International Journal of Engineering Trends and Technology
ISSN: 2231–5381 / https://doi.org/10.14445/22315381/IJETT-V73I12P105
Volume 73 Issue 12, 52-60, December 2025


*Original Article*

# Development of a Cost-Effective EEG System for Real-Time Monitoring of Cognitive States in Noisy Environments

Saranjuu Chulakit[1], Amirul Syafiq Sadun[1*], Nor Anija Jalaludin[1], Thiva Surena Krishnah Rao[1]

[1]*Faculty of Engineering Technology, Universiti Tun Hussein Onn Malaysia, Pagoh Campus, Johor, Malaysia.*

[*]*Corresponding Author : amirul@uthm.edu.my*

Received: 03 June 2025 Revised: 17 November 2025 Accepted: 21 November 2025 Published: 19 December 2025

***Abstract -*** *This research proposes a new design and testing of a low-cost EEG-based system to monitor a person's mental condition in a real-time environment under different noise conditions. The novelty designed uses a NeuroSky Mindwave headset and uses LabVIEW software as an interface to assemble the data, process it using Fast Fourier Transform (FFT), and display the EEG in real time. The research objectives are to assess attention and meditation states during task execution, and then the system has been tested on five participants performing a structured Lego assembly task in both controlled and loud noise environments. The result shows that under loud noise, mean alpha and beta activity nearly doubled ($\alpha$: 11.3% vs. 5.4%, $\beta$: 6.4% vs. 3.4%), delta activity decreased significantly (59.5% vs. 72.6%, $p = 0.019$), and attention scores rose markedly ($60 \pm 15$ vs. $26 \pm 18$, $p = 0.05$). It can be shown that the system's ability to depict variations in brainwave dynamics and cognitive states. The study validates the feasibility of consumer-grade EEG systems for real-time cognitive monitoring in noisy environments and highlights their potential applications in education, training, and ambient interface research.*

***Keywords -*** *Brain Computer Interface (BCI), Low-cost EEG system, Attention, Meditation.*

## 1. Introduction

Brain-Computer Interface (BCI) systems that use Electroencephalography (EEG) are becoming popular because they let users control devices using brain signals without using their hands, get feedback, and engage in neuroadaptive interaction. High-quality EEG systems with many channels can collect detailed brain data, but they are expensive, complicated to use, and mostly used in laboratories or hospitals. On the other hand, low-cost EEG devices such as NeuroSky MindWave are easier to use, more portable, and often used in education, small projects, and simple monitoring tasks [1-4]. Recent progress in connecting EEG devices with graphical tools such as LabVIEW has made it easier to collect, process, and show brain signals in real-time [5]. This improvement helps to create simple and useful applications that can give basic cognitive feedback when professional medical systems are not suitable. Despite these opportunities, there are several critical challenges that still exist. Firstly, it is still difficult to run raw EEG signals into real-time feedback that users can easily understand. Many existing platforms always depend on closed-source algorithms that make the result less clear and sometimes unreliable. The impact of the result is harder to apply in different situations. Secondly, the focus on creating simple and customizable interfaces for non-expert users is still not well developed. Lastly, environmental impact, such as noise, can affect cognitive load and task performance, and has limited studies in the evaluation of consumer-grade EEG systems. To tackle these gaps, this study proposed the development of a low-cost EEG monitoring system that combines a Bluetooth-enabled NeuroSky MindWave headset with a customizable LabVIEW interface. A Fast Fourier Transform (FFT) analysis is conducted to extract frequency band information and visualize the attention of the user and meditation states under various noise conditions. Instead of measuring accuracy at the clinical level, the aim of this study is to demonstrate a functional prototype that can be used to monitor real-time cognitive state using accessible and low-cost technologies.

## 2. System Architecture and EEG Foundations

Utilization of EEG technology in BCI systems has become increasingly relevant in both clinical research and applied environments due to its non-invasive nature, ease of use, and high temporal resolution. Among the various neuroimaging modalities available, EEG remains the most practical for real-time applications, specifically when aspects such as cost and portability are critical [6]. There are technologies such as Magnetoencephalography (MEG), Functional Magnetic Resonance Imaging (fMRI), and Electrocorticography (EcoG) that can show more detailed brain signals, but they are expensive, bulky, and unsuitable for low-resource or user-friendly environments [7-10]. A consumer-grade EEG system known as the NeuroSky MindWave was selected in this study to develop a low-cost, real-time monitoring system to get the attention and evaluation of the meditation state. NeuroSky MindWave is limited to a single frontal channel and lacks raw multi-site data access, but its simplicity and connectivity via Bluetooth make it suitable for feasibility studies, educational demonstrations, and rapid prototyping of BCI applications [11, 12]. The EEG signal received is then transmitted wirelessly to a computer that has LabVIEW software and will process the transmitted signals in real-time. Filtering and the application of FFT are signal processing techniques to extract power spectrum features across important frequency bands [13]. These features are shown in a custom graphical user interface to monitor cognitive activity during task implementation. This section outlines the justification for the chosen EEG headgear, the basic properties of EEG signals, and the rationale for interpreting brainwave activity within the scope of a consumer-grade interface.

### 2.1. EEG Headgear Selection and Comparison

Choosing the right EEG headgear is important to build effective and reliable BCI systems. Aspects that must be considered during choosing the EEG headgear include the balance of design between signal quality, user comfort, affordability, and ease of use. The common existing EEG headgear in the market today comes in three types: fully wired systems, wireless systems, and headband-style systems. Each type of EEG headgear offers trade-offs between stability, precision, and mobility. Wired headgear usually provides high-quality signals, but it is often not comfortable in long recording sessions since it limits movement. On the other hand, wireless headgear allows users to move freely but lose signal or face interference, especially in places with strong radio waves. In headband-based devices, a middle-ground headgear can be found. During low motion tasks, these devices can support both wired and wireless connections and gives relatively stable and acceptable signal consistency. Table 1 shows different types of EEG headgear in terms of cost, mobility, signal stability, and connectivity mode.

**Table 1. Comparison of EEG headgear types**

| Type | Cost | Precision | Mobility | Operation | Connectivity |
|---|---|---|---|---|---|
| Wired Headgear | Low | High | Low | Inconvenient | Wired |
| Headband | Moderate | High | High | Convenient | Wired/Bluetooth |
| Wireless Headgear | High | High | High | Convenient | Bluetooth/Wi-Fi |

The headband type was chosen in this study from the various EEG headgear types because it offers a practical compromise between ease of use and signal reliability. It also allows for the operation to be stable while still giving users the flexibility to move during tasks. Although all signal noise and artifact risks cannot be fully eliminated, its convenience and accessibility make it a suitable choice to be applied in short-term monitoring and experimental cognitive feedback systems.

### 2.2. EEG Signal Frequency Bands and Cognitive Interpretation

The electrical activity produced by neurons in the cerebral cortex of the brain represents EEG signals. Different frequency bands are produced from these signals, with each linked to various cognitive and physiological states. These bands can be complex and context-dependent, but each band generally consists of various level of alertness, relaxation, or cognitive engagement [14, 15]. The EEG frequency bands are divided into five types, which are delta, theta, alpha, beta, and gamma. Delta waves are usually associated with deep sleep or unconscious states and are characterized by low frequency and high amplitude. Theta waves always appear during light sleep or early stages of relaxation and are also connected to memory recall and meditative states. Alpha waves emerge when individuals are in a relaxed but awake condition, always associated with calm focus and low mental effort. Beta waves are produced during active thinking, decision-making, and alertness.

**Table 2. Brainwave properties and cognitive associations**

| Brain Wave Type | Frequency Spectrum (Hz) | Amplitude (µV) | Significance |
|---|---|---|---|
| Delta (δ) | 0.1 - 3.0 | 100 - 200 | Deep sleep, unconscious state, and cognitive tasks by the frontal lobe |
| Theta (θ) | 4.0 - 7.5 | < 30 | Common in young children, cognitive tasks are performed by the frontal lobe. |
| Alpha (α) | 8.0 - 12.0 | 30 - 50 | Relaxed but awake state, strong immune system, self-healing ability |
| Beta (β) | 13.0 - 30.0 | < 20 | Sensory and emotional influences, awake and conscious state |
| Gamma (γ) | 30.0 - 50.0 | < 10 | High mental activity, cooperative interaction of brain areas for motor or cognitive tasks |

Lastly, gamma waves that have the highest frequency are related to complex thinking and processing information in the brain. The main characteristics of these brainwave types, such as frequency ranges and usual signal amplitudes, are shown in Table 2 [1, 12,13]. The focus of this study is on the alpha and beta frequency bands, as both waves serve as indicators of cognitive load and engagement of the task. Delta and theta waves are also considered, specifically as they help in reflecting relaxation levels. It is important to note that the NeuroSky MindWave does not provide raw multi-channel EEG signals. However, it produces attention and meditation scores using its own built-in algorithms based on these frequency bands. Even though these metrics are not clinically proven, they are often used in consumer-grade EEG devices for feedback and training use. The system can produce a basic framework for cognitive state monitoring when analyzing these band powers alongside environmental factors such as noise exposure. The development of applications such as human-computer interaction, educational tools, and stress-aware environments can be supported by this approach when traditional EEG systems are not practical to use.

## 3. Research Methodology

### 3.1. Experimental Setup

The study involved five participants (4 males, 1 female) from a university. Their ages ranged between 22 and 40 years old, and all of them were in good physical and mental health without any history of neurological problems, skin issues, or conditions that could affect EEG recording.

All experiments were carried out in the evening to control variation in cognitive performance due to fatigue or daily natural body rhythm. During each session, participants were instructed to perform a Lego assembly task that involved matching colours and spatial relations, as shown in Figure 1.

This task was chosen because it is simple, structured, and easy to repeat, making it suitable for observing attention and mental engagement during a simple but active process. The Lego assembly had three main steps and ended with a small cube-shaped structure. The repeated process helped to maintain a consistent cognitive load across all trials.

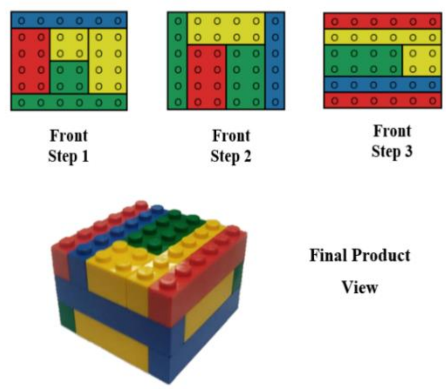


**Fig. 1 Lego assembling activity**

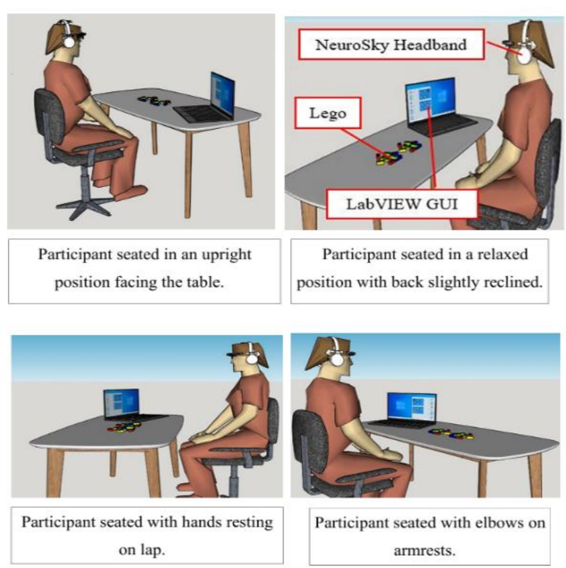


**Fig. 2 Experiment setup**

The experiment was carried out in two different conditions. The first condition was in a controlled noise environment with a range of background sound levels from 45 to 50 decibels. The second condition was a loud environment. Noise levels were produced using a connected laptop speaker that produced noise between 85 and 90 decibels. A decibel meter was used to verify these sound levels.

During both conditions, the same lighting and temperature were kept. Participants wore a NeuroSky MindWave headband EEG system equipped with a dry electrode sensor positioned on the forehead. The device collected data at 512 Hz and sent the signals wirelessly to a computer for real-time processing and display, as shown in Figure 2. Participants were instructed to stay in a neutral sitting position and maintain a steady posture to reduce motion interference.

Each participant completed three rounds of the Lego cube assembly task under each noise condition, with each session lasting for 5-7 minutes. Calibrated speakers were used to produce noise exposure with controlled environmental levels maintained at 47 ± 2 dB and loud condition levels at 88 ± 2 dB. Those sound levels were also verified using a digital sound level meter.

### *3.2. System Architecture and Signal Processing*

The overall structure of the EEG-based interface is shown in the system block diagram in Figure 3. The architecture has five main stages, which begin with the collection of raw EEG signals using the NeuroSky MindWave headset. These signals are then sent via Bluetooth to the LabVIEW software interface.

Sampling rate at 512 Hz, EEG signals were collected and split into 2-second segments with 50% overlap. Before FFT, a Hamming window was applied to reduce spectral leakage. Power spectral density was calculated for standard EEG bands: delta (0.1-3 Hz), theta (4-7.5 Hz), alpha (8-12 Hz), and beta (13-30 Hz). The power of each band was normalized as a percentage of the total power for each window. The results were averaged across all trials. After the EEG signal is accepted, it goes through a pre-processing stage that includes application of a bandpass filter and a lowpass filter to remove unwanted high-frequency noise and baseline drift. This is an important step to improve the signal-to-noise ratio. Next, to identify the frequency components that correspond to specific cognitive bands, including delta, theta, alpha, and beta, the signal was passed through an FFT and processed using its function.

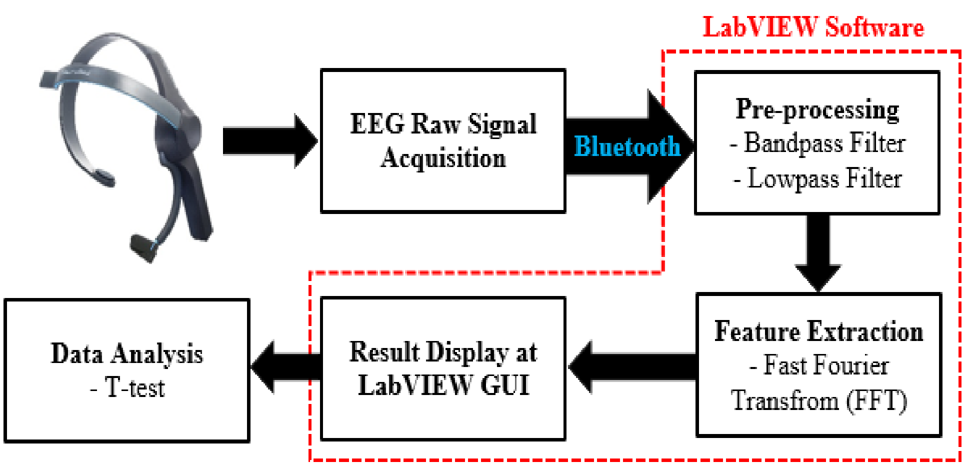


**Fig. 3 General block diagram**

Once the frequency-domain data is displayed on the graphical user interface of LabVIEW in real-time, the visualization of data includes the raw EEG waveform, the spectral density distribution, and the attention and meditation scores calculated by the NeuroSky device.

The scores are internally calculated by NeuroSky's algorithm, which uses the frequency and amplitude distribution of EEG signals. Finally, a paired sample t-tests were conducted to determine the comparison of the cognitive response between the controlled and loud noise environments in order to identify any significant differences.

### *3.3. LabVIEW Programming Framework*

The structure of LabVIEW programming was used in this system, as shown in Figure 4. The program starts with setting up the Bluetooth communication port, shown as Label A, that allows data transfer from the MindWave headset to the LabVIEW interface. Label B, including the NeuroSky-processed attention and meditation metrics, represents the data streams of EEG readings. These data are then arranged into waveform arrays for visual display, as shown in Label D. Once received, the EEG signal is first processed using bandpass and lowpass filters to remove high-frequency unwanted noise and baseline drift.

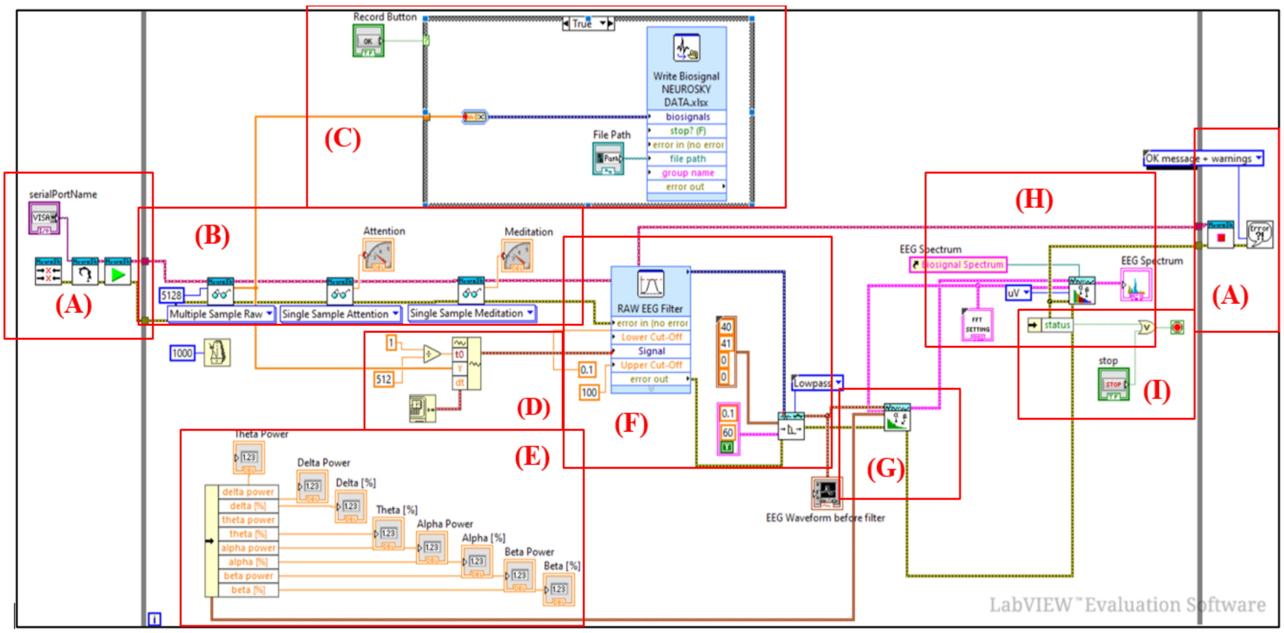


**Fig. 4 LabVIEW block diagram programming**

The pre-processing stage is presented as Label F. Before undergoing the FFT transformation as Label G, the raw signal is filtered. Label E is the calculated and displayed frequency power values, such as delta, theta, alpha, and beta waves, in both percentage and amplitude formats. These outputs are also sent into the EEG spectrum visualization module and labelled as H. The stop condition to end the system is labelled as I, while label C represents the active data recording module that allows users to store EEG signals for post-experiment analysis.

### *3.4. Graphical User Interface Design*

The LabVIEW front panel was designed to provide a simple and organized interface for real-time EEG monitoring, as shown in Figure 5. Several interfaces are divided into labelled sections.

Section A is used for users to receive personal identification data such as name, gender, and age range. Section B is used to set up the NeuroSky MindWave correctly by providing step-by-step instructions.

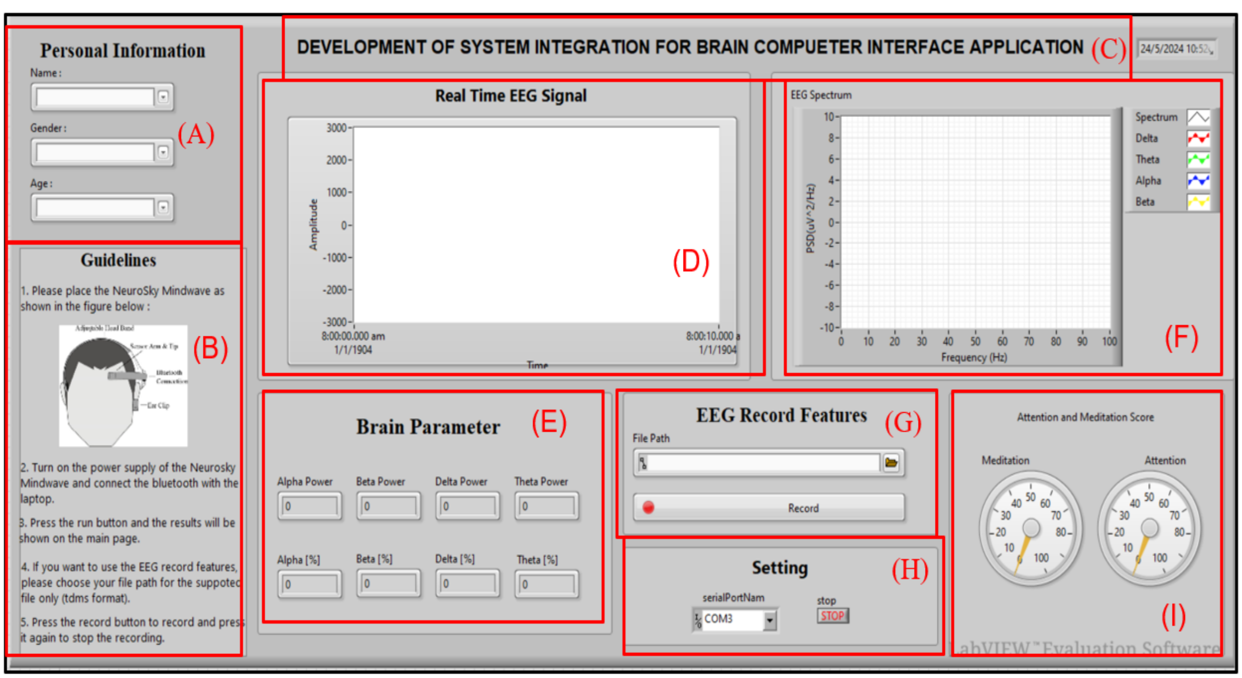


**Fig. 5 LabVIEW front panel for Graphical User Interface (GUI)**

Section C is used to show the project title and indicate that the interface is active. Section D is used to present a time-series graph of the EEG signal amplitude, while Section E displays each category of numerical power values. Section F contains a spectrum graph of EEG, and it shows the spectral power density for different frequency bands. Section G provides the input of the file path and the button to record. These features allow users to save the EEG data. Section H is the serial port selection and a button to end the system. The last section, Section I, shows attention in real-time and scores meditation produced by the NeuroSky system.

The proposed GUI offers an easy-to-use interface and provides real-time biofeedback. The proposed design is very useful for various fields such as education, research prototype, and low-cost monitoring, which are similar to previous EEG systems.

## 4. Findings

This part demonstrates how the different noise level may affect brain signals and activities by measuring the proposed system. Then the data have been recorded from five participants under both controlled and loud noise environments. The results are summarized in Table 3 and expressed according to relaxation, cognitive load, and attentiveness.

### *4.1. Controlled Noise Environment Results*

In order to perform this investigation, five participants aged 18 to 24 years old contributed to this experiment under controlled noise conditions. Each participant is required to sit in a comfortable posture while wearing an EEG headset as depicted in Figure 6. Before proceeding to collect data, the headset has been adjusted to ensure the forehead sensor has a very good connection with the skin to minimize signal disturbance.

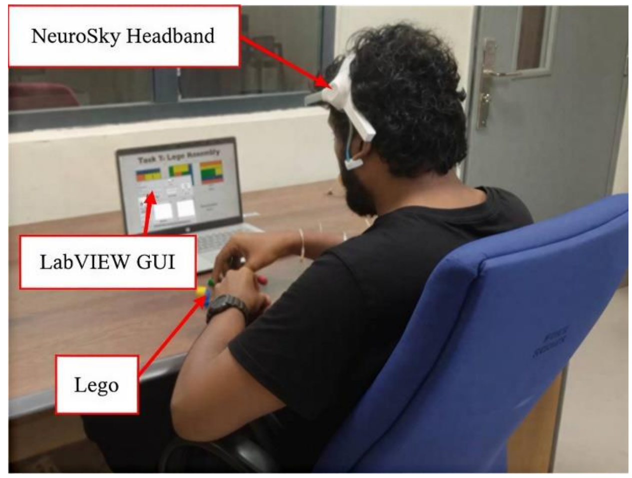


**Fig. 6 Subject undergoing the experiment**

During the controlled noise phase session, the background sound was evaluated using a digital sound level meter, which was around 47 decibels, which represents a quiet environment. As shown in Table 3, the EEG data, along with the meditation and attention scores from the NeuroSky system, were collected under this condition.

**Table 3. EEG and cognitive state data in a controlled noise environment**

| Respondents | Frequency Band (%) | | | | Meditation (%) | Attention (%) |
|---|---|---|---|---|---|---|
| | Alpha (α) | Beta (β) | Delta(δ) | Theta (θ) | | |
| 1 | 4.9 | 2.2 | 72.4 | 20.5 | 75 | 50 |
| 2 | 7.0 | 4.1 | 72.7 | 16.3 | 0 | 0 |
| 3 | 5.2 | 2.9 | 79.1 | 12.8 | 63 | 40 |
| 4 | 1.6 | 1.5 | 80.9 | 16.0 | 63 | 10 |
| 5 | 8.3 | 6.5 | 58.0 | 27.2 | 47 | 30 |

Based on Table 3, it is demonstrated that five respondents in the quiet environment showed brainwave patterns connected to relaxation and low cognitive demands.

Respondents 1 and 3 had strong delta and theta activity with high meditation scores, which represent focused but relaxed engagement. While respondent 2 had low meditation and attention scores instead of high delta waves, this might have happened due to poor sensor attachment or a lack of focus. Respondent 5 showed higher alpha and beta level, which indicate more mental focus and less relaxation.

Overall, from this investigation, the quiet environment supported relaxed mental engagement, where most respondents showed mid-level to high mediation and low attention efforts.

### *4.2. Loud Noise Environment Results*

The same participants repeated the Lego assembly task under a loud noise condition, where ambient sound was increased to 90 decibels using external speakers. EEG data and corresponding cognitive state metrics are presented in Table 4.

**Table 4. EEG and cognitive state data in a loud noise environment**

| Respondents | Frequency Band (%) | | | | Meditation (%) | Attention (%) |
|---|---|---|---|---|---|---|
| | Alpha (α) | Beta (β) | Delta (δ) | Theta (θ) | | |
| 1 | 17.2 | 6.4 | 49.3 | 27.1 | 53 | 69 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 2 | 13.1 | 5.9 | 59.0 | 22.0 | 30 | 66 |
| 3 | 11.5 | 7.0 | 61.9 | 19.6 | 88 | 37 |
| 4 | 5.2 | 3.1 | 77.3 | 14.4 | 56 | 70 |
| 5 | 9.3 | 9.6 | 49.9 | 31.7 | 1 | 57 |

An increment of Alpha and Beta wave activities has been detected among all respondents, indicating heightened cognitive and stress levels. Respondents 1 and 2 show higher attention scores, which imply a strengthened effort to maintain focus in the presence of auditory disturbance.

Different from Respondent 3, who shows high meditation and medium alpha activity but a decline in attention, suggesting a potential coping strategy involving partial disconnection.

Meanwhile, respondent 5 exhibited pronounced beta and diminished delta wave activity coupled with a low meditation score, representing cognitive strain and a minimal level of relaxation. These results indicate that the environmental noise raised mental workload and beta activity, also increased attention effort and reduced delta wave activity, and also meditation scores among respondents.

### *4.3. Comparative Group Analysis*

The comparative group analysis has been carried out to support the findings.

Group-level statistics have been determined for all respondents as shown in Table 5. The difference between conditions is increasing in Figure 7, as can be seen, during a noise environment, alpha and beta activities almost doubled, indicating a heightened cognitive workload. Meanwhile, delta activities have reduced significantly, consistent with a relaxed brain activity.

**Table 5. Group-level EEG frequency band and cognitive metric values (mean ± SD, n = 5)**

| Condition | Alpha (%) | Beta (%) | Delta (%) | Theta (%) | Meditation (%) | Attention (%) |
|---|---|---|---|---|---|---|
| Controlled noise | 5.4 ± 2.7 | 3.4 ± 1.8 | 72.6 ± 9.0 | 18.6 ± 6.1 | 50 ± 25 | 26 ± 18 |
| Loud noise | 11.3 ± 4.5 | 6.4 ± 2.5 | 59.5 ± 10.4 | 23.0 ± 7.2 | 46 ± 31 | 60 ± 15 |

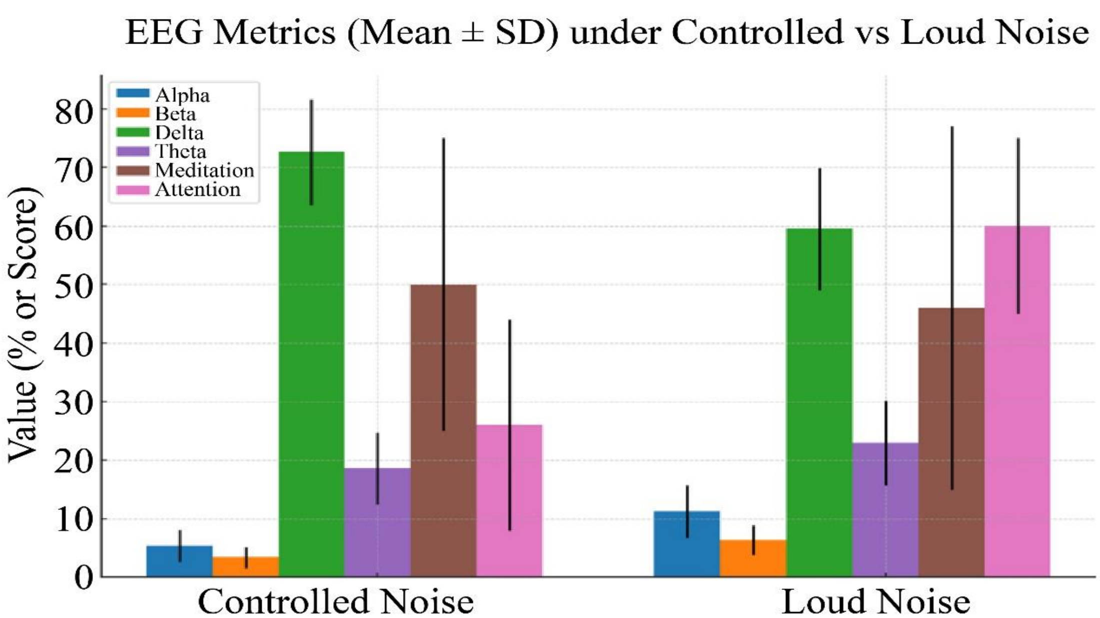


**Fig. 7 The contrast between conditions is visually pronounced when presented in bar plots**

As depicted in Figure 7, the comparative overview of EEG frequency bands and cognitive metrics under controlled and loud noise environments is shown. The grouped bar chart reveals a pronounced increase in alpha and beta activity during noise experience, linked with increased delta activity. Attention scores grew markedly; however, meditation scores showed a slight reduction. The error bars represent inter-individual variability across the respondents' group (n=5).

## 5. Discussion

The graphic patterns in Figure 7 have a good agreement as presented in Table 5. The increases in alpha and beta under noisy environments are statistically significant and show strong effect sizes as presented in the grouped bar chart. On the other hand, a decrease in delta power and a slight drop in meditation scores further highlight the disturbing effect of noise on cognitive relaxation.

Therefore, to evaluate the numerical result of the noticed changes in brainwave activity and cognitive metrics, a paired sample t-test has been carried out. The results of the t-test are shown in Table 6.

**Table 6. Paired t-test results comparing controlled and loud noise conditions**

| Types of Brainwaves | t-statistics | p-value | Interpretation |
|---|---|---|---|
| Alpha (α) | -3.122 | 0.035 | Significant increase in α wave activity |
| Beta (β) | -4.517 | 0.01 | Significant increase in β wave activity |
| Delta (δ) | 3.543 | 0.019 | Significant decrease in δ wave activity |
| Theta (θ) | -2.052 | 0.066 | No significant difference |
| Meditation Score | -0.029 | 0.49 | No significant difference |
| Attention Score | -2.345 | 0.05 | Marginally significant increase in attention |

The statistical results explain the investigational studies. Alpha wave activity has increased significantly under loud noise conditions, showing higher alertness. Similarly, the increase in beta wave activity reveals super cognitive load and mental effort. In contrast, the reduction in delta wave activity implies reduced relaxation, emphasizing the notion that noise disturbs a calm cognitive level. Theta wave activity changed slightly but not statistically significantly, likely due to differences between participants and the short test duration. Meditation scores also demonstrated no significant variation, possibly due to the NeuroSky algorithm not being very sensitive to small shifts in relaxation during brief experiments. However, attention scores increased slightly, suggesting that participants needed to focus harder to finish the task during noise exposures. The outcome from this research shows that environmental noise can affect cognitive level, even using a consumer–grade EEG system. Higher alpha and beta wave activity shows an increment in alertness and stress response, while lower delta activity reflects reduced relaxation. The findings verified the importance of managing noise in settings where focus and well-being are vital, such as in offices, lecture rooms, laboratories, and healthcare environments. Moreover, the investigation validates that the proposed EEG system can be useful to detect cognitive variations with low cost and real-time systems.

To place these findings in context, compared with previous EEG-based studies that relied on high-cost, multi-channel systems for noise-related cognitive analysis [6, 11-13], the present work demonstrates that comparable differentiation in alpha, beta, and delta activities can be achieved using a single-channel, low-cost NeuroSky headset integrated with an optimized LabVIEW interface. The system's enhanced performance stems from efficient FFT-based signal processing, controlled experimental design, and real-time visualization that minimize latency and noise interference. Unlike many existing methods that require offline post-processing or machine learning classification, this study provides an accessible and real-time cognitive monitoring solution. These improvements highlight the practicality and effectiveness of the proposed low-cost system for educational, industrial, and ergonomic applications, bridging the gap between research-grade EEG analysis and affordable real-world implementation.

## 6. Limitations and Future Directions

Several limitations constrain the general liability of the findings.

1. Sample size - The use of five participants limits statistical power. While paired-sample analysis revealed significant trends, larger cohorts are essential for confirming the reliability of these effects across diverse populations.
2. Single-channel EEG - The NeuroSky headset records only frontal-lobe activity. This provides limited spatial information and may not capture posterior cortical dynamics known to contribute to attentional processes.
3. Proprietary cognitive metrics - The attention and meditation scores are generated by undisclosed algorithms. While useful for exploratory research, they cannot be equated with validated neurocognitive measures.

Future work should therefore pursue three directions:

- Multi-channel expansion: Integrating more advanced EEG headsets would allow cross-regional analyses (e.g., frontal–parietal coherence), yielding richer insights into cognitive load distribution.
- Algorithmic transparency: Applying independent signal processing pipelines (e.g., machine learning classifiers on frequency-domain features) would mitigate reliance on black-box consumer metrics.
- Multimodal assessment: Coupling EEG with physiological measures such as heart rate variability or galvanic skin response would provide convergent validity and a more comprehensive picture of stress–cognition interaction.

Such developments would not only strengthen the scientific validity of consumer EEG research but also pave the way for adaptive human–computer interaction systems capable of responding intelligently to real-time cognitive states.

## 7. Conclusion

The proposed work proves that even low-cost EEG devices can detect significant neurocognitive differences generated by environmental noise. The incorporation of a consumer-grade headset with a LabVIEW-based processing framework enabled real-time monitoring of brainwave dynamics during task execution.

Three key contributions emerge from this research:

1. Empirical validation - Significant modulation of alpha, beta, and delta activity under noise confirms the sensitivity of consumer EEG systems to environmental stressors.
2. Methodological framework - The study introduces a replicable, low-cost pipeline for EEG signal acquisition, processing, and visualization suitable for educational, prototyping, and ergonomics research.
3. Applied implications - Findings highlight the role of acoustic conditions in shaping cognitive workload, underscoring the need for noise management in learning and industrial environments.

Although constrained by sample size and hardware simplicity, this study provides an important proof of concept. It shows that accessible EEG technologies, when carefully implemented, can serve as effective tools for cognitive state assessment, educational applications, and human–environment interaction research. With further refinement and scale-up, such systems hold promise for democratizing brain–computer interface applications beyond specialist laboratories.

## Funding Statement

This research was supported by the Ministry of Higher Education (MOHE) through the Fundamental Research Grant Scheme (FRGS/1/2023/ICT06/UTHM/02/2).

## References

[1] Mona Algarni, and Faisal Saeed, "Review on Emotion Recognition Using EEG Signals based on Brain-Computer Interface System," *International Conference of Reliable Information and Communication Technology*, Springer, Cham, Langkawi, Malaysia, pp. 449-461, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[2] Marwan Nafea et al., "Brainwave-Controlled System for Smart Home Applications," *2018 2nd International Conference on BioSignal Analysis, Processing and Systems (ICBAPS)*, Kuching, Malaysia, pp. 75-80, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[3] Li Yi Qin et al., "Smart Home Control for Disabled using Brain Computer Interface," *International Journal of Integrated Engineering*, vol. 12, no. 4, pp. 74-82, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[4] Syed M. Saddique, and Laraib Hassan Siddiqui, "EEG Based Brain Computer Interface," *Journal of Software*, vol. 4, no. 6, pp. 550-554, 2009. [CrossRef] [Google Scholar] [Publisher Link]

[5] Reza Fazel-Rezai et al., "P300 Brain Computer Interface: Current Challenges and Emerging Trends," *Frontiers in Neuroengineering*, vol. 5, pp. 1-14, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[6] Ashima Khosla, Padmavati Khandnor, and Trilok Chand, "A Comparative Analysis of Signal Processing and Classification Methods for Different Applications based on EEG Signals," *Biocybernetics and Biomedical Engineering*, vol. 40, no. 2, pp. 649-690, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[7] N. Veena, and N. Anitha, "A Review of Non-Invasive BCI Devices," *International Journal Biomedical Engineering and Technology*, vol. 34, no. 3, pp. 205-233, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[8] Sarah N. Abdulkader, Ayman Atia, and Mostafa-Sami M. Mostafa, "Brain Computer Interfacing: Applications and Challenges," *Egyptian Informatics Journal*, vol. 16, no. 2, pp. 213-230, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[9] Maggie S.M. Chow et al., "Functional Magnetic Resonance Imaging and the Brain: A Brief Review," *World Journal of Radiology*, vol. 9, no. 1, pp. 5-9, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[10] James E. Niemeyer, "Brain-Machine Interfaces: Assistive, Thought-Controlled Devices," *Lab Anim*, vol. 45, no. 10, pp. 359-361, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[11] Mahsa Soufineyestani, Dale Dowling, and Arshia Khan, "Electroencephalography (EEG) Technology Applications and Available Devices," *Applied Science*, vol. 10, no. 21, pp. 1-23, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[12] J. Katona et al., "Evaluation of the Neurosky Mindflex EEG Headset Brain Waves Data," *2014 IEEE 12th International Symposium on Applied Machine Intelligence and Informatics (SAMI)*, Herl'any, Slovakia, pp. 91-94, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[13] Shakshi, and Ramavtar Jaswal, "Brain Wave Classification and Feature Extraction of EEG Signal by using FFT on Lab View," *International Research Journal of Engineering and Technology*, vol. 3, no. 7, pp. 1208-1212, 2016. [Google Scholar] [Publisher Link]

[14] Michal Teplan, "Fundamentals of EEG Measurement," *Measurement Science Review*, vol. 2, no. 2, pp. 1-11, 2002. [Google Scholar] [Publisher Link]

[15] Rahmah Mokhtar et al., "Assessing Attention and Meditation Levels in Learning Process using Brain Computer Interface," *Advance Science Letter*, vol. 23, no. 6, pp. 1-5, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[16] S. Pawar, S.R. Chougule, and A.H. Tirmare, "Diagnosis of Epilepsy a Neurological Disorder using Electroencephalogram (EEG)," *International Journal of Modern Trends in Engineering and Research*, vol. 4, no. 6, pp. 144-149, 2017. [Google Scholar]