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A PROPOSAL ON A BRAIN-COMPUTER INTERFACE MODEL FOR REAL-TIME MENTAL FATIGUE INTERVENTION

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Abstract: *Mental fatigue (MF) is a common issue that impairs cognitive function and general well-being. Existing electroencephalogram (EEG)-based neurofeedback is time-consuming because it necessitates multiple follow-up sessions. Therefore, this paper proposes a non-invasive and personalized real-time mental fatigue intervention for online learners using Brain-Computer Interface (BCI). The model consists of two components: (1) MF detection, and (2) MF intervention. The Emotiv Insight will be used to collect EEG signals during online learning sessions. The mental fatigue detection model will be formulated based on 6 Emotiv's Performance Metrics (EPM). To intervene, the monitor contrast will be used to reduce mental fatigue. The model will be validated based on Chalder Fatigue Questionnaire (CFQ). Future research can focus on optimizing the intervention technique and testing the effectiveness of the model in different populations.*

Keywords: *Brain-Computer Interface, Mental Fatigue, Intervention, Electroencephalogram.*

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Introduction

Mental fatigue is a common phenomenon that affects many individuals, particularly those who engage in cognitively demanding tasks for extended periods of time. It is characterized by symptoms such as decreased alertness, difficulty focusing, and a feeling of tiredness or lethargy (Rudroff et al., 2020; Van Der Linden & Eling, 2006). Mental fatigue can have significant negative impacts on daily life, including reduced productivity, impaired decision-making, and decreased quality of life (Van Der Linden et al., 2003). Online learners frequently experience mental fatigue because they spend a lot of time in front of screens studying or participating in virtual classes, which can negatively impact academic performance and overall well-being (Jin et al., 2022; Rudroff et al., 2020). Understanding the mechanisms underlying mental fatigue is critical for developing effective interventions to prevent or alleviate its negative effects (Brandtner et al., 2022; Feldman & Dreher, 2012).

Interventions to mitigate mental fatigue can take various forms, such as rest breaks, physical exercise, cognitive training, or pharmacological agents or delivering electrical or magnetic stimulation to enhance brain activity (Axelsen et al., 2020; Zhu et al., 2020) (Sörensen et al., 2006). While these interventions can be effective in some cases, they may not be feasible or practical in all contexts. One promising approach can be the use of brain-computer interface (BCI) technology to detect and mitigate mental fatigue in real-time (Jap et al., 2009). By using BCI to monitor changes in brain activity associated with mental fatigue, it is possible to deliver targeted interventions to maintain or improve cognitive performance.

EEG-based BCI is one of the most commonly used BCI technologies for mental fatigue detection. EEG-based BCI has shown promising results in neurofeedback (NF) studies, and its potential applications extend beyond mental fatigue to other cognitive and neuropsychiatric disorders (Loriette et al., 2021; Noohi et al., 2017). Neurofeedback involves providing real-time feedback to individuals about their brain activity, allowing them to learn how to self-regulate their cognitive processes (Demarin et al., 2014; Marzbani et al., 2016).

This paper intends to propose a mental fatigue intervention model using a brain-computer interface (BCI), which will consist of the detection and intervention components for online learners' mental fatigue in real-time.

Literature review

Mental Fatigue Detection

The measurement of mental fatigue states uses a variety of methods, including self-reporting and observed behavior. In accordance with the participants' feelings, attitudes, and/or opinions, the target labels of mental fatigue were selected using the applied self-reporting instruments listed in Table 1. The Chalder Fatigue Questionnaire (CFQ) was used to assess fatigue severity in individuals with multiple sclerosis (Chilcot et al., 2015) and to assess chronic fatigue syndrome (CFS) (Cella & Chalder, 2010). The CFQ questionnaire scoring ranges from 0 to 3 where the overall score (which might range from 0-33) is calculated by adding the ratings of all the components. (Chilcot et al., 2015) scoring using the following labels: less than normal (0), up to but not beyond usual (1), above average (2), and significantly above average (3). High scores indicate a lot of fatigue. The researchers used confirmatory factor analysis (CFA) with weighted least-squares with mean and variance adjustment estimation to test one, two, and bi-factor models of fatigue. In the study, response options "less than usual" and "no more than usual" received ratings of 0 while "more than usual" and "much more than usual" received

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scores of 1, respectively. The research work used statistical analyses such as distribution plots and skewness values, the Shapiro-Wilk test, Cronbach's alpha coefficient, principal component analysis (PCA), and receiver-operating characteristic (ROC) to evaluate the results.

Table 1: Mental Fatigue Assessment

Reference	Assessment	Applications	Subject	Scoring	Evaluation
(Cella & Chalder, 2010; Chilcot et al., 2015)	Chalder Fatigue Questionnaire (CFQ)	Severity in multiple sclerosis	444	A score ranging 0-3	Confirmatory Factor Analysis (CFA)
		Chronic fatigue syndrome (CFS)	361	A score ranging 0-3	Statistical Analysis
(Schiehser et al., 2013; Simon et al., 2020)	Positive and Negative Affect Schedule (PANAS-X)	Impact in Parkinson's disease	100	five-point Likert scale	Statistical Analysis
		Effect on auditory temporal order judgments	29	five-point Likert scale	Statistical Analysis
(Miley et al., 2016; (Foong et al., 2019)	Karolinska Sleepiness Scale (KSS)	Comparing two versions of the KSS for drowsiness	12	9-point scale	Statistical Analysis
		Passive fatigue	29	9-point scale	Statistical Analysis
(Talukdar et al., 2020)	Visual Analogue Scale - Fatigue (VAS-F)	Tracking	11	A scoring ranges from 1-5	Statistical Analysis

Positive and Negative Affect Schedule (PANAS-X) is also a psychometric instrument that can be used to measure mental fatigue based on a set of questionnaires with five-point Likert scale for scoring from 1 (very slightly or not at all) to 5 (extremely or very much) (Schiehser et al., 2013). It was employed to measure the impact of fatigue on individuals with Parkinson's disease (Schiehser et al., 2013). In a different study, it was also used to measure the short-term cognitive fatigue effect on auditory temporal order judgments (Simon et al., 2020). It is commonly evaluated using statistical analyses such as principal component analysis (PCA), mean, and standard deviation (SD), and P-value (Simon et al., 2020).

Another self-reporting instrument for mental fatigue detection is the Karolinska Sleepiness Scale (KSS). It is used to quantify passive fatigue (Miley et al., 2016; Foong et al., 2019). The questionnaire used a nine-point scale for scoring (1 = extremely alert, 2 = very alert, 3 = alert,

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4 = rather alert, 5 = neither alert nor sleepy, 6 = some signs of sleepiness, 7 = sleepy, but no effort to keep awake, 8 = sleepy, some effort to keep awake, 9 = very sleepy, great effort keeping awake, fighting sleep). Statistical analyses including the McNemar test, Cohen's unweighted Kappa, mean, mean, standard deviation, and P-value are used to evaluate the results (Foong et al., 2019; Miley et al., 2016).

Another study investigated the adaptive feature extraction in EEG-based motor imagery BCI for tracking mental fatigue were used Visual Analogue Scale - Fatigue (VAS-F) (Talukdar et al., 2020). The degree of fatigue is assessed using a fatigue scale (a subjective scale) with a value from 1 to 5 that ranges between two extremes (1 = least fatigued and 5 = most fatigued). Subjects made a choice along a scale to express their level of fatigue. This study included mean, correlation coefficient, SD, and P-value as statistical analyses to evaluate the results.

Emotiv Performance Metrics (EPM) for Mental State Detection

There are many studies showed reliable performance in the detection of mental conditions using the Emotiv headset and six Emotiv Performance Metrics (EPM) including engagement, excitement, focus, stress, relaxation, and interest (Strmiska & Koudelkova, 2018). Some of the studies detailed in Table 2.

In most of the studies, all 6 EPM are analyzed to measure mental fatigue state. This includes the decoding of human speech directly from the human brain onto a digital screen where statistical analysis included correlations between performance metrics and histogram analysis of experimental datasets and external datasets (Faruk et al., 2021).

Table 2: EPM in Mental Condition Detection

Reference	Application	Emotiv Headset	Subjects	EPM
(Faruk et al., 2021)	Decode human speech directly	Epoc X	3	All
(Santoyo-Mora et al., 2022)	COVID-19 Long-Term Effects	Epoc X	147	focus, interest, & engagement
(Paranthaman et al., 2021)	Reliability of performance metrics	Epoc X	14	All
(Zhang et al., 2021)	Emotional responses to the visual patterns of urban street	Epoc X	26	All
(Asif et al., 2023)	Compare the levels of executive functions	Insight	60	All
(Holman & Adebesin, 2019)	Determine the presence of the emotion and EPM	Epoc X	10	All

In a study where emotional responses to the visual patterns of urban streets are studied, EPMs are analyzed through statistical approach, such as the mean, SD, correlation coefficients among metrics, and linear regression with standardized coefficients as statistical analysis (Zhang et al., 2021). Additionally, another study measured the EPM and used statistical analysis such as the Kolmogorov-Smirnov test, sample Wilcoxon signed test, t-test, mean, standard deviation, and p-value to observe and compare the levels of executive functions in gamified and non-gamified tasks. The study measured the Emotiv six metrics and used statistical analysis such as the Kolmogorov-Smirnov test, sample Wilcoxon signed test, t-test, mean, standard deviation, and

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p-value (Asif et al., 2023).The EPM is also used to determine the presence or absence of anger through brain activities (Holman & Adebesin, 2019).

There is also study that only analyze 3 EPM for a mental state detection. For example, EPM is used to study the long-term effects of COVID-19 based on the statistical analysis involved mean, median, standard deviation, z-value, and p-value calculations on reaction time and alternative-forced choice on recovered patients (Santoyo-Mora et al., 2022). The reliability of EPM in a virtual reality game was also analyzed through statistical analysis, such as mean, standard deviation, and p-value (t-test) (Paranthaman et al., 2021).

Light and Temperature Effect on Mental Fatigue

Watching videos at a medium screen brightness level resulted in the least amount of visual fatigue (Kalra & Karar, 2022). Patients with less light exposure experienced higher levels of fatigue compared to patients with more light exposure during chemotherapy (Liu et al., 2005). Exposure to bright light increases vigour and enjoyment while decreasing drowsiness in the context of performance. In the context of traumatic brain injury (Smolders & de Kort, 2014). In addition to that, the high-intensity blue light decreased fatigue and daytime drowsiness (Sinclair et al., 2014). In the impacts of display on visual fatigue domain are stronger brightness contrast in dark mode was related with less visual fatigue (Xie et al., 2021). Furthermore, multiple sclerosis patients with high temperatures also experienced high levels of fatigue (Bol et al., 2012).

Exercising on a cycle ergometer at a high body temperature resulted in a significant level of fatigue (Gonzàlez-Alonso et al., 1999). In a task environment at an office, it has been discovered that high temperature was linked to high fatigue (Tanabe et al., 2007). In addition, nurses experienced a lot of mental fatigue in a high temperature and high protection, whereas a low temperature and low protection caused the least amount of fatigue (Jin et al., 2022).

Research framework

The research framework shown in Table 3 is the result of combining the research objectives, questions, methods and expected outcomes with contributions

Table 3: Research Framework

Research Objectives	Research Questions	Methods	Expected Outcomes / Contributions
RO1: To identify mental fatigue detection and intervention techniques	RQ1: What is the mental fatigue detection and intervention technique?	Literature review	- MF-related factors for intervention -Identify MF detection - Identify NF signal generation strategy
RO2: To design and develop the BCI model for real-time mental fatigue intervention	RQ2: How to implement the BCI model for real-time mental fatigue intervention?	-Literature review -Content-development -EPM for MF detection - Ethical approval for EEG signal collection	-Architecture of the Model - Experimental design -Validate EPM for MF detection -Threshold value for real-time MF detection

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		-MF assessment questionnaire: CFQ	- A development of the BCI model for real-time MF intervention
RO3: To evaluate the real-time mental fatigue intervention model	RQ3: How to evaluate the real-time mental fatigue intervention model?	-Analysis on EPM values -MF assessment questionnaire: CFQ -Collect time stamps on every significant changes -Collect monitor brightness as light intensity	- Effectiveness of NF modality by calculating the duration of MF recovery after the intervention -Light intensity effects on individuals -The effectiveness of the BCI model for MF intervention -Evaluated Model -The findings will lead to the future development of more effective MF intervention

Proposed Brain-Computer Interface Model For Real-Time Mental Fatigue Intervention

Model Architecture

Neurofeedback signal generation review identified the neurofeedback model for different mental conditions treatment (Hossain & Yaacob, 2022). The Neurofeedback model pipeline consists of signal acquisition, pre-processing, feature extraction, mental condition detection algorithms, and feedback signal generation by presenting the Neurofeedback modality. On the other hand, Mental fatigue detection identified mental fatigue detection pipeline which includes signal acquisition, pre-processing, feature extraction, and mental fatigue detection. This leads to the design of the general architecture of the real-time mental fatigue intervention model using a brain-computer interface which includes signal acquisition, preprocessing, feature extraction, mental fatigue detection algorithm, and feedback signal generation by presenting a neurofeedback modality for intervention. This research is designed to use Emotiv Insight 2.0 headset and Emotiv performance focus metrics. This research will use Emotiv's built-in functionality to detect mental fatigue. The final architecture of the proposed real-time mental fatigue intervention model is depicted in Figure 1.

The model is designed as a closed-loop for mental fatigue intervention. The pipeline can be divided into two sections: (i) mental fatigue detection and (ii) mental fatigue intervention. At first, the model detects the MF. The continuous process of signal acquisition and MF detection algorithm occurs until the model detects the MF during the cognitive task period. If there is MF identified the model will activate the intervention strategy which includes a notification system and a control of neurofeedback modality. Now, the process of signal acquisition, MF detection algorithm, and control of neurofeedback modality occur until the detected MF is reduced. This model is a real-time automated mental fatigue intervention model for online learners. The model should control the neurofeedback modality based on the detection of mental fatigue to provide an intervention. This study aims to use monitor contrast/brightness as a neurofeedback modality for intervention.

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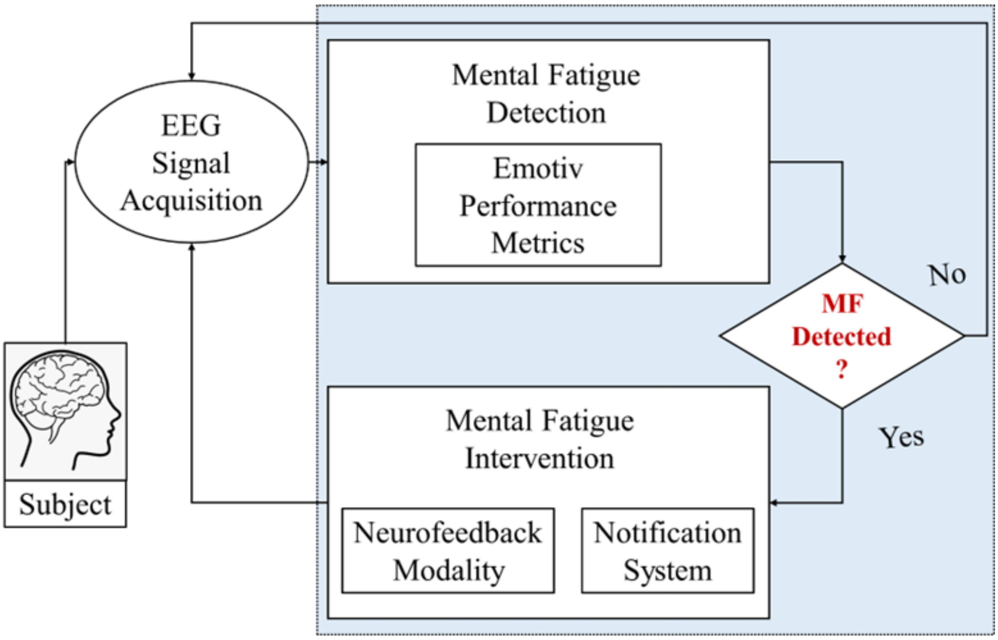

Figure 1: Brain-Computer Interface Model for Real-Time Mental Fatigue Intervention

Experimental Design

Participants

The subjects are students who will attend an online learning session. The subject inclusion-exclusion criteria are age, sickness, smoking, drug addiction, history of mental disorder and physical disorder. The demographic information will be collected before finalizing the selection of healthy participants. The subject will sign a consent form and be briefed on the whole process as well as provide instructions. In this purpose, data collection approval is taken from the Kulliyyah of Information and Communication Technology, International Islamic University Malaysia (IIUM). Furthermore, IIUM Research Ethics Committee (IREC) also approved the consent form and personal information form which contains questionnaire for selection of subjects. The subjects will do self-assessment of their experience for the session. There are designed of pre and post CFQ questionnaires for the self-reporting assessments.

EEG Signal Acquisition Device

This study will be conducted using Emotiv Insight 2.0 (https://www.emotiv.com/). The device and the integrated electrode placement are represented in Figure 2. Emotiv Insight has 5 channels including AF3, AF4, T7, T8, and Pz. Then, Common Mode Sense (CMS) and Driven Right Leg (DRL) are 2 references on the left mastoid process. Sensor material is a Hydrophilic semi-dry polymer. The Emotiv Insight is wireless and can be connected to Bluetooth. It supports Bluetooth 5. However, the EEG signal sampling rate in a single electrode is 128 HZ per second. Frequency response is 0.5-43 Hz with a digital notch filter at 50 Hz and 60 Hz. This device comes with a built-in digital 5th-order Sinc filter. An internal Lithium Polymer battery of 480mAh is used that can run for 20 hours on a single charge. It is designed for research and development purposes and can be used in a variety of applications, including cognitive training, neurofeedback, brain-computer interfaces, and gaming.

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Figure 2: Emotiv Insight 2.0

Mental Fatigue Detection

The mental fatigue detection model will be formulated based on the six metrics of EPM consisting of stress, engagement, interest, excitement, focus, and relaxation. The EPM scored from 0 to 1. As example, if engagement metrics value is 0.1 then the individual is not engaged, whereas the value represents high engagement of the individual (https://emotiv.gitbook.io/cortex-api/data-subscription/data-sample-object#performance-metric). The detection of the mental fatigue will be determined by the mean value of the EPM metrics. The less value of EPM mean will indicate high fatigue and high value of EPM mean value will indicate less fatigue. The equation is following:

Summation of EPM metrics value = EPM_S
Number of EPM metrics = EPM_N
EPM mean, $EPM_M = EPM_S / EPM_N$

A self-assessment CFQ questionnaire will be used to measure. Original CFQ (Chalder et al., 1993) included total 14 questions, but the revised version includes 11 questions which is found more reliable and best fit for model creation (Cho et al., 2007; Jackson, 2015; Jing et al., 2016). The questions of Chalder Fatigue Scale (CFS) have two scoring system: Bimodal score and Likert score. The Scoring of Bimodal can be graded as “Yes” = 1 and “No” = 0. The detailed CFS is described in Table 4.

Table 4: Chalder Fatigue Scale (CFS)

Questions	Scoring Likert Scoring				Bimodal	
	less than usual	no more than usual	more than usual	much more than usual	No	Yes
1. Do you have problems with tiredness?	0	1	2	3	0	1
2. Do you need to rest more?	0	1	2	3	0	1
3. Do you feel sleepy or drowsy?	0	1	2	3	0	1
4. Do you have problems starting things?	0	1	2	3	0	1
5. Do you lack energy?	0	1	2	3	0	1

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6. Do you have less strength in your muscles?	0	1	2	3	0	1
7. Do you feel weak?	0	1	2	3	0	1
8. Do you have difficulties concentrating?	0	1	2	3	0	1
9. Do you make slips of the tongue when speaking?	0	1	2	3	0	1
10. Do you find it more difficult to find the right word?	0	1	2	3	0	1
11. How is your memory?	0	1	2	3	0	1

The Bimodal scoring will be used as the CFS to measure mental fatigue. The mental detection through EPM metrics will be validated by comparing with the CFS score. After that, a threshold value will be identified as neutral value to detect the onset of MF and apply monitors brightness as neurofeedback modality for intervention.

Notification System

The notification system contains a beep sound and a pop-up message. The system will notify the user who is most prone to fatigue and send notifications at those times.

Control of Neurofeedback Modality

The monitor screen brightness is the neurofeedback modality as an MF intervention strategy. The contrast of the monitor will be set to a default value by the recommendation of participants. When mental fatigue is detected, the screen brightness will be automatically adjusted to help participants maintain focus and attention during online learning sessions.

Experimental Protocol

At first the subject will get briefing about the whole session. Then, the participant will sign the online consent form, fill the demographic information form and pre-task CFQ questionary form. After that they will wear the Emotiv Insight heaset and set the monitor brightness based on their preference. There is 1 minute of eyes closed and 1 minutes of eyes resting task to prepare them for the online learning session. Then an online learning video will be presented to them. At the background the real-time MF intervention model will run to perform mental fatigue detection and intervention. After the session participant need to fill-up post-CFQ questionary form. The experimental process depicted in Figure 3.

Evaluation

The evaluation aspects include to find the Emotiv's Performance Metrics (EPM) efficiency to detect mental fatigue. Earlier literature review has shown that EPM can detect different mental states, but there is no study that support EPM for mental fatigue detection. This research aims to evaluate EPM for mental fatigue detection. The EPM mean value will be compared to the CFS score (describe in earlier section: mental fatigue detection). There will be a correlation coefficients and regression models as to validate the mental fatigue detection.

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Another evaluation aspect is the duration of mental fatigue recovery after the intervention. The study may determine whether the system is effective in reducing mental fatigue and inform the development of future interventions for mental fatigue. This research also aims to evaluate the contrasts effect on Mental Fatigue. The study can help create future mental fatigue solutions by determining whether the method is helpful at lowering mental fatigue in a variety of environmental situations. The evaluation of the duration of mental fatigue recovery and the contrast effects on mental fatigue as intervention includes the Pre and Post self-assessments questionnaires and the EPM metrics.

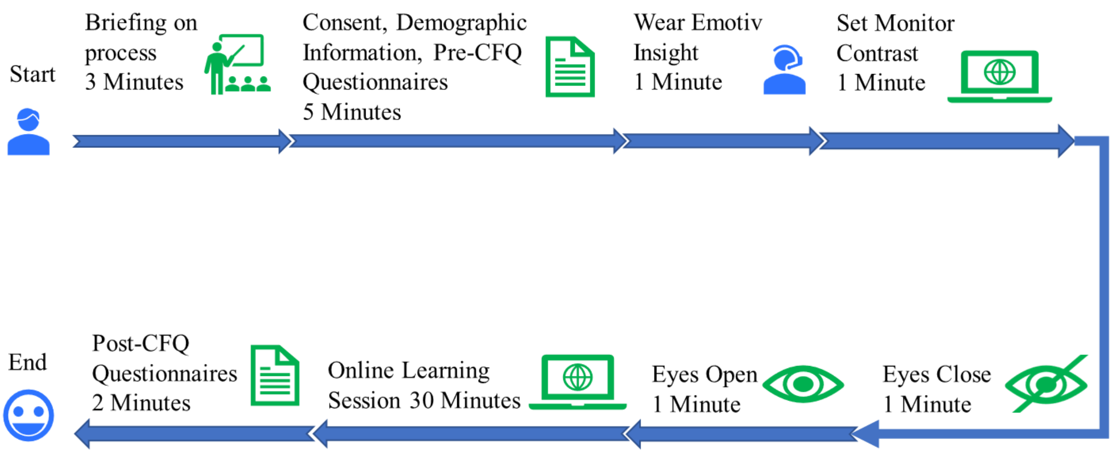

Figure 3: Experimental Protocol

Conclusion

The paper proposes a real-time mental fatigue intervention model using a Brain-Computer Interface (BCI) to detect and intervene in mental fatigue for online learners. By using EEG signals and Emotiv Performance Metrics (EPM) to detect mental fatigue and monitor brightness as a neurofeedback modality for intervention, this model can provide a personalized and non-invasive intervention strategy that is tailored to the individual's cognitive state. The closed-loop architecture of the model allows for continuous monitoring and intervention until mental fatigue is reduced. The proposed model has the potential to improve cognitive performance and reduce mental fatigue for online learners and can be applied in various settings. Future research can focus on optimizing the intervention technique and testing the effectiveness of the model in different populations.

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