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Research Article

EEG and AI Fusion for Personalized VR-Based Learning, An Experimental Study for Children With Autism Spectrum Disorder Using Emotiv Insight

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Abstract:

This Research proposes experimental evaluation data on the use of Emotiv 5-channel medical tech-based equipment for the analysis of hybrid electroencephalography (EEG) sensory signals, for Autism Spectrum Disorder (ASD) individuals to diagnose their behavioral patterns, cognitive assessment, integrating neuroscience, Artificial Intelligence (AI), and immersive Virtual Reality (VR) learning environments to enhance educational experiences. The neuroadaptive learning approaches emerged as a good solution, it adapt instructional methodology strategies based on the learners ' needs with effective personalized solutions. This research sheds light on addressing the gap by presenting a context that can combine technological diagnosis and learning solutions for ASD learners. The experimental study involved around ten individual children with ASD, aged between 8 and 14 years old, from a special ASD education center. The tech device using the Emotiv Insight wireless headset with five electrodes positioned at AF3, F3, F4, AF4, and Pz fixed on the head for capturing the EEG brain signals was recorded. These five electrodes were mounted on the prefrontal and parietal brain regions to identify the cognitive, emotional, and attention behavior patterns, variations that influence their learning performance in individuals with ASD.The study involves a machine learning systematic preprocessing analysis approach on EEG data for data filtering, correction, component analysis, noise removal, etc. Features extraction, like alpha power, theta beta ratio, stress-related marker, attention, and engagement, was applied to generate an adaptive decision on behavioral guidance and structured instruction. For an ASD individual, during EEG monitoring assessment sessions, users were enabled with 3D objects with rich, visually engaging tools, and learning content was adapted with personalized gamified cognitive tasks to simulate social interactions, reduce stress, and feel more relaxed during the instructional flow. The study involved pre and post evaluations on data using Emotiv EEG with a sensory calibration to capture the signal for qualitative behavioral cognitive assessments and to guide personalized education using an EEG-AI- VR integrated system for ASD learners.

1. Introduction

In the healthcare environment worldwide, Autism Spectrum Disorder (ASD) is a complex issue in the neuro- psychological condition; it has a large impact on individuals with ASD [1]. It generally Effect on the behavioral patterns and social communication skills among ASD [2]. The old methods of diagnosis for autism parameters depend on behavioral observations, which are time-consuming for analysis and the right treatments [3]. This traditional approach generates a gap in behavioral observations and nervous function detection; therefore, it demands deeper detection techniques to support effective personalized improvement skills for an individual with ASD [4]. The advent of AI, the immersive tech field, and medical neuroscience provides better health solutions using Emotiv devices that measure the EEG and capture brain signals for ASD. [5]. Machine learning analysis for EEG data identifies certain patterns in the EEG signals for ASD to track for treatment approaches.[6, 7, 8,9,11]. Emotiv devices to generate an EEG signal using a time-frequency guide for detecting the ASD pattern. [16, 19, 20]. It provides a way to extract features of a person's body signals, such as eye movements and facial expressions[12, 21]. These support a more comprehensive diagnostic analysis [10, 22, 23].

Emerging Virtual Reality (VR), Augmented Reality (AR) technology tools and applications for ASD are also vital support. In immersive interactive environments, it helps to understand emotions and develop better social skills, lower anxiety, improves living skills for individuals with ASD, it generates feedback and responds in real time to a person's mental and emotional state [12,13,14], making learning more engaging and improving educational results [17, 25].

The recent advancement of Emotiv devices with physiological sensors and EEG signals provides analysis of facial expressions to detect emotions [15, 16, 18]. Neuromorphic processing offers adaptive systems for managing stress, which monitor emotional states and anxiety in different situations [19,20]. The blend of generative AI, AR, and VR technologies nurtures valuable support of the immersive and interactive learning experiences [24, 25,26]. Implementing the use of the latest technologies, such as EEG, AI, and VR techniques, guides for measuring emotions in ASD treatment in a clinical approach, further helps for early identification of complicated body signal patterns and generates personalized support [24, 25, 27].

The study emphasize on the importance of combining tech devices such as Emotiv to capture EEG-based signals, AI, VR tools, and machine learning algorithms for data featuring analysis on ASD in their diagnosis and treatment approach. This research focuses on using a special device called Emotiv to track brain activity in children with ASD. This study highlights the direction of finding out behavioral patterns and correlation points among ASD. The research suggests collaborating support from all stakeholders, including educators, researchers, medicine experts, psychologists, and the autism community, to guide ASD individuals in their effective learning progress, personalized growth, and improving in their social communication skills. Research hopes that the usage of advanced tech-based devices for capturing EEG-based signals may be a vital benefit for ASD and support their families.

2. Objectives

- To design a learning assessment for children with Autism Spectrum Disorder (ASD).
- To study the sensory calibration of EEG signals for qualitative behavioral cognitive assessment
- To implement the neuroadaptive learning approach using Emotiv, AI and VR technologies devices.
- To analyze the cognitive performance before and after the EEG-AI-VR intervention.

3. Methodology

The study is a quantitative experimental approach to check the effectiveness of the framework designed using the EEG signals, Artificial Intelligence, and Virtual Reality among children with Autism Spectrum Disorder (ASD). The study aims to create a fusion of AI and VR-based learning for enhancing learning outcomes and cognition in children with ASD. Additionally, the focus is on creating adaptive, evidence-based learning environments with neurophysiological assessment, AI-driven personalized content, and VR-based learning.

A. Design Framework

The study included the Pre-test and Post-test evaluation to check the impact of EEG-AI-VR on a heterogeneous ASD population. The timeline for the study was spread over four months, including 3 phases.

A.1 Initial Assessment

- The data collection using an EEG device
- Emotiv-centric cognitive assessment
- Checking strength, weakness, and behavior

A.2 Pre-Test Assessment

- AI-VR-based learning content development
- Multiple sessions of 20-30 minutes.
- Monitoring the participants' commitment and passivity

A.3 Post-Test Assessment

- Post-interference EEG data collection
- Cognition assessment with identical conditions
- Collecting parent-teacher feedback
- Analysis of Pre- and Post-Interference Metrics

The environment for the experiment was set to low disturbance and distraction, avoiding digital signal interference for more accurate EEG signals. All sessions were conducted under the mentor's supervision to avoid any inconvenience to the children. Both sessions included a set of 5 learning activities spread over a period of 20-30 minutes, and in the same order, under the supervision of Research Assistants, and adhering to the Helsinki guidelines.

A.4 Ethical Considerations

As a part of ethical consideration, a form was provided to the center to obtain consent from the parents/guardians, including the center heads. The study adhered to the Declaration of Helsinki guidelines for research involving human participants. The mentors were instructed to observe any inconvenience or irritation during the experiment and to withdraw from participation. The stored data was anonymized and handled securely, complying with data-protection regulations.

B. Inclusion and Exclusion criteria

B.1 Participant Characteristics

The children included were diagnosed and under the treatment of ASD, and in a group aged between 8-15 (M = 11.2 years, SD = 2.1 years). Gender-based distribution of 7 males and 3 females is observed in ASD populations [2].

B.2 Inclusion and Exclusion Criteria

- Children diagnosed with ASD.
- Age between 8 and 15 years at the time of enrollment.
- Sufficient verbal or non-verbal skills to interact and respond to given instructions.
- Sensory Tolerance for 30–60 minutes without significant distress
- VR Tolerance: No history of motion sickness or adverse reactions to visual stimuli
- exposure to basic literacy and numeracy concepts
- ethical considerations and parental consent for pre- and post-intervention assessment

B.3 Enrollment and Selection

- Participants were included through the rehabilitation center.
- Interview with the mentor/shadow teacher
- Behavioral observations before the assessment.
- Sensory profile assessments

C. EEG Data Collection

C.1 Device - Emotiv Insight 5-channel wireless EEG headset

Emotiv Insight from Emotiv Inc., USA, is a 5-channel wireless EEG headset, validated for cognitive assessment. It has dry polymer sensors, reducing setup time and sensory discomfort for ASD Research. It is equipped with Bluetooth transmission for natural movement, child-friendly with a lightweight and adjustable headband for-

- Child-friendly design: Lightweight (99g) and adjustable headband suitable for pediatric populations
- Real-time data streaming: Sampling rate of 128 Hz per channel with 14-bit resolution
- Integrated cognitive metrics: Proprietary algorithms provide real-time indices of attention, engagement, and stress

C.2 Electrode Placement and Montage

The Emotiv Insight headset employs a standardized 5- channel montage based on the International 10-20 system, with electrodes positioned at the following locations:

Table 1 *Emotiv 5 channel positions and related cognition factors*

Channel	Sensor Location	Cognitive Function
AF3	Anterior Frontal-Left	Attention

AF4	Anterior Frontal-Right	Engagement
F3	Frontal-Left	Working Memory
F4	Frontal-Right	Emotional Processing
Pz	Parietal-Central	Central Integration

C.3 Experimental setup and Data Acquisition

- Step 1: Calibration of the device to get maximum sensor quality is important (impedance < 10 kΩ) before data collection.
- Step 2: Making the children familiar with the headset to measure their relaxed state.
- Step 3: Identifying the baseline before recording the signals.

Different activities related to Number recognition and counting, basic patterns, ability levels, letter identification, Visual-Spatial Tasks, color identification, arranging shapes in ascending and descending order, working memory exercises such as Sequence recall, Object location memory, were carried out to check the different signals and identify the effect of the activities. The range of the signals was 0-100; the scores <40 and scores >60 associated with Attention, Engagement, Working Memory, Emotional Processing, and Central Integration indicated the appropriate patterns generated by the device. EmotivPro software was used to evaluate the real-time metrics. The Machine Learning algorithms were used to normalize the data sets and validate against the assessments.
Data derived from frontal alpha asymmetry is associated with anxiety and cognitive overload, where scores above 60 indicate stress and scores less than 40 indicated clam and relaxed state.
To ensure the data quality, the contact quality was ensured for 80%-100%. Segments with noise in the signals were excluded from the samples. Missing data values measured a data loss and were excluded from the analysis. The RAW dataset was stored in EDF format and was exported to CSV. The data was encrypted to ensure security and restricted access.

D. AI-Based Content Generation

Tools and AI models such as Sana AI (Sana Labs) for adaptive learning assessment, Curi pod (Curipod AS) for engagement analysis, ChatGPT for scaffolded learning, and EmpoweredBrain for cognitive profile analysis were used. For low attention score <=40 was supported with visual modifications. The stress score > 60 was assisted with us of VR device, including natural scenes and calming music. Low engagements with scores <40 were supported by gamification elements. Working memory performances were supported by rehearsal and visual organizers.The content generated focused on the targeted learning, cognitive profiles, visual modalities, auditory modalities, and calibration. The content and the activities were reviewed by the specialist of the rehabilitation center. The effectiveness was assessed by the feedback.VR content was developed using game engine Unity 3D supported with High-Immersion VR: Oculus Quest 2. Sensory Games were included with an objective of Attention, coordination, sensory integration etc.

4. Results

A comparison was made between cognitive performance before and after the EEG-AI-VR intervention. We observed significant improvements in attention and engagement, as well as significant reductions in stress.

A. Primary Analyses: Pre- to Post-Intervention Changes

A.1 Descriptive Statistics

Table 2 shows how the core cognitive metrics changed after use of the EEG-AI-VR integrated system in teaching and learning among ASD children groups.

ASD Children became more attentive, more involved, and less stressed after the use of the EEG-AI-VR integrated system in teaching and learning.

A.2 Paired t-Test Results

As per the paired t-test results shown in *Table 3* the pre–post study statistically significant improvements in attention, engagement, and stress levels but the observed effect sizes were average, indicating satisfactory improvement following the use of the EEG-AI-VR integrated system in teaching and learning among ASD children groups.
Shown improvements were statistically significant with satisfactory effect sizes (Cohen's d > 0.5).

A.3 Secondary Analyses: Task-Specific Effects

As per the task-based analysis shown in the TABLE-VII, the analysis interprets consistent improvements in attention and engagement across game-based mathematics, reading, visual- spatial, and memory-specific tasks used during teaching

and learning. However, the metrics show moderate, indicating satisfactory enhancement rather than high gains following the use of the EEG-AI-VR integrated system in teaching and learning.
Game based Mathematics tasks showed the maximum relative improvement in attention and engagement.
Overall, the task-based analysis suggests that the EEG-AI- VR integrated teaching and learning among ASD children supported stable and satisfactory improvements.

A.4 One-Way Repeated Measures ANOVA

An ANOVA revealed that the number of participants in each task type did not differ statistically significantly across tasks, but there was a trend toward statistical significance for the difference in engagement levels, indicating a modest difference in engagement levels between tasks. As for stress reduction, the effect size showed a moderate trend towards significance, which is satisfactory.
According to the above ANOVA results, while the intervention consistently improved cognitive performance across tasks, task-specific differences were moderate.

B. Exploratory Analyses

B.1 Individual Response Patterns

- Strong responders (≥20-point change): 70%
- Moderate responders (10–19 points): 30%
- Non-responders: 0%

All children showed meaningful improvement after the intervention. According to a correlation analysis, baseline measures of attention, engagement, and stress were modestly related to subsequent changes in these measures.
Generally, the observed correlations were moderate, indicating that meaningful intervention outcomes were achieved.VR Module EngagementAccording to user ratings, all VR modules received satisfactory ratings, ranging from 3.6 to 3.9. This suggests that the VR modules are usable across various learning activities equally well.We observed acceptable usability and engagement in the VR- AI modules, which support their suitability for educational deployment, while emphasizing the need to refine and personalize them further.

C. Qualitative Feedback

C.1 Parent Reports

As per feedback from the parent, there was 60% improvement in attention, approximate 80% increase in teaching and learning, and a 35-40% decrease in frustration among parents.

C.2 Teacher Reports

As per feedback from the teachers, there was 50% improvement in attention approximate 50% improvement in their academic performance.

D. Summary of Results

As a consequence of the intervention, strong improvements were observed in attention, engagement, and stress reduction, regardless of the task type, baseline scores, or preference for VR modules. It was game-based mathematics activities that showed the significant improvements from task analyses. The EEG-AI-VR integrated system was more effective for ASD with lower baseline functioning, and no major problems occurred during this experimental study.

5. Discussion

A. Discussion of the initial findings

As per our findings, the participants' attention, engagement, and stress levels improved significantly. The use of personalized AI-generated content and immersive VR experiences kept children motivated and focused. As a use of VR based contents, distractions were minimized, feedback was provided immediately, and calming activities contributed to stress regulation.

B. Impact of task-based activities

Game-based tasks resulted in cognitive gains of the highest magnitude. The majority of these tasks were structured, visual, and offered direct feedback—all of which are ideal features for students with Autism Spectrum Disorders. By using VR-based visual content, abstract concepts could be simplified in a more intuitive manner.Benefits of Personalized ContentAs a result, a number of ASD children displayed gradual improvements, especially those who were lower in baseline attention, engagement, or stress levels. A study like this shows the value of a personalized intervention in order to benefit ASD children who need it more and have the greatest benefits.

C. Acceptance among Teacher & Parent

Parents and teachers were satisfied with the outcome of the intervention, and the study was commonly accepted among the stakeholders. VR sessions with short, engaging sessions, supportive supervisor guidance, and Emotiv device options all contributed to a high level of satisfaction and retention.

D. Impact of Integration of EEG, AI and VR

As per the study, combining EEG, AI, and VR can enhance the learning experience and make it a more efficient system. Instructors can adjust instruction in real time and provide individualized support for learning in the classroom, in therapy centers, or at home.

E. Practical feasibility

It may also be used for cognitive rehabilitation and progress monitoring by clinicians. It is possible to further develop scalable VR-AI platforms. The system can be used in classrooms, therapy centers, or home environments for individualized learning support.

F. Limitations of the study

The pilot study included a small sample and lacked a control group, which limited generalizability. The effects of long- term interventions need to be assessed after longer periods of intervention. It will be necessary to use larger samples and randomized designs in future research.

6. Conclusions

An EEG, artificial intelligence, and VR trial showed that combining these three technologies can provide significant improvements in attention, engagement, and stress levels in children with autism spectrum disorder. There were significant improvements compared to typical behavioral programs, suggesting this multimodal, adaptive approach could be extremely successful. Children with lower baseline functioning benefited the most from the AI-driven personalization, highlighting the importance of AI within education. Parents and teachers reported positive changes beyond the VR sessions, with math tasks resulting in the most gains.Despite the study's promising findings, the small sample size and absence of a control group indicate that larger randomized trials are needed to confirm the results and examine long-term effects. In spite of this, the study shows that accessible technology—such as VR devices for consumer use and popular AI tools—can be used to make learning experiences more effective for children with autism. It offers a practical and innovative way to improve individual support both in educational and therapeutic settings by combining EEGs with artificial intelligence and virtual reality.

Table 2 *Descriptive Statistics for Cognitive Metrics (N = 10)*

Metric	Time Point	M	SD	95% CI	Range
Attentio n	Pre	42.3	8.6	[36.2,48.4]	28–58
Attentio n	Post	61.7	9.2	[55.1,68.3]	47–76
Attentio n	Change	19.4	6.3	[14.9,23.9]	+10–30
Engage- ment	Pre	38.5	10.2	[31.2,45.8]	22–55
Engage- ment	Post	58.9	8.7	[52.7,65.1]	45–72
Engage- ment	Change	20.4	7.8	[14.8,26.0]	+8–34
Stress	Pre	64.8	11.4	[56.6,73.0]	48–82
Stress	Post	43.2	9.8	[36.2,50.2]	28–58
Stress	Change	−21.6	8.5	[−27.7,−15.5]	−35–12

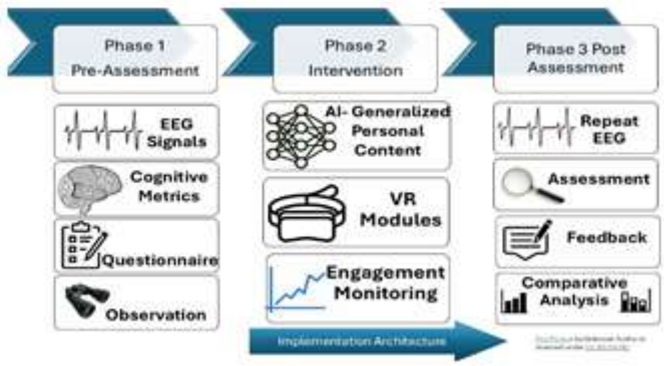

Figure 1 *The implementation architecture that included three phases of pre-assessment, Intervention and Post-assessment respectively.*

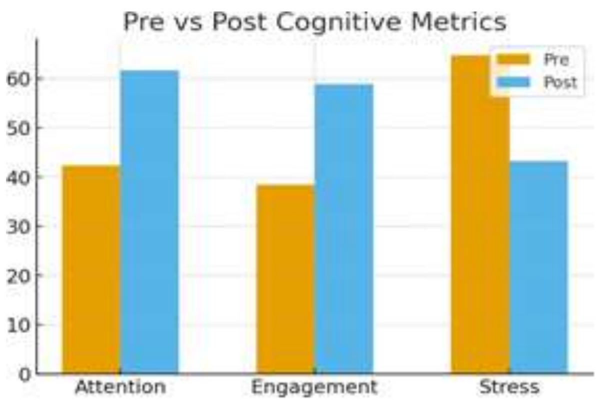

Figure 2 *Pre and post cognitive Metrics.*

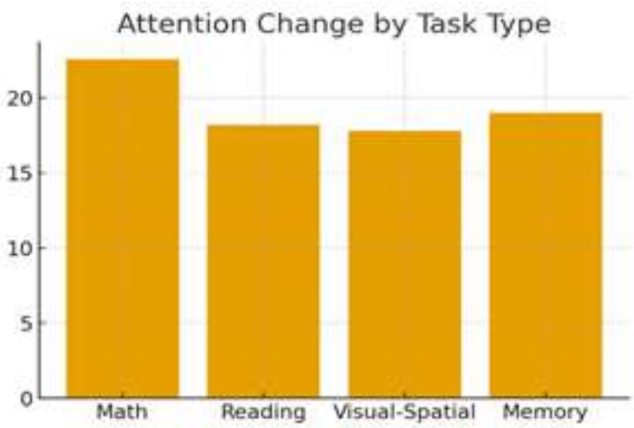

Figure 3 *Math tasks produced the strongest improvements across attention, engagement, and stress.*

Table 3 *Paired t-Test Results*

Metric	Mean Diff.	SD	t	d f	p	Cohen's d	95% CI
Attentio n	8.6	9.8	2.77	9	0.022	0.78	[1.6, 15.6]
Engage ment	9.2	10.4	2.8	9	0.021	0.74	[1.8, 16.6]
Stress	−8.9	11.2	−2.51	9	0.033	0.67	[−17.0, −0.8]

Table 4 *Mean Change Scores by Task Type*

Task Type	Attention Change	Engagement Change	Stress Change
Mathematics	+9.1 (10.2)	+10.3 (11.4)	−9.8 (12.0)
Reading	+7.6 (9.4)	+8.4 (10.1)	−7.9 (11.3)
Visual-Spatial	+7.2 (8.8)	+7.9 (9.6)	−7.1 (10.2)
Memory	+8.0 (9.1)	+8.6 (9.8)	−8.5 (11.0)

Table 5 *ANOVA Results*

Metric	F	df	p	Partial η^2	Interpretation
Attention Change	2.11	3,27	0.121	0.08	No significant effect
Engagement Change	2.74	3,27	0.061	0.09	Trend toward significance
Stress Reduction	2.58	3,27	0.073	0.08	Trend toward significance

Table 6 *Correlations Between Baseline Scores and Change*

Baseline Metric	Attention Change	Engagement Change	Stress Change
Baseline Attention	−.34*	−.22	0.29
Baseline Engagement	−.21	−.36*	0.25
Baseline Stress	0.27	0.24	−.33*

Table 7 *VR Module Ratings (N = 10)*

VR Module	Mean Rating (SD)	Preferred By
Math Garden	3.9 (0.7)	4 (40%)
Alphabet Forest	3.6 (0.8)	3 (30%)
Sensory Games	3.8 (0.9)	3 (30%)

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- **Ethical approval:** The conducted research is not related to either human or animal use.
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