Memory Training in Dementia: A VR-BCI Prototype with N-Back and Brainwave Analysis

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***Abstract* — Dementia, a neurodegenerative condition leading to significant memory impairment in the elderly, currently lacks a curative treatment. Management strategies focus on mitigating symptom progression. This study presents the development and preliminary evaluation of a novel Virtual Reality (VR) game prototype integrated with Brain Computer Interface (BCI) technology designed to enhance memory, a key deficit in dementia, and potentially delay its progression. The VR game employed an adaptive N-back task for memory training, while a 4-channel OpenBCI system non-invasively monitored electroencephalography (EEG) signals from five healthy young adult volunteers (aged 18-22). Analysis of EEG power ratios revealed a trend towards increased alpha wave activity during memory encoding phases of the game. Specifically, during the Alpha EEG test, theta wave amplitudes were consistently higher across all channels (F3, F4, O1, O2) compared to alpha and beta waves. Furthermore, a descriptive trend indicated that theta wave amplitudes tended to increase with increasing difficulty in the Alpha EEG test. During the N-back tasks, theta wave amplitudes were observed to be descriptively higher during the memory encoding period compared to the recall period in frontal channels (F3, F4). The initial observations, while not statistically significant due to the limited sample size, support the feasibility of using the VR-BCI system to engage memory-related brain activity. To thoroughly evaluate the potential of this approach for cognitive rehabilitation and dementia mitigation, further comprehensive research involving larger and older cohorts utilizing longitudinal designs is warranted.**

***Index Terms*—Dementia, Brainwave, Brain Computer Interface (BCI), Virtual Reality (VR) game.**

I. Introduction

The growth of medical technology has led to an increase in average human lifespan and a concurrent decrease in birth rates, resulting in the emergence of aging societies. Thailand is currently experiencing this demographic transition, with an estimated 13 million elderly individuals. A significant health challenge within this population is dementia, characterized by symptoms such as forgetfulness, functional dependence, and potentially life-threatening situations. While a 2015 survey by the Thai Ministry of Public Health identified approximately 600,000 individuals aged 30-65 with signs of brain function deterioration, the increasing elderly population has led to a corresponding rise in dementia cases. In 2023, estimates suggested around 700,000 individuals in Thailand were living with dementia, with projections indicating further significant increases in the coming years due to the growing proportion of older adults [1]. Interventions aimed at preventing or delaying the onset of dementia include consistent cognitive training through continuous learning, academic engagement, and the use of brain games. Engaging in activities such as Scrabble and Sudoku can effectively stimulate both cerebral hemispheres, potentially reducing the risk and delaying the progression of dementia, while also improving mental function and concentration. In the dementia group, there were differences in brain wave activity [2, 3, 4, 5]. This has spurred the development of applications that integrate gaming with brain function monitoring, exemplified by technologies such as NeuroSky Mindwave, which facilitates game control via thought or concentration (e.g., meditation games), and Emotiv Insight, which translates brain signals into digital commands for movement within virtual reality environments.

Brain Computer Interface (BCI) is a technology that connects the brain to a computer, enabling the use of brain waves to control devices as needed. By processing brain wave signals through mathematical and engineering techniques, BCIs can interpret the user's thoughts to display information or control various devices. This technology supports a wide range of human activities, from controlling robots to developing neural networks. Because BCI measures brain activity non-invasively, the equipment used is generally portable and cost-effective [1].

In the medical field, BCI has been applied to facilitate interaction with computers or machines through the nervous system [6]. For example, VIT College has utilized BCI for emotion analysis using the Self-Assessment Manikin (SAM)

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and has contributed to training brain potential as well as rehabilitating brain symptoms that affect intention [7].

Virtual Reality (VR) is a technology that creates a simulated environment in which users can interact through devices such as VR headsets or joystick controllers. When wearing VR glasses, users are immersed in a virtual world, allowing them to experience the surroundings as if they were in a real place. VR technology is widely applied across various fields. In education, it is used for training diverse skills [8]; in medicine, it simulates surgeries; and in engineering, it assists in maintaining machinery. In therapy [9], VR helps treat patients by exposing them to virtual scenarios to overcome fears. In design, architects and engineers use VR to visualize and modify projects before actual construction begins.

For these reasons, the team proposed designing a VR game aimed at slowing the progression of dementia in the elderly by integrating BCI technology to analyze brain wave signal ratios during gameplay. The game monitors three groups of brain waves—alpha and beta waves, theta and beta waves, and alpha and theta waves—as indicators of brain function. This research primarily focuses on developing a prototype brain training game intended to enhance memory function and potentially delay the onset of dementia in older adults.

II. MATERIALS AND METHOD

A. Participants

A total of five healthy volunteers, aged between 18 and 22 years, were recruited for the preliminary study. All participants reported no history of neurological disorders, brain injuries, or any conditions affecting the nervous system. The purpose of this initial experiment was to establish baseline patterns and observe the trends in brain wave activity—specifically alpha, beta, and theta waves—during controlled tasks. These baseline data serve as a reference for subsequent studies involving older adults, enabling comparison and validation of the brain wave changes induced by the VR game intervention. The controlled environment and participant screening ensured the reliability of the brain wave measurements prior to application in the target population.

B. Neuropsychological Measures

Before beginning the test, all volunteers were required to complete a cognitive assessment to ensure suitability for participation. This screening utilized the Montreal Cognitive Assessment (MoCA) [10], a widely recognized tool designed specifically for the early detection of dementia. The MoCA evaluates multiple cognitive domains including attention, concentration, executive functions, memory, visuospatial skills (such as visuoconstruction), conceptual thinking, calculation abilities, and orientation. By comprehensively assessing these brain functions, the test helps identify subtle cognitive impairments that may indicate the onset of early dementia. This step was essential to select appropriate volunteers and establish a baseline cognitive profile before proceeding with the experimental tasks.

C. EEG Recordings and Analysis

Electroencephalogram (EEG) signals were recorded using an OpenBCI EEG measurement device. Data were collected from four electrode channels: F3, F4, O1, and O2. The EEG signals were transmitted wirelessly to a computer via Bluetooth for processing. Microsoft Visual Studio was used to enhance signal quality, process the incoming data, and separate the EEG signals into alpha, beta, and theta wave components. These signals were then used to compute three types of EEG power ratios [11]: the ratio between alpha waves and theta waves as in Equation 1 [12, 13, 14], the ratio between beta waves and theta waves as in Equation 2 and the ratio between alpha waves and beta waves as in Equation 3. To ensure consistency across participants, the data were normalized to equalize signal levels. The processed results were then visually represented as three dynamic bars within the VR game interface. These bars updated in real time based on the calculated power ratios. All power ratio values were continuously recorded and transmitted to the VR headset using a predefined communication protocol, enabling the integration of EEG data into gameplay mechanics, as illustrated in Figures 1 and 2.

$$\text{Alpha/Theta Power Ratio} = \frac{\text{Alpha Wave}}{\text{Theta Wave}} \quad (1)$$

$$\text{Beta/Theta Power Ratio} = \frac{\text{Beta Wave}}{\text{Theta Wave}} \quad (2)$$

$$\text{Beta/Alpha Power Ratio} = \frac{\text{Beta Wave}}{\text{Alpha Wave}} \quad (3)$$

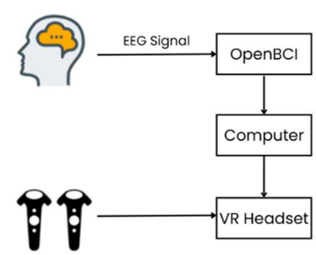

Fig. 1. Real-time EEG integration for gameplay

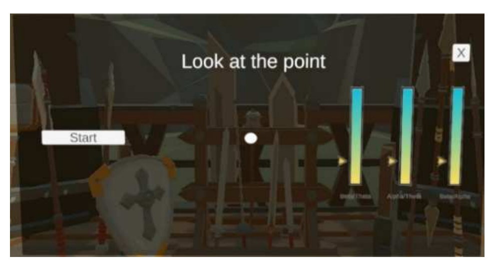

Fig. 2. In-game display with EEG power bar

D. VR Game and Character Design

The N-back task, commonly used in psychology and neuroscience, is an assessment tool designed to evaluate working memory and short-term recall. It is based on the principle that recalling previously presented stimuli is a core function of working memory, which is closely linked to the brain's capacity for handling complex cognitive tasks.

In this study, the N-back task was incorporated into the design of a VR game prototype aimed at enhancing memory function [15]. At the beginning of the game, players are presented with a map displaying a sequence of locations and objects. Players must navigate the virtual environment by following the correct order shown on the map. Upon reaching each designated point, players undergo an Alpha EEG test featuring varying difficulty levels, corresponding to alpha thresholds of 30, 50, and 80. These thresholds are intended to train the brain to increase alpha wave activity.

For each successful test, players earn a star as a point-based reward. To progress to the next level, all three stars must be collected within the given time limit. In the subsequent level, the map is removed. Players are required to recall and navigate to the correct positions from the previous level, introducing a Level 1 N-back task. This is further continued and advanced in Level 2. The objective of these tasks is to stimulate memory and recall abilities through repeated and increasingly challenging gameplay [16].

In addition, real-time EEG feedback is provided within the game interface. A visual bar graph displays the player's brain wave activity, and a countdown timer is shown from the start to the end of each level, adding a time-based performance element to the training.

E. Experimental Protocol

Prior to the experiment, all volunteers completed the Montreal Cognitive Assessment (MoCA) to establish baseline cognitive function. The MoCA scores were later used in conjunction with EEG data and in-game performance scores for analysis. Each volunteer was fitted with EEG electrodes and a VR headset, all connected to a laptop for real-time data processing and monitoring. To stabilize the initial EEG readings, volunteers were instructed to close their eyes for 30 seconds before beginning the VR game. The gameplay session lasted 45 minutes.

At the end of the session, volunteers were again asked to close their eyes for an additional 30 seconds to help stabilize EEG signals after the cognitive activity, as recommended in prior studies [17]. The full experimental setup is illustrated in Figure 3.

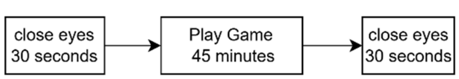

Fig. 3. Experimental protocol

III. RESULTS

The experiment to investigate the effects of the prototype VR game on memory improvement was conducted with five volunteers. The experimental procedure involved the following steps: Before beginning the game, volunteers were instructed to close their eyes and relax for 30 seconds to stabilize the baseline EEG signals. They then played the VR game for 45 minutes. Upon completing the game, volunteers again closed their eyes for an additional 30 seconds to stabilize post-task EEG readings.

EEG data were collected from four electrode positions: F3, F4, O1, and O2. Three types of brain waves—theta, alpha, and beta—were extracted and analyzed from the recorded EEG signals. The processed EEG data were then visualized in bar chart format to facilitate comparison and analysis of wave activity before, during, and after the task.

A. Comparison of EEG Levels Before, During, and After the Test

The results of the alpha wave enhancement task were analyzed across all four EEG channels. For each channel, the average values of theta, alpha, and beta waves were computed. These are illustrated in Figure 4, where:

Blue bars represent the EEG values *before* the test

Red bars represent EEG values *during* the test

Yellow bars represent EEG values *after* the test

From the bar chart, it can be observed that:

1. At position F3 (Channel 1), theta wave amplitude was consistently higher than that of the other waves throughout all periods. Only slight variations were observed between the pre-test, during-test, and post-test phases. Alpha and beta wave amplitudes remained relatively constant and were clearly lower than theta waves.

2. At position F4 (Channel 2), the pattern was similar to that observed at F3. Theta waves maintained the highest amplitude across all time points, with no significant changes detected between periods. Alpha and beta waves exhibited similar, consistently low amplitudes compared to theta waves.

3. At position O1 (Channel 3), theta waves again showed the highest amplitude. Slight differences were noted across the different time periods, particularly between the pre-test and post-test phases. Alpha and beta wave amplitudes remained relatively stable, consistent with observations from other channels.

4. At position O2 (Channel 4), theta waves were the dominant activity throughout all time periods. Minor fluctuations were observed during and after the test, while alpha and beta waves remained lower in amplitude than theta waves.

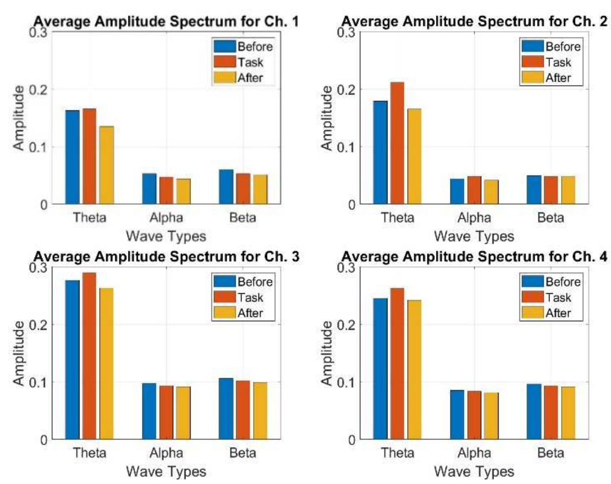

Fig. 4. Comparison of EEG levels before, during, and after the test

B. Comparison of EEG Levels Across Test Difficulty Levels

In the prototype VR game, the alpha EEG test was designed with three difficulty levels: 30, 50, and 80. Figure 5 presents the comparison of the average amplitudes of theta, alpha, and beta waves across the four EEG channels, segmented by test difficulty. The results are as follows:

1. At position F3 (Channel 1), theta wave amplitude was highest during the most difficult test level compared to the easier levels. Alpha and beta wave amplitudes remained relatively stable across all difficulty levels.

2. At position F4 (Channel 2), theta wave amplitude increased progressively with test difficulty, reaching its peak at the highest difficulty level. In contrast, alpha and beta waves showed minimal variation across different difficulty levels.

3. At position O1 (Channel 3), theta wave amplitude was greatest during the most difficult test and decreased as difficulty lessened. Alpha and beta wave amplitudes remained relatively constant and were consistently lower than theta wave amplitudes.

4. At position O2 (Channel 4), theta waves continued to dominate during the most challenging test level, mirroring patterns observed at other electrode sites. Alpha and beta wave amplitudes did not exhibit significant changes across the different difficulty levels.

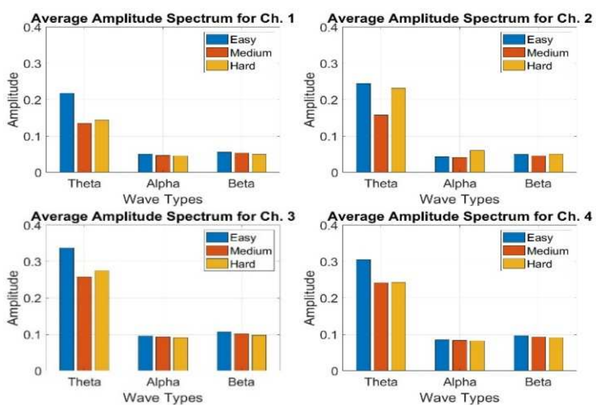

Fig. 5. Comparison of EEG levels across test difficulty levels

C. Comparison of EEG Levels with N Back Level 1

In the prototype VR game, memory difficulty levels were structured progressively from easy to difficult, comprising three levels: 1-back, 2-back, and 3-back.

At N back level 1, the volunteers played the game initially with example cues to observe and follow, followed by a second round without examples to test memory retention. This process served as a review of the volunteers' memory performance. At N back level 2, the volunteers completed two rounds with example cues and then repeated the same two rounds without examples, further evaluating their memory recall.

Figure 6 presents a comparison of EEG activity during the memory (with examples) and recall (without examples) periods, based on the average amplitudes of the three brain waves across channels:

1. At F3 (Channel 1), theta wave amplitudes were slightly higher during the memory period compared to the recall period. Alpha and beta wave amplitudes remained similar across both periods.

2. At F4 (Channel 2), theta waves followed a pattern similar to F3, with significantly higher amplitudes during the memory period than the recall period. Alpha and beta wave amplitudes remained low and stable throughout.

3. At O1 (Channel 3), theta wave amplitudes were high in both periods but were slightly greater during the recall phase, suggesting that memory retrieval may evoke stronger theta activity at this location. Alpha and beta waves remained low and consistent.

4. At O2 (Channel 4), theta wave amplitudes were higher during the memory period compared to recall, though the difference was less pronounced. Alpha and beta waves remained constant across both periods.

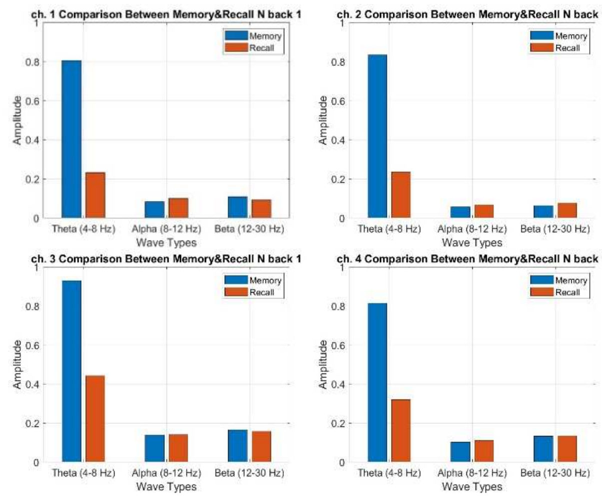

Fig. 6. Comparison of EEG levels with N back level 1

D. Comparison of EEG Levels with N Back Level 2

The results for N-back level 2, a more complex memory test, show a comparison of EEG activity between the memory and recall periods. Figure 7 presents the average amplitudes of the three brain waves across the four electrode positions, as detailed below:

1. At position F3 (Channel 1), theta wave amplitude was slightly higher during the recall period than during the memory period, indicating increased theta activity during recall. Alpha and beta wave amplitudes were similar during both periods and were significantly lower than theta waves.

2. At position F4 (Channel 2), theta wave amplitudes were comparable between the memory and recall periods, suggesting minimal change. Alpha and beta waves maintained similar values across both periods and were clearly lower than theta waves.

3. At position O1 (Channel 3), theta wave amplitudes were nearly identical during both memory and recall periods, remaining significantly higher than alpha and beta waves. Alpha

and beta waves showed consistent and low amplitudes across both periods.

4. At position O2 (Channel 4), theta waves were slightly more prominent during the memory period compared to recall, indicating somewhat greater theta activity during memory at this location. Alpha and beta waves remained approximately the same in both periods and were lower than theta waves, consistent with other channels.

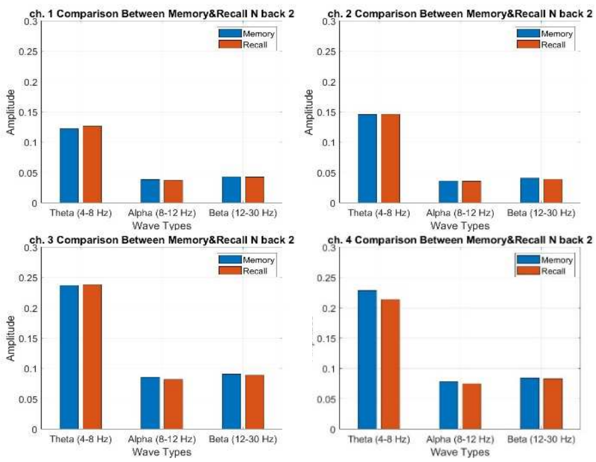

Fig. 7. Comparison of EEG levels with N back level 2

IV. DISCUSSION

The design and development of the VR brain training game, which integrates real-time brain wave monitoring through Brain-Computer Interface (BCI) technology, offer promising avenues for cognitive enhancement and rehabilitation. This study utilized the OpenBCI system, a non-invasive EEG device capable of measuring electrical brain activity across four channels (F3, F4, O1, O2), to capture neural signals during gameplay. The successful implementation of this technology demonstrated that brain wave data could be processed and translated into meaningful feedback within a VR environment, providing an immersive and interactive platform for cognitive training.

Volunteers were required to wear a dry electrode EEG headset during the experiment, which involved thorough skin preparation and precise electrode placement to ensure optimal electrical conductivity and signal quality. While dry electrodes offer greater convenience and are less invasive than traditional wet electrodes, they are also more susceptible to noise and motion artifacts. As such, maintaining cleanliness at the electrode sites was essential for obtaining reliable data. Furthermore, volunteers with no history of neurological or nervous system disorders were carefully selected to reduce potential confounding variables, ensuring that any observed changes in brain wave patterns could be reliably attributed to the effects of the memory training paradigm.

The EEG data revealed that, under resting and task conditions, theta waves consistently exhibited higher amplitudes than alpha and beta waves. This finding aligns with the understanding that lower-frequency brain waves such as theta (4-7 Hz) often dominate in relaxed or drowsy states, and may be amplified during prolonged gameplay due to cognitive fatigue or reduced alertness. Alpha waves (8-13 Hz), which are typically associated with relaxation and focused attention, showed a significant increase during the memory tasks within the VR game, suggesting heightened cortical engagement and concentration. Beta waves (13-30 Hz), linked to active thinking and problem-solving, remained relatively stable or decreased slightly with increasing task difficulty, possibly reflecting the shift in cognitive resource allocation towards sustained attention rather than rapid information processing.

The variation in brain wave activity with respect to task difficulty was particularly insightful. As the challenge level increased, both alpha and theta wave amplitudes rose, indicating that participants engaged more deeply with the task, possibly recruiting neural circuits involved in working memory and attention regulation. The decrease in beta wave activity could be interpreted as a neurophysiological trade-off, where the brain prioritizes resources for focused attention and inhibitory control over rapid cognitive processing. This dynamic modulation of brain rhythms underscores the sensitivity of EEG measures to cognitive load and suggests that the VR game effectively taxed working memory systems.

Further analysis comparing brain activity during memory encoding (the process of actively memorizing information) versus recall (retrieving stored information) at different N-back task levels provided additional insights. At N-back level 1, encoding elicited stronger theta wave activity than recall, consistent with the role of theta oscillations in facilitating hippocampal-cortical communication and working memory processes. The greater cognitive effort required during encoding activates prefrontal and parietal networks more intensely, reflected in the EEG patterns observed. At the more complex N-back level 2, theta wave differences between encoding and recall were less pronounced, suggesting that as task demands increase, the neural signatures of these cognitive processes may converge or that participants engage compensatory strategies during recall. These results align with neurocognitive theories that distinguish the neural correlates of working memory load and retrieval.

Despite the promising findings, the experimental protocol revealed practical considerations for future research. Some volunteers reported mild dizziness or discomfort following the 45-minute gameplay and extended EEG recording sessions. Such symptoms are common in VR environments due to sensory mismatch and prolonged immersion, and they underscore the need to optimize session length and include breaks to maintain participant well-being and data quality.

In summary, this study demonstrates the feasibility of combining BCI technology with VR gaming to create a novel platform for cognitive training. The observed modulation of alpha, beta, and theta waves in response to task demands and memory phases highlights the potential of this approach to engage and enhance brain functions relevant to memory. Future work should aim to refine electrode technology, expand participant demographics to include older adults or clinical populations, and explore long-term training effects to establish efficacy in slowing cognitive decline or improving memory performance.

V. CONCLUSION

This study on designing and developing a prototype VR game aimed at improving memory highlights several key findings. First, when comparing EEG signals before, during, and after the Alpha EEG test, theta waves consistently showed higher amplitudes than alpha and beta waves across all positions and time periods, with only minor variations observed throughout the test. Alpha and beta waves exhibited similar patterns across all positions and showed a slight increase during and after the test. Second, examining EEG activity in relation to the difficulty levels of the Alpha EEG test revealed that theta wave amplitudes increased noticeably as the test became more challenging. Alpha waves also showed a slight upward trend with increasing difficulty, while beta waves tended to decrease slightly across all difficulty levels. Despite these changes, alpha and beta waves remained significantly lower in amplitude compared to theta waves. Lastly, when comparing EEG activity during different N-back task levels, theta waves again demonstrated higher amplitudes than alpha and beta waves. Differences between the memorization and recall phases were more pronounced, although no significant variation was found across different electrode positions. During recall periods, alpha and beta waves were notably lower than theta waves, with a slightly greater difference compared to the memorization phase.

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