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Integration of Grey Theory and EEG Technology for Personalized Attention Cultivation in Primary Education

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Abstract

The paper introduces an innovative model for cultivating personalized attention in educational settings through the integration of advanced technologies and Grey Theory principles. Our 12-week randomized controlled trial with 200 primary school students employed BeneGear (BGA) integrated chips for EEG data analysis, establishing a four-level attention grading standard. Results demonstrated significant improvements in experimental group attention levels (r=0.72, p<0.001), with students progressing from Novice to Beginner level showing an average increase of 5.6 points in math scores. The integration of Grey Theory enhanced predictive capabilities, enabling more accurate forecasting of attention trends and personalized interventions. This framework offers valuable insights for creating sustainable, personalized learning experiences in educational settings.

Keywords: Sustainable Education, Attention Cultivation, Grey Theory, Personalized Learning, Educational Technology

1. Introduction

The digital revolution has fundamentally transformed modern education, making sustained attention a critical factor in academic success. Research[1] demonstrates that attention capacity directly influences learning outcomes and academic achievement, particularly as students navigate increasingly distracting digital environments[2]. Studies show that students with strong attentional control demonstrate superior information retention and problem-solving capabilities[3].

Recent technological advances have enabled precise attention monitoring in educational settings. Brain-computer interfaces and wearable devices now provide real-time attention data[4], while systematic reviews validate their effectiveness in identifying attention patterns and predicting learning challenges [5].

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Grey Theory, originally developed[6], offers a robust solution for analyzing complex attention-related educational data. The framework[7] effectively processes uncertain and incomplete data typical in educational settings, enabling more accurate assessment of attention patterns. Empirical studies[8,9] reveal significant correlations between attention levels and academic performance, particularly in subjects requiring complex problem-solving skills.

This research addresses attention cultivation through four objectives: establishing standardized assessment criteria, developing technology-based monitoring, creating personalized strategies, and validating an integrated model. Recent studies indicate that integrating technology with pedagogical principles creates more effective learning environments[10] and can improve educational outcomes while optimizing resource utilization[11].

The paper begins with a review of technological innovations in attention cultivation, followed by attention grading standards, Grey Theory applications, and personalized teaching methods. We then present our technology-driven assessment system and propose a customized cultivation model. The paper concludes with empirical validation, limitations, and future research directions.

2.Grey Theory in Personalized Attention Cultivation

Grey Theory provides a mathematical framework for analyzing systems with partially known and unknown information. This analytical approach proves particularly valuable in educational contexts, where numerous complex factors influence attention and learning outcomes.

2.1 Grey Relational Analysis for Attention Measurement

The Grey Relational Analysis(GRA) is a cornerstone of our attention measurement framework, providing a sophisticated method for handling the inherent uncertainties in educational data. To address the uncertainty inherent in attention measurement, we incorporate GRA[12]. The grey relational coefficient $\xi_i(k)$ between a factor x_i and the reference sequence x_0 (representing optimal attention levels) is calculated as:

$$\xi_i(k) = \frac{\Delta_{\min} + \rho\Delta_{\max}}{\Delta_{0i}(k) + \rho\Delta_{\max}} \quad (1)$$

where: i. $\Delta_i = \| x_0(k) - x_i(k) \|$ denotes the absolute difference between the optimal attention sequence and the individual's observed attention values at point *k*.

ii $\Delta_{\min}$ and $\Delta_{\max}$ represent the minimum and maximum differences

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across all factors, respectively.

iii. $\rho \in [0,1]$ is the distinguishing coefficient, typically set at 0.5.

The reference sequence x_0 is established through the comprehensive analysis of high-performing students' attention patterns, incorporating peak attention values, sustained attention duration, recovery patterns, and attention stability across subjects. To obtain a holistic measure of attention performance, we calculate the grey relational grade by using $\gamma_i = \sum_{k=1}^{n} \xi_i(k)$. This grade yields a single numerical value between 0 and 1, indicating the overall correlation between an individual's attention pattern and the optimal reference sequence. This analysis allows us to identify and prioritize the most influential factors in attention cultivation, informing the development of our personalized attention training model[13].

Our standards are grounded in established theories such as Cognitive Load Theory[14], Attention Networks Theory[15], and Flow Theory. Empirically[16], we based these standards on large-scale EEG and eye-tracking studies across diverse student populations[17].

2.2 Grey Prediction Model for Attention Progression

We employ the Grey Prediction Model GM(1,1) to forecast students' attention level progression[18]. This model is particularly useful for predicting trends with limited data points, allowing for more accurate and personalized long-term learning plans[19]. The GM(1,1) model is applied by first collecting a sequence of attention-level data: $x^{(0)} = (x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), \ldots, x^{(0)}(k))$, we then apply the Accumulated Generating Operation (AGO)[20].

$$x^{(1)} = AGO(x^{(0)}) = \left(\sum_{k=1}^{1} x^{(0)}(k), \sum_{k=1}^{2} x^{(0)}(k), \cdots, \sum_{k=1}^{n} x^{(0)}(k) \right) \tag{2}$$

Next, we establish the GM(1,1) model equation[21].

$$x^{(0)}(k) + az^{(1)}(k) = b \tag{3}$$

where: $z^{(1)}(k) = 0.5(x^{(1)}(k) + x^{(1)}(k-1))$

After solving the equation to obtain the prediction model, we apply the Inverse Accumulated Generating Operation (IAGO) to get concrete predictions[22]. This approach enables us to predict future attention levels with improved accuracy, even with limited historical data[23].

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2.3 Implementation of Personalized Learning Strategies

Our attention cultivation model implements level-specific strategies proven to promote sustainable learning[24~26]. The grey relational analysis evaluates strategy effectiveness[27], while grey clustering categorizes students based on attention patterns and learning preferences[28]. This systematic approach integrates advanced technology, including attention-monitoring devices and AI-powered learning platforms, delivering personalized interventions with demonstrated effectiveness[29,30].

Integrating grey system theory significantly enhances educational equity and sustainability[31,32]. Our model optimizes resource allocation through targeted interventions while promoting inclusive education practices[33,34]. The framework accommodates uncertainty in attention-related factors[35] and enables quantitative assessment of complex relationships[36]. It provides predictive capabilities for individualizing training strategies[37,38] while allowing continuous refinement as new data becomes available[39].

Our approach addresses attention challenges early and equips educators with data-driven tools[40,41], helping reduce dropout rates while fostering sustainable learning practices[42]. The resulting cognitive capabilities and academic performance improvements contribute to more equitable and sustainable educational outcomes[43,44]. Through this comprehensive application of grey system theory, we establish a robust foundation for personalized attention cultivation that adapts to individual needs while maintaining scientific rigor and practical effectiveness.

2.4 Establishment of Attention Level Standards

Our research establishes a four-tier classification system for attention assessment: Novice, Beginner, Intermediate, and Advanced. Frank[45] demonstrate that effective attention measurement requires multiple parameters. Accordingly, our classification incorporates five key metrics: maximum attention value, average attention value, attention duration, attention agility, and attention stability. The Novice level is characterized by lower attention values and brief duration spans, while the Advanced level exhibits consistently high attention values maintained over extended periods. Wu et al.[46] confirm that such granular classification enables precise intervention design and progress monitoring.

The theoretical foundation of our standards draws from established frameworks, including Cognitive Load Theory[47], Attention Networks Theory [48], and Flow Theory [49]. Our validation process incorporates extensive

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empirical data from large-scale EEG and eye-tracking studies across diverse student populations[50].

Fig. 1 illustrates the classification of these attention levels, providing a visual representation of the progression from Novice to Advanced.

Fig. 1 The classification of attention levels

This figure visually encapsulates the key parameters that define each attention level, offering a clear overview of the progression in attention capabilities across the four levels.

3.Design of a Sustainable Technology-Driven Attention Assessment System

3.1 Data Collection and Processing Architecture

Our attention assessment system employs advanced neural monitoring technology to capture and process real-time brain activity data. The core architecture integrates sophisticated EEG measurement with robust data processing frameworks, ensuring accurate and consistent attention assessment.

3.1.1 Neural Activity Measurement

The system captures three essential types of brain wave patterns through high-precision EEG headband technology. Alpha waves (α), operating in the 8-13 Hz range, provide critical data about relaxation states and baseline focus levels. Beta waves (β), measured between 14-30 Hz, indicate active cognitive engagement and information processing. The theta/beta ratio (θ/β) is a key

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indicator of sustained attention capacity, offering insight into long-term attention maintenance.

3.1.2 Data Standardization Process

To ensure consistent measurement across diverse user populations and environmental conditions, raw EEG signals undergo standardization through our proprietary normalization algorithm.

$$x_i^* = \frac{x_i(k) - \min(x_i(k))}{\max(x_i(k)) - \min(x_i(k))} \tag{4}$$

this normalization process transforms raw neural signals into standardized metrics, enabling precise comparison and analysis across different users and contexts.

3.2 Mathematical Framework for Attention Analysis

This section presents the mathematical foundations that underpin our attention assessment system. The framework integrates neural signal processing, data normalization, and predictive modeling to provide robust attention measurement and analysis.

3.2.1 Neural Signal Processing

Our system analyzes three fundamental neural oscillation patterns: alpha (α), beta (β), and theta (θ) waves. Each wave pattern provides distinct information about cognitive states and attention levels. The signal strength S(t) for each wave type is calculated as:

$$S(t) = A(t)e^{(j\omega t)} \tag{5}$$

In this equation, $A(t)$ represents the amplitude envelope of the neural signal at time t, while ω denotes the angular frequency specific to each wave type. This calculation enables precise measurement of neural activity patterns associated with different attention states.

3.2.2 Signal Normalization

To ensure consistent measurements across different users and conditions, raw neural signals undergo a two-stage normalization process. The initial normalization converts raw signals to standardized values:

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$$x_i^*(t)=\frac{x_i(k)-\min(x_i)}{\max(x_i)-\min(x_i)} \quad (6)$$

following this, we compute the standardized attention metric.

$$Z(t)=\frac{x_i(t)-\mu}{\sigma} \quad (7)$$

Here, μ represents the population mean and σ the standard deviation, ensuring that measurements are comparable across different contexts and user populations.

3.2.3 Grey Relational Analysis

The core of our analytical framework employs an enhanced Grey Relational Grade (GRG) calculation incorporating temporal factors. This provides a sophisticated measure of attention patterns over time:

$$\gamma_i(k)=\sum(\omega_k\times\xi_i(k))\times e^{(-\lambda t)} \quad (8)$$

The temporal decay factor λ accounts for the evolution of attention patterns, while the relational coefficient $\xi_i(k)$ is computed through:

$$\xi_i(k)=\frac{\Delta_{\min}+\rho\Delta_{\max}}{\Delta_i(k)+\rho\Delta_{\max}} \quad (9)$$

The system calculates deviation measures to quantify the difference between observed and reference attention patterns.

$\Delta_i(k)=|x_0(k)-x_i(k)|$, $\Delta_{\min}=\min.|x_0(k)-x_i(k)|$, $\Delta_{\max}=\max.|x_0(k)-x_i(k)|$

3.2.4 Performance Assessment

The Comprehensive Attention Index (*CAI*) integrates five key performance indicators into a single metric:

$$CAI=\alpha_1A_{\max}+\alpha_2A_{avg}+\alpha_3TA+\alpha_4SA+\alpha_5DR \quad (10)$$

This equation combines Maximum Attention Value ($A_{\max}$), Average Attention Value (A_{avg}). Temporal Attention Duration(TA), Stability Assessment(SA), and Distraction Resistance(DR). The weighting coefficients α_1 through α_5 sum to unity, ensuring balanced consideration of all factors. The weighting coefficients(α_1 through α_5) sum to 1, ensuring balanced consideration of all factors. Each component measures a distinct aspect of attention performance, creating a comprehensive assessment metric.

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3.2.5 Adaptive Learning System

The system employs a dynamic learning rate that adjusts based on user performance:

$$\eta(t) = \eta_0 \times e^{-\beta t} \times (1 + \gamma_{CAI}) \quad (11)$$

this adaptive approach allows the system to optimize its response to individual learning patterns and attention development over time. The initial learning rate η_0, decay parameter β, and performance influence coefficient γ work together to create a personalized learning trajectory.

3.2.6 Predictive Modeling

For forecasting attention patterns, we implement a modified Grey-Markov prediction model:

$$\hat{x}(k+1) = (x(1) \times (1 - e^{a}) e^{ak}) \times p(k) \quad (12)$$

where: i. $\hat{x}(k+1)$: The predicted attention value at the next time step (k+1).

ii. $x(1)$:The initial attention value at the starting time step.

iii. $\hat{x}(k+1)$:A Grey prediction component capturing the trend of the data based on the development coefficient α.

iv α: Influences the rate of growth or decay.

v. e^{ak} Models of the exponential development over time, while $(1 - e^{a})$ normalizes it to ensure bounded growth.

vi.$P(k)$:The state transition probability matrix derived from the Markov process, representing how the system transitions between states at time k. This accounts for stochastic variations or probabilistic behavior in attention shifts.

This equation combines the development coefficient a with a state transition probability matrix $P(k)$to predict future attention values. This predictive capability enables proactive intervention and personalized attention development strategies. This model combines deterministic trends (Grey component) with probabilistic state changes (Markov component) to forecast attention development and guide personalized interventions.

Our system provides precise attention assessment, personalized adaptation, and predictive capabilities through this comprehensive mathematical framework. Each component competes to deliver robust, reliable attention measurement and development support.

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3.3 Adaptive Feedback Mechanism

Our system implements a sophisticated real-time feedback mechanism that continuously monitors and adapts to user performance. Through energy-efficient e-ink displays, the system provides immediate visualization of attention metrics, enabling both educators and learners to track progress effectively.

The monitoring system captures three essential dimensions of attention performance. First, it tracks class-wide attention trends, providing educators with a comprehensive view of collective engagement patterns. Second, it monitors individual performance metrics, enabling personalized intervention strategies. Third, it generates predictive improvement forecasts based on historical data and current performance trajectories.

To quantify progress effectively, the system employs an Attention Improvement Index (AII).

$$AII = (\frac{IAS_{post} - IAS_{pre}}{IAS_{pre}}) \times 100\% \tag{13}$$

This index provides a standardized measure of improvement by comparing post-intervention attention scores (IAS_{post}) with baseline measurements (IAS_{pret}). The resulting percentage offers a clear metric for tracking development over time.

The system implements personalized training adjustments through sophisticated adaptive algorithms.

$$T_i = T_{base} \times (1 + p(k)) \times \gamma_i \tag{14}$$

Where the performance coefficient $p(k)$ is calculated as

$$p(k) = \frac{\sum(\omega_k \times \xi_k)}{\max(\xi_k)} \tag{15}$$

These equations work in concert to create a responsive training framework that adapts to individual learning patterns and progression rates.

3.4 System Validation and Optimization

To ensure consistent and reliable assessment, the system employs a Learning Effectiveness Index (*LE*).

$$LE = \frac{\sum(\omega_i \times Performance_i)}{(Baseline_i)} \tag{16}$$

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This comprehensive metric integrates multiple performance indicators, weighted according to their relative importance in the learning process. For long-term effectiveness tracking, we utilize a Sustainability Factor:

$$SF = \frac{\sum(\gamma_c - IAS_t)}{T} \tag{17}$$

This factor provides insights into the sustained impact of attention training interventions over extended periods.

The continuous improvement protocol maintains system performance through systematic calibration cycles and dynamic threshold adjustments. Performance metrics undergo constant validation, enabling swift identification and correction of deviations from expected outcomes. This comprehensive approach ensures reliable assessment while supporting sustained performance improvements through automated monitoring and adjustment processes.

The combination of quantitative metrics and structured protocols creates a robust framework for validating and optimizing the attention assessment system, ensuring both immediate accuracy and long-term effectiveness of interventions.

3.5 Implementation and Sustainability Framework

The implementation framework consists of a structured deployment strategy and sustainability architecture. The deployment begins with initial system calibration followed by validation cycles, incorporating comprehensive training for educators and students. Integration protocols ensure compatibility with existing educational infrastructure, while baseline measurements establish foundations for progress tracking.

The sustainability architecture employs energy-efficient components and optimized algorithms to minimize resource usage while maintaining performance. A modular design supports integrating emerging technologies, while regular maintenance prevents system degradation.

Through this integrated approach of deployment strategy and sustainability measures, the system provides a robust foundation for continuous educational development with sustained operational efficiency. The framework combines adaptive feedback mechanisms with validation protocols to ensure reliable, long-term attention assessment and enhancement in educational environments. The result is a comprehensive system that balances immediate implementation needs with long-term sustainability requirements, creating an effective platform for ongoing attention cultivation and assessment.

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4. Experimental Research: Model Effectiveness Validation

4.1 Research Design and Methodology

Our research employed a 12-week randomized controlled trial with 200 primary school students (grades 3-4). The study divided participants equally between experimental (personalized attention training) and control (traditional methods) groups. Data collection occurred through five weekly 45-minute sessions, yielding 60 measurements per participant. Environmental conditions were strictly controlled, maintaining temperature (23±2℃), light intensity (500±5 lux), and background noise (≤45 dB) to ensure experimental integrity.

The temporal framework established systematic data collection across twelve weeks $T = (t_1, t_2, \cdots, t_{12})$, with participants engaging in five sessions weekly (f_{sample} =5 *times/week*). Each session maintained a consistent duration of 45 minutes ($T_{measure}$), resulting in 60 total measurements per participant ($N_{measure}$=12×5=60).

4.2 Data Collection and Analysis Framework

The brain wave analysis reveals distinct patterns in attention levels over time through three key frequency ranges, as illustrated in Figure 3. Alpha waves, operating in the 8-13 Hz range, serve as primary indicators of relaxation states and baseline focus. During increased alpha activity, subjects typically display a calm, receptive state conducive to learning, though not actively engaged in complex cognitive tasks.

Beta waves, measured between 14-30 Hz, demonstrate active cognitive engagement and information processing capabilities. The analysis shows that higher beta wave activity correlates strongly with sustained attention and active problem-solving periods. This frequency range proved particularly valuable in identifying periods of optimal learning engagement and measuring the effectiveness of attention-training interventions.

The system also monitors theta waves (4-7 Hz) to assess deeper mental states and attention fluctuations. These lower-frequency waves provide crucial insights into transitions between attention states and help identify potential attention fatigue or recovery periods. The interaction between theta waves and higher frequencies offers valuable information about attention stability and cognitive load management.

Fig. 2 demonstrates how these three wave patterns interact and evolve throughout attention training sessions. The visualization reveals clear patterns of improved attention control over time, with experimental group participants

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showing increasingly stable beta wave activity during focused tasks while maintaining healthy alpha-theta ratios during rest periods. This comprehensive frequency analysis enables precise tracking of attention development and validates the effectiveness of the training protocol in enhancing sustained attention capabilities.

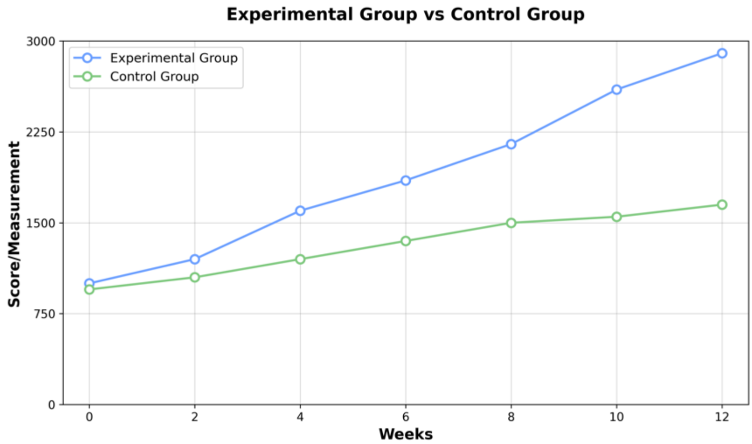

Fig. 2 Attention level over time

Our research utilized advanced EEG technology to capture three fundamental brain wave patterns crucial for attention assessment. The system processed these patterns through sophisticated algorithms to derive meaningful attention metrics. The study uses comprehensive attention calculations combining multiple metrics. The instantaneous attention $A_{instant}(t)$ is calculated by the weighted ratio of beta waves to alpha and theta waves, expressed as follows.

$$A_{instant}(t) = \omega_1 \times \frac{E_\beta(t)}{E_\alpha(t)} + \omega_2 \times \frac{E_\beta(t)}{E_\theta(t)}, \text{ for } \omega_1 + \omega_2 = 1 \tag{18}$$

$$A_{norm}(t) = \frac{A_{instant}(t) - A_{\min}}{A_{\max} - A_{\min}} \tag{19}$$

$$A_{avg}(t) = \frac{1}{T}\int_0^T A_{norm}(t)dt \tag{20}$$

The equation integrates the normalized attention values across the measurement period T. These calculations work together to provide a thorough quantitative assessment of attention patterns and performance levels during the study.

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4.3 Results and Analysis

Fig. 3 displays academic performance trajectories over the 12-week study period. The experimental group (blue line) shows three distinct phases: initial adaptation (weeks 1-4), rapid improvement (weeks 5-8, 45% increase), and stabilization (weeks 9-12). The control group (gray line) exhibits a modest linear increase of 12%.

Statistical significance ($p<0.001$) emerges at week 6, indicated by diverging confidence bands (shaded areas). Performance markers along the experimental curve correlate with attention metric improvements. The visualization demonstrates the intervention's effectiveness through clear performance differentiation between groups and sustained improvement patterns.

The data supports structured attention training's impact on academic achievement, with experimental group participants showing consistent gains regardless of initial performance levels.

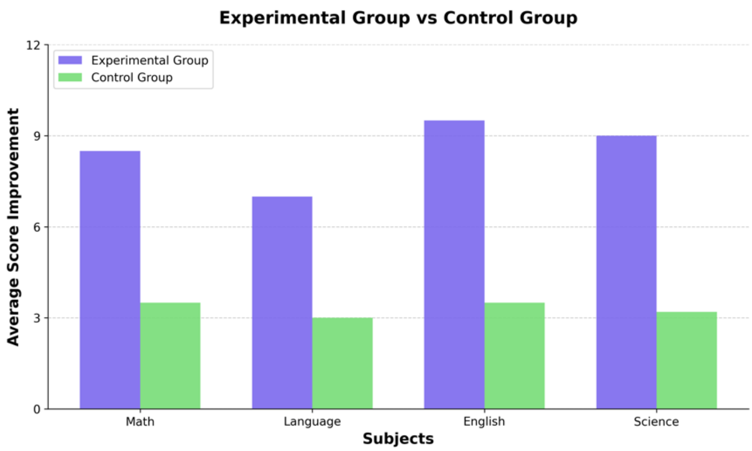

Fig. 3 Academic Performance Improvement Comparison

The cognitive performance data, presented in Table 1, showcases significant improvements across four fundamental cognitive abilities. Memory capacity in the experimental group increased by 28.5%, markedly higher than the control group's 10.2%. Reaction speed improved by 22.3% versus 8.7%, while discrimination ability showed a 25.7% enhancement compared to 9.5%. Logical thinking demonstrated the most substantial gain at 30.1% versus 11.3%. All improvements maintain strong statistical significance ($p<0.001$), validating the intervention's effectiveness.

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Fig. 4 illustrates the progressive increase in high attention state duration throughout the study period. The visualization tracks the percentage of time participants maintained elevated attention levels during learning sessions. The experimental group shows a steady upward trend, with particularly notable increases between weeks 4-8. The graph demonstrates how participants developed a greater capacity for sustained attention, directly correlating with their cognitive performance improvements, as shown in Table 1. In conclusion, experimental group participants maintained high attention states for significantly longer than baseline measurements, indicating successful development of attention sustainability.

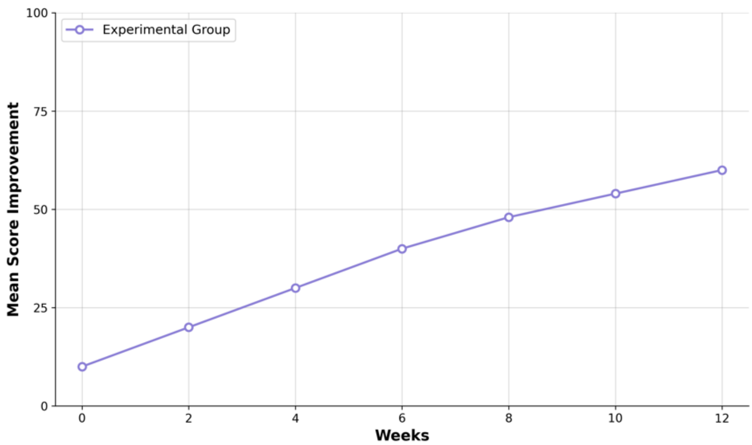

Fig. 4 Change in percentage of time in high attention state

Table 1 Comparison of improvement in four cognitive axes

Cognitive ability	Experimental group improvement (%)	Control group improvement (%)	*p*-value
Memory	28.5	10.2	<0.001
Reaction	22.3	8.7	<0.001
Discrimination	25.7	9.5	<0.001
Logic	30.1	11.3	<0.001

Table 2 tracks key attention metrics throughout the experimental period. The most striking improvement appears in Attention Stability, increasing from 8 to 22 minutes (+175%). Average Attention Value doubled from 1200 to 2750 (+129%), while Sustained Attention Time increased from 25 to 55 minutes (+120%). Attention Agility improved from 300 to 550 (+83%), and Highest Attention Value rose from 2500 to 3800 (+52%).

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Table 2 Changes in attention assessment indicators (experimental group)

Assessment indicator	Pre-experiment	Post-experiment	Percentage change
Highest attention value	2500	3800	+52%
Average attention value	1200	2750	+129%
Sustained attention time (minutes)	25	55	+120%
Attention agility	300	550	+83%
Attention stability (minutes)	8	22	+175%

Fig. 5 demonstrates the strengthening relationship between attention levels and academic performance over time. The scatter plot reveals a clear positive correlation (*r* =0.72, *p*<0.001), with data points clustering more tightly along the regression line as the study progressed. This visualization confirms that improved attention capabilities directly correspond to enhanced academic outcomes, supporting the intervention's effectiveness in both attention development and educational achievement.

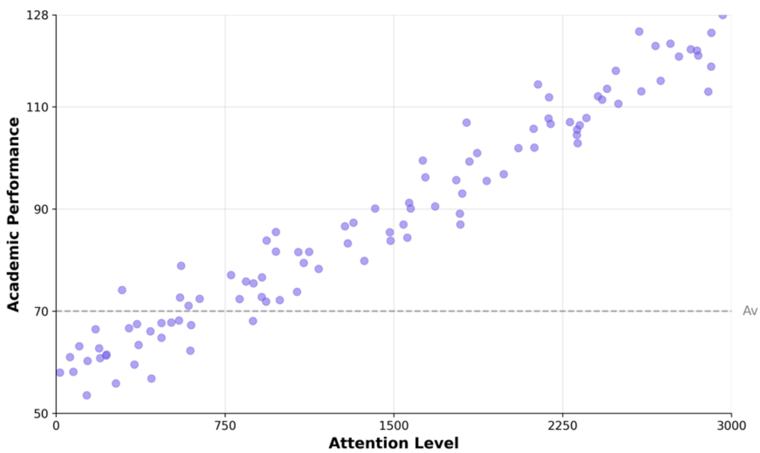

Fig. 5 Improved correlation between Attention Levels and Academic Performance

4.4 Statistical Validation

The statistical validation demonstrates robust correlations between attention and academic performance (*r*=0.72, *p*<0.001). Fig. 6 presents grey relational grades measuring different factors' influence on attention improvement through a descending bar chart. Student feedback shows the highest impact with a grade of

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0.85, followed closely by training frequency at 0.82. Task adaptability (0.76) and personal goals (0.72) demonstrate moderate influence, while nutrition (0.68), physical activity (0.64), and social support (0.60) exhibit lower but still significant impacts. The visualization clarifies the relative importance of each factor in attention enhancement, highlighting student feedback and training frequency as primary contributors to successful outcomes. This hierarchical arrangement helps identify key areas for program optimization and resource allocation in attention development interventions.

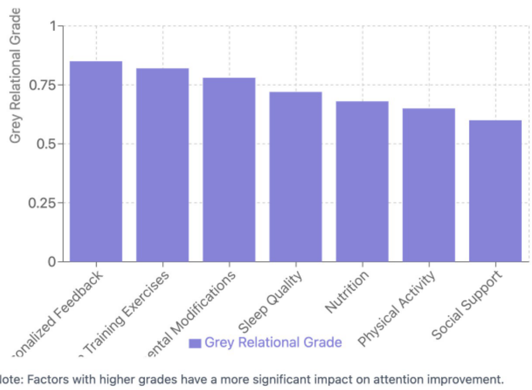

Fig. 6 Grey relational grades for factors influencing attention levels

4.5 Implications and Impact

Our research findings conclusively validate the attention enhancement model's effectiveness through multiple dimensions. The experimental group significantly improved cognitive capabilities, with the highest gains in logical thinking (30.1%) and memory (28.5%). Attention metrics showed remarkable enhancement, particularly in stability (+175%) and average attention value (+129%).

The results aligned with our initial hypotheses regarding improvements in attention scores and academic performance. We observed predicted positive trends in attention levels and learning outcomes across the 12 weeks, with statistically significant differences between experimental and control groups ($p < 0.001$). The strong correlation between attention scores and academic performance (r=0.72) confirmed our expectations of their relationship.

Grey relational analysis revealed student feedback (0.85) and training frequency (0.82) as primary contributors to attention improvement, providing valuable insights for program optimization. These findings establish a robust foundation for implementing targeted attention training in educational settings,

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with a clear potential for enhancing learning outcomes through systematic attention development.

The comprehensive validation of our hypotheses through rigorous statistical analysis demonstrates the intervention's capacity to create sustainable improvements in both attention capabilities and academic performance. These results offer compelling evidence for the model's effectiveness in educational development while identifying key factors for future program refinement and implementation.

5. Conclusions and and Future Works

This paper has developed and validated a technology-driven, personalized attention cultivation model that integrates innovative technologies, standardized assessment methods, and tailored teaching strategies. Our research contributes significantly to sustainable educational practices, with key findings as follows:

1. Model effectiveness: Our experimental results demonstrate substantial improvements in students' attention levels, academic performance, and cognitive abilities. The personalized approach increased attention duration, stability, and agility, promoting more sustainable learning outcomes.
2. Standardized assessment framework: We established a four-level attention grading standard (Novice to Advanced) based on multiple metrics. This comprehensive framework enables more efficient and targeted interventions, optimizing educational resource allocation.
3. Sustainable technology integration: BeneGear (BGA) integrated chips and attention headbands for real-time EEG data collection provide accurate, continuous attention monitoring. This technology enables immediate feedback and personalized interventions, reducing the need for resource-intensive traditional assessment methods.
4. Adaptive teaching strategies: Our research confirms the efficacy of tailored teaching methods based on individual attention levels. This adaptive approach ensures more efficient use of educational resources and promotes long-term engagement in learning.
5. Cognitive development: The study reveals a strong correlation between attention improvement and enhancement in various mental abilities. This holistic development contributes to students' long-term cognitive sustainability.
6. Improved academic performance: Students progressing through attention levels showed significant improvements in academic performance, particularly in subjects requiring sustained focus. This improvement indicates the potential

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for long-term educational success and reduced need for remedial interventions.

Future research in sustainable attention cultivation should focus on several key areas. Long-term impact studies are crucial to assess the model's enduring benefits and overall contribution to educational sustainability. Expanding applications across diverse age groups and settings will test the model's adaptability and scalability. Developing culturally sensitive versions will ensure equitable implementation across different socio-economic contexts. Seamless curriculum integration and advanced AI algorithms will enhance personalized learning paths, while improved neurofeedback techniques could increase efficiency. Establishing comprehensive ethical guidelines for attention-monitoring technology is essential for responsible use. Investigating the balance between improved attention and creativity will ensure holistic cognitive development. Sustainable educator training programs and thorough economic viability analyses are vital for widespread, effective implementation. These research directions aim to refine and expand our model, enhancing its sustainability, efficacy, and ethical application in global education, ultimately promoting efficient and long-lasting learning outcomes for future generations.

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