An Adaptive Brain-Computer Interface Game with Blink Controls and Cognitive State Monitoring

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Abstract

Predicting affective and cognitive states through brain activity can enhance user experience, particularly in adaptive games that need to adjust difficulty according to the user's mood as gameplay progresses. While previous studies have focused on isolated applications of brain signals, integrating multiple brain-related features remains a challenge. We present an adaptive Brain-Computer Interface (BCI) game that processes electroencephalogram (EEG) signals in real-time, dynamically adjusting the difficulty and environment of the game based on detected mental fatigue, with blink activity serving as a control mechanism. Our preliminary results demonstrate an effective integration of multimodal biofeedback, providing valuable information on the usability of EEG for adaptive games.

CCS Concepts

• **Hardware → Biology-related information processing**; • **Human-centered computing**;

Keywords

Brain-Computer Interfacing; Electroencephalography; Adaptive Games; Cognitive load; Mental Fatigue; Blink Controls

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1 Introduction

Adaptive systems play an important role in improving user experiences by responding to real-time changes in cognitive and emotional states [16, 23]. With Brain-Computer Interfacing (BCI), such systems can leverage neural signals to tailor interactions, providing a personalized and engaging user experience [2, 15, 29, 35]. Electroencephalography (EEG), a noninvasive method for measuring brain activity, is a powerful tool for assessing user mental states, including cognitive load, fatigue, and affective responses [3, 4, 33].

We present an adaptive BCI game designed to dynamically adjust its difficulty and environment based on real-time EEG signals. The system integrates cognitive load and mental fatigue analysis with blink detection as a control mechanism. Unlike traditional games that rely solely on performance-based metrics for difficulty adjustment [12, 17], our proposed system incorporates neurophysiological data to provide a more nuanced understanding of the user's mental state, allowing for more effective adaptations.

The concept of adaptive games has already been explored in the research literature [1, 18, 21, 28, 30, 31], with applications ranging from dynamic difficulty adjustment [9, 26] to personalized learning environments [25]. Previous studies have demonstrated task-specific adaptations using EEG signals [5, 7, 10, 12, 18, 20]. However, these approaches often focus on isolated dimensions, such as minimizing cognitive load. In contrast, our game integrates multiple neurophysiological features to create a holistic adaptive framework that supports both the prediction of affective state and the control of active gameplay.

2 System Description

Our BCI game, based on the classic Chrome browser's "Dinosaur Game" [27], is designed to assess player performance and cognitive load using EEG signals. The player controls a dinosaur character by blinking their eyes, aiming to clear obstacles and reach a predetermined score of 50 points, following insights from previous work [14, 27].

2.1 Game Interface

The game interface, as illustrated in Figure 1a, incorporates the following elements. **(1) Score:** represents user performance and is calculated based on the number of successful jumps over obstacles. For each cleared obstacle, the player receives a point. **(2) Time:** indicates how long has passed since the start of the game. **(3) Difficulty:** indicates the current difficulty level. **(4) Progress bar:** shows how close the player is to completing the game. **(5) Background object:** passes through the screen from right to left and serves as a distraction. **(6) High obstacles:** are represented by a bird (or group of birds) flying over the character. **(7) Red obstacles:** the player

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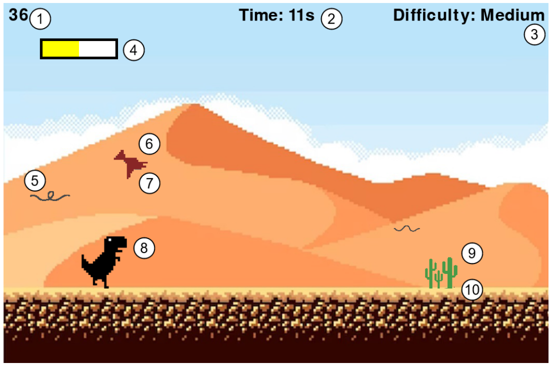
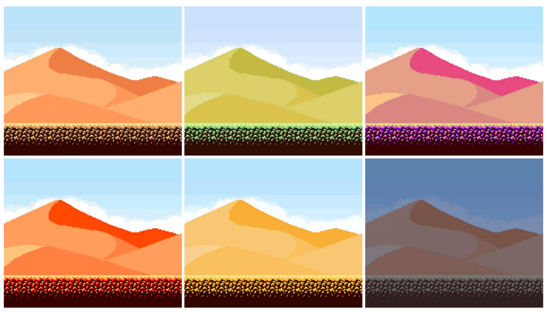
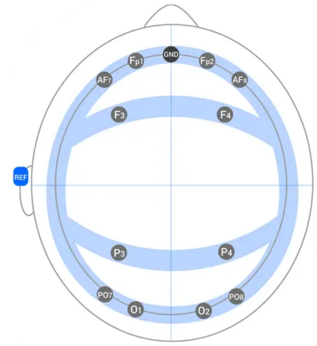


(a) Game screen

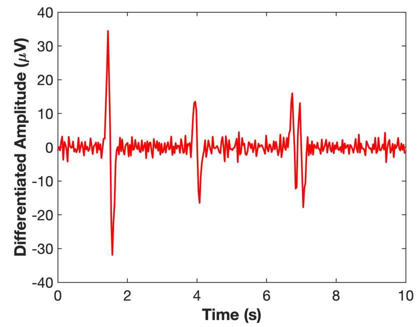


(b) Backgrounds

Figure 1: Annotated screenshot of the game (a) and background types (b).



(a) EEG channels



(b) Blink extraction

Figure 2: EEG channel locations (a) and extracted eye blink data (b) from an EEG signal.

must stay on the ground to avoid high obstacles and jump over low obstacles. **(8) Player character:** represented by a dinosaur, the only action it can perform is jumping at a predefined height of 218 px (considering that the screen is 700 px high and the ground level is at a height of 250 px). **(9) Low obstacles:** are represented by one or multiple cacti that approach the player at the character's running height. **(10) Green obstacles:** need to be passed through and *not* avoided.

2.2 Game Difficulty Levels and Adaptation

The BCI game is played in three difficulty levels: Easy, Medium, and Hard. In the **Easy** level, obstacles move slowly, are narrow, and appear less frequently, giving players ample time to react. At the **Medium** level, obstacles increase in speed and width, presenting a moderate challenge. In the **Hard** level, obstacles become significantly faster, wider, and more frequent, making the game highly challenging.

The game operates in two versions: non-adaptive and adaptive, each adjusting the difficulty in different ways. In the non-adaptive version, difficulty increases based solely on the player's score. The game adjusts the difficulty when the player reaches 33% and 66% of the target score, adding more obstacles and increasing their speed. There is no consideration of cognitive load in this version, and the difficulty progression is predictable, based only on the score.

The difficulty level in the adaptive version is adjusted based on both the player's success rate and cognitive load, with these factors considered concurrently to ensure balanced engagement. After the player has encountered ten low obstacles, the game calculates their success rate for the last 10 obstacles. If the success rate is 70% or higher, the difficulty increases, provided the player is not already at the highest difficulty. If the success rate is 40% or lower, the difficulty decreases, provided the player is not already at the lowest difficulty. If the success rate is between 50% and 60%, the difficulty remains unchanged. These thresholds were derived from pilot data analysis, where a 70% success rate indicated sufficient proficiency to increase difficulty without causing frustration, while the 40% lower bound prevented excessive failure and disengagement. The 50–60% range was identified as a balanced challenge, ensuring sustained engagement without unnecessary difficulty shifts.

2.2.1 Cognitive Load and Mental Fatigue Monitoring. Cognitive load is continuously monitored using the Theta-Alpha Ratio (TAR). If a significant change in trend or saturation in TAR is detected, the game adjusts the difficulty level to maintain optimal engagement (see Section 3). Furthermore, mental fatigue is continuously monitored using the frontal beta power, using Wavelet Packet Decomposition (WPD). If a significant increase in WPD is detected, the game alters the background color as a visual feedback mechanism to alert the player (Figure 1b). This background color change helps to reduce monotony, improves focus, and supports the player in maintaining a balanced cognitive load and mental fatigue.

2.3 Signal Processing

EEG data were acquired using the Bitbrain Diadem 12-channel EEG device (Figure 2a) with a sampling rate of 256 Hz. A 50 Hz notch filter was applied to remove powerline interference from the acquired EEG data. The eye blinks, cognitive load and mental fatigue features are derived from the 12-channel EEG data and they are extracted in real time during gameplay using two buffers: a 0.5-second buffer for eye blinks and a 2-second buffer for cognitive load and mental fatigue. These buffers are continuously updated, allowing for real-time adaptation and control based on feature changes [11, 34]. **Eye Blink Extraction.** Eye blinks are detected using the FP1 EEG channel. The raw data is down-sampled to 32 Hz, and a third-order Butterworth FIR band-pass filter (0.5 to 10 Hz) is applied to smooth the signal. To eliminate gradual trends, the discrete difference of the filtered data is computed [8]. Voluntary eye blinks are identified by detecting peaks in the signal and applying a threshold set individually for each participant; see Figure 2b.

Cognitive Load Estimation. As explained earlier, cognitive load is measured using TAR [22], calculated from EEG data recorded from the F3, F4, P3, and P4 channels. The data is band-pass filtered between 0.5 and 35 Hz, followed by a Fast Fourier Transform (FFT) to compute the TAR.

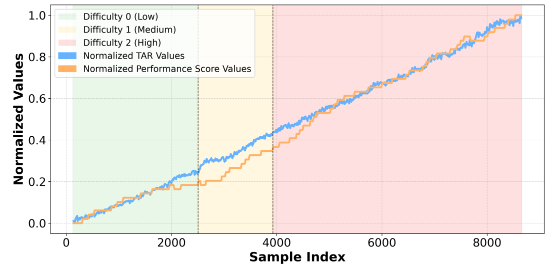
Mental Fatigue Estimation. As explained earlier, mental fatigue is assessed by analyzing frontal beta power via WPD, with Daubechies 10 wavelet (db10) as the mother wavelet [24, 32]. The EEG data, filtered between 0.5 and 45 Hz, is decomposed using a 7-level WPD. From the Wavelet Packet Coefficients (WPC), the Wavelet Packet Energy (WPE) is computed across frequency bands, with a specific focus on relative beta energy from the frontal channels (F3, F4).

3 Evaluation

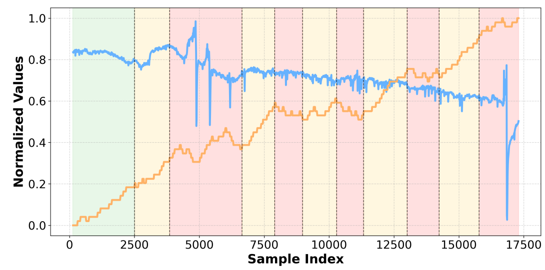
We recruited twenty-two participants (5 F, 17 M) with an average age of 26.23 years. Ten participants were pilot users, from whom we analyzed their data to understand the challenge of real-time adaptation based on cognitive load and mental fatigue. Based on their data, we fine-tuned the logic of the adaptive BCI game and subsequently tested it with the remaining 12 participants. There were no specific inclusion criteria for participating in the study. The study was approved by the Ethics Review Panel of the University of Luxembourg, under application ID ERP 22-071.

As a baseline condition, we considered the non-adaptive version of the game. Each participant played both the adaptive and non-adaptive versions, with the order of both conditions counterbalanced (Latin square design).

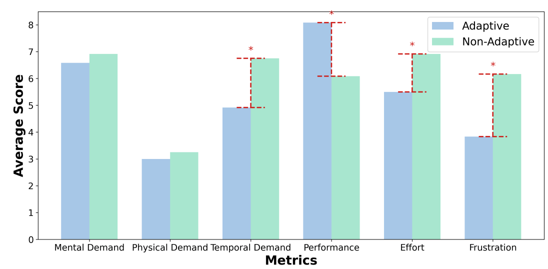
Figure 3a illustrates the behavior of the best performing participant in adaptive gameplay. The pastel green, yellow, and red areas represent changes in the difficulty of the game. As the game progresses, the overall score follows a linear curve, as expected, and the TAR also follows a similar linear trend, indicating controlled gameplay with focused attention and concentration. The allocation of cognitive load resources in the brain remains linear as the difficulty level increases. Figure 3b illustrates the behavior of the participant with the poorest performance in adaptive gameplay. Their score exhibits an oscillatory pattern and TAR is not linear. When the score enters a decaying phase, and the TAR fluctuates and exhibits a non-linear pattern, the difficulty level is decreased by one step. Therefore, the adaptive version helps the user maintain performance and reach the target score by dynamically adjusting the difficulty level based on their cognitive load.



(a) Best gameplay performance



(b) Worst gameplay performance



(c) NASA-TLX scores

Figure 3: Examples of best (a) and worst (b) gameplays, together with NASA-TLX scores (c). Asterisks denote statistically significant differences.

WPD remains steady when the participant is not fatigued. However, deviations from the mean and fluctuations in frontal beta power indicate the onset of mental fatigue. To mitigate visual saturation caused by prolonged exposure to the same background, the game changes the background color whenever the frontal beta power deviates by more than twice the standard deviation.

After each gameplay session (adaptive and non-adaptive), participants completed the NASA-TLX questionnaire [6, 13]. A paired t-test with Bonferroni correction was performed to assess statistical significance. As shown in Figure 3c, physical and mental demand were similar between the two game versions, whereas temporal demand, effort to finish the game, and frustration were higher for the non-adaptive version. In contrast, performance was higher for the adaptive version (this TLX dimension is measured in opposite direction). In sum, users performed better in the adaptive version.

4 Limitations and Future Work

Our limited sample size precludes generalizability but demonstrates the feasibility of our approach for cognitive state monitoring. Future work will scale up our evaluation and test different gaming environments. On the other hand, assuming a linear relationship between TAR and cognitive load may be simplistic. Future work should explore non-linear relationships and alternative EEG features, such as beta-band activity and alpha asymmetry. Finally, incorporating multimodal approaches, like combining EEG with eye-tracking, could further improve cognitive state estimation and adaptive systems, as shown in previous studies [19].

5 Conclusion

We have described the design, implementation, and evaluation of an adaptive BCI game that integrates cognitive load and mental fatigue detection with blink activity as input control. Our game demonstrates the potential of EEG-driven systems to enhance the user experience by adjusting game difficulty and environment in real-time. Our research highlights the viability of using biofeedback to create more user-centered interfaces, paving the way for future applications in both gaming and mental well-being enhancement.

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References

[1] Hamdi Ben Abdessalem, Maher Chaouachi, Marwa Boukadida, and Claude Frasson. 2019. How do Players' Eye Movements Relate to Their Excitement in a VR Adaptive Game?. In *The Thirty-Second International Flairs Conference*.

[2] Minkyu Ahn, Mijin Lee, Jinyoung Choi, and Sung Chan Jun. 2014. A review of brain-computer interface games and an opinion survey from researchers, developers and users. *Sensors* 14, 8 (2014), 14601–14633.

[3] Lena Andreessen, Peter Gerjets, Detmar Meurers, and Thorsten Zander. 2021. Toward neuroadaptive support technologies for improving digital reading: a passive BCI-based assessment of mental workload imposed by text difficulty and presentation speed during reading. *User Modeling and User-Adapted Interaction* 31 (03 2021).

[4] Nienke Atteveldt, Tieme Janssen, and Ido Davidesco. 2020. Measuring Brain Waves in the Classroom. *Frontiers for Young Minds* 8 (08 2020), 96.

[5] Valeria Carofiglio, Berardina Nadja De Carolis, Francesca D'errico, et al. 2019. A BCI-based Assessment of a Player's State of Mind for Game Adaptation.. In *GHITALY@ CHItaly*.

[6] Francesco Chiossi, Changkun Ou, Carolina Gerhardt, Felix Putze, and Sven Mayer. 2025. Designing and evaluating an adaptive virtual reality system using eeg frequencies to balance internal and external attention states. *International Journal of Human-Computer Studies* 196 (2025), 103433.

[7] Francesco Chiossi, Changkun Ou, Felix Putze, and Sven Mayer. 2024. Detecting Internal and External Attention in Virtual Reality: A Comparative Analysis of EEG Classification Methods. In *International Conference on Mobile and Ubiquitous Multimedia*.

[8] Saravanakumar D and Ramasubba Reddy M. 2020. A high performance asynchronous EOG speller system. *Biomed. Signal Process. Control.* 59 (2020), 101898.

[9] Kate C. Ewing, Stephen H. Fairclough, and Kiel Gilleade. 2016. Evaluation of an Adaptive Game that Uses EEG Measures Validated during the Design Process as Inputs to a Biocybernetic Loop. *Frontiers in Human Neuroscience* 10 (2016).

[10] Kate C Ewing, Stephen H Fairclough, and Kiel Gilleade. 2016. Evaluation of an adaptive game that uses EEG measures validated during the design process as inputs to a biocybernetic loop. *Frontiers in human neuroscience* 10 (2016), 223.

[11] Katie C. Ewing, Stephen H. Fairclough, and Kiel Mark Gilleade. 2016. Evaluation of an Adaptive Game that Uses EEG Measures Validated during the Design Process as Inputs to a Biocybernetic Loop. *Frontiers in Human Neuroscience* 10 (2016).

[12] Kosmas Glavas, Georgios Prapas, Katerina D Tzimourta, Nikolaos Giannakeas, and Markos G Tsipouras. 2022. Evaluation of the user adaptation in a bci game environment. *Applied Sciences* 12, 24 (2022), 12722.

[13] Sandra G Hart. 2006. NASA-task load index (NASA-TLX); 20 years later. In *Proceedings of the human factors and ergonomics society annual meeting*, Vol. 50. Sage publications Sage CA: Los Angeles, CA, 904–908.

[14] Yavuz Inal, Frode Volden, Gabrielle Nørgaard, Anna Eline Thømt Roksvåg, Eilert Forsberg Sommerfelt, and Erlend Stenersen Sæth. 2024. Effects of Gameplay Dynamics on Visual Attention. *IEEE Access* 12 (2024), 126961–126969.

[15] Wenjie Jin, XinXin Zhu, Lifeng Qian, Cunshu Wu, Fan Yang, Daowei Zhan, Zhaoyin Kang, Kaitao Luo, Dianhuai Meng, and Guangxu Xu. 2024. Electroencephalogram-based adaptive closed-loop brain-computer interface in neurorehabilitation: a review. *Frontiers in Computational Neuroscience* 18 (2024), 1431815.

[16] Tumaini Kabudi, Ilias Pappas, and Dag Håkon Olsen. 2021. AI-enabled adaptive learning systems: A systematic mapping of the literature. *Computers and Education: Artificial Intelligence* 2 (2021), 100017.

[17] Hasan Kandemir and Hatice Kose. 2022. Development of adaptive human–computer interaction games to evaluate attention. *Robotica* 40, 1 (2022), 56–76.

[18] Alexander Y. Kaplan, Sergei L. Shishkin, Ilya P. Ganin, Ivan A. Basyul, and Alexander Y. Zhigalov. 2013. Adapting the P300-Based Brain–Computer Interface for Gaming: A Review. *IEEE Transactions on Computational Intelligence and AI in Games* 5, 2 (2013), 141–149.

[19] Xingyu Long, Sven Mayer, and Francesco Chiossi. 2024. Multimodal Detection of External and Internal Attention in Virtual Reality using EEG and Eye Tracking Features. In *Proceedings of Mensch Und Computer 2024* (Karlsruhe, Germany) *(MuC '24)*. Association for Computing Machinery, New York, NY, USA, 29–43.

[20] David Marshall, Damien Coyle, Shane Wilson, and Michael Callaghan. 2013. Games, Gameplay, and BCI: The State of the Art. *IEEE Transactions on Computational Intelligence and AI in Games* 5, 2 (2013), 82–99.

[21] João Perdiz, Luís Garrote, Gabriel Pires, and Urbano J. Nunes. 2021. A Reinforcement Learning Assisted Eye-Driven Computer Game Employing a Decision Tree-Based Approach and CNN Classification. *IEEE Access* 9 (2021), 46011–46021.

[22] Bujar Raufi and Luca Longo. 2022. An Evaluation of the EEG alpha-to-theta and theta-to-alpha band Ratios as Indexes of Mental Workload. *Frontiers in Neuroinformatics* 16 (2022), 861967.

[23] Alina Schmitz-Hübsch, Sophie-Marie Stasch, Ron Becker, Sven Fuchs, and Maria Wirzberger. 2022. Affective response categories—toward personalized reactions in affect-adaptive tutoring systems. *Frontiers in artificial intelligence* 5 (2022), 873056.

[24] M Sifuzzaman, M Rafiq Islam, and MZ Ali. 2009. Application of wavelet transform and its advantages compared to Fourier transform. (2009).

[25] Adi Stein, Yair Yotam, Rami Puzis, Guy Shani, and Meirav Taieb-Maimon. 2017. EEG-Triggered Dynamic Difficulty Adjustment for Multiplayer Games. *Entertainment Computing* 25 (12 2017).

[26] Adi Stein, Yair Yotam, Rami Puzis, Guy Shani, and Meirav Taieb-Maimon. 2018. EEG-triggered dynamic difficulty adjustment for multiplayer games. *Entertain. Comput.* 25 (2018), 14–25.

[27] Keyword Team. 2018. As the chrome dino runs, we caught up with the Googlers who built it. https://blog.google/products/chrome/chrome-dino/

[28] Stephen Vickers, Howell Istance, and Aulikki Hyrskykari. 2013. Performing Locomotion Tasks in Immersive Computer Games with an Adapted Eye-Tracking Interface. *ACM Trans. Access. Comput.* 5, 1, Article 2 (Sept. 2013), 33 pages.

[29] Carmen Vidaurre, A Schlogl, Rafael Cabeza, Reinhold Scherer, and Gert Pfurtscheller. 2006. A fully on-line adaptive BCI. *IEEE Transactions on biomedical engineering* 53, 6 (2006), 1214–1219.

[30] C. Vidaurre, A. Schlogl, R. Cabeza, R. Scherer, and G. Pfurtscheller. 2006. A fully on-line adaptive BCI. *IEEE Transactions on Biomedical Engineering* 53, 6 (2006), 1214–1219.

[31] Amanda Wikholm, A Önnered, CM Gulmann, S Egli, and V Wipp Ekman. 2019. Real-time adjustable feedback based on eye tracking algorithms in educational games. *Haake, M., Gulz, a., Balkenius, C., Wallergård, M.(Eds.).(2019). Intelligent, socially oriented technology IV. LUCS* 175 (2019).

[32] Rui Xu, Chuncui Zhang, Feng He, Xin Zhao, Hongzhi Qi, Peng Zhou, Lixin Zhang, and Dong Ming. 2018. How physical activities affect mental fatigue based on EEG energy, connectivity, and complexity. *Frontiers in neurology* 9 (2018), 915.

[33] Xiangkun Yu, Zhengjie Li, Zhibang Zang, and Yinhua Liu. 2023. Real-Time EEG-Based Emotion Recognition. *Sensors* 23 (09 2023), 7853.

[34] Xiangkun Yu, Zhengjie Li, Zhibang Zang, and Yinhua Liu. 2023. Real-Time EEG-Based Emotion Recognition. *Sensors* 23, 18 (2023), 7853.

[35] Rui Zhang, Chushan Wang, Shenghong He, Chunli Zhao, Keming Zhang, Xiaoyun Wang, and Yuanqing Li. 2023. An adaptive brain-computer interface to enhance motor recovery after stroke. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 31 (2023), 2268–2278.