



ELSE (Elementary
School Education
Journal)

Measuring Impaired Student Brainwaves for Determining Their Preparedness to Study

Tining Haryanti^{1*}, Muhamad Amirul Haq¹, Sulton Dedi Wijaya¹, Marista Oktaviani¹, Alwan Fayyadh¹, Elmira Ivana¹, Hafiz Firman Abdullah¹

¹Universitas Muhammadiyah Surabaya, Surabaya, Indonesia

Abstrak

Penelitian ini bertujuan untuk menganalisis hubungan antara gelombang otak dan tingkat kesiapan siswa difabel dengan kategori mild-cognitive impairment dalam belajar menggunakan sinyal EEG (Electroencephalography). Sinyal EEG digunakan untuk merekam aktivitas listrik otak yang dihubungkan dengan berbagai kondisi mental, termasuk kesiapan belajar. Metode yang digunakan melibatkan pengumpulan data dari siswa difabel dengan melakukan pengukuran gelombang otak sebelum dan selama proses pembelajaran. Hasil dari penelitian ini menunjukkan bahwa terdapat korelasi signifikan antara jenis gelombang otak tertentu, seperti gelombang alfa dan beta, dengan tingkat kesiapan siswa dalam menerima materi pembelajaran. Temuan ini diharapkan dapat memberikan wawasan baru dalam pengembangan metode pembelajaran yang lebih efektif dan sesuai dengan kondisi mental siswa difabel, serta menjadi acuan untuk optimasi kurikulum pendidikan inklusif berbasis teknologi.

Kata Kunci: Electroencephalography; gelombang otak; pembelajaran inklusi; mild-cognitive impairment

Abstract

This study aims to analyze the relationship between brain waves and the level of readiness of students with disabilities categorized as mild-cognitive impairment in learning using EEG (Electroencephalography) signals. EEG signals are used to record electrical brain activity that is associated with various mental conditions, including learning readiness. The method used involves collecting data from students with disabilities by measuring brain waves before and during the learning process. The results of this study indicate that there is a significant correlation between certain types of brain waves, such as alpha and beta waves, with the level of student readiness in receiving learning materials. These findings are expected to provide new insights in the development of more effective learning methods that are in accordance with the mental conditions of students with disabilities, as well as being a reference for optimizing technology-based inclusive education curriculum.

Keywords: Electroencephalography; brainwaves; inclusive education; mild-cognitive impairment



This is an open access article under the [Creative Commons Attribution-ShareAlike 4.0 International](https://creativecommons.org/licenses/by-sa/4.0/) license.

OPEN ACCESS

e-ISSN 2597-4122

(Online)

p-ISSN 2581-1800

(Print)

*Correspondence:

Muhamad Amirul

Haq

[amirul.haq@ft.um](mailto:amirul.haq@ft.um-surabaya.ac.id)

[-surabaya.ac.id](mailto:amirul.haq@ft.um-surabaya.ac.id)

Received: 30-12-2024

Accepted: 26-02-2025

Published: 28-02-2025

DOI

<http://dx.doi.org/10.30651/else.v9i1.25098>

INTRODUCTION

Inclusive education is an approach that seeks to provide equal opportunities for all students to access quality education based on their unique needs and abilities [1]. This concept has gained global recognition and has become a key priority in education systems worldwide, including in Indonesia. The government of Indonesia has made strides to promote inclusive education through the establishment of Sekolah Luar Biasa (SLB), which are specialized schools designed to cater to children with special needs. These institutions aim to create a supportive environment where students with disabilities can develop academically, socially, and emotionally. According to data provided by the World Health Organization (WHO), Indonesia is home to approximately 10 million individuals with disabilities. Despite this sizable population, people with disabilities often remain marginalized and face significant barriers to education and employment [2]. SLBs serve as a crucial platform to bridge this gap, ensuring that children with special needs have access to appropriate learning opportunities.

However, despite the efforts made, SLBs continue to face substantial challenges in delivering effective education. One of the major issues is the lack of integration of advanced technologies into the teaching and learning process. Many SLBs operate with limited resources and outdated teaching methods, making it difficult to meet the diverse needs of their students. Additionally, assessing the cognitive readiness of students with disabilities can be complex, requiring experienced educators who can interpret behavioral and verbal cues. This reliance on manual observation introduces subjectivity and inconsistency, which may affect the overall learning outcomes. Furthermore, the absence of real-time data on students' mental states leaves teachers unable to adapt lessons or provide personalized strategies effectively. Addressing these gaps is critical to improving the quality of education offered to students with special needs.

Currently, SLBs rely heavily on experienced teachers who can gauge a student's preparedness for learning based on their behavior and responses. While this approach has proven useful, it also has limitations. It requires years of training and hands-on experience for teachers to develop the ability to interpret subtle signs of focus, fatigue, or stress. Moreover, the process is time-consuming and prone to human error, especially in classrooms with a higher student-to-teacher ratio. Teachers often need to monitor multiple students simultaneously, making it difficult to provide individualized attention. These limitations highlight the need for objective and technology-assisted methods to assess and track students' cognitive states. By leveraging modern tools, teachers can enhance their ability to create personalized learning plans that cater to each student's unique requirements.

Our proposed solution involves integrating Electroencephalogram (EEG) technology into the classroom to monitor and assess students' cognitive readiness in real-time. EEG devices measure brainwave activity through electrodes placed on the scalp, providing insights into mental states such as focus, relaxation, and stress. By processing this data, teachers can identify whether students are mentally prepared for learning or need conditioning activities to improve their readiness. The use of EEG technology eliminates much of the subjectivity involved in traditional observation methods and provides teachers with data-driven insights to guide their decisions. Furthermore, EEG-based systems can visualize brain activity patterns, allowing educators and parents to monitor progress over time. This approach not only improves the accuracy of assessments but also helps build a more inclusive learning environment by ensuring that each student receives the attention and support they need.

In summary, inclusive education holds the promise of creating equitable learning opportunities for all students, including those with special needs. However, achieving this goal requires overcoming the challenges associated

with outdated teaching methods and subjective assessments of student preparedness. By incorporating EEG technology, we can address these challenges and create a more effective and personalized learning environment. This research contributes to the development of inclusive educational tools by providing a framework for assessing cognitive readiness through EEG data. It also highlights the potential of informatics students to apply their knowledge in meaningful ways, bridging the gap between technology and education. Through this work, we aim to demonstrate how modern technology can complement traditional teaching methods, making inclusive education more accessible and impactful.

LITERATURE REVIEW

Electro-Encephalography (EEG)

EEG is a tool used to detect brain signal activity by attaching electrodes to the head, which are then connected to a monitor to record all brain signal activity. The data obtained are electrical activity data measured in microvolts (μV). Brainwave frequencies are categorized into Gamma (30-100 Hz), Beta (13-30 Hz), Alpha (8-13 Hz), Theta (4-8 Hz), and Delta (0.1-4 Hz) signals [3]. Brainwaves are categorized based on frequency into several types, such as: (i) Delta (0.5-4 Hz): Associated with deep sleep; (ii) Theta (4-8 Hz): Related to meditation or creativity; (iii) Alpha (8-12 Hz): Occurs during light relaxation and focus states; (iv) Beta (12-30 Hz): Linked to mental activity and intense focus; (v) Gamma (30-100 Hz): Associated with high-level cognitive processing, such as learning and problem-solving.

Bluetooth

Bluetooth is a short-range wireless communication technology used to transmit data between electronic devices without requiring cables. Bluetooth operates at a frequency of 2.4 GHz in the ISM (Industrial, Scientific, and Medical) band, which is a standard frequency for wireless devices. Bluetooth uses radio waves to transmit data between two or

more devices. Devices must be paired through a handshaking process that secures the connection. Once paired, data is transmitted in packets using the Bluetooth protocol. Devices typically communicate over short distances (up to 100 meters for newer Bluetooth versions, depending on device class). Bluetooth 5.0 and 5.1: Extend range up to 100 meters and increase data transmission speeds. These versions also support more stable and faster data delivery, which is essential for web-based systems receiving real-time data from EEG. Bluetooth enables real-time transmission of brain data from EEG to web-based systems, allowing immediate visualization of brain activity, which is vital for intelligence mapping or cognitive analysis.

Web-Based Systems

A web-based system is an application accessible through internet browsers like Google Chrome, Firefox, or Safari without requiring local installation on user devices. These systems rely on servers to execute application logic and browsers to display the user interface. Web-based systems generally use client-server architecture consisting of two or three main layers:

- **Client-Side (Front-End):** The part of the system that directly interacts with users through browsers. It includes elements such as HTML (Hypertext Markup Language), CSS (Cascading Style Sheets), and JavaScript, which are used to present and format content and handle user interactions.
- **Server-Side (Back-End):** The part responsible for application logic and data management. Server-side can use programming languages like PHP, Python, Ruby, or Node.js to process user requests, access databases, and send data back to the client.
- **Database Layer:** Web-based systems often connect to databases to store and retrieve information. Examples include MySQL, PostgreSQL, and MongoDB.

Technologies used in web-based systems include HTML, CSS, JavaScript, frameworks like React, Vue.js, and Angular, back-end languages like PHP, Python, Ruby, and Node.js, and databases like MySQL and MongoDB. HTTP/HTTPS protocols are employed to transmit requests and responses between clients and servers.

PROPOSED METHOD

The system design involves EEG devices connected via Bluetooth to a web-based system for processing and visualizing data. Teachers use the system to collect and analyze students' brainwave data, assisting in cognitive assessments. The architecture includes database design and flowcharts to streamline the brain mapping detection tool usage.

Data Collection

EEG data collection involves setting up EEG devices with electrodes attached to students' scalps. The devices are connected via Bluetooth to ensure stable data transmission. EEG signals are recorded in electrical form and categorized by frequency bands (alpha, beta, delta, theta, and gamma) related to learning readiness. Observations and interviews with teachers and students complement the data collection, providing insights into their experiences. Experiments are conducted to test EEG devices and collect real-time data during learning sessions.

Data Processing

The process of transforming the raw EEG data into a format that can be analyzed begins with converting the time-based signals into a frequency-based representation. This is done using a mathematical approach known as the Fast Fourier Transform (FFT). EEG data, by its nature, is collected as a continuous stream of electrical activity recorded over time. However, analyzing such signals directly can be challenging because the information is distributed across different time intervals. To make the data easier to interpret, FFT breaks the

signal into individual frequency components, effectively translating the data from the time domain into the frequency domain.

By performing this transformation, the EEG signal can be separated into distinct frequency bands such as Delta, Theta, Alpha, Beta, and Gamma. Each of these frequency bands corresponds to specific mental states, ranging from deep relaxation to high cognitive activity. For example, the Theta band, which typically ranges from 4 to 8 Hz, is associated with relaxation and creativity, while the Beta band, which spans from 12 to 30 Hz, is linked to focused mental activity and problem-solving. The process of identifying these frequency components allows the system to detect patterns in the brainwaves that may indicate the cognitive readiness of a student. Once the EEG signal is converted into frequencies, the data is stored and analyzed further. The system continuously collects and processes the incoming signals in real-time, updating visual graphs that display the frequency distribution. These visualizations help educators monitor changes in brain activity as they occur, providing insights into the student's mental state during the learning process.

To ensure that the data processing is both fast and accurate, the system is designed to handle variations in the signal without delays or errors. This reliability is critical because the data must reflect real-time brain activity to be useful in classroom settings. Additionally, the processing pipeline is tested to verify that it can maintain consistent performance, even when analyzing signals from multiple students simultaneously. This ensures that the system can be scaled for broader use without compromising its ability to deliver meaningful results. In summary, the FFT method simplifies the complexity of EEG signals, making it possible to uncover patterns that are not visible in raw data. These patterns, when analyzed, provide valuable information about brain activity, enabling

teachers and researchers to better understand students' learning readiness and mental states.

Student Preparedness Classification

The classification of a student's readiness to learn is based on identifying the most dominant frequency bands present in their EEG data. After the raw signals are transformed into frequency components, the system calculates the frequency that appears most often within the data. This calculation is referred to as the Mode, which represents the value that occurs more frequently than any other. Instead of relying on just one frequency, the system selects the two most frequent frequency bands to improve the accuracy of the classification process.

The next step involves interpreting these two dominant frequencies to determine the student's cognitive state. If the Mode reveals that the most common frequencies are in both the Theta (4–8 Hz) and Beta (12–30 Hz) ranges, the student is classified as "PREPARED FOR LEARNING." The presence of Theta waves suggests a relaxed but attentive mental state, while Beta waves indicate active focus and engagement. Together, these frequencies represent an optimal balance between calmness and alertness, which is ideal for absorbing new information and participating in learning activities.

On the other hand, if the dominant frequencies do not include both Theta and Beta bands, the student may be classified as needing additional preparation before learning can effectively take place. For example, if the data shows higher frequencies in the Delta range, which is associated with deep relaxation or drowsiness, it may indicate that the student is not yet mentally prepared to focus. Similarly, if Alpha waves dominate, the student may be too relaxed and require stimulation to reach a more focused state.

This classification system allows educators to take targeted actions to condition students

who are not yet ready for learning. Conditioning methods may involve short physical activities, breathing exercises, or even brief breaks to reset the students' mental state. The ability to identify and address these states in real-time is one of the major advantages of integrating EEG technology into the classroom environment.

Web-based System Design

The overall system design of the student preparedness is shown in Figure 1. First, the teachers who act as the users can connect the EEG via Bluetooth from their smartphone or computer. Then, they need to login in the web-based user interface to record and read the students brainwaves. After that, the EEG reads the brainwaves signal and pass the reading to the computer. Then, the computer classifies the student preparedness based on their brainwaves. If the students are not prepared to learn, then they are recommended to do physical activity and concentration-based games to improve their preparedness before their brainwaves are read again.

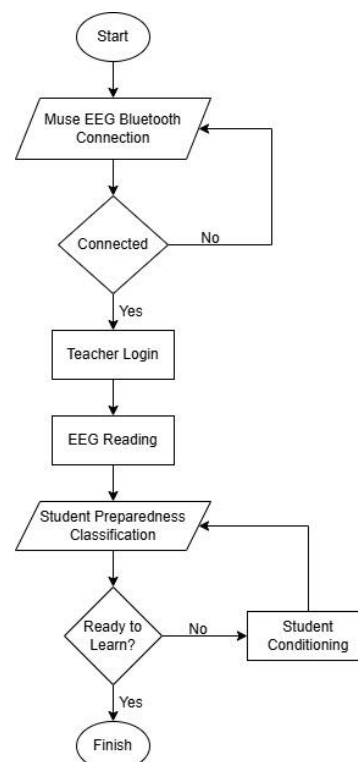


Figure 1. Flowchart of the System Design

RESULTS AND DISCUSSION

The results of this study demonstrate the effectiveness of EEG-based systems in assessing the cognitive readiness of students with disabilities. Data collected through EEG devices were analyzed using Fast Fourier Transform (FFT) to convert raw time-series signals into frequency components. These frequencies were then classified based on their dominant patterns, revealing insights into the students' mental states during learning activities. The findings show that students with frequencies predominantly in the Theta and Beta bands exhibited a balanced mental state characterized by focus and relaxation, which aligns with the classification of being "Prepared for Learning." Conversely, students whose EEG signals were dominated by Delta or Alpha waves showed signs of either drowsiness or excessive relaxation, indicating a need for conditioning activities before engaging in structured learning tasks.

The implementation of EEG technology provided measurable and objective data, enabling teachers to make informed decisions about their teaching strategies, as shown in Figure 2. For example, students displaying Beta wave dominance demonstrated heightened attention and cognitive engagement, which supported the hypothesis that Beta waves correlate with mental focus and problem-solving abilities. On the other hand, students who exhibited strong Theta waves alongside Beta waves appeared relaxed yet attentive, indicating a readiness to absorb information effectively. These results validate the use of EEG as a tool to monitor and enhance cognitive readiness in real-time.

The classification model based on the Mode of frequency distribution successfully categorized students' preparedness, reducing the subjectivity that often accompanies manual observation. Teachers reported a higher degree of confidence in identifying students' cognitive states, which streamlined lesson planning and delivery.

Additionally, interviews conducted with teachers indicated that the system saved time by automating data collection and analysis, allowing educators to focus more on interaction and personalized instruction rather than guesswork.



Figure 2. System Demonstration in SLB 'Aisyiyah Krian

CONCLUSION

EEG signals can provide an accurate representation of the learning readiness of students with disabilities. By analyzing brainwave frequencies, particularly alpha and beta waves, it is possible to determine the cognitive state of students, including their levels of focus, concentration, and relaxation. This study highlights the potential of EEG technology as a valuable tool for educators and therapists to gain deeper insights into the learning needs of students with disabilities. The ability to monitor brain activity in real-time enables the identification of students' mental readiness, allowing teachers to adapt their strategies to create a more supportive and effective learning environment. Furthermore, this research emphasizes that integrating EEG-based systems in classrooms can improve both the effectiveness and efficiency of the teaching process. By leveraging this technology, educators can develop targeted approaches that address the unique needs of each student, ensuring better learning outcomes and fostering inclusivity in education.

REFERENCES

- Biasiucci, A., Franceschiello, B., Biology, M. M.-C., & 2019, undefined. (n.d.). Electroencephalography. *Cell.Com*. Retrieved December 30, 2024, from [https://www.cell.com/current-biology/fulltext/S0960-9822\(18\)31551-3](https://www.cell.com/current-biology/fulltext/S0960-9822(18)31551-3)
- Downing, J. E., & Peckham-Hardin, K. D. (2007). Inclusive education: What makes it a good education for students with moderate to severe disabilities? *Research and Practice for Persons with Severe Disabilities*, 32(1), 16–30. <https://doi.org/10.2511/RPSD.32.1.16>
- Gauthier, S., Reisberg, B., Zaudig, M., Petersen, R. C., Ritchie, K., Broich, K., Belleville, S., Brodaty, H., Bennett, D., Chertkow, H., Cummings, J. L., de Leon, M., Feldman, H., Ganguli, M., Hampel, H., Scheltens, P., Tierney, M. C., Whitehouse, P., & Winblad, B. (2006). Mild cognitive impairment. *Lancet*, 367(9518), 1262–1270. [https://doi.org/10.1016/S0140-6736\(06\)68542-5/ASSET/4E39A3F5-4E58-4388-9747-876A097297B1/MAIN.ASSETS/GR1.JPG](https://doi.org/10.1016/S0140-6736(06)68542-5/ASSET/4E39A3F5-4E58-4388-9747-876A097297B1/MAIN.ASSETS/GR1.JPG)
- Muazza, M., Hadiyanto, H., ... D. H.-J. K., & 2018, undefined. (n.d.). Analyses of inclusive education policy: A case study of elementary school in Jambi. *Journal.Uny.Ac.Id*. Retrieved December 30, 2024, from <https://journal.uny.ac.id/index.php/jk/article/view/14968>
- neurology, G. M.-P.-H. of clinical, & 2020, undefined. (n.d.). Electroencephalography. *Elsevier*. Retrieved December 30, 2024, from <https://www.sciencedirect.com/science/article/pii/B9780444639349000184>
- Paludan Malver, L., Brokjaer, A., Staahl, C., Graversen, C., Andresen, T., Mohr Drewes, A., & Asbjørn Mohr Drewes, P. (2013). Electroencephalography and analgesics. *Wiley Online Library*, 77(1), 72–95. <https://doi.org/10.1111/bcp.12137>
- Petersen, R. C. (2016). Mild cognitive impairment. *CONTINUUM Lifelong Learning in Neurology*, 22(2, Dementia), 404–418. <https://doi.org/10.1212/CON.0000000000000313>
- Petersen, R. C., & Negash, S. (2008). Mild Cognitive Impairment: An Overview. *CNS Spectrums*, 13(1), 45–53. <https://doi.org/10.1017/S1092852900016151>
- Sanford, A. M. (2017). Mild Cognitive Impairment. *Clinics in Geriatric Medicine*, 33(3), 325–337. <https://doi.org/10.1016/J.CGER.2017.02.005/ASSET/544652A5-3648-4EDB-8121-3941F31C2F89/MAIN.ASSETS/GR3.SML>
- Sen, D., Mishra, B. B., & Pattnaik, P. K. (2023). A Review of the Filtering Techniques used in EEG Signal Processing. *7th International Conference on Trends in Electronics and Informatics, ICOEI 2023 - Proceedings*, 270–277. <https://doi.org/10.1109/ICOEI56765.2023.10125857>
- Siron, Y., ... R. M. D. and D. I. in, & 2017, undefined. (n.d.). Implementing inclusive education: What are elementary teacher obstacles? Case study in East Jakarta, Indonesia. *Atlantis-Press.Com*. Retrieved December 30, 2024, from <https://www.atlantispress.com/proceedings/icddims-17/25893016>