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Analysis of the Relationship between Brain Waves and Learning Readiness of Students with Disabilities Using Electroencephalography (EEG) Signals

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Abstract: This study aims to analyze the relationship between brainwave activity and the learning readiness of students with disabilities by utilizing EEG (Electroencephalography) signals. EEG signals are used to detect the brain's electrical activity that reflects mental states, including focus, concentration, and readiness to receive learning. This study was conducted at SLB 'Aisyiyah Krian with a quantitative approach through EEG signal measurement before and during the learning process. The results showed a significant correlation between the dominance of alpha and beta waves with learning readiness, while the dominance of theta and delta waves indicated unpreparedness. These findings provide a foundation for the development of a more inclusive, objective, and adaptive neurotechnology-based learning approach for students with disabilities.

Keywords: Disabilities; Electroencephalography; Inclusive Education; Learning Readiness; Neurotechnology

Introduction

Inclusive education is a form of educational service that ensures that every child, including those with special needs, has equal access to quality learning. Based on the WHO report, Indonesia has more than 10 million people with disabilities, most of whom still face obstacles in accessing equal education services. Extraordinary Schools (SLB) as special educational institutions in Indonesia play an important role in bridging this need (Nasution & Andriana, 2016; Syaifurrohman & Nasution, 2021).

However, in practice, many SLBs still face limitations in the use of technology to support the learning process. Conventional approaches that rely on manual observation are often not objective enough in identifying students' mental readiness to learn. In fact, learning readiness is an important factor that determines the success of the learning process, especially for students with special needs.

It is in this context that EEG (Electroencephalography) technology comes into play as a solution that offers objectivity and accuracy in detecting mental states. EEG has been widely used in the fields of neurology and psychology to analyze brain activity and is now beginning to be integrated in the field of education. The use of EEG in education allows educators to understand students' psychophysiological conditions in more depth and in real-time (Vicchietti et al., 2023).

This study aims to analyze the relationship between brain waves and the learning readiness of students with

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disabilities at SLB 'Aisyiyah Krian. The results of the research are expected to be the foundation for the development of an adaptive learning system based on brain signals to support more inclusive education.

Literature Review

Electroencephalography (EEG)

Electroencephalography (EEG) is one of the methods used to record the electrical activity of the brain through the placement of electrodes on the surface of the scalp. This activity is monitored and displayed in the form of brain waves, which reflect a person's cognitive and emotional state. Each type of brain wave has certain characteristics and functions that are relevant in the context of learning, especially in inclusive education (Amini et al., 2021; Baker et al., 2008; Teplan, 2002; Vicchietti et al., 2023).

In general, there are five main types of brain waves that are categorized based on their frequency: Delta (0.5–4 Hz): Appears dominant when the individual is in a state of deep sleep. This wave indicates a lack of awareness and mental activity; Theta (4–8 Hz): Relates to a state of deep relaxation, active imagination, and the transition phase to sleep. These waves are often associated with creativity and subconscious processing; Alpha (8–12 Hz): Associated with a state of relaxation but staying alert, as well as learning readiness. This frequency is an optimal indicator to start the learning process because it shows a balance between focus and calmness; Beta (12–30 Hz): Relates to active concentration, logic, and intense cognitive activity. These waves often appear when students are understanding concepts or completing complex tasks; and Gamma (30–100 Hz): These highest-frequency waves indicate involvement in high-level information processing, such as problem-solving, conceptual comprehension, and memory integration.

A number of studies show that alpha and beta waves play an important role in determining students' readiness to learn. EEG has been used in the world of education to evaluate stress levels, cognitive load, and the effectiveness of learning methods. In the context of students with disabilities, the use of EEG allows for a more objective and measurable approach to learning readiness, replacing conventional observation methods that tend to be subjective.

Bluetooth technology in EEG

The development of wireless technology, especially Bluetooth, has made a major contribution to the ease of use of EEG devices. Bluetooth versions 5.0 and 5.1 allow real-time data transmission with a range of up to 100 meters. This feature is essential in the development of portable tools that support the measurement of brain activity in educational settings, without interfering with student mobility (Baker et al., 2008; Honcharenko et al., 1997; Mackay et al., 2003; Marco et al., 2019; Matalatala et al., 2019; Teplan, 2002).

Bluetooth connections also minimize the use of cables and increase the comfort of use, especially for students with special needs. EEG data collected through the device can be directly transmitted to a cloud-based system for analysis and visualization, allowing teachers to monitor students' condition directly and efficiently.

Web-Based Systems for EEG Visualization

The use of web-based systems in EEG research is an important component in supporting the implementation of this technology in educational institutions. This system functions to process, store, and display EEG data in the form of graphs, visual indicators, and analytical reports that are easy for teachers and educators to understand.

By leveraging a client-server architecture, web-based systems allow real-time access to data from a variety of devices. The User Interface (UI) is designed to be intuitive and responsive, making it easier for teachers to read data related to the condition of student learning readiness. This informative visual presentation helps the decision-making process in adapting the right learning approach (Haryanti, 2020; Haryanti et al., 2022, 2023a; Haryanti & Pribadi, 2019; Haryanti & Subriadi, 2021).

The system also supports integration with cloud technology, which allows data to be stored and managed securely and accessible anytime and anywhere. This is especially useful in inclusive learning contexts that require high flexibility and personalization.

Method

Location and Research Subject

This research was carried out at the 'Aisyiyah Krian Special School (SLB), Sidoarjo Regency, East Java. This SLB serves students with various categories of disabilities, including blindness, mild disability, and other developmental disabilities. The selection of this location is based on the school's openness to technological innovation and the availability of students who meet the participation criteria.

A total of 15 students were selected as research subjects with inclusion criteria including: ability to follow basic instructions, have no history of epilepsy or severe neurological disorders, and be willing to follow the entire series of research procedures. The selection process is carried out with teachers and educators to ensure that students' participation is in accordance with their physical and psychological conditions

Research Design

This study uses a descriptive quantitative approach with a quasi-experimental design. The main objective of the study was to explore the correlation between the type of brain waves recorded through EEG and students' readiness to participate in learning activities.

The implementation procedure consists of two main stages: Baseline EEG Measurement (Pre-learning): Conducted before the learning process begins to obtain data on the initial state of student brain activity. This measurement reflects the student's initial readiness before receiving a learning stimulus. EEG Measurement During Learning: Performed while the learning process is ongoing, to find out the dynamics of brain waves during the student is engaged in learning activities.

Each measurement session lasts approximately 15–20 minutes, depending on the condition of each student. During the measurement, the teacher remains accompanying to maintain the comfort and safety of students.

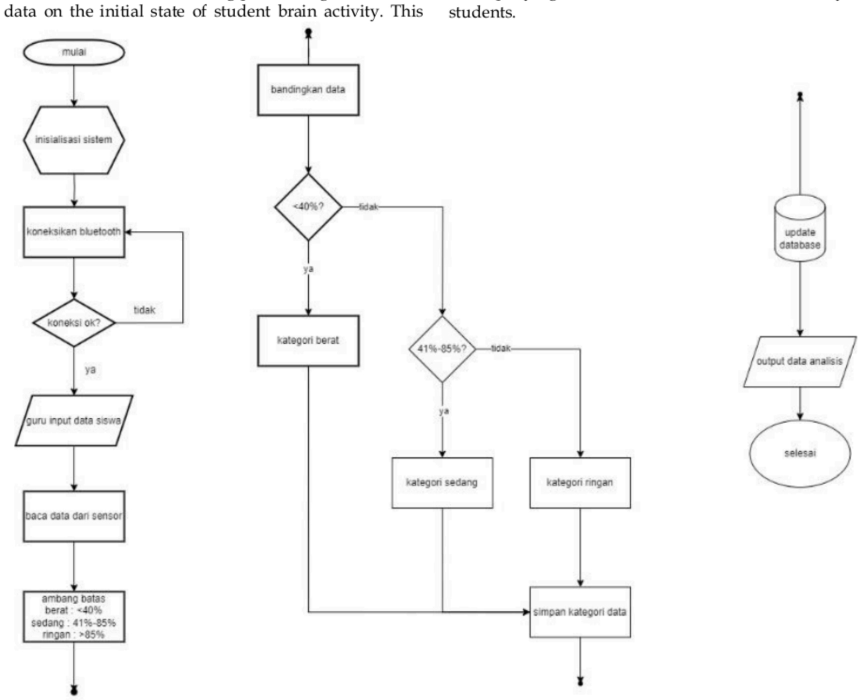

Figure 1. Flowchart of the Process of Using Brain Mapping Detection Tools

Tools and Instruments

This research uses several supporting tools and instruments, including Portable EEG Device: A headband-shaped device with four main channels that record brain activity from the frontal, parietal, temporal, and occipital areas. This device was chosen because it is easy to use and non-invasive (Haq et al., 2024; Haryanti et al., 2024; Nugroho et al., 2023).

EEG Visualization System: A web-based application that displays EEG data in real-time through a visual dashboard. The data is presented in the form of brain wave graphs, indicators of frequency dominance, and learning readiness levels Figure .

Observation Form: Used by researchers and teachers to record student behaviors during EEG data collection, such as focus levels, reactions to instruction, and engagement in learning activities

Data Analysis Techniques

The EEG data obtained from each student was classified based on the most dominant brain waves at each stage (baseline and learning). This data was then analysed using descriptive statistics to illustrate the distribution and frequency of dominance of brain waves. Furthermore, to find out the relationship between brain waves and student learning behaviour, a Pearson correlation test was performed. A significant positive correlation between alpha or beta wave dominance with students' focus and engagement behaviors would indicate higher learning readiness.

Results and Discussion

EEG Measurement Results

The results of measuring brain activity using EEG devices showed a pattern of brain wave dominance that varied among the study subjects. Of the 15 students who became participants, as many as 11 students showed the dominance of alpha and beta waves during the learning process. These two types of waves are associated with a state of focus, relaxation, and good cognitive readiness in receiving learning materials. Meanwhile, the other 4 students showed dominance of theta and delta waves, which are generally associated with fatigue, sleepiness, or a state of not being ready to learn.

These findings are in line with the results of teachers' observations, where students with the dominance of alpha and beta waves show better learning performance. They can follow instructions well, focus on tasks, and complete learning activities in a relatively short time. In contrast, students with theta dominance tend to be easily distracted, take longer to understand instructions, and exhibit passive behavior during sessions.

Correlation Analysis

To find out the extent of the relationship between brain wave patterns and learning readiness, statistical analysis was carried out using the Pearson correlation test. The results of the analysis showed that there was a significant positive correlation between the dominance of the beta wave and the indicator of learning readiness ($r = 0.74$, $p < 0.05$). This means that the higher the beta wave activity is detected, the higher the readiness of students to follow the learning process. In contrast, a significant negative correlation was found between theta wave dominance and learning focus ($r = -0.68$, $p < 0.05$), indicating that increased theta wave activity was likely to be followed by decreased focus and learning motivation.

System Implementation

As part of learning technology innovation, a web-based EEG visualization system was developed to make it easier for teachers to monitor students' learning readiness in real-time. The system displays EEG data that has been processed into dynamic graphs and visual indicators of learning readiness, making it easier to interpret by non-technical users such as teachers or educators.

The system view includes indicators of readiness zones (ready, unprepared, neutral), graphs of brain wave frequencies per student, and intervention recommendations. This feature assists teachers in making informed decisions, such as determining the best time to start lessons or providing breaks for students who do not show optimal readiness.

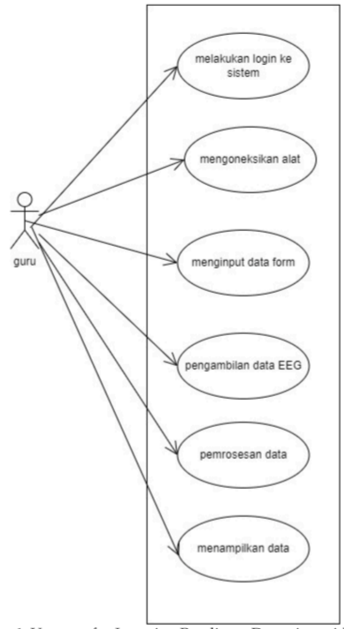

Figure 1. Use case for Learning Readiness Detection with EEG

Role of Regulatory Activity

In the case of students who show unpreparedness to learn based on EEG (dominant theta or delta) results, the teacher provides interventions in the form of regulative activities such as drawing, performing light gymnastic movements, or short breathing exercises and meditations. These activities are designed to help students' lower levels of tension or boredom and improve focus and relaxation (Nagy & Somosi, 2022; Nosratabadi et al., 2023). After the treatment, a remeasurement was carried out using EEG. The results showed an increase in alpha and beta wave activity in most of the students who were previously unprepared, indicating the effectiveness of this approach in regulating students' mental state to be better prepared for learning. Thus, the integration between EEG data and simple intervention strategies can be a practical solution to support more inclusive and adaptive learning in SLB environments.

Discussion

The results of this study are in line with previous findings that show that EEG signals can be an indicator of learning readiness. The use of EEG in SLB provides added value in designing adaptive learning methods, where students get an approach according to their mental state in real-time (Haryanti et al., 2022, 2023b, 2023c). The prototype of the brain mapping detection tool was developed through several stages, ranging from concept design, hardware creation, to software development that can analyze brain activity data (Francis et al., 2010; Hennink et al., 2017; Hidayat et al., 2023). The prototype is equipped with an EEG (Electroencephalogram) sensor that can detect brain waves, as well as software that processes the data into easy-to-understand visualizations.

After going through the test stage, this prototype successfully functioned as expected. The data generated by this tool shows the brain activity of students with disabilities as they perform a variety of simple cognitive tasks. The prototype is also able to identify patterns of brain waves related to concentration, relaxation, and stress, which can be important indicators in the learning process. Prototype trials were carried out on several students with disabilities with various categories of disabilities at SLB 'Aisyiyah Krian. The results of the trial show that this tool can detect and record students' brain activity well. For example, students with disabilities exhibit different patterns of brain waves when they are faced with challenging tasks, compared to students with better cognitive abilities.

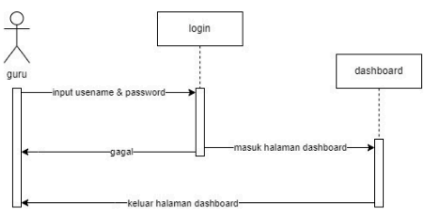

Figure 2. EEG-based Learning Readiness System Sequence

During the trial, this tool was also used to monitor changes in students' brain activity when given different learning methods. The data showed a significant difference in students' brain responses to visual learning methods compared to verbal methods. This shows that brain mapping detection tools can provide valuable information about the most effective learning methods for each student (Lehne et al., 2015).

The results of the trial show that the prototype of this brain mapping detection tool is effective in measuring and visualizing the brain activity of students with disabilities. The data obtained can assist teachers in understanding how each student reacts to different types of assignments and learning methods. Thus, this tool has the potential to be used as a tool in designing a more personalized learning strategy and according to the needs of each student (Almaiah & Jalil, 2014; June et al., 2014; Kusumo et al., 2012; Rachman et al., 2020).

Figure 3. EEG-based student readiness system display

The success of this tool in detecting the brain's response to various learning methods also shows that a data-driven approach can improve the quality of education in SLB. By understanding the patterns of student brain activity, teachers can be more precise in choosing teaching methods that can maximize the learning potential of each student. Although the results obtained were quite satisfactory, the development of this prototype also faced some challenges. One of them is the limitations in real-time data processing, which causes delays in the brain's data visualization. In addition, because the tool is still a prototype, the design is not yet fully ergonomic for long-term use by students with disabilities.

In addition, there are obstacles in adapting this tool for different types of disabilities. For example, students with disabilities face difficulties in using this tool independently, so additional assistance is needed. Another challenge is the need for intensive training for teachers to be able to accurately interpret the data generated by these tools and utilize them in the learning process.

Conclusion

This study proves that EEG signals can be used to objectively measure the learning readiness of students with disabilities. The dominance of alpha and beta waves is an indicator of mental readiness to learn, while the dominance of theta and delta indicates the need for regulatory intervention. The implications of this research are very significant for the development of special education in SLB. The use of brain mapping detection tools allows for a more data-based and individualized approach to learning, which can improve the learning outcomes of students with disabilities. This tool also opens opportunities for further research in the field of educational neuroscience, particularly in the context of special education (Neto, 2015; O'Brien & Deans, 1996; Serditova & Belotserkovsky, 2020). For further development, several aspects need to be improved, such as increasing the speed of data processing and improving the design to make it more ergonomic. In addition, further research is needed to test the effectiveness of these tools in the long term and in a variety of learning contexts. The development of additional features, such as integration with mobile devices or supporting apps, can also be the focus of subsequent development. Further research is suggested to explore the use of EEG in the context of educational game-based learning or artificial intelligence systems that can predict student learning readiness patterns.

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Author Contributions
Conceptualization, T.H and A.M.; methodology, T.H and A.M.; software, T.H and A.M.; validation, T.H and A.M.; formal analysis, T.H and A.M.; investigation T.H and A.M.; resources, T.H and A.M; data curation, T.H and A.M.; writing—original draft preparation, T.H and A.M.; writing—review and editing, T.H and R.N.; visualization, T.H and R.N.; supervision, T.H and R.N.; project administration, T.H and R.N;

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Conflicts of Interest
The authors declare no conflict of interest.

References

Almaiah, M. A., & Jalil, M. A. (2014). Investigating students' perceptions on mobile learning services. *International Journal of Interactive Mobile Technologies*, *8*(4). https://doi.org/10.3991/ijim.v8i4.3965

Amini, M., Pedram, M. M., Moradi, A. R., & Ouchani, M. (2021). Diagnosis of Alzheimer's Disease by Time-Dependent Power Spectrum Descriptors and Convolutional Neural Network Using EEG Signal. *Computational and Mathematical Methods in Medicine*. https://doi.org/10.1155/2021/5511922

Baker, M., Akrofi, K., Schiffer, R., & Boyle, M. W. O. (2008). EEG Patterns in Mild Cognitive Impairment (MCI) Patients. *The Open Neuroimaging Journal*, *2*. https://doi.org/10.2174/1874440000802010052

Francis, J. J., Johnston, M., Robertson, C., Glidewell, L., Entwistle, V., Eccles, M. P., & Grimshaw, J. M. (2010). What is an adequate sample size? Operationalising data saturation for theory-based interview studies. *Psychology and Health*, *25*(10). https://doi.org/10.1080/08870440903194015

Haq, M. A., Huy, L. N. Q., Ridlwan, M., & Naila, I. (2024). Leveraging Self-Attention Mechanism for Deep Learning in Hand-Gesture Recognition System. *E3S Web of Conferences*, *500*. https://doi.org/10.1051/e3sconf/202450001009

Haryanti, T. (2020). Document Management System and Reminder using SMS Gateway. *IOP Conference Series, 469 (Earth and Environmental Science)*, 1–7. https://doi.org/10.1088/1755-1315/469/1/012088

Haryanti, T., Haq, M. A., Wijaya, S. D., Oktaviani, M., Fayyadh, A., Firmansyah, H., & Emira. (2024). The Screening of Learning Readiness of Students with Disabilities at SLB Aisyiah Krian Sidoarjo using Electroencephalography (EEG. *JURNAL PENGABDIAN KEPADA MASYARAKAT*, *14*(2), 309–313. https://doi.org/10.30999/jpkm.v14i2.3352

Haryanti, T., & Pribadi, A. (2019). E-Commerce Service Design Readiness using ITIL framework with IT Balanced Scorecard Objective (Case Study: University E-Commerce. *Procedia Computer Science*, *161*, 283–290. https://doi.org/10.1016/j.procs.2019.11.125

Haryanti, T., Rakhmawati, N. A., & Subriadi, A. (2022). The Design Science Research Methodology (DSRM) for Self-Assessing Digital Transformation Maturity Index in Indonesia. *2022 IEEE 7th International Conference on Information Technology and Digital Applications (ICITDA*. Retrieved from https://ieeexplore.ieee.org/abstract/document/9971171

Haryanti, T., Rakhmawati, N. A., & Subriadi, A. P. (2023a). Journal of Industrial Engineering and Management A Comparative Analysis Review of Digital Transformation Stage in Developing Countries. *Journal of Industrial Engineering and Management*, *16*(1), 150–167. https://doi.org/10.3926/jiem.4576

Haryanti, T., Rakhmawati, N. A., & Subriadi, A. P. (2023b). Measuring the digital transformation maturity level independently with the design science research methodology. *Systems Engineering*. https://doi.org/10.1002/sys.21714

Haryanti, T., Rakhmawati, N. A., & Subriadi, A. P. (2023c). The Extended Digital Maturity Model. *Big Data and Cognitive Computing*, *7*(1). https://doi.org/10.3390/bdcc7010017

Haryanti, T., & Subriadi, A. P. (2021). E-commerce acceptance in the dimension of sustainability. *Journal of Modelling in Management*. https://doi.org/10.1108/JM2-05-2020-0141

Hennink, M. M., Kaiser, B. N., & Marconi, V. C. (2017). Code Saturation Versus Meaning Saturation: How Many Interviews Are Enough? *Qualitative Health Research*, *27*(4). https://doi.org/10.1177/1049732316665344

Hidayat, A. A. A., Uliyah, M., & Haryanti, T. (2023). Mobile nursing care plan information system for nursing service in hospitals. *European Review for Medical and Pharmacological Sciences*, *27*(1). https://doi.org/10.26355/eurrev_202301_30848

Honcharenko, W., Kruys, J. P., Lee, D. Y., & Shah, N. J. (1997). Broadband wireless access. *IEEE Communications Magazine*. https://doi.org/10.1109/35.568192

June, S., Yaacob, A., & Kheng, Y. K. (2014). Assessing the use of youtube videos and interactive activities as a critical thinking stimulator for tertiary students: An action research. *International Education Studies*. https://doi.org/10.5539/ies.v7n8p56

Kusumo, N. S. A. M., Kurniawan, F. B., & Putri, N. I. (2012). eLearning Obstacle Faced by Indonesian Students. *Nternational Journal of The Computer, The Internet, and Management*, *20*(1). Retrieved from https://shorturl.asia/Q27kG

Lehne, M., Engel, P., Rohrmeier, M., Menninghaus, W., Jacobs, M., A., & Koelsch, S. (2015). Reading a Suspenseful Literary Text Activates Brain Areas Related to Social Cognition and Predictive Inference. *PLoS ONE*, *10*(5). https://doi.org/10.1371/journal.pone.0124550

Mackay, S., Wright, E., Park, J., & Reynders, D. (2003). Understanding Wireless Fundamental. In *Practical Industrial Data Networks: Design, Installation and Troubleshooting* (1st ed., pp. 291–292). Elsevier Science Publishers B. V. https://doi.org/10.1016/b978-0-7506-5807-2.x5024-9

Marco, D., Dolara, A., Longo, M., & Yaïci, W. (2019). Design and Performance Analysis of Pads for Dynamic Wireless Charging of EVs using the Finite Element Method. *Energies*, *12*(21), 4139. https://doi.org/10.3390/en12214139

Matalatala, M., Deruyck, M., Shikhantsov, S., Tanghe, E., Plets, D., Goudos, S., Psannis, K. E., Martens, L., & Joseph, W. (2019). Multi-Objective Optimization of Massive MIMO 5G Wireless Networks towards Power Consumption, Uplink and Downlink Exposure. *Applied Sciences*, *9*(22), 4974. https://doi.org/10.3390/app9224974

Nagy, S., & Somosi, M. V. (2022). The relationship between social innovation and digital economy and society. *Regional Statistics*, *12*(2). https://doi.org/10.15196/RS120202

Nasution, P., & Andriana, S. D. (2016). *Aplikasi Pembelajaran Berbasis Mobile Untuk Tuna Aksara*. MATICS. https://doi.org/10.18860/mat.v8i1.3475

Neto, M. (2015). Journal of Student Engagement: Education Matters Educational motivation meets Maslow: Self- actualisation as contextual driver. *Journal of Student Engagement: Education Matters*, *5*(1), 18–27. Retrieved from http://ro.uow.edu.au/jseemhttp://ro.uow.edu.au/jseem/vol5/iss1/4

Nosratabadi, S., Atobishi, T., & Hegedűs, S. (2023). Social Sustainability of Digital Transformation: Empirical Evidence from EU-27 Countries. *Administrative Sciences*, *13*(5). https://doi.org/10.3390/admsci13050126

Nugroho, K. A., Amirul Haq, M., Wang, C. K., Ruan, S. J., Polikarpov, M., Wagstyl, D., & Deuse, J. (2023). Towards Smart Manufacturing using Reinforcement Learning in a Sparse-Rewarded Environment for Through-Hole Technology. *GCCE 2023 - 2023 IEEE 12th Global Conference on Consumer Electronics*. https://doi.org/10.1109/GCCE59613.2023.10315655

O'Brien, E. M., & Deans, K. R. (1996). Educational supply chain: A tool for strategic planning in tertiary education? *Marketing Intelligence & Planning*, *14*(2), 33–40. https://doi.org/10.1108/02634509610110787

Rachman, A., Rusandi, M. A., & Setiawan, M. A. (2020). Effect of Phubbing Behavior on Student Academic Procrastination. *PSIKOPEDAGOGIA Jurnal Bimbingan Dan Konseling*, *8*(1). https://doi.org/10.12928/psikopedagogia.v8i1.17895

Serditova, N. E., & Belotserkovsky, A. V. (2020). Education, quality and the digital transformation. *Vysshee Obrazovanie v Rossii*, *29*(4). https://doi.org/10.31992/0869-3617-2020-29-4-9-15

Syaifurrohman, S., & Nasution, F. A. (2021). Optimalisasi Pendidikan Politik melalui Literasi Digital bagi Penyandang Disabilitas dalam Industri 4.0 di Indonesia. *Jurnal Komunikasi*

Pendidikan, *5*(1). https://doi.org/10.32585/jkp.v5i1.800

Teplan, M. (2002). Fundamentals of EEG measurement. *Measurement Science Review*, *2*(2). Retrieved from http://www.edumed.org.br/cursos/neurociencia/MethodsEEGMeasurement.pdf

Vicchietti, M. L., Ramos, F. M., Betting, L. E., & Campanharo, A. S. L. O. (2023). Computational methods of EEG signals analysis for Alzheimer's disease classification. *Scientific Reports*, *13*(1). https://doi.org/10.1038/s41598-023-32664-8

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