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DEVELOPMENT OF A PERSONALIZED LEARNING TRAJECTORY USING A BRAIN-COMPUTER INTERFACE

The object of research is electroencephalogram (EEG) signals obtained as a result of a non-invasive test that records the electrical activity of the brain by placing small sensors (electrodes) on the scalp. The article analyzes brain wave patterns to monitor a learner's memory ability.

One of the persistent issues in contemporary education is the misalignment between the competencies of graduates and the evolving demands of the labor market. A key contributing factor to this gap lies in the individual differences in how students perceive and process information. Empirical studies suggest that, excluding individuals with clinically diagnosed cognitive impairments, the population exhibits varied abilities in information retention depending on the modality of content delivery.

To address this issue, the study explores brain-computer interface technologies, particularly electroencephalography (EEG), as a means of assessing individual learning profiles. An artificial intelligence (AI)-based model employing a decision tree algorithm was developed to analyze EEG signals acquired from a 256-electrode system. A publicly available dataset from Kaggle was utilized to train and refine the model, enabling the classification of preferred memorization modalities – namely, reading, multimodal, auditory, and visual.

The applied phase of the study involved 32 students who had previously received failing ("F") grades. Based on their EEG-derived cognitive profiles, these students were subsequently taught using tailored content delivery methods aligned with their dominant memorization styles. Remarkably, this personalized approach resulted in significant academic improvement, with students achieving "C", "B", and even "A" grades in subsequent assessments.

The proposed model offers a scalable and time-efficient method for identifying optimal learning modalities at the individual level. It holds promise for enhancing educational outcomes by enabling more personalized and neuroadaptive instructional strategies.

Keywords: *electroencephalography (EEG), brain-computer interface (BCI), cognitive profiling, learning modalities, personalized education, artificial intelligence (AI), decision tree algorithm, memory retention, neuroadaptive learning, educational technology.*

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1. Introduction

In the modern era, the rapid advancement of technology has laid the foundation for significant changes in the development of personalized learning models. Brain-computer interface (BCI) technology plays a crucial role in organizing the educational process in a more adaptive and effective manner by analyzing brain activity in real time. Through these systems, brain signals can be used to assess indicators such as attention, stress, motivation, and cognitive load, thereby enabling the creation of a personalized learning trajectory. Unlike classical methods, the use of BCI systems in the educational process facilitates the implementation of neuroadaptive learning approaches. These systems hold significant potential, particularly in the design of inclusive and individualized educational strategies.

BCI-based trajectory models optimize the learning process by making adaptive decisions not only based on learner performance but also according to their cognitive states. The topic under investigation holds high relevance both practically and academically, and it is considered one of the innovative directions of educational research. Although research in this area has increased in recent years, existing studies remain limited, which creates substantial opportunities for the development of new models and their practical applications.

BCI systems are technologies that establish a connection between brain activity and the external environment. Recent advances in artificial intelligence and machine learning have significantly increased interest in electroencephalogram (EEG)-based BCI applications. EEG-based intelligent BCI systems can facilitate continuous monitoring of fluctuations in human cognitive states during monotonous tasks, which proves beneficial both for individuals requiring healthcare support and for general researchers across various fields [1].

The neuroadaptive approach provides great potential for working with students who exhibit neurodevelopmental differences, such as attention deficit. For example, when a student's attention level declines, the system can analyze the situation and propose appropriate new methods. Moreover, this technology makes learning more engaging through simulation-based instructional environments and educational games.

Existing research confirms the positive outcomes of applying BCI technology in educational contexts. The primary focus of this article is the identification of challenges that arise when attempting to precisely determine individual learning styles within modern educational systems. These challenges often lead to shortcomings in constructing effective learning trajectories. Personalization in education is a key trend in electronic learning [2]. Every learner possesses unique characteristics in terms of learning preferences, memory capacity, attention levels, and emotional states. A key requirement for modern educational resources used in knowledge management systems is the ability to adapt education to specific learning tasks, competency levels, and personality traits [2]. Therefore, the task of forming meaningful competencies for specialists with different specialties is extremely relevant today, and there is no specific solution [3]. Traditional instructional models, by providing a standardized teaching approach, may prevent students from fully realizing their learning potential. Even newly implemented technologies, such as learning management systems (LMS) and observational methods, are insufficient in capturing the full dynamics of the learning process.

In contrast, analyzing brain signals allows for the detection of specific cognitive indicators and the delivery of adaptive instructional content aligned with the learner's current state. This approach not only addresses learning outcomes but also enables the personalization of the learning process itself.

Due to the potential benefits of brain-computer interfaces (BCIs) in the learning process, their application in education has become a growing area of research. In the modern world, education is a globally significant concern, and all states must prioritize the creation of inclusive and accessible educational systems through appropriate legal frameworks and infrastructure. Various studies have shown that instructional design models can enable optimal learning environments for all individuals [3]. However, when these models are tested, results indicate that they do not always adequately support inclusive education. The results of studies that have applied different models, approaches and methods to develop virtual learning environments raise some concerns. Recent advances in brain-computer interface technologies have highlighted their potential for adaptive learning. However, inclusion challenges remain. According to a previous study, very few peer-reviewed scientific articles addressed disability-related topics, and only 42 (0.36%) of the 11,732 participants in the source had any form of disability. These findings suggest that existing models face limitations in inclusion [4]. These results suggest that significant steps must be taken to ensure inclusive and equitable education and to create virtual learning environments that fully guarantee learning for all.

Current technological advancements have radically transformed the teaching process. Learning has become more engaging and effective as it now increasingly involves practical, technology-supported methods. EEG-based Brain-Computer Interfaces (BCIs) have been used as controllers in medical applications and video games; however, their use for educational purposes at the secondary school level remains limited due to the high cost of the devices and the lack of trained teachers capable of operating them [5].

As in many fields, the application perspectives of fuzzy set theory methods in the field of human computer interface and decision-making using knowledge of the problem domain are demonstrated [6].

A study focusing on the design of brain-computer interface (BCI) systems by students examined how educational models could be developed to support such initiatives. The research involved the analysis of EEG data, with particular emphasis on device programming and the appropriate adaptation of signal outputs. The implementation of BCI technology in music education was a central aspect of the investigation. Survey results indicated active student engagement in the hands-on course. As in other domains, the distinction between traditional and technology-enhanced approaches to music education was of notable interest. Conducted over a period of approximately 1.5 years at a music school, the study included a systematic evaluation of students' musical skills throughout the intervention [7]. Two groups, each consisting of 24 students, were formed, and specific tests were administered at the end of the academic year. An expert panel evaluated the following performance parameters: the number of errors in music reproduction, performance rhythm, artistic expression, continuity and completeness of performance, dynamics, mastery of strokes, and the posture of the body and hands during performance [7]. Results revealed that, with the exception of the last parameter, the students in the experimental group showed higher performance scores. Depending on the nature of the recorded signal, BCIs are classified as exogenous or endogenous. Exogenous systems rely on neural activity triggered by external stimuli [8].

BCI systems can be classified based on the methods used to acquire neural signals. Among them, invasive BCIs represent a category that requires surgical procedures to implant electrodes directly into the brain. These systems monitor the activity of individual neurons within the subject's brain [9]. Invasive BCIs have been applied in areas such as motor control [10], diagnosis and treatment of diseases, communication assistance, cursor control, and more.

In partially invasive BCI systems, electrodes are not fully implanted into the brain. Instead, they are placed beneath the skull or on the surface of the brain, which makes them less risky compared to fully invasive systems. Based on electrode placement, these systems are categorized as *epidural* and *subpial* types [11]. They are commonly used in virtual reality (VR), the gaming industry, and intelligent interfaces for device control. In non-invasive BCI systems, no physical intervention is made into the body. Their ease of use, absence of physical injury risk, and relatively lower cost compared to invasive methods have contributed to their widespread adoption [12]. The most commonly used non-invasive technique is electroencephalography (EEG), where electrodes are placed on the scalp to detect brain signals. The initial applications of these systems were seen in technological equipment developed to support individuals with disabilities. Currently, their use has expanded beyond medicine to include education, entertainment, and robotics. As an emerging interdisciplinary field, BCI offers many exciting research opportunities and promises numerous career prospects in the future [13]. For this reason, the inclusion of BCI topics in university curricula is essential for student development. Particularly, integrating this technology into engineering education programs significantly contributes to the advancement of students' professional and research skills and enhances the innovation potential within engineering fields. BCI courses will enable students to explore interdisciplinary connections by fostering collaboration across areas such as mechanical engineering, computer engineering, psychology, and neuroscience [14].

The use of BCI systems in educational environments provides new opportunities for monitoring students' attention levels, emotional states, and information processing capabilities, and they are even widely used for analyzing comfort levels. The integration of information systems into education offers new solutions to existing systemic problems. For example, the Emotiv Epoc+ is a portable BCI device developed by Emotiv that contains 14 electrodes [15]. However, the inclusion of EEG laboratories in neuroscience curricula has traditionally been a costly endeavor, with research-grade systems ranging from USD 50,000 to 100,000 per unit. The delicate and bulky equipment requires installation in a specialized laboratory environment, which further increases the cost.

In the study [15] demonstrate the development of a Brain-Computer Interface Educational (BCIE) system capable of capturing, configuring, and displaying EEG signals in real time using the MindWave Mobile device developed by NeuroSky. BCIE enables the acquisition of attention values while the student is engaged in various activities, allowing attention profiles to be identified in an accessible manner. Consequently, although BCI systems are not yet widely adopted in education, they offer promising opportunities for the development of practical educational models and the enhancement of interdisciplinary collaboration.

The management of cognitive load related to task performance is a critical factor for the success of the learning process. Both cognitive overload and underload occur when the problems presented to a student either exceed or underutilize the capacity of working memory, leading to suboptimal learning outcomes. The study establishes a well-founded relationship between cognitive load regulation and its impact on the learning process. It is important to note that the current

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education system is not yet able to effectively simplify the learning process by utilizing cognitive load for personalized education. However, evolving neuroadaptive interfaces, particularly those enabled by BCI systems, have the capability to create real-time interactions between the brain and computer, allowing for individualized adaptation of learning tasks.

The aim of research is to predict learners' retention levels of information presented in different formats through the artificial intelligence-based analysis of EEG signals. To achieve this aim, the following objectives have been defined:

1. To obtain a dataset containing EEG signal indicators, normalize the signals, and eliminate noise.
2. To provide the mathematical representation of the problem, develop a predictive model based on the decision tree method for data processing, train the model using the collected dataset, and analyze the results.
3. To evaluate the effectiveness of the model by collecting EEG indicators from several volunteer learners who previously received "F" grades, and applying their real data to the model in order to predict their retention abilities. In the subsequent academic year, to deliver instruction based on customized learning content aligned with learners' retention capacities, and to assess the model's practical utility through comparative analysis of the obtained outcomes.

Within the scope of this study, a model is proposed for personalizing the learning process using BCI technology that records students' cognitive activity in real time. Alongside technical challenges encountered during model development, the study also addresses potential ethical issues that may arise during the system's implementation.

The findings from this research are expected to help identify the opportunities and challenges associated with the use of BCI technologies in education. Ultimately, the results of the study may contribute to the more effective development of personalized learning systems in the future.

2. Materials and Methods

The object of research is electroencephalogram (EEG) signals obtained through a non-invasive test that records the brain's electrical activity by placing small sensors (electrodes) on the scalp. The article analyzes patterns of brain waves to monitor the student's memory capacity.

The multidimensional and nonlinear nature of electroencephalographic (EEG) signals makes the selection of appropriate modeling methods for their classification particularly important. In this context, the decision tree (DT) model is chosen due to its ability to clearly visualize the data structure, explain the influence of features, and simplify the interpretation of results. DT models are especially advantageous in decision-making processes because of their high interpretability and transparency. Furthermore, this model can automatically identify significant features in high-dimensional EEG data and effectively distinguish between different classes. Therefore, the application of the Decision Tree model in EEG-based multiclass classification problems is theoretically and practically justified.

Dataset Description: The EEG data used in this study were obtained from the Kaggle platform. The dataset consists of 2,500 samples and 257 attributes, where the first 256 attributes represent signal vectors collected from 256 electrodes, and the final attribute corresponds to the target classes. The target variable is divided into four main categories: 0 – visual stimulus, 1 – auditory stimulus, 2 – reading process, and 3 – multimodal (graphical) approach. Thus, the dataset possesses a high-dimensional and multi-level structure that enables the analysis of brain responses to various neuropsychological stimuli. This structure provides a suitable environment for the implementation of interpretable and feature-selective models such as Decision Trees.

Data Normalization: The next stage involved preparing the data for processing. Bringing EEG signals into a consistent measurement framework across all channels not only minimizes information loss during model training but also helps reduce the risk of overfitting and accelerates the learning process. For this purpose, data normalization is essential. In our study, the StandardScaler method was chosen for this phase. This selection is justified by the fact that EEG signals typically vary within the range of −70 μV to +70 μV and approximately follow a normal distribution. Moreover, signals from some electrodes may have higher amplitudes, which can be balanced through the use of StandardScaler. This normalization approach provides more stable and robust convergence, especially in models utilizing ReLU activation functions, and Adam or SGD optimization methods. Even in the presence of outliers, the effectiveness of this method is preserved. The applied Z-score-based normalization is expressed by the following formula

$$x' = \frac{x-\mu}{\sigma}, \tag{1}$$

where x represents the original numerical value of the EEG signal, m denotes the mean value of the corresponding electrode across all samples, and s indicates the standard deviation of that electrode.

Noise Removal and Signal Preprocessing: In datasets obtained from diverse domains such as EEG, EMG, ECG signals, speech and music signals, natural language processing (NLP), image and video data, IoT system indicators, meteorological stations, smart devices, financial and economic parameters, and web-based sources, it is common to encounter inaccurate or low-informative data referred to as "noise". Such noisy data often do not reflect reality, adversely affecting the accuracy of analysis and modeling, thereby weakening the model's generalization ability. Therefore, data cleaning and preprocessing are considered critical stages in the development of high-quality artificial intelligence models.

In particular, EEG signal acquisition is highly sensitive to artifacts caused by eye movements (EOG), muscle activity (EMG), power line interference at 50/60 Hz, electrode displacement, and cardiac impulses, which result in the inclusion of inefficient and "false" components in the data. To eliminate such artifacts and transform the data into a more useful form, modern signal processing techniques such as band-pass filtering, independent component analysis (ICA), and notch filtering are commonly applied [16].

Mathematical Representation of the Model: Before constructing the decision tree model, let's examine the mathematical formulation of the problem. The input data for EEG signal processing can be represented as

$$x = \left(Ch_1, Ch_2, \ldots, Ch_{1256}\right). \tag{2}$$

In this case, the splitting conditions at each node of the decision tree will take the following form

$$Node_i : Ch_{ij} \le t_i, \tag{3}$$

where $j_i \in \{1,2,\ldots,256\}$ denotes the index of the selected EEG channel at the i-th node, and t_i represents the threshold value for that node.

Thus, the general mathematical representation of the decision tree model for EEG signal processing can be expressed as

$$f(x) = \begin{cases} C_1, Ch_{j1} \le t_1 \wedge \ldots \wedge Ch_{ji} \le t_i, \\ C_2, Ch_{j1} \le t_1 \wedge \ldots \wedge Ch_{ji} \le t_i, \\ C_3, Ch_{j1} \le t_1 \wedge \ldots \wedge Ch_{ji} \le t_i, \\ C_4, Ch_{j1} \le t_1 \wedge \ldots \wedge Ch_{ji} \le t_i. \end{cases} \tag{4}$$

Tools Used: For this study, the Python programming language was utilized within the Google Colab environment. The dataset obtained from Kaggle.com was processed by undergoing normalization and noise reduction stages. Based on the preprocessed signals, a Decision Tree model was constructed and applied to the dataset. Once the model's performance indicators were deemed satisfactory, the practical validation of the problem was carried out using EEG data collected from volunteer students.

This research was conducted under real conditions at the hospital of Nakhchivan State University with the participation of 32 volunteers. Specifically, during the 2024–2025 academic year, 32 volunteer students who had received an "F" grade participated, each undergoing a session lasting approximately 100–120 minutes on average. Each session consisted of two main stages: around 60–80 minutes were devoted to electrode placement, removal, and preparation for testing, while the remaining 40 minutes were allocated to the testing phase.

During the test phase, each participant was exposed to the following tasks:

1. *Reading tasks*: Each student read four texts consisting of 100–150 words. The texts were read silently, with a 60-second break after each text.

2. *Listening tasks*: Two audio texts, each lasting 60–90 seconds, were presented. One was synthesized using text-to-speech technology, while the other was recorded using a natural human voice. A 60-second interval was given between the audio texts.

3. *Image presentation*: A slideshow of 60 images was displayed. Each image was shown for 8 seconds with a 2-second interval between images.

4. *Video viewing*: Three video clips, each lasting 3 minutes, were presented. The videos were played in full-screen mode with synchronized audio, and a 1-minute break was given between each video.

The EEG data collected during these tests were then fed into the developed model to determine which forms of content led to higher levels of learning.

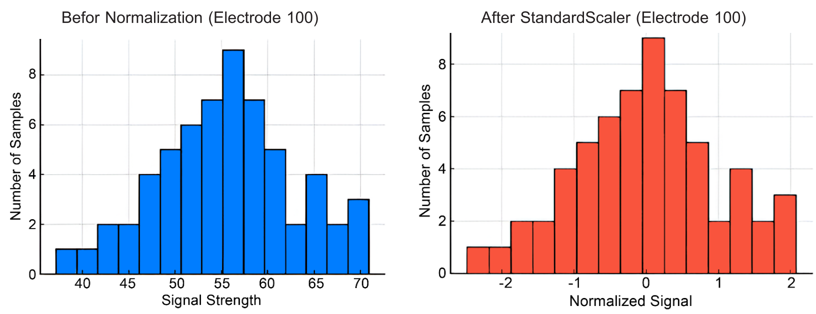
3. Results and Discussion

Fig. 1 presents a sample of the signal obtained after the normalization process of the dataset. As can be observed, signal deviations have been effectively eliminated, which enables progression to the subsequent stages of processing and analysis.

Fig. 2 presents signal samples obtained through the application of all three aforementioned methods band-pass filtering, ICA, and notch filtering. As can also be observed from the values presented in Table 1, a cleaner and more informative dataset suitable for modeling has been obtained (Table 1 and Fig. 2).

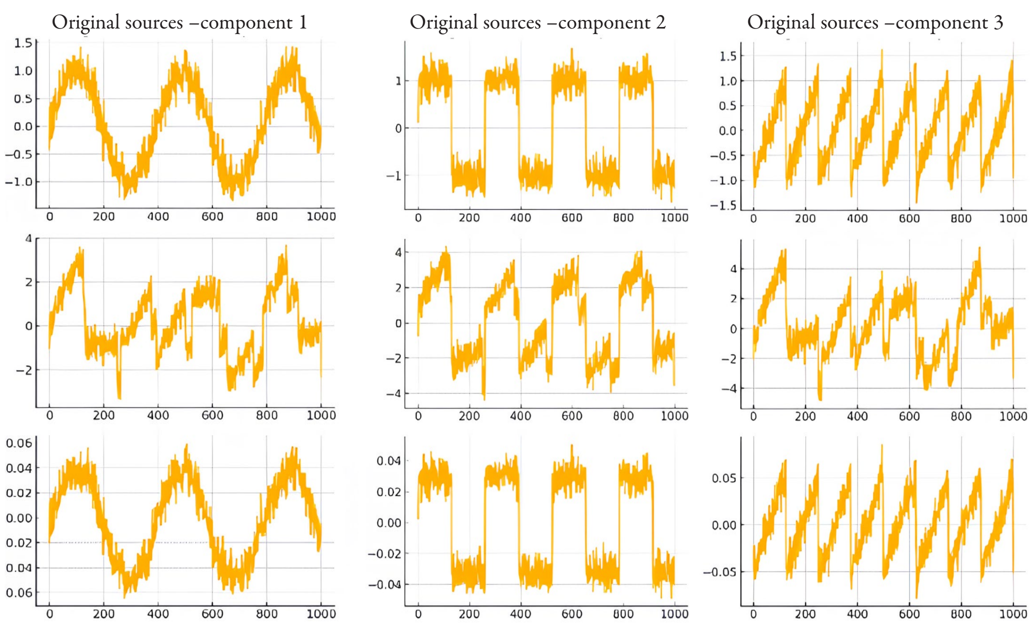
Fig. 3 presents the visual representation of the decision tree model that satisfies the problem conditions together with Equations (1)–(3).

The performance indicators obtained as a result of the presented dataset processing are as follows: Accuracy ≈ 1.0, Recall ≈ 1.0, F1-score ≈ 1.0, and Precision = 1.0.



a *b*

Fig. 1. EEG signal sample: *a* – before normalization; *b* – after standardscaler



a *b* *c*

Fig. 2. EEG signal conditions before and after noise removal:
a – original sources – component 1; *b* – original sources – component 2; *c* – original sources – component 3

Table 1

EEG signal conditions before and after noise removal

Time	Original – Component 1	Original – Component 2	Original – Component 3	Mixed – Component 1	Mixed – Component 2	Mixed – Component 3	ICA Recovered – Component 1	ICA Recovered – Component 2	ICA Recovered – Component 3
0	–0.404	0.132	–0.775	–1.047	–0.713	–2.024	–0.021	0.003	–0.042
1	0.353	0.743	–0.944	0.152	0.719	–0.615	0.012	0.021	–0.048
2	0.064	0.875	–0.430	0.508	1.351	0.110	–0.003	0.025	–0.022
3	–0.231	0.947	–0.808	–0.091	0.972	–1.014	–0.014	0.028	–0.042
4	0.063	1.035	–0.470	0.628	1.631	0.191	–0.003	0.030	–0.024

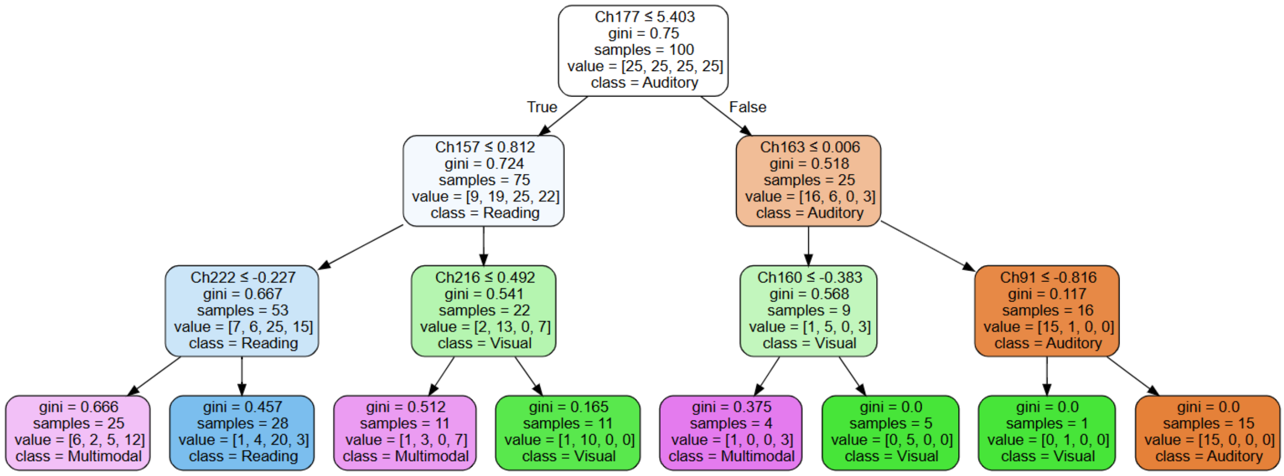


Fig. 3. Schematic representation of the model

A table summarizing the model's performance is provided in Table 2, while the visualization of the confusion matrix is shown in Fig. 4.

Table 2

Decision tree results

Class	Precision	Recall	F1-score	Support
Auditory	1.00	1.00	1.00	58
Multimodal	1.00	1.00	1.00	61
Reading	1.00	1.00	1.00	66
Visual	1.00	1.00	1.00	62
Macro avg	1.00	1.00	1.00	247

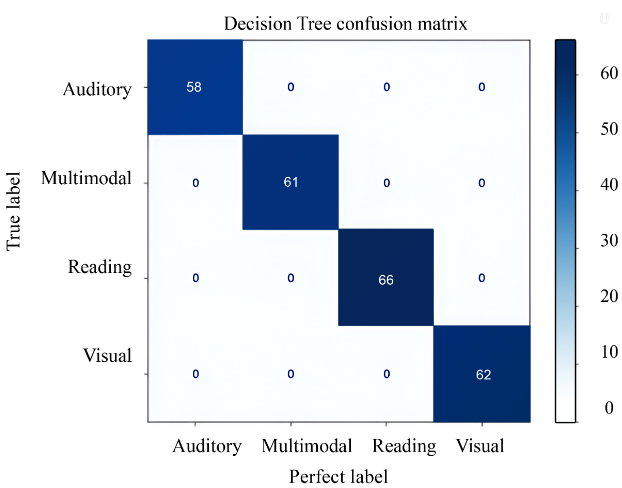


Fig. 4. Decision tree confusion matrix

This indicates that the model was executed with maximum accuracy. Consequently, it can be concluded that the input EEG signals were effectively denoised and properly normalized.

The inclusion of EEG data from volunteer students into the developed model revealed that, among the 32 volunteers, 7 learned more effectively through reading, 6 through listening, 8 through viewing images, and 11 through watching video clips.

Samples of the predicted memory retention capabilities resulting from the processing of the EEG data incorporated into the model are presented in Table 3.

Table 3

Classification results of representative input samples

No.	Data	Prognosis	Result
1	0.275, 0.893, 0.726, 0.852, 0.044, 0.068, 0.335, 3.66, 0.010, 1.278	V	V
2	0.271, 1.360, 0.905, 1.034, 1.714, 0.636, 0.851, 0.872, 2.210, 0.360	R	R
3	1.85, –0.168, 0.612, 0.725, 0.899, –0.3371, 0.690, 0.301, 0.88, 2.45	M	M
4	0.588, –1.108, 0.604, 0.762, 1.30, 0.319, 1.87, –1.163, 1.860, 0.202	A	A

Subsequently, during both semesters of the following academic year, the students were provided with content tailored to their predicted memory retention capabilities as indicated by the model. The diagram reflecting the students' academic performance as a result of this instruction is presented in Fig. 5, while the chart showing the average performance for each memory retention category is shown in Fig. 6.

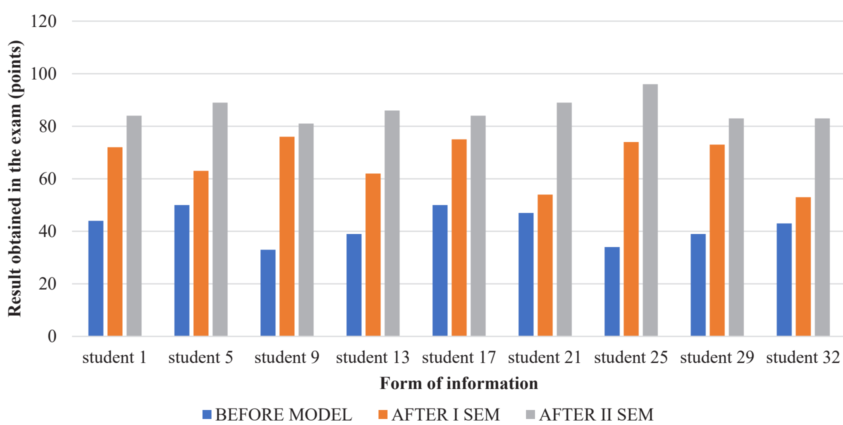


Fig. 5. Changes in students' learning activity after the model was implemented

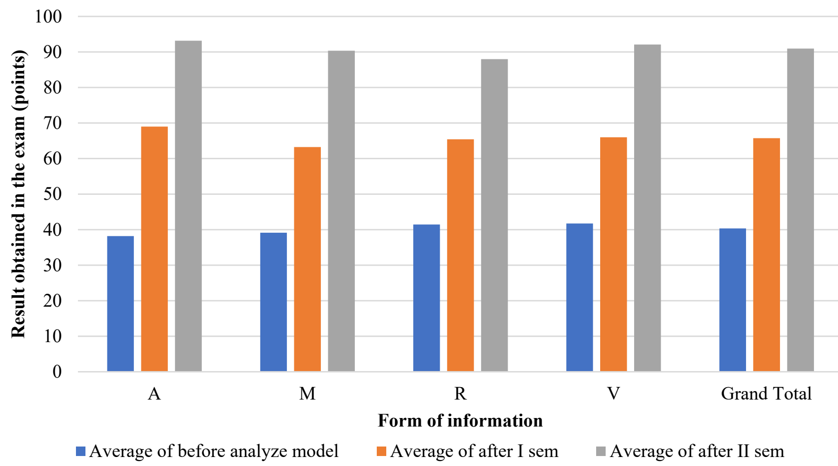


Fig. 6. Students' average grades by categories before and after the model was implemented

The observed improvements in student performance at the end of both semesters can be considered an advantage of the model. These results are higher compared to those reported in other studies. However, the study also has certain limitations. Specifically, the presented model and methods do not allow for determining the exact amount of information that students can retain most effectively. Therefore, this research cannot be regarded as conclusive. Future studies may focus on investigating the relationship between the quantity of information a student can comfortably retain and cognitive "fatigue", as well as conducting more in-depth research aimed at shaping learning outcomes for specific professions or subjects.

4. Conclusions

Since the signals were successfully denoised and normalized in the model, the decision tree model achieved high performance due to its interpretability advantages and the use of a balanced dataset.

1. A comprehensive dataset comprising EEG signal indicators was constructed, with the signals subsequently normalized and denoised to ensure accuracy and reliability.

2. A mathematical formulation of the problem was developed, and a predictive model for data processing was designed based on the decision tree method. The model was trained on the constructed dataset, and the resulting outcomes were thoroughly analyzed.

3. To evaluate the practical applicability of the model, EEG data were collected from 32 volunteer learners who had previously received "F" grades. These real indicators were incorporated into the developed model, enabling the prediction of the learners' memorization abilities. In the following academic year, instruction was delivered through content tailored to the learners' predicted retention capacities. The comparative analysis of learning outcomes confirmed the suitability and effectiveness of the model for this purpose. As a result, the model is able to distinguish memory styles with high accuracy. The personalized learning approach based on EEG profiles significantly improved students' academic performance. By identifying students' weaknesses in a timely manner and providing them with individual learning resources, educational outcomes were enhanced.

The results obtained during this study can practically assist in identifying students' individual cognitive abilities in student-centered education. Consequently, personalized learning trajectories for each student can be designed more accurately, thereby enhancing the quality of education. To apply these results in practice, it is sufficient to collect EEG data from students with their consent and input it into the model.

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Conflict of interest

The authors declare that they have no conflict of interest in relation to this study, including financial, personal, authorship or other, which could affect the study and its results presented in this article.

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Data availability

Manuscript has associated data in a data repository.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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