BRIGHTMINDS - Adaptive Learning Platform with Focus Tracking for Autistic Children

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***Abstract*—Educators working with autistic students face challenges in addressing highly individualized learning and attention patterns using conventional e-learning platforms. These systems lack the adaptability required to respond to the cognitive and neurological diversity of autistic learners, limiting learning effectiveness. This paper presents an AI-driven neuroadaptive learning framework that integrates electroencephalography (EEG) sensors to continuously monitor attention and cognitive engagement. A Generative Artificial Intelligence (GenAI) model is employed to produce personalized instructional content and assessments, while a reinforcement learning (RL) agent uses quiz outcomes and EEG-derived attention scores as reward signals to adapt content difficulty, modality, and pacing. The framework also includes a personalized analytics dashboard that provides educators with insights into attention trends and learning progress. By aligning instructional content with real-time neurophysiological feedback, the proposed system enhances engagement, personalization, and learning efficiency for autistic students, demonstrating the potential of neuroadaptive AI in inclusive education.**

***Index Terms*—Autism Spectrum Disorder (ASD), Neuroadaptive Learning, Electroencephalography (EEG), Generative Artificial Intelligence, Reinforcement Learning.**

I. Introduction

The growing convergence of technology and inclusive education has opened up unprecedented opportunities to create engaging learning environments that can accommodate a wide range of cognitive and sensory needs. However, designing effective educational systems for children with Autism Spectrum Disorder (ASD) requires an understanding that autism is not a single, uniform condition. Neuroimaging research has revealed substantial variation in brain structure and function among individuals with ASD, demonstrating that autistic children exhibit diverse cognitive, neurological, and behavioral profiles rather than a common developmental pattern [9]. This diversity highlights the need for educational approaches that go beyond one-size-fits-all solutions.

ASD is a neurodevelopmental condition characterized by differences in social communication, the presence of restricted or repetitive behaviors, and variability in attention, sensory processing, and learning styles. Within this broad spectrum, children with mild or borderline ASD often display functional verbal and cognitive abilities, but may experience difficulties with sustained attention, social interaction, and adapting to changing learning demands. Addressing these challenges, this work focuses on developing an integrated learning environment tailored for children aged 10–15 years with mild or borderline ASD. The proposed system supports a range of learning activities designed to align with their specific cognitive and attentional needs.

Recent estimates indicate that approximately 1–1.5% of children in India are affected by ASD, corresponding to roughly one in every 70 to 100 children. This represents a significant population of students who may benefit from specialized educational support in both mainstream and special education settings. Children with mild autism are often of average or above-average intelligence, yet they may face challenges related to social communication, sensory sensitivities, and adapting to change. Conventional educational systems and computer-based learning platforms frequently present excessive visual stimuli, leading to complex navigation, unpredictable interface behavior, and sensory overload. Such environments can cause anxiety and reduce comprehension among autistic learners.

This project is grounded in the understanding that thoughtfully designed technology can serve as a powerful equalizer by offering structured, predictable, and customizable learning experiences aligned with school curricula. The proposed platform is built on the principle of adaptive personalization. Rather than relying on fixed learner categories, it dynamically adjusts instructional content based on each child's evolving preferences and needs. Multiple learning dimensions—including content delivery style, difficulty level, visual intensity (such as color schemes, animations, and layout density), narration tone, pacing, and overall complexity—are personalized in real time. This adaptive approach helps ensure that learning remains engaging without becoming overwhelming, thereby supporting the diverse attention patterns, comfort levels, and sensory preferences of children with autism.

II. Methodology

The proposed methodology presents an AI-driven neuroadaptive learning platform that integrates Generative Artificial Intelligence, Reinforcement Learning (RL), and EEG-based attention monitoring to deliver personalized instruction for autistic learners. The system is designed as a closed-loop adaptive framework that continuously optimizes learner engagement and instructional effectiveness by jointly leveraging neural and behavioral feedback signals [1]–[3].

This section describes the overall system design, architectural modules, and the adaptive feedback mechanism that enables long-term personalization.

A. System Overview

This is an adaptive learning system that personalizes educational content in real time for autistic learners by combining behavioral interaction data with EEG-derived attention measures. Generative AI is employed for dynamic content generation, Reinforcement Learning is used for sequential pedagogical decision-making, and non-invasive EEG sensing provides continuous monitoring of cognitive engagement during learning activities [1], [4], [5].

The primary objective of the system is to dynamically adjust instructional parameters—such as task difficulty, visual presentation, and auditory cues—based on the learner's moment-to-moment attention and performance patterns. This approach aligns with recent advances in RL-based intelligent tutoring systems and neuroadaptive learning environments [2], [6].

B. System Architecture

The overall system architecture follows a modular closed-loop design comprising four core components:

- EEG-Based Attention Monitoring Module
- Reinforcement Learning–Based Adaptive Decision Module
- Generative AI Content Generation Module

These components interact through a shared state representation and continuous feedback signals, allowing the system to iteratively refine personalization strategies across learning sessions [3], [6].

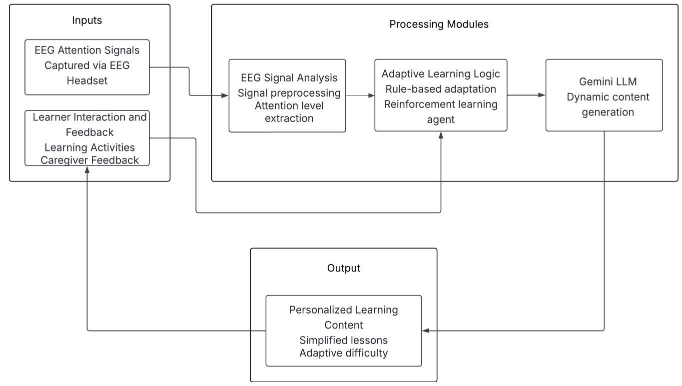

Fig. 1. Working architecture of the EEG-driven adaptive learning system.

At each decision step, the learner interacts with content generated by the Generative AI module. Behavioral and EEG data are collected and fused into a unified state vector. Based on this state, the RL agent selects an adaptation action, and the resulting reward signal guides policy updates aimed at long-term engagement optimization [2].

C. Learner Interaction Module

The Learner Interaction Module serves as the digital interface through which autistic learners participate in structured activities such as reading tasks, visual prompts, and simple problem-solving exercises aimed at developing foundational skills. As learners interact with these activities, the system records behavioral data such as response time, task completion rate, accuracy, and selection patterns. These measures are commonly used in intelligent tutoring systems as indicators of engagement and learning progress. [4], [6], [7].

The behavioral features derived from learner interactions play a dual role in the system. They provide a reliable backup for estimating attention when EEG signals are noisy or momentarily unavailable, and they also form part of the reinforcement learning state representation by supplying performance-related information that guides future adaptation decisions. [3].

D. EEG-Based Attention Monitoring

Attention monitoring employs non-invasive EEG devices, which are progressively utilized in autism research and educational neuroscience owing to their portability, safety, and compatibility with children [4], [10]. In this study, EEG signals were obtained using a wearable headset at a sampling rate of approximately 256 Hz, a standard rate employed in portable EEG systems for real-time cognitive monitoring [1]. The system concentrates on frequency-domain EEG characteristics, specifically the alpha (8–13 Hz) and beta (13–30 Hz) bands derived from short-time analysis windows, as these rhythms are significantly linked to attentional regulation and cognitive involvement during learning activities [5], [8].

Beta-band activity is generally correlated with concentrated cognitive effort and active participation in tasks, while alpha-band rhythms are connected to a state of relaxed vigilance and the inhibition of extraneous sensory input [5]. The EEG signals are first preprocessed through a signal conditioning pipeline consisting of band-pass filtering (1–40 Hz) to remove low-frequency drift and high-frequency noise, followed by artifact correction to reduce interference from eye blinks, motion, and muscle activity [1]. After being filtered, the signals are normalized and split into short time windows. Then, the Fast Fourier Transform (FFT), a common method for spectral analysis of EEG signals, is used to find frequency-domain features [8].

From these spectral features, an attention index is computed based on the relative power of attention-related frequency bands. In particular, the system estimates attention using the ratio between beta activity and slower rhythms, which has been shown to correlate with cognitive engagement during attention-demanding tasks [1], [5]. The attention score is calculated as:

$$Attention\ Score = \frac{\beta\ power}{\alpha\ power + \theta\ power}$$

where β represents beta-band power, α represents alpha-band power, and θ represents theta-band power. The resulting value is normalized to a standardized 0–100 scale to enable consistent comparison across learners and sessions. Similar normalized attention scoring approaches are commonly used in EEG-based cognitive monitoring systems and neurofeedback applications [1], [8]. Based on this normalized score, the learner's attentional state is categorized into three levels: low attention (0–40), medium attention (40–70), and high attention (70–100), following commonly used thresholds in EEG-based attention classification studies [5], [10].

Recent studies on EEG analytics in autism indicate that EEG-based models can reliably characterize attentional states and atypical neural patterns in autistic populations, supporting the feasibility of integrating EEG-derived attention measures into adaptive educational systems [10]. The resulting attention level is incorporated into the reinforcement learning (RL) state representation, allowing the adaptive learning system to ground its pedagogical decisions in both neural and behavioral evidence.

E. Reinforcement Learning for Content Adaptation

The adaptive decision-making process is formulated as a Markov Decision Process (MDP). The state S_t at time step t includes:

1) EEG-derived attention level,
2) the student's recent performance metrics (accuracy, response latency, and task completion rate),
3) current task difficulty, and
4) presentation parameters such as color themes and voice characteristics.

This representation is analogous to state representations used in reinforcement learning-based adaptive tutoring and recommendation systems [2], [3]. By incorporating both neural and behavioral measures, the model accounts for cognitive engagement and performance.

The action set A_t comprises various adaptations that can be made by the model to optimize engagement. This includes making the content easier or harder, changing visual themes and density, changing narration speed or tone, and adding breaks or reinforcement sounds. These adaptations are common in intelligent tutoring systems and are used to modulate cognitive load and engagement [6]. The reward function R_t is designed to encourage sustained attention and improved learning outcomes. Positive rewards are assigned when attention levels increase or when quiz performance improves, while negative rewards are applied when attention decreases or tasks are abandoned. Formally, the reward signal is defined as

$$R_t = w_1 \Delta A_t + w_2 P_t$$

where ΔA_t represents the change in attention level between consecutive time steps, P_t denotes quiz performance (accuracy), and w_1 and w_2 are weighting parameters controlling the contribution of attention and performance signals. In this implementation, greater emphasis is placed on sustained engagement to ensure that learning remains cognitively comfortable for autistic learners.

Due to the absence of fully labeled datasets and the requirement for online personalization, a model-free reinforcement learning approach is employed. Specifically, the system uses a Q-learning algorithm to learn an optimal policy $\pi(a|s)$ that maximizes long-term cumulative reward. The Q-value update rule is defined as:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \left[r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t) \right]$$

where α is the learning rate, γ is the discount factor controlling the importance of future rewards, and r_t is the reward received after executing action a_t in state s_t. The agent iteratively updates its policy through repeated learner interactions, gradually discovering adaptation strategies that improve both engagement and learning performance.

The process of exploration during training is managed using an ϵ-greedy policy, where an agent chooses a random action with a probability ϵ and the best known action otherwise. However, as time progresses, ϵ is reduced to enable an agent to move from an exploratory state to an exploitative state as it learns learner-specific adaptation patterns [3]. Such a reinforcement learning model allows the platform to continually refine its strategies across various learning sessions.

F. Generative AI for Dynamic Content Creation

The Generative AI module creates and adjusts learning materials in response to the current system state and the adaptation choices made by the RL agent. The generated content is guided by factors such as task difficulty, sentence structure, vocabulary level, and the use of visual or social context cues, in line with instructional strategies that are considerate of the needs of autistic learners. [4], [7].

In addition to cognitive adaptation, the module adjusts stylistic factors including emotional tone, level of encouragement, and narrative framing. This is particularly important for autistic learners, who may exhibit heightened sensitivity to sensory and affective stimuli. By generating diverse yet pedagogically consistent content variants, the system reduces repetition, mitigates habituation, and maintains engagement without overstimulation [1], [6].

G. Closed-Loop Learning and Adaptation

This platform operates as a closed-loop neuroadaptive learning system. After each interaction episode, updated EEG-derived attention measures and behavioral performance metrics are aggregated to compute a reward signal. This reward is used to update the RL policy, enabling continuous refinement of personalization strategies for individual learners [2], [3].

Subsequently, the Generative AI module produces content aligned with the updated policy, and the new instructional material is presented to the learner. Over multiple sessions, this iterative feedback process enables convergence toward learner-specific adaptation profiles, extending prior RL-based personalized tutoring approaches by incorporating EEG-informed attention modeling and generative content synthesis tailored for autistic learners [1], [2], [6].

III. Results and Discussion

In this section, we describe what we observed when testing the BRIGHTMINDS neuroadaptive learning platform and discuss what these findings mean. We link the outcomes back to the goals stated in the abstract and introduction, focusing on three main aspects: how well the system can adapt to a learner's attention, how effective the reinforcement learning–based adaptation is, and how engaged the children with mild Autism Spectrum Disorder (ASD) were during use.

A. Experimental Setup

We tested the system in a controlled pilot study with children aged 10–15 years who have mild ASD. During the learning sessions, we used a NeuroPlayGround Lite device to record EEG-based focus scores, which gave us a moment-by-moment estimate of how attentive each learner was.

The adaptive behavior of the system was driven by a reinforcement learning (RL) agent based on Q-learning. The agent received feedback in the form of a reward signal that combined two elements: the learner's real-time focus level and their performance on short quizzes. Using this reward, the RL agent learned when to adjust the content—for example, when to increase or decrease difficulty or modify pacing.

To generate and adapt learning materials, we integrated a generative AI model (Gemini). This model produced lessons and quizzes whose difficulty and delivery speed were continuously tuned according to the RL agent's decisions, allowing the platform to respond dynamically to each learner's needs in real time.

B. Reinforcement Learning Model Performance

The RL agent demonstrated effective convergence toward optimal content adaptation strategies over multiple learning episodes. Table I summarizes the key hyperparameters used for the Q-learning model.

TABLE I
Reinforcement Learning Model Parameters

Parameter	Value
Learning Rate (α)	0.1
Discount Factor (γ)	0.9
Exploration Rate (ϵ)	0.2 (decayed)
State Space	Focus level, difficulty
Action Space	Increase, decrease, maintain difficulty
Reward Signals	Focus stability, quiz success

TABLE II
Attention and Engagement Metrics

Metric	Before Adaptation	After Adaptation
Average Focus Score	52.4	68.9
Sustained Focus Duration (min)	6.8	11.3
Quiz Completion Rate (%)	63.5	82.1
Task Dropout Rate (%)	21.4	9.6

The agent learned to reduce content difficulty and pacing during periods of low attention and to introduce more challenging tasks when sustained focus was detected. This adaptive behavior aligns with the neurodiversity-aware learning goals described in the introduction.

C. Attention and Engagement Analysis

EEG-derived focus scores were normalized to a 0–100 scale and analyzed across learning sessions. Table II presents the observed improvement in learner engagement.

The results indicate a notable improvement in sustained attention and task completion after adaptive learning was enabled. These findings support the premise stated in the abstract that real-time neurophysiological feedback can enhance learning effectiveness for autistic students.

D. Learning Performance Outcomes

Learner performance was evaluated using quiz accuracy and progression speed across difficulty levels. The integration of EEG-based feedback with RL-driven personalization resulted in smoother difficulty transitions and reduced cognitive overload. Learners demonstrated higher accuracy when content difficulty was aligned with their cognitive state, validating the adaptive personalization strategy described in the introduction.

E. Caregiver Feedback and Qualitative Observations

Caregivers shared that learners seemed more comfortable, less frustrated, and more willing to engage with educational activities. They especially appreciated the analytics dashboard, which gave them clear, useful insights into each learner's attention and progress over time. Together, these experiences underscore how important openness and active caregiver involvement are when designing inclusive educational technologies.

F. Discussion

The results show that BRIGHTMINDS can effectively connect the varied ways students think and learn with flexible educational technology. By using EEG to track attention, reinforcement learning, and generative AI, the system doesn't just offer one-time personalization—it continuously adapts to each learner in real time. This leads to clearer gains in how steadily learners can focus, how long they stay engaged, and how well they perform on quizzes, matching the goals set out at the start of the study.

Although the current study was done in a small, controlled pilot environment, the findings suggest that the approach could be scaled up and used in real-world classrooms. Future research with more participants over longer periods will be important to confirm how reliable and effective this neuroadaptive learning framework is in practice.

In summary, the results suggest that neuroadaptive AI can significantly support inclusive education by recognizing and honoring the differences in how autistic learners think and process information, rather than forcing them into a one-size-fits-all model.

IV. Conclusion

This paper introduced *BRIGHTMINDS*, an AI-based neuroadaptive learning system for children aged 10–15 with mild Autism Spectrum Disorder (ASD). The system combines electroencephalography (EEG)-based attention tracking, reinforcement learning, and generative AI to deliver learning content that adapts in real time to each child's mental state.

In a controlled pilot study, EEG-driven adaptation led to higher engagement, better sustained attention, and improved task completion compared to a non-adaptive setup. The reinforcement learning agent tuned difficulty, pace, and teaching style using live focus scores and quiz results, while the generative AI kept materials relevant and age appropriate. These findings support the idea that using brain-based feedback to guide instruction can improve learning for autistic students.

Caregivers reported that children seemed more comfortable, less frustrated, and that the analytics dashboards helped them understand progress, underscoring the value of human-centered monitoring. The dual-interface design also supported both stimulation-seeking and sensory-sensitive learners, reflecting the diversity within the autism spectrum.

Although this work is based on a small pilot, it lays important groundwork for scalable neuroadaptive education. Future directions include longer-term studies, richer affective sensing, and deployment in more varied learning environments. Overall, BRIGHTMINDS shows how neuroadaptive AI can support more personalized, empathetic, and cognitively aligned learning experiences for autistic learners.

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