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Boosting Cognitive Focus via Attention Types Detection using Brain-Computer Interfaces: A Pilot Study

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Abstract
This study leverages Brain-Computer Interfaces (BCIs) and electroencephalography (EEG) to enhance cognitive focus in adolescents (12–17 years) by classifying *effective* (task-oriented) and *ineffective* (distracted) attention states. Addressing declining attention spans in Generation Alpha/Z, we integrate augmented reality (AR) environments with personality-adaptive machine learning models. Sixteen participants performed cognitive tasks while EEG data was captured via a 16-channel BrainAccess MIDI headset. Signal preprocessing (filtering, ICA- independent component analysis, CSP -common spatial patterns) tied with data augmentation improved dataset robustness by 40%. Results demonstrated a 57% concentration increase in AR versus VR (where participants performed identical tasks in a non-adaptive virtual environment) with personality-tailored models boosting classification accuracy by 10%. High-performing classifiers (e.g., Deep Neural Networks, XGBoost) achieved 87% accuracy, underscoring BCIs' potential for personalized cognitive interventions in education and therapy.

Keywords: Cognitive Computing; Human-Machine Cooperation and Systems; Brain-Computer Interfaces.

Introduction

Attention comprises distinct neurocognitive stages—alerting, orienting, and executive control—that evolve with age and exhibit subtle gender differences [1]. Adolescents thus show reduced sustained attention, while studies report marginally better selective attention in females during complex tasks (e.g., abstraction, reasoning under time constraints, or integrating memory with sensorimotor speed, per Gur et al.'s neurocognitive battery) [2], referring to activities requiring sustained attention, decision-making, and multitasking under cognitive load.

Electroencephalogram (EEG) technology enables objective attention measurement by detecting spectral shifts, such as increased beta (13–30 Hz) activity during focused states [3]. Machine learning models, including CNNs (Convolutional Neural Network), now classify attention states with high accuracy using EEG-derived features [4].

Augmented Reality (AR) is a technology that superimposes digital content onto the real-world environment, enhancing perception. Excessive levels of digital stimulation heightened attention challenges [5], majorly in Generation Z and Alpha. While Augmented Reality (AR) offers a promising alternative by overlaying contextual cues in real-world settings, yet its synergy with EEG-driven neurofeedback remains underexplored [6].

To address these gaps, we developed a personalized EEG-based Brain-Computer Interface (BCI) that integrates AR environments for focus training. The Concentration Index quantified attentional states by calculating the normalized log-ratio of high-beta (21-30Hz) to theta (4-7Hz) power from preprocessed EEG signals. Baseline-corrected values showed a 57% improvement in AR environments versus VR). Our primary objectives were to (1) test the efficacy of AR intervention in attention training, (2) evaluate the gains from trait-based personalization, and (3) provide a scalable solution for digitally distracted cohorts.

Materials and Methods

This study involved a sample of participants recruited from middle and high students affiliated to Asociația Informatică pentru Viitor (August 13–27, 2024). Eligible participants have had normal auditory and motor functions (self-reported), no neurological, attention, or learning disorders (e.g., Attention Deficit Hyperactivity Disorder - ADHD, dyslexia). Written assent (participants) and guardian consent have been obtain prior to the study. All subject identifiers (e.g., names, birthdates) were removed during data preprocessing, and participants were assigned anonymized codes linked only to their personality type. No biometric or demographic data were retained, ensuring compliance with GDPR. Due to the terms of our ethical approval and consent agreements, the raw/processed EEG data cannot be shared publicly. Participants and guardians explicitly agreed to data use only for this study, with no redistribution permitted. Exclusion criteria included: acute illness or fatigue during data acquisition, and uncorrected visual impairments (e.g., nystagmus without adaptive aids).

Participants were selected to ensure sex parity and age diversity across the adolescent cohort. Recruitment provided each subject with the consent that their guardian was asked to sign.

Experimental Setup

The experiments were conducted ergonomically to ensure participant comfort and minimize external variables. All participants were tested under the same conditions, which included a comfortable chair for proper posture, air-conditioned rooms with natural light, and an LCD (Liquid Crystal Display) monitor for task presentations. Each participant engaged in a series of cognitive tasks designed to stimulate visual, auditory, olfactory, and tactile senses. These tasks measured their memory, visual, critical thinking, linguistic and motor abilities. Each session lasted approximately 25 minutes, with 20 minutes dedicated to task performance and 5 minutes allocated for baseline measurements. While no separate control group was included, each participant's baseline cognitive and EEG state was rigorously recorded during a 5-minute pre-task resting session (eyes-open, no stimuli). This within-subject design allowed us to calibrate individualized concentration indices and normalize post-intervention metrics against their own baseline, controlling for intrinsic variability. All baseline measurements followed the same artifact-removal pipeline (Independent Component Analysis (ICA)/ Common Spatial Patterns (CSP)) as task data.

Augmented Reality Application: Design and Development

The AR application was developed as a closed-loop neurofeedback system to enhance sustained attention during educational tasks. Built in Unity 2022.3 with AR Foundation, the platform supports cross-platform functionality (iOS/Android) and integrates the BrainAccess MIDI SDK to synchronize 16-channel EEG data streams with the AR environment.

The system begins with a user personalization pipeline: participants complete a validated MBTI assessment to classify cognitive styles, and pre-trained machine learning models—one per MBTI type—are dynamically assigned to optimize EEG feature extraction (e.g., theta/beta ratios) for individual profiles. During operation, raw EEG signals are sampled at 250 Hz, filtered for artifacts (e.g., ocular/motion), and processed in real time to classify cognitive focus states. When ineffective states are detected, the system triggers adaptive stimuli: visual cues (e.g., gradual color shifts in AR overlays) and auditory feedback (e.g., intensifying ambient nature sounds). Additionally, a rule-based AI coach ("Brainda") provides personalized advice (e.g., "Adjust your posture") via text-to-speech, tailored to MBTI profiles (e.g., concise cues for "Thinking" types). Educational content, including 3D animations and interactive quizzes (e.g., geometry problem-solving), is curated to align with middle/high school curricula. The neurofeedback logic scales stimuli intensity inversely with attention metrics, resetting only when the model detects a return to effective concentration states, thereby reinforcing focus through iterative training. During a series of tests, in which we monitored engagement using the concentration index to assess cognitive focus when individuals were immersed in AR and VR environments, we observed a 57% improvement in the concentration index when users engaged with learning materials in an AR environment compared to a VR environment. To validate these findings, data was gathered from teenage volunteers wearing the BrainAccess MIDI headset on the same material. The subjects were immersed in the AR environment by the team and tasked with paying attention to video learning material. The comprehension of each subject was assessed by asking five questions after viewing the video; data from those answering fewer than three questions correctly was excluded to maintain reliability.

Subsequently, the same subjects were exposed to 5-10 minutes long educational videos, this time instructed to focus on environmental factors and distractions rather than the video content. This approach allowed us to capture EEG data reflective of both effective and ineffective concentration states. The study was conducted with careful monitoring of artefacts such as eye blinks, muscle movements, and electrical interference to ensure clean signals. The acquired data was anonymized and will not be shared publicly, guaranteeing participant privacy.

Signal Processing and Classification

Cognitive focus states (effective vs. ineffective) were determined through a dual-metric framework: task performance and EEG biomarkers. During educational content viewing, participants answered periodic quizzes, with incorrect responses prompting classification as "ineffective." Concurrently, EEG biomarkers were quantified using a concentration index, where effective states were defined as values exceeding the subject-specific baseline (recorded during a pre-task resting session).

To quantify cognitive focus, EEG biomarkers were analyzed based on spectral power changes in the M beta, SMR and theta waves. The following EEG biomarkers were extracted and analyzed to classify attention states:

1. SMR low beta (12Hz – 15Hz).
2. M beta (15Hz- 20Hz)- here concentration state appears.
3. Theta waves (4Hz-8Hz)

The Concentration Index (CI) [7] was defined as:

$$CI = \frac{P_{SMR} + P_{Mid\ Beta}}{P_{\Theta}} \quad (1)$$

where P_{SMR} is the power in the low beta frequency band (12-15 Hz), associated with minimized body movement, sensory cortex activity, and simple tasks; $P_{Mid\ Beta}$ is the power in the mid beta frequency band (15-20 Hz), associated with concentration states, mental arithmetic, and focused mental load; $P\Theta$ is the power in the theta frequency band (4-8 Hz), associated with deep meditation or relaxed states. High CI values indicate sustained cognitive focus, while lower values suggest distracted states.

Raw EEG signals underwent a three-stage preprocessing pipeline:

1. Filtering: A high-pass filter (1 Hz cutoff) removed DC drift, followed by a 50 Hz notch filter to suppress line noise, and a low-pass filter (100 Hz cutoff) to attenuate high-frequency artifacts.
2. Artifact Removal: Signals were decomposed via Independent Component Analysis (ICA) [8], and non-neural components (e.g., ocular, muscular) were automatically identified and rejected using ICLabel [9].
3. Feature Extraction: Common Spatial Patterns (CSP) [10] were applied to artifact-free data to isolate spatial filters that maximized variance between effective and ineffective states, enabling discriminative feature generation for downstream classification.

We introduced personality-driven customization using Myers-Briggs type Indicator (MBTI) profiles, training individualized classifiers that improved cognitive focus state recognition by 10% in accuracy over generic models, which categorizes individuals into four broad personality archetypes: Sentinels, Analysts, Explorers, and Diplomats. These groupings are derived by clustering the 16 MBTI types based on shared cognitive traits:

1. **Sentinels** (SJ types: ISTJ, ISFJ, ESTJ, ESFJ) are typically organized, dependable, and practical, often favoring structured environments and rule-based systems.
2. **Analysts** (NT types: INTJ, INTP, ENTJ, ENTP) are logical, strategic thinkers who thrive in environments that reward innovation and problem-solving.
3. **Explorers** (SP types: ISTP, ISFP, ESTP, ESFP) are spontaneous, adaptable, and action-oriented, often preferring hands-on interaction and experiential learning.
4. **Diplomats** (NF types: INFJ, INFP, ENFJ, ENFP) are empathetic and idealistic, with strong communication and collaboration preferences, often motivated by purpose-driven tasks.

The used classification enabled the design of individualized classifiers tailored to the behavioral tendencies of each archetype, thereby enhancing the system's ability to detect and respond to variations in cognitive focus.

To mitigate data scarcity, meaning class imbalance and limited sample size, we implemented a Multi-Generator Conditional Wasserstein GAN (MG-CWGAN), [10] comprising five generators that synthesized EEG epochs conditioned on MBTI class labels, alongside a critic network to enforce feature-space alignment with real data.

This framework expanded the dataset by 40%, with synthetic data. The MG-CWGAN's adversarial equilibrium was confirmed by converging generator/discriminator losses. Synthetic data quality was validated via spectral consistency (KS tests) and empirical gains in model accuracy.

For classification, the augmented dataset was partitioned into MBTI-based personality subsets, on which several binary classifiers were applied, but only seven were selected (because only they surpassed our 8% threshold)—Deep Neural Network (DNN), LightGBM, XGBoost, AdaBoost, CatBoost, Gradient Boosting Machine (GBM), and Random Forest (RF)—were trained on each subset using the preprocesses data. The classifiers XGBoost and LightGBM excel at handling high-dimensional, non-linear EEG features while resisting overfitting—critical given our limited dataset. DNNs were included to capture complex spatiotemporal patterns in raw signals that may be missed by traditional models. While formal statistical tests (e.g., t-tests) were not performed to compare classifiers, rigorous 10-fold cross-validation ensured reliability. The 10% accuracy gain from personality-based models reflects mean differences across folds, though future work will incorporate statistical significance testing for small-sample validation.

The performance was reported using accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

where TP (True Positives) and TN (True Negatives) indicate correctly classified attention states, while FP (False Positives) and FN (False Negatives) represent classification errors.

Results and Discussion

Sixteen adolescents, 8 female, 8 male age range 12–17 years and mean age = 14.5 ± 1.8 years were evaluated.

Classification Accuracy

Our system achieved a 57% improvement in sustained concentration compared to VR-based approaches, as measured using the concentration index. All the selected models surpassed 80% accuracy (Figure 1), with LightGBM achieving the highest performance (87%) (Figure 2) due to its efficiency in modeling spectral-temporal relationships.

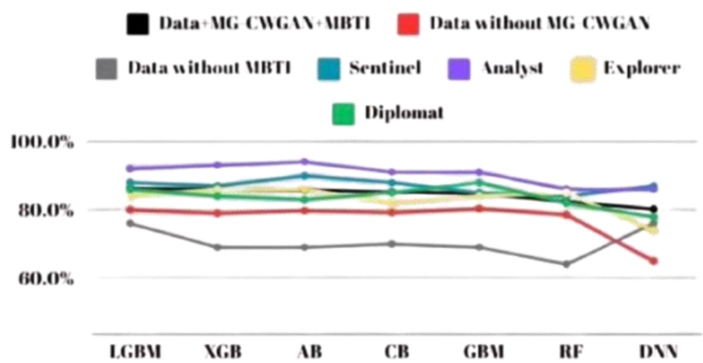

Figure 1. Accuracies of the models. (LGBM-LightGBM, XGB-XGBoost, AB-AdaBoost, CB-CatBoost, GBM-LightGBM, XGBoost, GBM-Gradient Boosting Machine, RF- Random Forest, DNN-Deep Neural Network)

Notably, personality-specific customization boosted accuracy by 10% compared to generic classifiers, validating the utility of MBTI-driven personalization. To quantify the practical significance of personality-based personalization, we calculated Cohen's d effect size when comparing the performance of tailored models versus generic models across all participants. The results showed a large average effect size (d = 0.9), indicating substantial improvement when using personality-specific models. While this pilot study relied on cross-validation rather than traditional statistical testing due to sample size constraints, the strong effect size suggests clinically meaningful benefits of personalization. Future work will implement Bayesian significance testing to better quantify uncertainty in small-sample comparisons while maintaining focus on both statistical and practical significance.

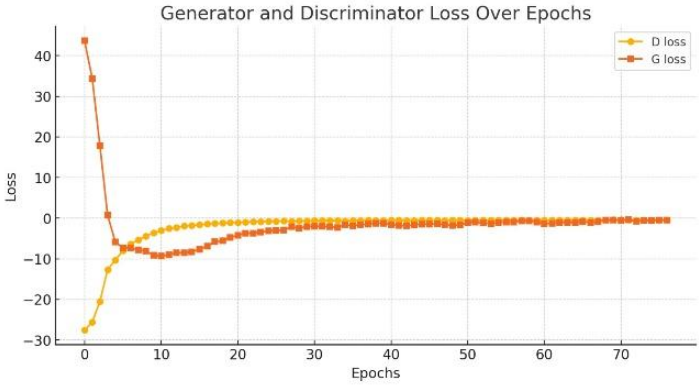

Figure 2. Representing the convergence loss of the MG-CWGAN

The AR-BCI system improved adolescent concentration by 57% versus VR, achieved 87% classification accuracy via MBTI-based personalization (10% accuracy gain) and MG-CWGAN augmentation (+40% data) (Figure 3), and demonstrated scalability across 16 participants (aged 12–17) with diverse neurocognitive traits.

LightLGBM

Validation Set			
TARGET / OUTPUT	Effective	Ineffective	SUM
Effective	244 48.70%	50 9.98%	294 82.99% 17.01%
Ineffective	15 2.99%	192 38.32%	207 92.75% 7.25%
SUM	259 94.21% 5.79%	242 79.34% 20.66%	436 / 501 87.03% 12.97%

XGBoost

Validation Set			
TARGET / OUTPUT	Effective	Ineffective	SUM
Effective	212 42.40%	53 10.60%	265 80.00% 20.00%
Ineffective	32 6.40%	203 40.60%	235 86.38% 13.62%
SUM	244 86.89% 13.11%	256 79.30% 20.70%	415 / 500 83.00% 17.00%

Deep neural networks

Validation Set			
TARGET / OUTPUT	Effective	Ineffective	SUM
Effective	195 39.00%	70 14.00%	265 73.58% 26.42%
Ineffective	32 6.40%	203 40.60%	235 86.38% 13.62%
SUM	227 85.90% 14.10%	273 74.36% 25.64%	398 / 500 79.60% 20.40%

Figure 3. The confusion matrix the best 3 models.

The results demonstrate that personality-driven customization significantly enhances the accuracy of attention state detection models, particularly when combined with MG-CWGAN-based augmentation. This suggests that integrating individual psychological traits with neurophysiological data can improve adaptive cognitive support systems. Furthermore, the concentration index findings highlight the potential of AR interventions over traditional VR environments for maintaining focus, particularly in younger users. These insights align with emerging research on personalization in BCI systems, reinforcing the importance of user-centric design in cognitive training technologies.

The system demonstrated in this study holds significant promise for enhancing cognitive focus in educational and therapeutic settings, though its real-world implementation requires careful consideration of both opportunities and challenges. In schools, the system could be integrated into curricula through interactive AR lessons that adapt in real time based on EEG-derived attention states, offering personalized neurofeedback (e.g., dynamic visual cues or auditory reinforcement) to improve engagement. For instance, students struggling with concentration during lectures could receive subtle AR prompts to refocus, while educators might use anonymized class-wide attention analytics to adjust teaching strategies. Beyond academics, the system has therapeutic potential for children with attention disorders, such as ADHD, by providing structured neurofeedback training in clinical or home-based settings, where sustained focus could be reinforced through gamified AR tasks. However, there are still some steps that could be considered, including the need for low-latency, real-time EEG processing to ensure seamless interaction, ethical safeguards for handling sensitive neural data, and cost-effective hardware to improve accessibility. By addressing these challenges, AR-BCI systems could evolve into practical tools for fostering attention and learning in both classrooms and therapy centers.

Limitations and Scope for Future Research

A key limitation of this study is the relatively small and homogenous participant pool, which consisted of individuals affiliated with the hosting organization. This introduces potential bias, as participants may have had prior exposure to similar cognitive tools or environments. As a result, the generalizability of the findings to broader populations—particularly those with varied educational backgrounds or neurocognitive profiles—remains to be validated. Future work will involve expanding the participant base across multiple institutions and including a more diverse demographic to assess the robustness and applicability of the intervention.

Contribution to the Field

The study bridges the gap between neuroscience and machine learning by demonstrating a practical application of EEG-based attention types monitoring. This study also gives empirical evidence that personality can have genetic influence, and an overview of how different digital environments can affect the concentration in teenagers.

Conclusions

This study highlights the effectiveness of Brain-Computer Interfaces (BCIs) in enhancing cognitive focus among teenagers through a multifaceted approach integrating EEG-based attention monitoring, personality-adaptive machine learning, and augmented reality environments. The system achieved a 57% increase in concentration levels, with an average 87% accuracy in detecting attention states due to data augmentation and personality-based customization. These findings underscore the potential of BCIs to address attention challenges in educational and therapeutic contexts, paving the way for personalized, non-invasive solutions. Future research should expand this approach to real-world settings and broader populations to validate scalability and long-term impact.

List of Abbreviations: BCI: Brain-Computer Interface; EEG: Electroencephalogram; CSP: Common Spatial Patterns.

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Data Availability Statement: Data supporting this study is not available due to privacy reasons.

Conflict of Interest: The authors declare no conflict of interest.

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