Li et al. J Wireless Com Network (2022) 2022:76
https://doi.org/10.1186/s13638-022-02166-8

EURASIP Journal on Wireless Communications and Networking

RESEARCH

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Effects of psychological fatigue on college athletes' error-related negativity based on artificial intelligence computing method

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Abstract

Psychological fatigue includes mental fatigue and burnout. In order to investigate the impact of psychological fatigue on athletes' response monitoring, event-related potentials technique is typically used, and the most critical indicator is error-related negativity. Two experiments were carried out to explore cause-effect relationships of psychological fatigue and response monitoring. The event-related potentials data processing was based on Artificial Intelligence computing methods, including wavelet transform, grayscale transformation and other algorithms. The first experiment was done to explain mental fatigue and response monitoring. 15 participants operated continuously 60 min Flanker task, and then operated 15 min task accompanied by light music. From the results of behavioral performances, the fatigue period compared with the fatigue-free period showed significant differences, including reaction time ($p = 0.029$) and correct rate ($p = 0.046$). From the results of error-related negativity, the amplitude of the fatigue-free period was bigger than that of the music adjustment period, the latter was bigger than that of the fatigue period ($p < 0.001$). The second experiment was conducted to explore burnout and response monitoring. Twenty-four participants were separated averagely into two groups. One group was burnout group, the other group was no burnout group. They both operated 15 min task. From the results of behavioral performances, no burnout group was better than burnout group. From the results of error-related negativity, no burnout group's amplitude was bigger than that of burnout group, but the difference was marginally significant. The conclusions are as follows: Artificial intelligence technology is feasible for processing event-related potentials data. Psychological fatigue weakens athletes' response monitoring ability, and the effect of mental fatigue is significant. In future researches, the following topics should be concerned, including the mediating or moderating effects of third variables, different ways of recovering from mental fatigue, computer data simulator and date accuracy, brain-computer interfaces and error-related negativity, etc.

Keywords: College athlete, Mental fatigue, Burnout, Response monitoring, Artificial intelligence, Error related negativity

1 Introduction

In the field of sports, psychological fatigue is a phenomenon that the psychological function of athletes cannot maintain the original level of psychological activity when they are coping with the internal and external pressure and their psychological and physiological resources are constantly consumed but not supplemented in time, which is manifested in the changes of emotional, cognitive, motivational, behavioral and physiological dimensions [1]. According to the length of time, psychological fatigue can be divided into mental fatigue (It is acute and is more about cognitive fatigue) and burnout (It is long term and more inclined to emotional fatigue) [1, 2]. Athletes all have the desire to succeed and the ambition to win the championship. To achieve this goal, they must constantly monitor their actions, even if the technical movements have reached the level of automation. Performance monitoring means to detect and correct differences between the right response and the actual response (i.e., errors). The monitoring of one's own response errors is called response monitoring. Response monitoring is a type of performance monitoring. Once mistakes occur, athletes should timely and accurately monitor and adjust to adapt to the new situation, and ensure the follow-up play. Its main content is to detect and correct errors. It plays a key role in cognitive control and behavior monitoring [3]. For example, in shooting training and competition, whether athletes under psychological fatigue are more likely to miss the targets, and whether they can perceive this phenomenon and the causes after they appear and take effective regulation to avoid the continuation of this phenomenon.

Negative emotions such as psychological fatigue affect response monitoring greatly. In the situations of psychological fatigue, the probability of an error occurring increases and the probability of correct processing decreases. In order to investigate the impact of psychological fatigue on athletes' performance monitoring, empirical researches are necessary to be carried out. The related literatures have entered the field of cognitive neuroscience. Event-related potentials (ERP) technology has its unique advantages [4]. The core indicator of response monitoring used in ERP studies is the Error-Related Negativity (ERN). ERN is a superposition of response locking, and a negative brain wave that is closely linked to the monitoring of action and error perception, with a maximum amplitude point near the central frontal lobe FCz [5], and mostly occurring 20–100 ms after an erroneous response [6]. Its source of production is localized in the anterior cingulate cortex [7]. ERN not only perceives errors (usually expressed in terms of reaction time and correct rate), but also evaluates them and even causes decision-making (usually expressed in terms of wave amplitude) [8]. Its higher amplitude indicates better monitoring. In order to improve the reliability, validity and security of data calculation, the analysis of ERN data was based on Artificial Intelligence (AI) computing methods, including time domain analysis, wavelet transform, grayscale transformation and other algorithms.

Mental fatigue is associated with response monitoring and has a negative effect on cognitive control and behavioral performance [9–13]. The conclusion is also supported by the recent literatures [14, 15]. However, the effect on response monitoring after mental fatigue is regulated needs to be further determined. Some researchers have used factors such as odours [13], alcohol [16] and caffeine [17] to regulate mental fatigue and to observe the effects of monitoring. The importance and feasibility of this study to analyze the relationship between music and mental fatigue are enhanced by the role of music on mood effects and behavioral performance monitoring, as well as research findings exploring ERP components related to music, e.g., N2, N400. In addition, the relationship between burnout and response monitoring needs to be clarified, although there are some literatures on the topic [18, 19].

In this paper, the first experiment was conducted to induce mental fatigue and to observe changes in ERN and behavioral performance during fatigue-free, fatigue and adjustment period. The same stimulus paradigm is used in the second experiment to observe whether subjects with burnout had longer response times and higher error rates and lower ERN amplitudes, and did not produce mental fatigue. Thus, a 15-min cognitive task only was chosen instead of 75 min.

1.1 Theoretical explanation of psychological fatigue and response monitoring

No explanations for mental fatigue have been reported in sports field. Other domains such as brain fatigue where the precipitating stimulus is a one-time cognitive exhaustion task, and performance decline is caused by attentional deficits [20]. Cognitive psychology suggests that the generation of brain fatigue is related to attention, i.e., information processing capacity is limited. If no resources are utilized, a bottleneck phenomenon will occur, which in turn mental fatigue. Moreover, neuropsychology suggests that the generation of mental fatigue is related to arousal. The prolonged cognitive tasks reduce arousal levels, and produce mental fatigue. These provide the basis to explore mental fatigue and response monitoring using ERP technique.

In terms of burnout, the Stress Model suggests that factors associated with elevated stress levels trigger psychological exhaustion (i.e., burnout). The Cognitive-Emotional Model suggests that psychological exhaustion includes physiological, psychological, and behavioral elements as well as predictable situational stress, cognitive assessment, physiological responses, behavioral responses. Personality and motivation moderate the response to stress [21]. The Negative-Training Model suggests that training stresses athletes physically and mentally. Negative effects occur when stress is treated negatively and too much training is done [22]. Maslach et al. created the Three-Dimensional Theory (exhaustion, depersonalization and reduced efficacy), which considered burnout as a long-term response to chronic emotional and interpersonal stress at work [23]. However, Raedeke argued that explaining burnout exclusively by chronic stress was not comprehensive enough and proposed the Psychological Depletion Input Model. The model suggests that burnout is more likely to occur if athletes feel forced [24]. This theory fits the reality of sports and can explain the burnout caused by the imbalance between give and take. Coakley argued that stress was not the cause of burnout. He found that the time athletes spent on training and competition limited their external activities and interpersonal relationships, which restricted the development of their normal identity [25]. Accordingly, Single Identity Development and External Control Model was developed. In addition, burnout was explained from the perspective of basic needs and motivation, i.e., Self-Determination Theory, suggesting that long-term frustration or unfulfilled psychological needs can lead to burnout [26].

1.2 Measurement methods of psychological fatigue

The measurement of mental fatigue can be divided into three types. The first type is psychological tests, including the Visual Analog Scale, the 14-Item Fatigue Scale, the Subjective Fatigue Symptoms Questionnaire, and the Borg's CR100, etc. The second category is behavioral data. A decrease in operational performance (longer reaction times, lower correct rate, etc.) is a symptom of mental fatigue. The third is physiological indicators, such as Heart Rate Variability and Electroencephalogram and ERP, etc.

Researchers have also accumulated a number of findings in the measurement of burnout. Firstly, the psychological aspects are mainly psychological scales such as the Burnout Measure and the Athlete Burnout Questionnaire. Secondly, the biochemical measures, including Hemoglobin, Blood Testosterone, etc. Thirdly, the physiological aspects include Heart Rate, Heart Rate Variability, Electroencephalogram and ERP, etc.

To sum up, there were four similarities between psychological fatigue and response monitoring, and these similarities provided research ideas for this paper. Firstly, psychological fatigue has the function of adaptive mental function reconstruction, and response monitoring has also great value in adaptive behavior development. Both have adaptive significance. Secondly, psychological fatigue is influenced by endogenous and exogenous factors, and response monitoring can also reflect self-response errors and external feedback errors. Thirdly, the basic nature of psychological fatigue emphasizes central fatigue, and response monitoring also involves cognitive control. The relationship between the two can be explained through cognitive neuroscience. Finally, electrophysiological indicators are effective for measuring psychological fatigue. Cognitive neuroscience is a current hot topic at the forefront of international science and technology. Its technique based on artificial intelligence computational methods is a breakthrough in exploring the two concepts mentioned above. In this technique, behavioral response data is also measured. This reflects the crossover and integration of disciplines.

The theoretical value of this study is to try to interpret mental fatigue and burnout from the perspective of cognitive neuroscience, to explore the characteristics of athletes' response monitoring under psychological fatigue, and to seek new ideas for the study of fatigue and self-control. The practical value is to help athletes learn to prevent and restore mental fatigue, keep a high level of monitoring, and maintain good performance. It is helpful to athletes' physical and psychological recovery, and to help them achieve higher behavioral efficiency and better results.

2 Related works

In order to verify the negative effect of psychological fatigue on response monitoring, ERP data processing is crucial. Data were recorded using Neuroscan 32 leads ERP workstation, and ERP data from Fz, FCz, and Cz were acquired using scan4.3 software.

The criteria for experimental data recording and analysis were modified according to the experimental requirements, including the reference electrode position (at the left mastoid), bipolar electrode position (below the left eye, above the brow bone of the left eye, and outside of both eyes), sampling frequency (1000 Hz), and contact resistance (less than 5 KΩ), etc. Moreover, band-pass filtering frequency for offline analysis by curry7 software (0.05–30 Hz), artifact exclusion criteria ($-50\ \mu V \pm 50\ \mu V$), and analysis time (100 ms pre-response to 400 ms post-response, with 100 ms pre-response as baseline for baseline correction). Group averaging, peak detection, and brain topography analysis were performed according to the above parameters.

Because ERP signals are random and non-stationary, their frequency components vary with time, which makes single time-domain or frequency-domain analysis very limited. This study used time domain analysis indicators such as amplitude, mean value, variance and standard deviation, as well as time–frequency analysis indicators using wavelet transform.

2.1 Time domain analysis

1. Amplitude

   The instantaneous amplitude of the ERP signal $x(t)$ at a certain point of t is the modulus of $x(t)$, is denoted as $|x(t)|$.
2. Mean value
   The ERP signal is $x(t) \in \{x_1(t), x_2(t), \ldots x_n(t)\}$. The formula of ERP signal mean value is as follows.

$$X = \frac{1}{n}(x_1 + x_2 + \cdots + x_n) \tag{1}$$

3. Variance
   The formula of ERP signal variance is as follows.

$$S^2 = \frac{1}{n}\left[(x_1 - X)^2 + (x_2 - X)^2 + \cdots + (x_n - X)^2\right] \tag{2}$$

4. Standard deviation
   The formula of ERP signal standard deviation is as follows.

$$\sigma^2 = \sqrt{\frac{(x_1 - X)^2 + (x_2 - X)^2 + \cdots + (x_n - X)^2}{n - 1}} \tag{3}$$

2.2 Time–frequency analysis

Wavelet transform occupies an important position in time–frequency analysis methods because of its dual advantages in time and frequency domain resolution. The wavelet transform can analyze the time and frequency of a local signal, and progressively refine the signal (function) on multiple scales by translation and scaling. The analyzed signal can be made to have high time resolution at high frequencies and high frequency resolution at low frequencies. Therefore, wavelet transform can focus on arbitrary details of the signal, solving the difficult problem of Fourier transform, and can adapt to the basic requirements of signal analysis with different resolutions in different frequency ranges. The function equation of wavelet transform is as follows.

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t - b}{a}\right) \tag{4}$$

In the formula, a and b are two constants and $a > 0$. $\psi_{a,b}(t)$ is the function obtained by translating and stretching the basic function $\psi(t)$, which is also called fundamental wavelet, or mother wavelet.

When a and b are continuously varying, the collection of function $\psi_{a,b}(t)$ can be obtained. Given a square integrable signal $x(t)$, is denoted as $x(t) \in L^2(R)$. The Wavelet transform formula of $x(t)$ can be expressed as the following equation.

$$WT_x(A, B) = \frac{1}{\sqrt{a}} \int x(t)\psi^* \left(\frac{t-b}{a}\right) dt \tag{5}$$

In the formula, a, b and t are all continuous variables. Alphabet a is the scale factor and b is the time shift. It is also known as the continuous wavelet transform.

2.3 Brain topography statistics

In addition to the amplitude statistics, brain topography analysis was performed in combination with AI algorithms, including brain topography grayscale transformation and edge detection.

The main principle of brain topography grayscale transformation is that there are many factors in the image acquisition and generation process that lead to poor clarity of the subtle parts of the brain topography. The brain topography grayscale transformation algorithm can effectively improve the sharpness contrast of the subtle parts of the image. The grayscale algorithm alters the digital image by stretching the gray-level bandwidth frequency domain of the digital image.

Suppose the original ERP topographic image has a gray value of $D = f(x, y)$, and the processed ERP topographic image has a gray value of $D' = g(x, y)$. Thus, the enhancement of the grayscale domain of the ERP topographic image can be equal to $g(x, y) = T[f(x, y)]$ or $D' = T(D)$. The interval between the values of D and D' in the formula are within the standard range of gray scale values of ERP topography.

The grayscale transformation function $T(D)$ of ERP topography represents the conversion relationship between the image input and the image output grayscale value. After the gradient conversion process, the corresponding contrast of the ERP topography is enhanced, making the original ERP topography image clearer and easier to recognize.

Brain topography edge detection mainly describes the jump transform of pixel points of a set of digital images. Edge detection algorithms are an important part of topographic brain image analysis. Edge detection has two characteristics, the vector and the width of the edge of the ERP map. The pixels in the digital image that fall on the edge of the brain topography map adjust the gray level within a certain gray value interval. The vector of ERP topography and the two points of gray conversion rate play important roles. The edge detection technique algorithm for brain topography images uses the Robert edge detection operator, which is designed to detect each pixel point to make it vectorized, and its current gray value. The formula is as follows: $f(x, y)$ is the coordinate positioning of the ERP topographic pixel points.

$$G[f(x, y)] = \sqrt{[f(x, y) - f(x-1, y-1)]^2 + [f(x-1, y) - f(x, y-1)]^2} \tag{6}$$

3 Methods

3.1 The first experiment for mental fatigue and college athletes' response monitoring

The purpose of the first experiment was to reveal whether mental fatigue affected the ability to response monitoring effects by collecting and calculating behavioral and ERP data which based on AI computing methods, and to explore whether the use of music adjustment significantly improved the ability to response monitoring after mental fatigue. The experimental hypotheses are that the ability to response monitoring decreases under mental fatigue, and the ability regains during the process of music adjustment. The participants of this study were college students majoring in physical education. 15 participants took part in this experiment (9 males, 6 females, average age 20.533 ± 0.743). They were all national class two and above athletes. All participants signed an informed consent form.

The experiment regarded operational performances (correct rate, reaction time) and ERN as dependent variables, and regarded mental fatigue as independent variable. The levels of specific observation indicators including behavioral data and ERN wave amplitude, in order are before mental fatigue, during music adjustment, and mental fatigue.

The stim2 software was used to edit the Flanker task, including two kinds of consistent cases <<<<< or >>>>>, and two kinds of inconsistent cases <<<<< or >><<>, with the same probability of occurrence. Flanker task stems from the impact of errors, i.e., errors are often accompanied by conflicting responses in tasks that require quick responses. Tasks such as Stroop and Go/No-go, stem from the influence of response override, i.e., overcoming dominant, relatively automatic, but task-independent responses. Given the broad applicability of the Flanker task and its own specificities (rapid response, distracting stimuli, etc.), this task was chosen as the stimulus task for this study. However, it has to be set up according to the specific situation (e.g., reaction time, correctness, self-control, etc.), and also to induce mental fatigue. Therefore, the stimulus modality has to be validated, including specific details such as the type of stimulus task, the timing of stimulus presentation, the interval between stimuli, the number of stimuli, and the choreography of stimuli.

The subjects responded quickly and well to the direction of the middle arrow by placing the left and right thumbs on the left and right mouse buttons respectively. They were asked to press the left mouse button lightly with the left thumb when the arrow was to the left, and press the right mouse button lightly with the right thumb when the arrow was to the right.

The stimulus presentation was a modification of the Flanker task developed by Yeung et al. [27]. The subjects were positioned at a fixed distance of approximately 90 cm from the screen which was presented with a gaze point, a response stimulus, and a response window. The gaze point was presented for 500 ms, the response stimulus was presented for 66.67 ms, the viewing angle was 0.3° (vertical) $\times$ 0.7° (horizontal), and the response window was 1100–1300 ms random (as shown in Fig. 1).

It was conducted in a sports psychology laboratory of a sports institute, ensuring ventilation, lighting, temperature and humidity. The experimental task was presented through an IBM ThinkPad R52 18465MC notebook with a screen size of 14.1 inches and a display with a resolution of 1024×768 and a refresh rate of 60 Hz. The experiment consisted of a continuous 60-min block and a 15-min block containing a total of

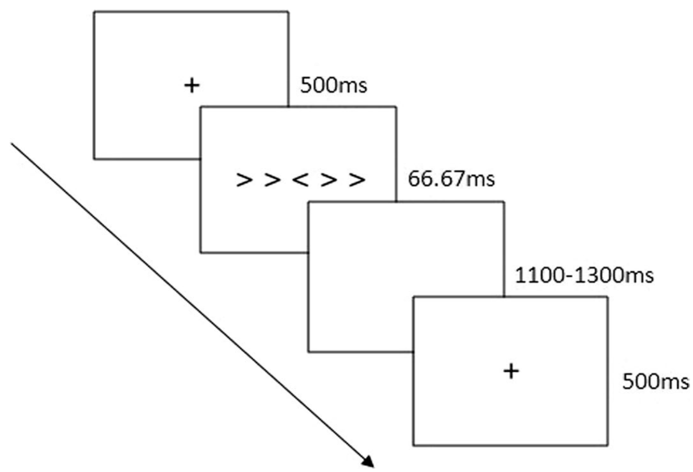

Fig. 1 Experimental stimulus presentation process

2520 trials with equal probability of consistent and inconsistent cases, and occurred randomly. During the recovery phase, the light music chosen for this experiment is four tracks from the Bandari's 'Misty Woods': Diamonds, New Morning, Starry Sky and Morning Sun. In order to verify the relaxation effect, the Music Adjustment Material Manipulation Checklist was carried out beforehand.

Some studies had confirmed that the maximum peak of ERN appeared in the middle of the frontal lobe, most clearly at the FCz point, and was followed by the positive phase potential Pe (error positivity). Scholars had divided the Pe component into early Pe at 200–300 ms and late Pe at 400–600 ms, and found that the maximum peak of early Pe was located in the frontal lobe and the maximum peak of late Pe was located in the parietal lobe [28]. Researchers believed that ERN combined with Pe can deepen the understanding of ERN understanding [3]. Some scholars have presented both ERN and Pe in their research results [29, 30]. ERN had been proposed to reflect early performance monitoring and error detection, while Pe had been connected to subsequent error awareness [31]. Therefore, Fz, FCz, and Cz located in the median axis were used as observation electrodes, which was consistent with most researchers [32]. In addition, the analysis time duration of this experiment reached 400 ms after the response, and early Pe was also used as an auxiliary observation to jointly explore the characteristics of information processing under mental fatigue.

3.2 The second experiment for burnout and college athletes' response monitoring

The purpose of the second experiment was to investigate the effect of burnout on response monitoring in college athletes. The experimental hypothesis is that the ability of response monitoring decreases under burnout. The specific observations are as follows. For behavioral and ERN data, the no burnout group is better than the burnout group.

Using the Burnout Questionnaire for College Students [33], 166 college students were measured. The internal consistency coefficients were 0.746 for the low mood subscale, 0.628 for the inappropriate behavior subscale, and 0.685 for the low achievement subscale. Referring to some researchers' critical values for each subscale of job burnout (ranking the subscale scores and taking the upper third value at the upper third as the critical value for the degree of burnout) [34], i.e., a low mood score of 26, a misbehavior score of 21, and a low achievement score of 23. For the group with burnout was defined as subjects who scored above the critical value on all three subscales and those who scored above the critical value on two subscales and had a higher total scale score.

Twenty-four participants were separated averagely into two groups. Burnout group (7 males, 5 females, average age 20.750 ± 0.866). No burnout group (7 males, 5 females, average age 20.667 ± 0.779). They were all national class two and above athletes, and signed an informed consent form.

For the experimental task, the procedures were the same as the first experiment except that only one 15-min operation was performed. For data analysis, these were the same as the first experiment.

4 Results and discussion

4.1 Results and discussion of mental fatigue and college athletes' response monitoring

4.1.1 Behavioral data

Descriptive statistics for correct rate and correct response time (Unit: ms) were performed for all time periods, and the means and standard deviations were shown in Table 1. Some studies using subjective perception, behavioral data, and HRV frequency domain data have confirmed that 0–15 min can be used as a fatigue-free time period, 46–60 min as a fatigue time period, and the last 15 min as a fatigue recovery time period [35]. The focus here was on whether there were significant differences between these three time periods, and the data were statistically processed using repeated measures ANOVA.

The results showed a significant difference in correctness across all time periods, $F(4, 56) = 2.592$, $p = 0.046$, $\eta^2 = 0.156$. Post hoc tests revealed that the fourth time period was significantly lower than the first time period, and the first time period was slightly higher than the last 15 min (i.e., the music adjustment time period). There was a significant difference in correct response time for all time periods, $F(4, 56) = 2.931$, $p = 0.029$, $\eta^2 = 0.173$. Post hoc tests revealed that the fourth time period was significantly higher than the first time period and the first time period was slightly lower than the last 15 min. The behavioral data suggest that performance was better in the no mental fatigue time period than in the music adjustment time period, and that the music adjustment time period was better than the mental fatigue time period.

Table 1 Correct rate and correct response time for different time periods

Variables	Correct rate		Response time	
	M	*SD*	*M*	*SD*
0–15 min	0.907	0.065	337.600	22.459
16–30 min	0.897	0.074	344.000	25.071
31–45 min	0.889	0.079	344.733	22.394
46–60 min	0.880	0.085	348.933	21.914
Last 15 min	0.898	0.076	341.800	23.134

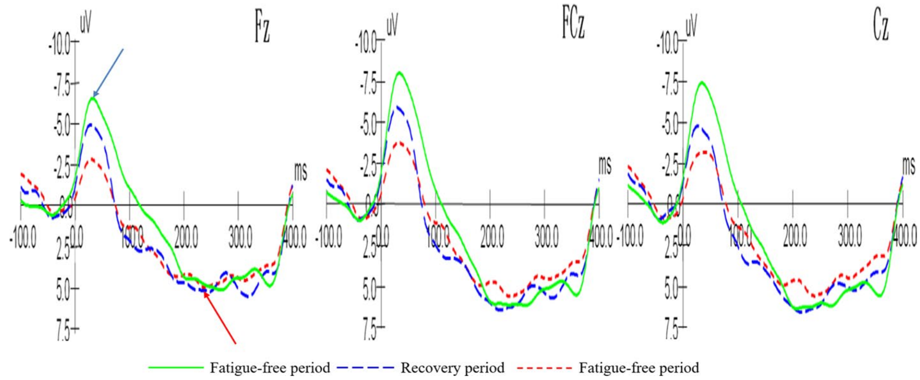

Fig. 2 Waveforms of ERN and early Pe in three time periods for Fz, FCz, Cz

Table 2 ERN and early Pe for three electrode positions at different time periods

Variables	0-15 min		45-60 min		Last 15 min	
	M	*SD*	*M*	*SD*	*M*	*SD*
Fz						
0–100 ms	− 7.496	2.510	− 3.419	1.873	− 5.942	2.957
200–300 ms	6.278	3.612	5.800	2.453	6.617	5.111
FCz						
0–100 ms	− 9.077	3.275	− 4.541	2.034	− 6.899	3.368
200–300 ms	7.459	3.973	6.429	2.196	7.470	5.119
Cz						
0–100 ms	− 8.412	3.804	− 4.046	2.085	− 5.941	3.395
200–300 ms	7.581	3.628	6.486	2.330	7.316	4.697

4.1.2 ERN data

The ERN (in the case of Fz, indicated by the arrow above the horizontal axis) and early Pe (indicated by the arrow below the horizontal axis) waveforms of the three electrodes Fz, FCz, and Cz during the fatigue-free, fatigue, and adjustment period were shown in Fig. 2.

The magnitude of Fz, FCz and Cz electrodes in the three periods ERN were in order of the fatigue-free period, the adjustment period and the fatigue period, and the magnitude of FCz was the largest. The amplitude of early Pe was relatively not obvious in the three periods, and the fatigue-free period was basically comparable to the adjustment period and larger than the fatigue period. The maximum position was also not obvious, and the amplitude of FCz and Cz were comparable.

The maximum magnitude values (Unit: μV) of 0-100 ms for each subject were extracted, and the mean and standard deviation of ERN were shown in the table below. The maximum magnitude values of 200-300 ms for each subject were extracted, and the mean and standard deviation of early Pe were shown in Table 2.

A 3(time period)*3(electrode) two-factor repeated measures ANOVA on the mean amplitude of 0–100 ms (ERN) showed a significant main effect of time period, $F(2, 28) = 16.062$, $p = 0.000$, $\eta^2 = 0.534$. The 45–60 min amplitude (− 4.002) was significantly smaller than the last 15 min (− 6.261), and the last 15 min was significantly smaller than 0–15 min (− 8.328). The main effect of electrodes was significant, $F(2, 28) = 4.445$, $p = 0.046$, $\eta^2 = 0.241$. Fz (− 5.619) and Cz (− 6.133) were significantly smaller than FCz (− 6.839). The interaction of time period* electrode was significant, $F(4, 56) = 4.461$, $p = 0.010$, $\eta^2 = 0.242$. Simple effects were found for electrodes at 0–15 min ($F(2, 28) = 7.240$, $p = 0.003$, $\eta^2 = 0.341$) and the last 15 min ($F(2, 28) = 4.080$, $p = 0.028$, $\eta^2 = 0.226$), and the time period effects were significant at Fz ($F(2, 28) = 13.400$, $p = 0.000$, $\eta^2 = 0.489$), FCz ($F(2, 28) = 17.080$, $p = 0.000$, $\eta^2 = 0.550$) and Cz ($F(2, 28) = 16.780$, $p = 0.000$, $\eta^2 = 0.545$).

A two-factor repeated measures ANOVA with 3 (time period) * 3 (electrode) for the mean amplitude of 200–300 ms (early Pe) showed that the main effect of time period was not significant, $F(2, 28) = 0.398$, $p = 0.675$, $\eta^2 = 0.028$. The main effect of electrode was significant, $F(2, 28) = 7.447$, $p = 0.003$, $\eta^2 = 0.347$. Fz (6.231) was significantly smaller than FCz (7.119) and Cz (7.128). Time period* electrode interaction was not significant, $F(4, 56) = 1.094$, $p = 0.368$, $\eta^2 = 0.072$.

Figure 3 shows the 2D topography of ERN and early Pe after group averaged, including the brain topographic distribution during 0–50 ms and 200–250 ms for three time periods, which can visually describe the brain discharge. Referring to some previous studies, these two analysis periods were chosen mainly to consider the timing of ERN and early Pe wave amplitude appearance. As shown in Fig. 2, the ERN appeared before 50 ms and the early Pe appeared before 250 ms. The 0–50 ms showed the ERN amplitude variation, and the shades of blue were used to indicate the amplitude magnitude. The 200–250 ms showed the early Pe amplitude variation, and the shades of red were used to indicate the amplitude magnitude. The following was the same.

Between 0 and 50 ms after the error, there was a significant negative shift in the prefrontal lobe, with the maximum value occurring in FCz, and the magnitude was in the order of fatigue-free period, adjustment period and fatigue period. Between 200–250 ms after the error, there was a significant positive shift in the prefrontal lobe, with FCz and Cz more obvious, and the magnitude was in the order of adjustment period, fatigue-free period and fatigue period.

4.2 Discussion

From the behavioral data, there was a directional change, with the fatigue-free period slightly better than the (high correct rate and fast response time) music adjustment period, and the fatigue-free period significantly better than the fatigue period, indicating a decrease in cognitive control during the fatigue period. The music adjustment period was better than the fatigue period, but no significant difference. From the ERN data, fatigue-free period was significantly greater than fatigue period, which is consistent with the studies of Boksem et al., Kato et al. and Lorist et al. [11–13, 36], indicating that error monitoring is impaired under mental fatigue. Also, the fatigue-free period was significantly greater than the music adjustment period, and the music adjustment period was significantly greater than the fatigue period, suggesting that ERN is a more sensitive indicator in evaluating the effect of music relaxation. From the early Pe data, the main effect of time period was not significant (suggesting that the effect of fatigue is not significant), the main effect of electrode location was significant (more pronounced with

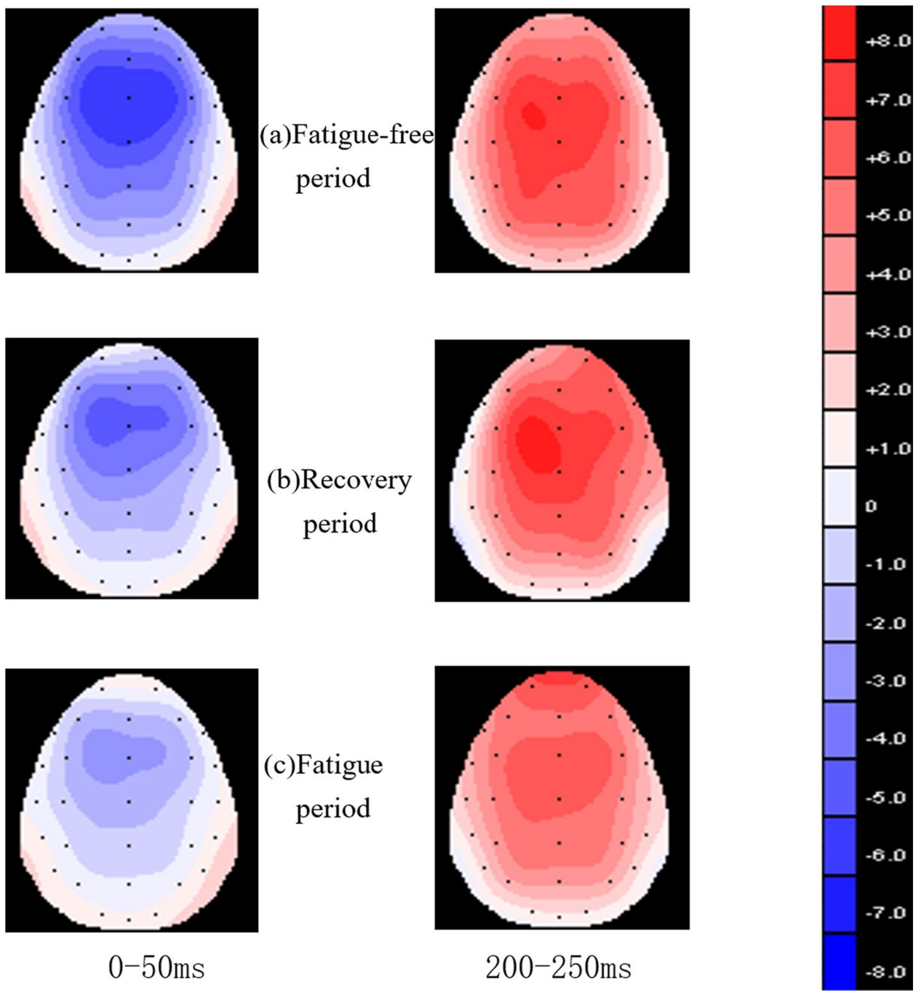

Fig. 3 2D cartoon display of ERN and Early Pe for three time periods

FCz and Cz), and no directional changes similar to ERN were found. The reason for this can be explained using the following explanation. The study [37] had shown that Pe is a member of the P300 family and is associated with subjects' perception of errors and with the updating of the background in the brain regarding errors. It had also been shown [38] that a certain amount of ERN is produced whether the error is perceived or not, that Pe is evident only when the subject perceives the error. ERN and Pe reflect different error monitoring processing activities, ERN emphasizes error detection, Pe emphasizes awareness of error. The results of the behavioral and ERN data verified that the ability to monitor response effects decreased under mental fatigue. Mental fatigue can manifest itself in physical, psychological and behavioral ways. Consistency in trends and levels of typical indicators in these three areas can demonstrate the success of the manipulation of mental fatigue. Although the ERN and Pe data explained well the effect of mental fatigue on monitoring, in order to move ERPs toward standardization and norms, the meaning of differences in ERN and Pe scores should be further researched [39]. It rebounded during music adjustment. The reason is that music has a direct or indirect effect on the limbic system of the brain and the reticular formation of the brainstem, which regulate the internal organs and somatic functions of the body. At the same time, these results confirmed the reliability, validity and security of the data based on AI algorithms.

There are some issues to be noted in the experiment. Firstly, because this study involved both mental fatigue and ERN elicitation, experiments with twice the number of presented subjects were conducted to obtain a better waveform, which was a great waste of subject data, and therefore should be strengthened in both follow-up studies and data processing. Secondly, this study focused on two variables, psychological fatigue and response monitoring. Based on the mechanism of psychological fatigue and the factors influencing response monitoring, third variables such as attention, arousal and stress should be included for mediating or moderating effects. Thirdly, in this study, based on the generalization of previous research results [3, 12], three electrodes, FCz, Cz and Fz, were chosen. The brain wave situation at the electrode positions of CPz and Pz could be continued to be explored if possible. It can enrich the statistics of the study. Finally, regarding the search for other means of mental fatigue prevention and recovery. One of the subjects who did not successfully induce mental fatigue said that the first few minutes of the formal experiment, more mistakes were made, thinking that they could not be changed anyway. So he began to look for certain ways to cope with the situation, mainly with two elements. When performing the operation, according to the order of picture presentation, mentally meditating on 1, 2 and 3, which correspond to the gaze point, response stimulus and button respectively. This created the rhythm. He meditated on the number of consecutive correct, to see if there is a boost. There were more than 10, more than 20, the most time is 96. In this way, the more you do it, the easier it becomes. He did not experience mental fatigue. This case speculates that mental fatigue can be prevented and alleviated by developing a sense of rhythm and setting goals, which also requires algorithms to verify based on the idea of cross-fertilization of disciplines. In addition, recent researches have demonstrated that mindfulness [40], nature [41], and other modalities can also help in the recovery of response monitoring in such cases.

4.3 Results and discussion of burnout and college athletes' response monitoring

4.3.1 Behavioral data

To verify that the 15-min task did not significantly induce mental fatigue in the burnout group, subjective perception tests were conducted on 12 subjects. Repeated measures ANOVAs were conducted for difficulty, effort, and fatigue before and after the 15-min cognitive task. Their means and standard deviations were shown in Table 3.

In terms of direction, the burnout group was basically on the rise. There was no significant difference in difficulty scores before and after the cognitive task, $F(1, 11) = 0.805$, $p = 0.389$, $\eta^2 = 0.068$. There was no significant difference in effort scores before and

Table 3 Scores of difficulty, effort and fatigue before and after the cognitive task

Variables	Beginning		After 15 min	
	M	*SD*	*M*	*SD*
Difficulty	3.083	1.311	3.333	1.155
Effort	2.833	0.937	3.083	0.996
Fatigue	1.167	0.718	1.500	0.522

Table 4 Correct rate and correct response time of college athletes with and without burnout

Variables	No burnout group		Burnout group	
	M	*SD*	*M*	*SD*
Correct rate	0.920	0.069	0.913	0.067
Response time	334.000	36.492	346.167	36.486

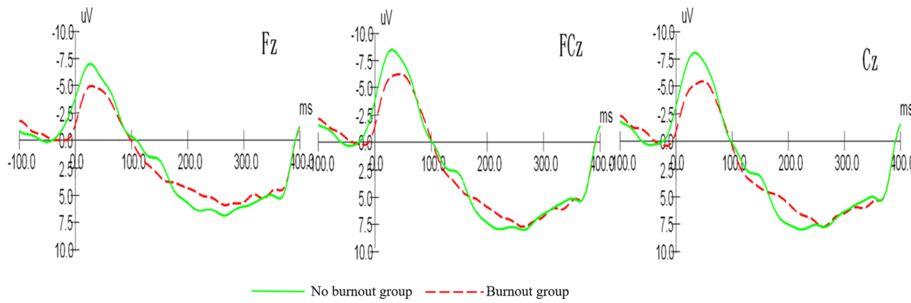

Fig. 4 Waveforms of ERN and early Pe in college athletes with and without burnout

after the cognitive task, $F(1, 11) = 1.941$, $p = 0.191$, $\eta^2 = 0.150$. Fatigue before and after the cognitive task scores were not significantly different, $F(1, 11) = 3.143$, $p = 0.104$, $\eta^2 = 0.222$. The above results indicated that no mental fatigue occurred with the 15-min task.

A multivariate ANOVA was performed on the correct rate and correct response time (Unit: ms) of the two groups of subjects with and without burnout in college athletes, and the means and standard deviations of the two groups were shown in Table 4.

The results showed that the no burnout group had a higher correct rate than the burnout group, with no significant difference, $F(1, 22) = 0.062$, $p = 0.806$, $\eta^2 = 0.003$. The no burnout group had a lower reaction time than the burnout group, with also no significant difference, $F(1, 22) = 0.667$, $p = 0.423$, $\eta^2 = 0.029$. These indicated that the no burnout group's behavioral performance was better than that of the burnout group.

4.3.2 ERN data

The waveforms of the three electrodes Fz, FCz, and Cz in college athletes with and without burnout were shown in Fig. 4.

The maximum magnitude (Unit: μV) of 0–100 ms for each subject was extracted, and the mean and standard deviation of ERN for 12 subjects were shown in the following table. The maximum magnitude of 200–300 ms for each subject was extracted, and the mean and standard deviation of early Pe were shown in Table 5.

A 2(group)*3(electrode) two-factor repeated measures ANOVA was performed on the mean amplitude of 0-100 ms. The results showed a margin significant main effect for group, $F(1, 11) = 4.748$, $p = 0.052$, $\eta^2 = 0.301$. The amplitude of the burnout group (−6.547) was smaller than that of the no burnout (−9.297). The main effect of electrodes was significant, $F(2, 22) = 17.552$, $p = 0.001$, $\eta^2 = 0.615$. Fz (−7.081) was significantly smaller than Cz (−7.968) and Cz was significantly smaller than FCz (−8.717). Group* electrode interaction was not significant, $F(2, 22) = 0.845$, $p = 0.443$, $\eta^2 = 0.071$.

Table 5 ERN and early Pe of college athletes with and without burnout

Variables	No burnout group		Burnout group	
	M	*SD*	M	*SD*
Fz				
0–100 ms	− 8.338	2.703	− 5.823	2.630
200–300 ms	7.905	3.803	7.474	4.156
FCz				
0–100 ms	− 9.988	2.970	− 7.447	2.622
200–300 ms	9.354	4.285	9.311	4.063
Cz				
0–100 ms	− 9.564	2.992	− 6.372	3.351
200–300 ms	9.376	4.336	9.103	4.191

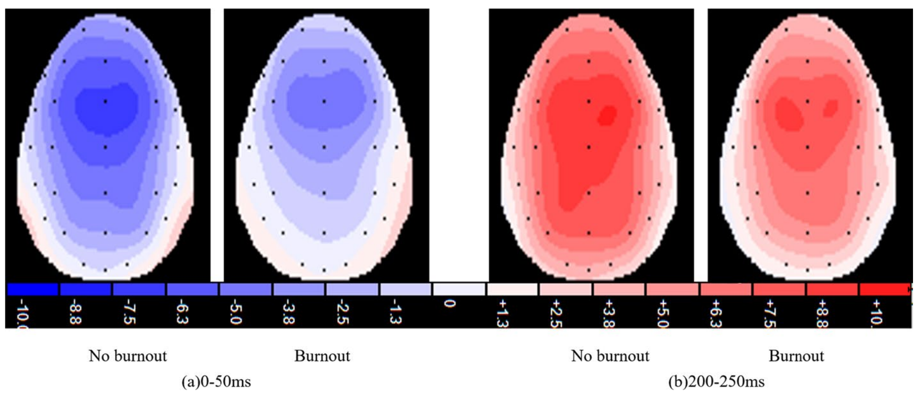

Fig. 5 2D cartoon display of college athletes' ERN and early Pe with and without burnout

A 2(group)*3(electrode) two-factor repeated measures ANOVA was also performed on the mean amplitude of 200-300 ms. The results showed that the main effect of group was not significant, $F(1, 11) = 0.025$, $p = 0.878$, $\eta^2 = 0.002$. The amplitude of the burnout group (8.629) was slightly smaller than that of the no burnout (8.878). The main effect of electrodes was significant, $F(2, 22) = 16.573$, $p = 0.000$, $\eta^2 = 0.601$. Fz (7.689) was significantly smaller than Cz (9.239) and FCz (9.332). Group* electrode interaction was not significant, $F(2, 22) = 0.123$, $p = 0.751$, $\eta^2 = 0.011$.

Figure 5 showed the 2D topography of ERN and early Pe after group averaging, including the distribution of brain topography at 0–50 ms and 200–250 ms with and without burnout. Between 0 and 50 ms after the error, there was a significant negative shift in the prefrontal lobe (FCz was most pronounced), and the degree was greater in the group without burnout than in the group with burnout. Between 200 and 250 ms after the error, there was a significant positive shift in the prefrontal lobe (FCz and Cz were more pronounced), and the degree was slightly greater in the no burnout group than in the burnout group.

4.4 Discussion

From the behavioral data, the group without burnout was better than the group with burnout, but the difference was not significant, consistent with the previous study [42]. From the ERP data, the ERN index in the no burnout group was greater than that in the burnout group, and the difference was borderline significant, indicating that the ability to monitor response effects is impaired under burnout and that ERN has some sensitivity in evaluating burnout in college athletes. The maximum electrode position is at FCz, which is consistent with ERN under mental fatigue in the first experiment. Regarding the early Pe index, there was no significant difference between the two groups with and without burnout. The maximum electrode location was at FCz and Cz, which is consistent with the case of early Pe under mental fatigue. When doing the 2D Cartoon chart, the time period used was 200–250 ms. In fact, most of the early Pe in this experiment appeared between 250 and 300 ms. But for two reasons the choice was still chosen to be 200–250 ms, one was to correspond to the preceding and following text, and the other was that the waveforms are basically consistent with the graphical pattern of 250–300 ms. As a result, the ability to monitor response effects decreases under burnout. The reasons for the absence of significant differences in results may be related to the mechanisms by which burnout occurs. Burnout is related to factors such as personality, sense of self-control, motivation and social support. Burnout is also more a symptom of mood changes than of changes in cognitive functioning. As a result, individuals do not show reduced levels of behavior and cognition, but are simply less willing to complete the task in question.

In addition, the collection and analysis of data need to be strengthened. The experimental paradigm should be improved, and the experimental data should be further processed using other AI algorithms. Firstly, the creation of computer data simulator. A study had been conducted to build a simulator of visual N2/N2pc event-related potential components in order to assess the accuracy of estimates [43]. Secondly, the design of brain-computer interfaces. ERN and Pe can be widely used for neurorehabilitation of different populations [44, 45]. Error-related potential-based brain-computer interfaces have become a hot topic of research in this area. Generally, ERN and Pe are obtained by stacking several times. The single detection of ERN and Pe is a technical bottleneck in their application to brain-computer interface systems. The advantages of the wavelet transform algorithm will continue to be exploited. Therefore, researches in brain science have provided new inspiration for the development of devices and the evolution of artificial intelligence algorithms.

5 Conclusions and future works

In this paper, to investigate the relationship between psychological fatigue and response monitoring using AI algorithms, two experimental studies were conducted and behavioral and ERP data were derived. Artificial intelligence technology is feasible for processing ERP data. Psychological fatigue weakens athletes' response monitoring ability. The effect of mental fatigue is significant, and light music helps to regulate mental fatigue.

In future researches, the following topics should be concerned, including the mediating or moderating effects of third variables, different ways of recovering from mental fatigue, computer data simulator and date accuracy, brain-computer interfaces and error-related negativity, etc.

Abbreviations

AI	Artificial intelligence
ERP	Event-related potentials
ERN	Error-related negativity
Pe	Error positivity

Acknowledgements
The authors sincerely thank the reviewers and editors for their valuable suggestions and comments.

Author contributions
SL and JL proposed the paper writing design, JL and YW explained the experimental algorithm. JL and SL performed the related experimental manipulations. In addition, they completed the English manuscript together, and JL and SL revised and improved the manuscript. All authors read and approved the final manuscript.

Funding
This work has not yet applied for related funding.

Availability of data and materials
The behavioral and ERP data used and analyzed during the study are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare that they have no competing interests.

Received: 4 July 2022 Accepted: 25 August 2022
Published online: 03 September 2022

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