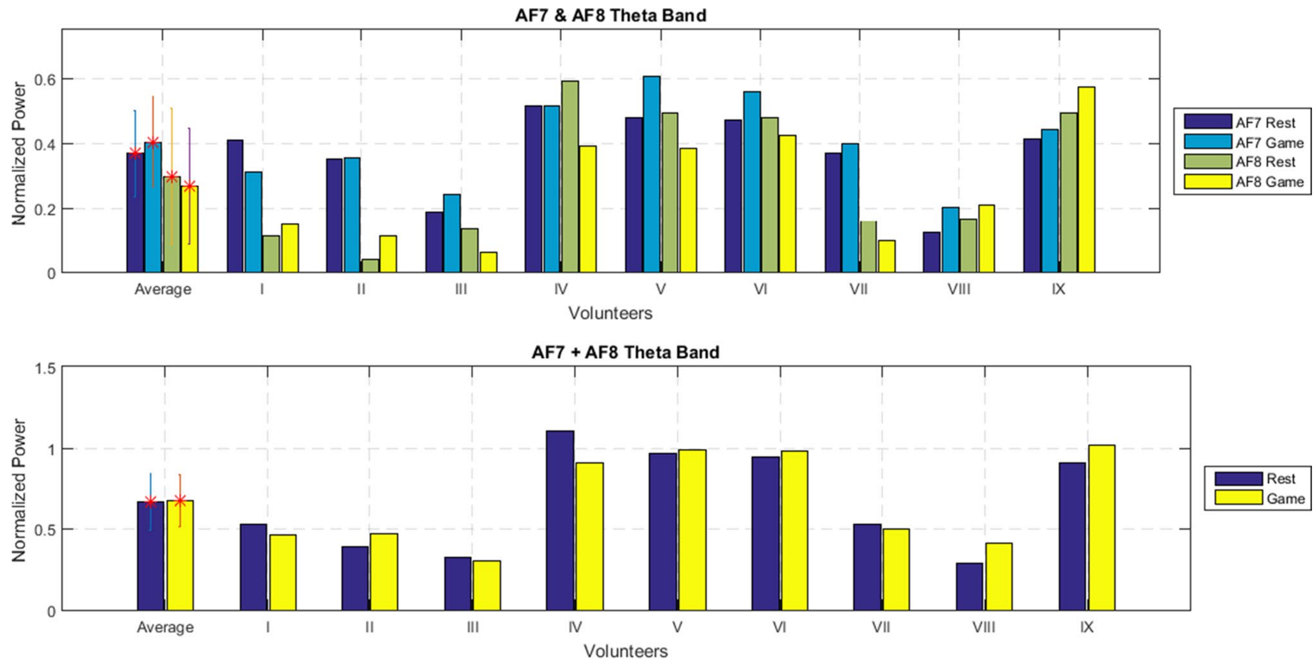

Fig. 13 Comparison of normalized powers of EEG theta signals generated by volunteers during rest and game: **a** AF7 and AF8 regions; **b** sum of AF7 and AF8 regions

3.5 HRV data analysis

The mean and standard deviations of the measurements related to HRV obtained and recorded prior to game and during game are summarized in Table 2. According to the table, while mean RR (IBI), SDNN, RMSSD, LF, and HF decreased according to rest status during game, average HR and LF/HF values increased. There are statistically significant differences between before and after the game in terms of RR parameter (p=0.013<0.05).

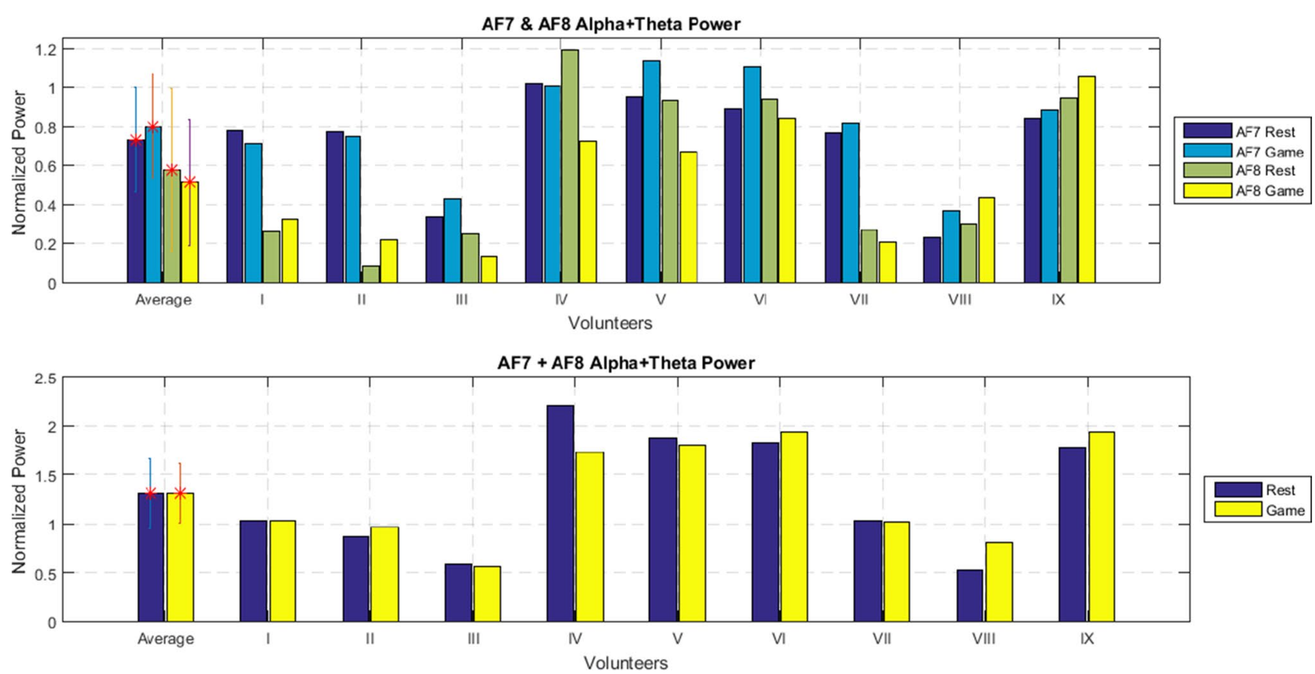

Fig. 14 Comparison of normalized powers of EEG alpha+theta signals generated by volunteers during rest and game: **a** AF7 and AF8 regions; **b** sum of AF7 and AF8 regions

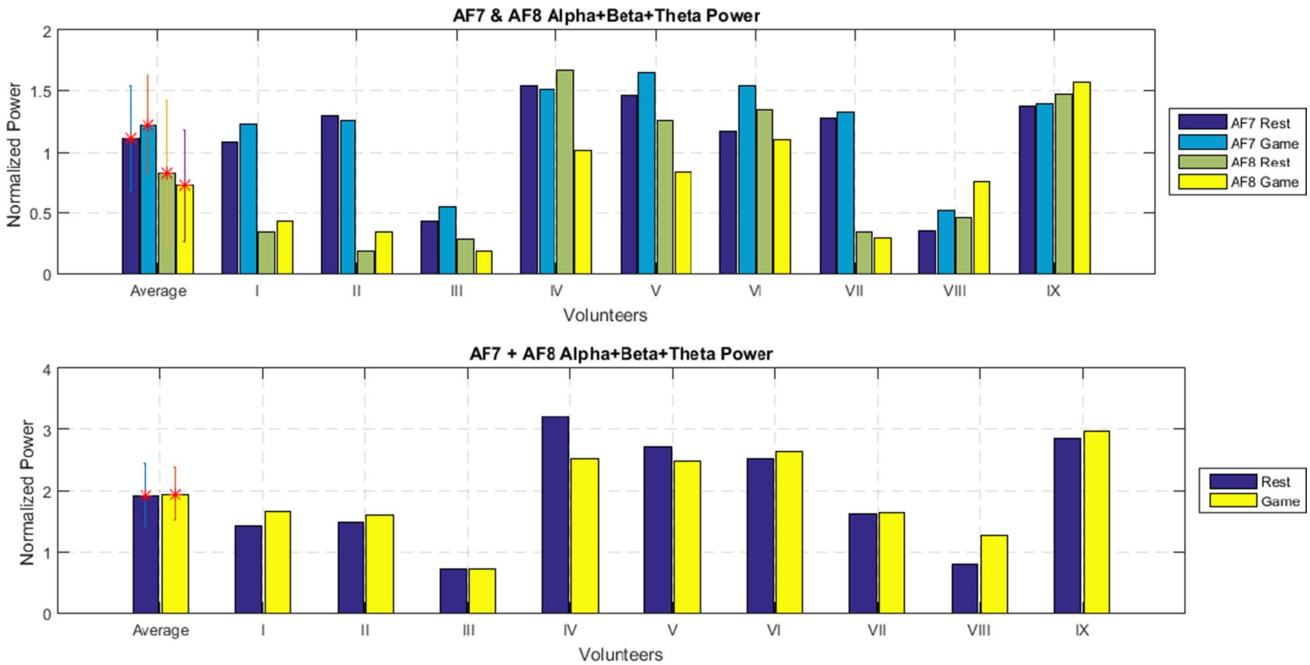

Fig. 15 Comparison of normalized powers of EEG alpha+beta+theta signals generated by volunteers during rest and game: **a** AF7 and AF8 regions; **b** sum of AF7 and AF8 regions

In Fig. 17, EEG signal obtained from the participants during rest and game (AF8 region records specifying right forehead) and LF/HF (HRV measurement type) comparison are provided.

In the other 8 participants who involved in the study except for 5th volunteer, it was determined that the LF/HF ratios of those with increased EEG AF8 alpha power increased and LF/HF ratios decreased in those with EEG AF8 alpha power decrease.

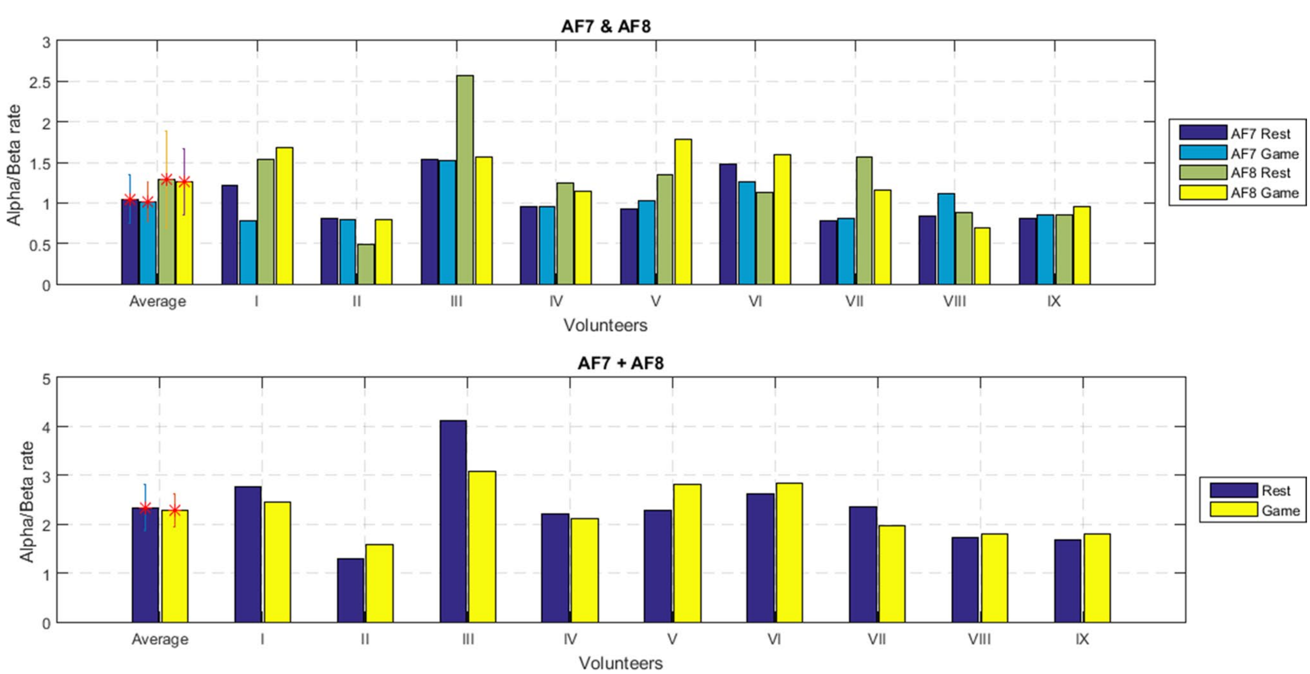

Fig. 16 Comparison of normalized powers of EEG alpha/beta signals generated by volunteers during rest and game: **a** AF7 and AF8 regions; **b** sum of AF7 and AF8 regions

Table 2 HRV features for between rest session and e-sport session

HRV parameters	Rest session		E-sport session	
	$\overline{X}$	σ	$\overline{X}$	σ
Mean RR (IBI) (ms)	769.69	126.98	725.65	146.87
Mean HR (bpm)	80.00	11.70	85.59	14.72
SDNN (ms)	42.44	31.80	38.15	20.53
RMSSD (ms)	34.69	28.20	26.17	17.70
LF (ms^2)	1520.56	3157.98	338.24	309.09
HF (ms^2)	784.57	1129.90	288.32	480.43
LF/HF	2.37	2.18	3.39	3.03

$\overline{X}$ mean value, σ standard deviation

Statistical correlations of HRV and EEG features were examined. According to the results, EEG alpha power change in the AF8 electrode of the volunteers and the change in LF/HF ratio were in a similar direction in transition from resting state to play state. A strong positive correlation ($r = 0.8$) was found between the direction of change of these two parameters ($p <0.01$). The relationship between the change in EEG beta power on the AF8 and the change in LF/HF ratio electrode was different. No statistically significant correlation ($r = 0.1$) was found between beta power and LF/HF ($p = 0.798> 0.05$). Spearman's rank correlation coefficient was used to measure the association between them.

3.6 Eye tracker data analysis

A participant's game was over at the end of approximately 90 s; other participants completed 2 min. The results of eye monitoring heat map of four persons who got top scores in Tetris played in fourth level and four persons who got the lowest scores are provided in Figs. 18 and 19, respectively. Red represents the most time focused on an area of the screen. This means that the red areas have been given the most focus by the user.

The purpose of Tetris is to create blocks and to ensure that the relevant parts are lost. When Fig. 18 was reviewed, it is seen that the persons with high scores become intense in the area where Tetris parts come from, change and parts consist of blocks.

When Fig. 19 was reviewed, it is indicated that the heat map of the persons with low scores spread on a larger area.

3.7 GSR data analysis

The average and standard deviations of the feature types which were obtained by GSR measurements and recorded during rest and game are summarized in Table 3. According to the table, it was observed that all feature averages during game except for skewness increased in accordance with the rest status. There are statistically significant differences between rest and the game session in terms of mean of GSR (p=0.005<0.05).

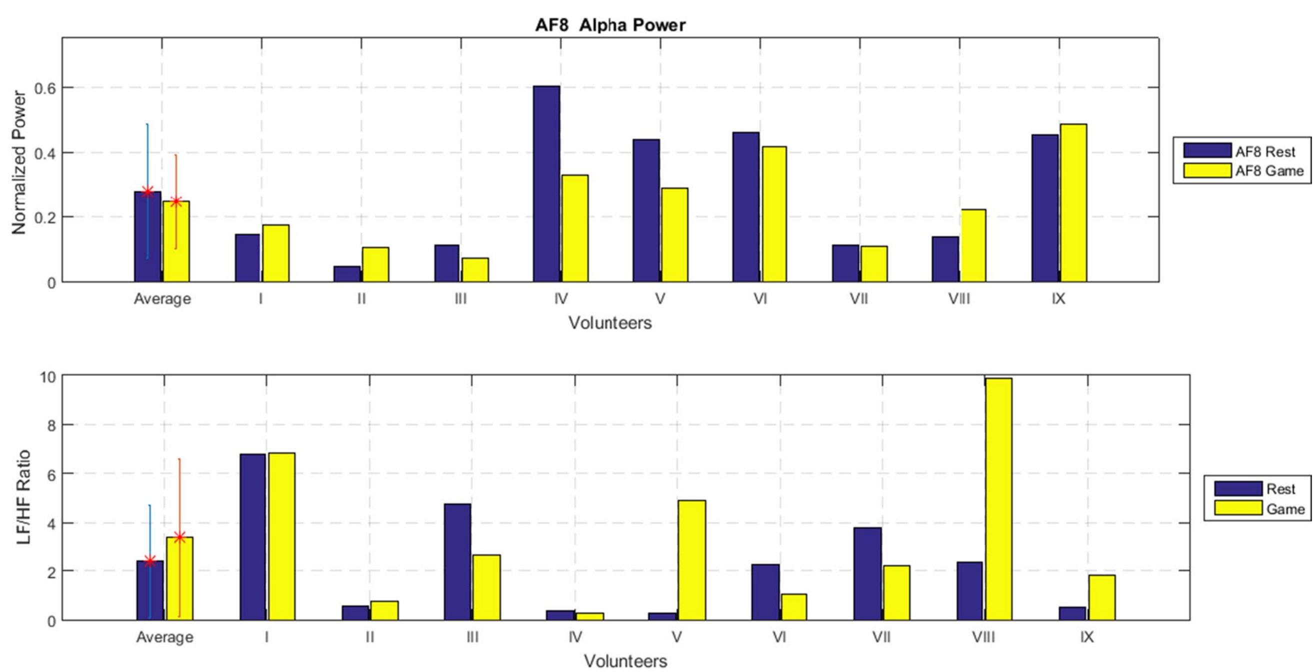

Fig. 17 Comparison between normalized power of EEG alpha signals taken in AF8 region of volunteers and HRV-LF/HF ratio

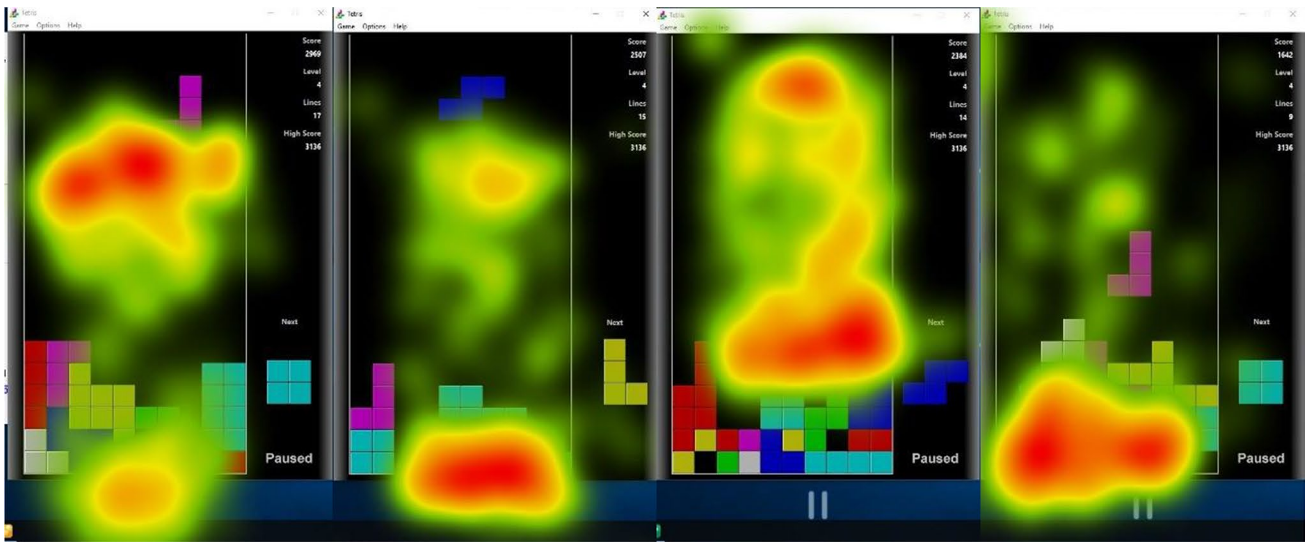

Fig. 18 The results of eye monitoring heat map of four persons who got top scores in Tetris played in fourth level

While skin conductance data is being evaluated, determination of GSR changes also becomes crucial for signal analysis. The values of conductance increase from its minimum value to upwards and it reaches to a maximum value in a local time zone. Markings in Fig. 20 showed minimum and maximum points during this increase of GSR signal. The difference between maximum and minimum expresses amplitude.

The analyses were made by using skin conductance data which was acquired from the participants in the study and Table 4 was obtained. The 0.01 µS was selected as threshold value for analyses. It was determined that the amplitudes which showed alteration at least 0.01 µS (threshold value) of a GSR signal increasing from any point of minimum. These amplitudes of change were taken as reference and the average and standard deviations of rest and game status were provided in order to make comparison of statistical data such as number of above-threshold indicating skin conductance changes of the participants, averages of amplitude, standard deviations, median, minimum, maximum, etc.

According to Table 4, the number of above-threshold, its average, standard deviation, median, and difference average between maximum and minimum which were calculated during game with respect to amplitudes with above-threshold value have increased in accordance with rest status. When an evaluation was made in terms of determination of those with above-threshold value, the changes of GSR were observed much more during the game.

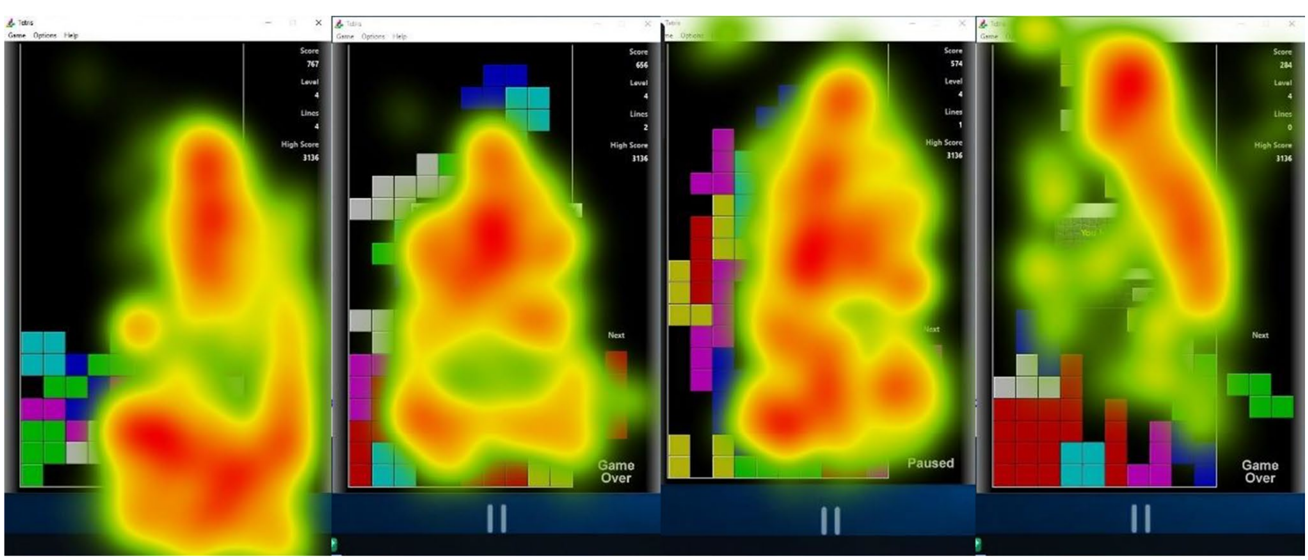

Fig. 19 The results of eye monitoring heat map of four persons who got the lowest scores in Tetris played in fourth level

Table 3 Statistical calculations of galvanic skin conductance data

GSR features	Rest session (μS)		E-sport session (μS)	
	$\overline{X}$	σ	$\overline{X}$	σ
Minimum	1.82	1.38	2.61	1.85
Mean	2.04	1.64	2.91	1.96
Maximum	2.32	2.01	3.25	2.17
Standard deviation	0.13	0.17	0.15	0.11
Power	6.65	10.19	12.08	16.03
Median	2.05	1.65	2.90	1.96
Maximum-minimum	0.50	0.66	0.65	0.47
Skewness	0.10	0.35	−0.03	0.64
Kurtosis	2.11	0.60	2.69	0.73
RMS	2.05	1.65	2.91	1.96

4 Discussion

In VAS evaluations, it is seen that the game has increased stress and mental fatigue. While total number of item processed which revealed with d2 test (process speed [50]), concentration performance and total items minus errors (process speed) increased compared to before the game; the number of omission errors which indicate selective attention (lack of attention states negligence), fluctuation rate expressing release of attention, and total error (%) decreased. These variables which increase and decrease showed that the participants are positively affected in relation to attention, psychomotor speed, and release of attention. Sethi et al. [51] indicated in research that the yoga increased attention significantly. d2 test was used in this study in order to measure the subjects' attention. Two studies showed parallelism and the effect of playing Tetris on attention was positive like yoga. In 'position, color 2-back' mean of score, a little decrease was observed in comparison with before game. It has been revealed that the game caused mental fatigue; however, it remained extremely limited.

According to the results of EEG which was obtained by collecting the signals of two regions (AF7+AF8), it was understood that alpha, beta, theta, alpha+theta, and alpha+beta+theta powers increased and the rate of alpha/beta decreased according to rest status. The decrease of alpha/beta rate states that the beta waves in game showed much more increase in comparison with alpha. Lin and John [14] used voltage (absolute) values of signals belonging to EEG bands in research they had made. In our study, the average powers of the signals were normalized and they were included in analysis. Even though the voltage in one and power variables in another were used, eventually the signals of theta, alpha+theta, and alpha+beta+theta increased in stress status and similar results were accomplished through decrease of alpha/beta rate. Thus, the relationship between changing frontal activity and stress and mental fatigue was determined in participants while playing e-sports.

Craig et al. [52] indicated that slow wave activity increased in theta and alpha 1 and 2 bands in fatigue status of the person and there was no significant change in delta wave activity of the person. Gharagozlou et al. [53] stated that the increase in alpha power was the beginning of mental

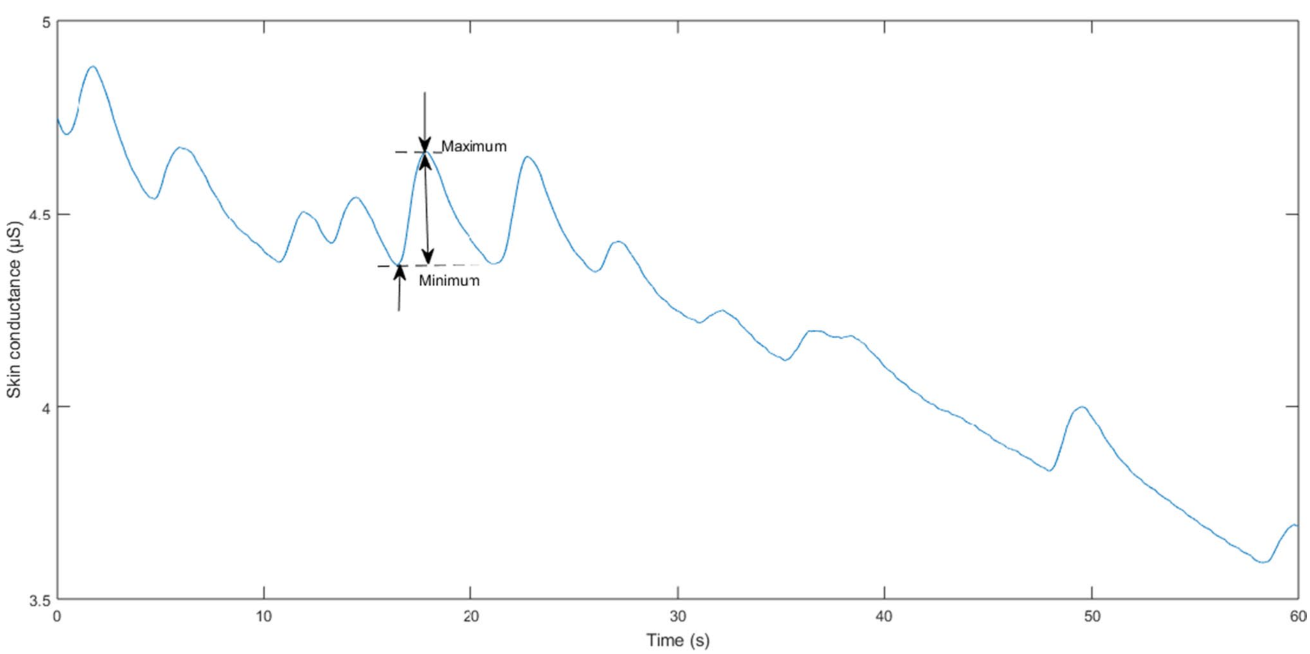

Fig. 20 Examination of changes on the sample GSR signal

Table 4 Statistical calculations of above-threshold value related to skin conductance change

Amplitude features of above-threshold GSRs with response window	Rest session		E-sport session	
	$\overline{X}$	σ	$\overline{X}$	σ
Number of above-threshold GSRs in 1 min (rest)	5.20	4.18	*	*
Number of above-threshold GSRs in 2 min (e-sport)	*	*	15.10	9.47
Mean (μS)	0.07	0.07	0.12	0.10
Standard deviation (μS)	0.04	0.05	0.08	0.07
Median (μS)	0.07	0.07	0.11	0.11
Minimum (μS)	0.02	0.02	0.01	0.00
Maximum (μS)	0.15	0.15	0.31	0.31

fatigue when it reached to the last part of the simulated drive they had participants made. It was seen that the change of alpha and theta signals in our study increased in a similar to previous studies. This indicated that game causes mental fatigue even if just a little.

Heart rate variability (HRV) provides insight about cardiovascular autonomic function by using measurement of RR intervals. Analyses related to HRV are regarded as an indicator without interference of activity of autonomous nervous system that is responsible for involuntary movements of the body [54]. Physical and mental overloads significantly affect cardiovascular response. Stressors lead to decrease of releases which reflect the activity of parasympathetic nervous system in heart rate variability (HRV). In addition to this, the LF/HF ratio increases. It was reported in researches that the stressors having impact at short notice pressurized the activity of parasympathetic nervous system and led to increase activity of sympathetic nervous system [55, 56]. In our study, the average heart rates of the participants increased with the exception of two participants during playing game and their RR intervals reduced. LF/HF ratio of four participants was decreased in the game; other 6 participants' LF/HF rate increased. While the AF8 alpha powers of four participants in game status increased, LF/HF ratios also increased, and while AF8 alpha powers of other four participants (in game status) decrease, their LF/HF ratios also decreased.

Four participants whose AF8 alpha powers and HRV-LF/HF rates decreased during the game became four persons who got highest score in the evaluation of concentration performances in d2 test they had applied after game.

When the LF, HF, and LF/HF values obtained from HRV were evaluated by using the classification made by Toledo et al. [57]:

- For 2 participants, an increase in LF, a decrease in HF, and an increase in LF/HF indicate increased sympathetic activity and decreased vagal activity. Stress VAS evaluations of these individuals increased by 4.45 cm after the game.
- For 3 participants, a decrease in LF, a decrease in HF, and an increase in LF/HF indicate a shift in balance towards relative sympathetic development with decreased vagal and sympathetic activities. Stress VAS evaluations of these individuals increased by 1.03 cm after the game.
- For 4 participants, a decrease in LF, a decrease in HF, and a decrease in LF/HF indicate a decrease in vagal and sympathetic activity and a change in stability towards relative vagal development. Stress VAS evaluations of these individuals increased by 0.75 cm after the game.

Ateş et al. [55] stated in study they conducted in a workplace that the low heart rate variability of the managers in comparison with other employees is because of a significant mental overload due to their works. In the study carried out by us, RR intervals (during game) also decreased according to rest status.

The decrease of RR intervals of all participants during game (reduction from 769.69 to 725.65 ms); increase of average value of VAS mental fatigue (increase from 4.10 to 5.31); and decrease of 'position color 2-back' score average after game (reduction from 45.40 to 41.40) are indicative of mental fatigue.

The changes in skin conductance were recorded in GSR equipment. Bersak et al. [58] realized in study they made that the changes in GSR revealed stress levels in individuals during race game. It was observed that the work performance [59] and cognitive load [60] which are considered stress factors have strong correlation with GSR. Shi et al. [60] indicated in the study they made that as long as cognitive load increased, GSR increased. In this study, average values of all statistical data except for skewness showed an increase during game status. Tetris increased skin conductance of each participant. The correlation was found between cognitive load increase and GSR in our study.

Skin conductance does not only reflect one psychological process, it is generally used as an indicator of emotional processes and emotional arousal and it is safely measured [61]. GSR is a reflection of physiological reactions related to excitement. Physiological or psychological arousals such as fear, joy, or stress are circumstances which affect skin conductance.

Psychophysiologists revealed that physiological arousal developing in sweat glands may reflect psychological activity, and thereby the change in electrodermal activities in sympathetic nervous system may be the result of interest, arousal, and satisfaction [62, 63]. In our study, it may be said that the changes of skin conductance during play are the results of interest, arousal, and satisfaction. Since Tetris increased all features of skin conductance (according to rest), it showed that much more arousal has on participants. Gökay et al. [64] stated that the emotional responses can be arranged in two dimensions; accordingly, it may be stated that Tetris does not lead to boredom or rest states on participants, but it causes excitement or stress.

It is thought that analyses which were made for heart rate variability may be benefited in determination of what emotional process the participants are closer. It is understood that sympathetic/vagal changes may help to make decisions about emotional behavior. The result was obtained with regard to that vagal increases/shifts are indicative of excitement and sympathetic increases/shifts show stress. Tetris did not refer everyone to same emotional behavior.

In accordance with heat maps arising from eye movements while playing game in our study, it is seen that the gaze of participants who get high points from Tetris is intensively in area where the parts are only come from, change and parts consist of blocks. Their focusing was in limited regions. It was observed that the heat map of the participants who got low points spreads on a larger area.

5 Conclusion

In this study, it was aimed to determine the stress, mental fatigue, and attention states that Tetris may cause on players (by using VAS, d2 attention test, N-back test, EEG, HRV, GSR, and eye tracking data).

According to the VAS evaluations of the participants, stress and mental fatigue increased. As a result of d2 tests which were conducted after the game, it is seen that game has a positive impact on attention and concentration.

When the power of the frequency bands in the AF7 and AF8 regions of the participants was examined for the evaluation of EEG in rest and game state, the game is thought to create stress and mental fatigue.

According to HRV analyses, the sympathetic and vagal activities created by the game on humans were different. Statistical values related to skin conductivity increased during the game. When the emotional processes of the participants together with HRV and skin conductivity were examined, some were stress and some were excited.

When the heat maps consisting of eye movements were reviewed, it was seen that glances of the persons who got high points concentrated on only area where Tetris parts come, changed and where blocks consisted; the glances of persons who got low points were concentrated on a larger area.

While carrying out subjective and objective evaluations regarding participants in the study, average values were used. According to the results of this study, subjective and objective evaluations were consistent.

It is expected that the measurements and analyses obtained will make significant contributions to the literature for next studies related to electronic sports.

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Declarations

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards (ethical approval date, number: Akdeniz University, Clinical Research Ethics Committee, 06/12/2017–715).

Conflict of interest The authors declare no competing interests.

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